Essays on the Irish Labour Market

Nóirín McCarthy

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Abstract

The objective of this thesis is to explore issues in the Irish labour market from both the enterprise and employee perspective over the period 2005-2013. We draw on literature from the areas of job flows, displacement and monopsony.

Our analysis is primarily based on the unique P35 linked employer-employee dataset, containing almost two million employee observations annually. We also link this dataset to the Census of Industrial Production survey in Chapter 3.[1]

The first chapter introduces the thesis by detailing its main goals, the importance of this work, as well as summarizing the following chapters.

In Chapter 2, we provide an overview of the Irish labour market. Evidence suggests the economy experienced a significant increase in unemployment during the period. We also explore aspects of the resulting policy response.

We investigate job flows in the labour market in Chapter 3. Results indicate that job destruction increased significantly between 2006 and 2010 while job creation declined. When examining the impact of changing export intensity on job creation and destruction, our results suggest a small effect.

In Chapter 4, we estimate the earnings losses of displaced workers. We focus on two displacement events; mass-layoff and closure. Results indicate that workers who experience a mass-layoff incur greater losses relative to those displaced following a closure, as do those who switch to a new sector to secure re-employment following displacement.

[1] Both sources are available from the Central Statistics Office, Ireland.

We examine the labour market for evidence of monopsony in Chapter 5. We find that estimated labour supply elasticities to the firm are low, implying that elasticity is not infinite as suggested by perfect competition, and so employers possess a degree of monopsony power.

Chapter 6 summarizes the findings, highlights contributions to the literature, outlines policy implications and describes possible directions for future research.

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Chapter 1 : Introduction

1.1 Overview of the thesis

This thesis examines the Irish labour market during a period of remarkable change between 2005 and 2013. While the Irish economy experienced exceptional growth during the Celtic Tiger[2] years, it also suffered an unprecedented decline in 2008. We investigate the labour market from both the enterprise and worker perspective using linked employer-employee data. In the first essay (Chapter 3), we estimate the magnitude of job flows in the Irish economy over the period 2006-2010, as well as investigating the relationship between job creation and destruction and international trade. In the second essay (Chapter 4), we estimate the impact of job displacement on the earnings of workers in the Irish economy between 2005 and 2011. In the third essay (Chapter 5), we investigate if there is evidence of monopsony in the Irish labour market by estimating enterprise-level labour supply elasticities, using data from 2005 to 2013. The contribution of this thesis is to provide new empirical evidence to the relevant literatures. The thesis also focuses on the Irish labour market throughout.

Exploring each of these issues in the labour market using linked employer-employee data is an important contribution. Firstly, this is the first time that such an extensive linked employer-employee administrative dataset has been used in an Irish context. Specifically we use the P35 dataset constructed by the Central Statistics Office (CSO), using data from the Revenue Commissioners and the Department of Social Protection, as well as the CSO's Business Register. With all employers required to make returns for all their employees, the end results are annual files, commencing in

[2] The Celtic Tiger generally refers to a period between the 1990's and mid 2000's when the Irish economy experienced high economic growth.

2005 with around two million individual observations in each year. Much of the empirical evidence from other studies presented in this thesis is based on survey data or a sample of linked employer-employee data. The P35 dataset contains key information on enterprises[3] and workers including their annual earnings. The coverage of the data facilitates the tracking of individuals and enterprises over time. Its size also adds weight to the representativeness of our findings and conclusions.

Secondly, taking a demand-side perspective in the labour market provides policy makers with important information on the allocation of jobs in the economy. Through an analysis of job flows, we can unmask the trends in labour market employment which may remain hidden when looking at aggregate employment changes. Such trends include differing job creation and job destruction rates by enterprise size or sector, as well as an exploration of the role of exporting and importing activity on these job flows. Policy makers can use this information to identify the importance of job creation in small enterprises, as well as inform their assessment of the relationship between involvement in international trade and employment growth. This is investigated in Chapter 3.

Thirdly, by exploring the supply-side of the labour market, we can identify the impact on earnings of employees who are displaced from their jobs, either due to a closure or mass-layoff event. To the best of our knowledge, this is the first time such an investigation has been conducted in an Irish context. Understanding the magnitude of these losses can help inform any policy response to such events. The earnings losses and future re-employment probabilities of displaced workers may be

[3] An enterprise is defined by the CSO as per EU statistical legislation. It is the smallest combination of legal units that is an organisational unit producing goods or services, which benefits from a certain degree of autonomy in decision-making, especially for the allocation of its current resources. An enterprise carries out one or more activities at one or more locations (OECD 2016).

related to demographic characteristics or other factors such as whether they secure re-employment in the same sector or move to another sector after displacement. This is investigated in Chapter 4.

Fourthly, we provide evidence on the degree of wage setting power of employers. As Manning (2003: 336) notes the lack of a good estimate of the elasticity of the labour supply curve facing a firm is detracting from the empirical evidence on monopsony power. This is because it is this elasticity that ultimately determines that power. We attempt to fill this gap using our large administrative dataset.

1.2 Summary of Chapter 2

In Chapter 2, we provide an overview of the Irish labour market. There were significant changes in employment from 2005-2013 and this chapter provides the background and context to the rest of this thesis. We document employment, earnings and migration changes, as well as the policy response of government to rising unemployment and declining economic growth.

1.3 Summary of Chapter 3

This chapter explores job flows in the Irish economy over the period 2006-2010. We initially focus on NACE Rev.2 sectors B-N and document rates of job creation and job destruction across sectors and enterprise-size categories, as well as the persistence of job flows. Given the importance that is placed on export-led growth by policy makers in Ireland, we look for evidence on the relationship between international trade and job flows in the Irish manufacturing sector. In order to do this, we link our P35 data with Census of Industrial Production (CIP) survey data as the P35 data does not contain information on enterprises exporting and importing activities.[4] This is the first time these datasets have been linked.

We follow the methodology of Davis & Haltiwanger (1992) in constructing our job flow measures. This involves computing an employment growth rate by comparing enterprise-level employment at year *t* and *t-1*. To sum employment growth across enterprises, a weight is defined to account for the size of the enterprise in computing job creation and job destruction rates for all enterprises using the P35 data. Having merged the two data sources, we focus on the manufacturing sector and use regression to estimate the relationship between employment growth and exporting and importing activity.

This chapter represents the first study to explore job flows using this extensive dataset in the Irish labour market. This is important for two reasons. Firstly, we gain a deeper understanding of the magnitude of job flows and how these have changed over the period in question. Secondly, we contribute to the literature and empirical evidence on the relationship between job flows and enterprise size, and between job flows and international trade activity of enterprises.

1.4 Summary of Chapter 4

In this chapter we estimate the impact of worker displacement on earnings losses over the period 2005-2011. Our available data facilitates the identification of two displacement events – enterprise closure and a mass-layoff. In doing so we are able to compare the losses of those affected by each displacement event. We also examine whether securing re-employment in the same sector a worker was displaced from matters in explaining earnings losses of these workers. As well as earnings

[4] Both micro-data sources are available from the Central Statistics Office, Ireland subject to successful application for access.

losses, we also examine the probability of re-employment after both closure and mass-layoff events.

The approach used in this chapter initially involves implementing propensity score matching to match displaced workers with non-displaced workers who have a similar propensity to be displaced. We then use a difference-in-differences estimator to estimate earnings losses of the displaced group relative to the non-displaced group of workers. Many of the previous studies that have investigated this issue either used survey data or have used a smaller sample of administrative data, when compared to this thesis.

Another important contribution of our work is to consider both closure and mass-layoff events. Due to data constraints, some previous empirical studies have focused on one of these events. We add to the existing literature by examining whether the earnings losses differ by the type of displacement event. Also, given the large number of workers who are unemployed during the period, this research helps to identify if particular groups of workers, such as older workers, are at greater risk of displacement and if they suffer larger earnings losses once they re-enter employment compared to other groups.

1.5 Summary of Chapter 5

The widespread applicability of the classical view of monopsony, with one employer and a large number of sellers of labour is questionable. However in this chapter we draw on the previous work of Manning (2003) and others who have extended the traditional view of monopsony to a dynamic monopsony model. Such an approach allows for employers to have significant wage setting power, even when there are many employers competing for workers. Using P35 data from 2005-2013, we build on previous empirical work to estimate the firm-level labour supply elasticities. We also explore the role of monopsonistic discrimination in explaining pay differentials among groups such as native-immigrant workers and the gender pay gap.

To estimate these labour supply elasticities our methodology is based on survival analysis. To this end we construct a spell-based panel which allows us to follow the labour market transitions of workers. Our dataset allows the identification of transitions to and from employment as well as to and from non-employment. This has not always been possible in previous studies.

This chapter contributes to the existing literature and evidence on the relevance of monopsony, rather than perfect competition, as an explanation of the wage setting behaviour of firms. It also adds to the discussion on the role of monopsonistic discrimination in explaining wage differentials across segments of the labour market such as the native-immigrant wage gap or the gender pay gap. To the best of our knowledge, the dataset used here is more extensive in terms of the number of workers included than those used in previous studies.

1.6 Concluding remarks

This thesis seeks to contribute to the current knowledge and evidence in the literature on job flows, displacement and monopsony. Each of these essays gives unique insights into different aspects of the labour market and represents distinct contributions to the literature. In an Irish context, chapters 4 and 5 represent the first time such issues have been explored. Internationally, the data used in this thesis is unique given its coverage. Chapter 3 is a first in an Irish context, given the use of administrative data.

We focus on Ireland over a period of dramatic changes in the economy and labour market, which makes it a particularly interesting study. This will be highlighted and explored in Chapter 2.

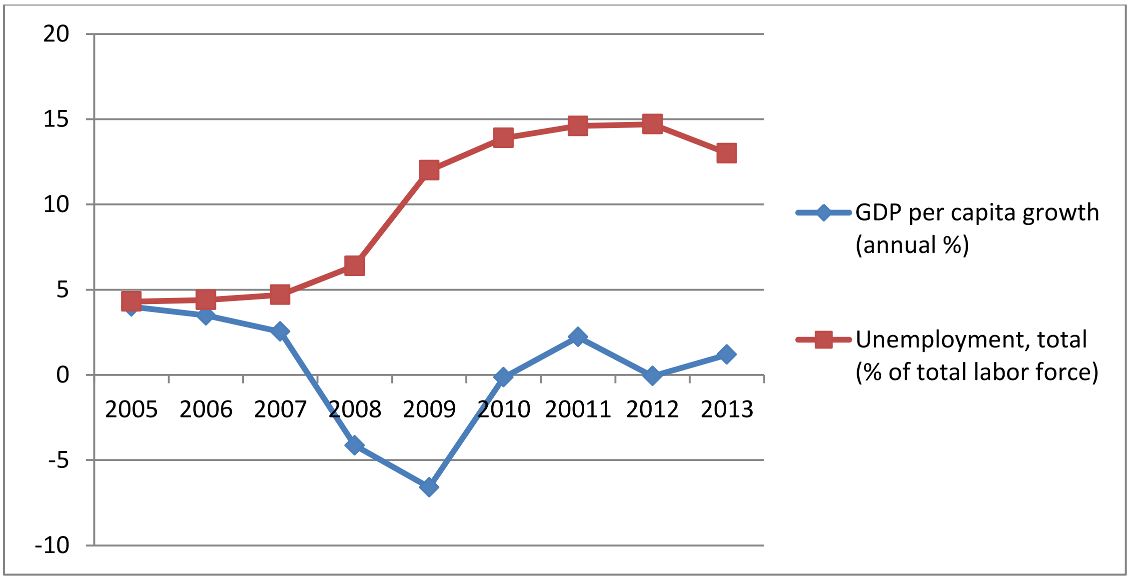
The data used is a unique feature of our work and an important aspect of the contribution of this thesis. The P35 data is extensive and covers all employees in the Irish labour market. This is highly novel as it means we do not rely on survey data or a sample of administrative data. A key advantage of our data is that this coverage facilitates the tracking of enterprises and individuals over time and ensures we can add to existing knowledge in the areas of job flows, displacement and monopsony. A potential drawback of the data is that it does not include as rich a set of explanatory variables as may be available through the use of survey data. However, we suggest the universal coverage of employees more than offsets this drawback.

Chapter 2 : An Overview of the Irish Labour Market

2.1 Unemployment and Economic Growth

Over the past decade, Ireland has experienced both an unprecedented period of sustained growth followed by a sharp downturn. The year of 2008 proved to be a dramatic turning point for the Irish economy and by 2009 economic growth slowed significantly with year on year GDP growth falling by almost 7%. As the figure below demonstrates, this led to large changes in unemployment which rose from approximately 4% in 2005 to over 14% in 2011.

Figure 2.1 GDP growth and Unemployment rate in Ireland 2005-2013



Source: The World Bank (2016)

By the end of 2013 the unemployment rate had fallen slightly to 13%. In this turbulent economic environment, any insights that can be obtained about the operation of the labour market are likely to be extremely valuable from a policy perspective.

While unemployment increased significantly, the incidence of unemployment was not spread evenly across all sectors. The construction sector (F) was particularly adversely impacted with the numbers in employment falling from over 272,000 in quarter 1 of 2007 to just over 184,000 in quarter 1 of 2009. This fall continued up to quarter 1 of 2013 when the number employed was just over 97,000. Other sectors also experienced declines, especially sectors B-E, including the manufacturing sector (C), which accounts for a large proportion of total employment within this grouping. A general trend of increasing employment up to 2008 was followed by a rapid decline thereafter with many experiencing a slight recovery, or at least a lower rate of employment decline in 2012/13.[5] The percentage of workers in part-time employment also increased over the period, rising from 17% in 2005 to a high of 25% in 2013. At the same time, there was an increase in the percentage of part-time workers who reported that they were under-employed, rising from 24% in 2008 to 33% in 2011, suggesting that some workers in part-time employment were seeking more hours (Central Statistics Office, Ireland 2015b).

While many sectors experienced a decline in employment, others experienced growing employment. Sectors O, P and Q (broadly classified as the 'Public Sector') saw large increases in the number employed in public administration & defence (O), education (P) and especially human health & social services sector (Q). This sector experienced an expansion of over 63,000 workers between quarter 1 of 2005 and quarter 1 of 2013.[5]

A further trend over the period was the large increase in the long-term unemployed (those unemployed for more than 12 months). In the first quarter of 2005, the long term unemployment rate was 1.5% (Central Statistics Office, Ireland 2015b). However, by the end of 2012 this figure had increased to over 12%. Young workers aged 15-24 years saw a big increase in unemployment with youth unemployment

[5] See Appendix Table 1.1 for further details.

rising significantly from around 8% in 2005 to just over 30% in 2012, after which it began to decline slowly (Central Statistics Office, Ireland 2016c). Such high unemployment rates mean the unemployed face a great challenge in securing re-employment. For younger workers, lack of work experience and human capital may impact in the long-term on their future employability.

Part of the substantial increase in unemployment can be explained by an increasing number of enterprise deaths over the period. Across NACE sectors B-N there was a significant increase in the percentage of deaths, with an average death rate of 5% in 2006, doubling to a rate of 10% in 2010.[6] The largest increase occurred in construction (F) where deaths increased from 10% in 2006 to 16% in 2009 (Central Statistics Office, Ireland 2016a). These changes across all sectors suggest that there has been a sizeable number of jobs destroyed and employees displaced in the Irish economy, either due to enterprise deaths or the layoff of workers. Declining economic growth and a rising incidence of unemployment certainly makes securing re-employment challenging.

Much emphasis has been placed on the role that small firms can play in the creation of jobs in Ireland. As part of the Action Plan for Jobs (2012), small firms are said to be in a unique position to create jobs in this country. According to the Central Statistics Office (2016d) Business Demography data, there were 185,530 active[7] enterprises in Ireland in 2012, the most recent year for which data is available. Of those enterprises, 182,642 are classified as being small with less than 50 employees and employ 598,404 employees or 49% of all employees. The majority of these

[6] See Appendix Table 1.2 for further details.
[7] Active enterprises have employees and make corporation tax and income tax returns.See http://www.cso.ie/en/surveysandmethodology/multisectoral/businessdemography/backgroundnotes/

enterprises (168,281) have less than 10 employees and employ about 27% of all employees.

2.2 The earnings of workers

Not surprisingly, given the turbulent economic conditions, many of those in employment experienced falls in employment earnings over the period (Central Statistics Office, Ireland 2016b).[8] There is significant variation in gross average weekly earnings across sectors with those in arts, entertainment, recreation and other service activities (R,S) earning approximately €468 in Q1 of 2013, while those in the electricity, water supply and waste management (D,E) sectors, dominated by semi-state companies, earn approximately €1,070 per week. As a result of the significant decline in the property market during the period, there is evidence that both the construction sector (F) and real estate activities (L) saw declines in weekly earnings of 11% and 22% respectively. Public sector employees (O, P, Q) were not insulated from this trend. Public sector pay cuts were announced in 2009 and this is reflected in average weekly earnings falling by between 3% and 5%. When we look at employment and earnings figures together, we see that certain sectors like Industry, which includes NACE sectors B-E, did see a decline in the numbers employed over the period. However, those who remained in employment in these sectors actually experienced a slight increase in their wages of 5%. Thus it seems that those who remained in employment in these sectors did not see an adverse impact on their wages, with the burden of adjustment appearing to fall on those who lost their jobs.

Changes in taxation also had an impact on the earnings of workers in both the public and private sector. In 2011, the Universal Social Charge (USC) was introduced. Those with gross earnings of less than €13,000 were exempt from the tax while other

[8] See Appendix Table 1.3 for further details.

workers pay at rates dependant on their gross income, with rates of up to 8% on any income over €100,000.

2.3 The Government response to rising unemployment

In response to the high levels of unemployment, the Irish government took a series of steps to support job creation and increase employment. The National Recovery Plan 2011-2014 was published in 2010 and placed a strong emphasis on the significant role exporting could play in the country's economic recovery. The relatively small size of the domestic market means that the Irish economy cannot rely solely on this market for sustainable long term growth and its export base is of great importance for such a small open economy. With the anticipation of export-led growth, there was also an expectation in the Plan that this would lead to the generation of employment deemed to be vital for the recovery process. It recognised the need for the creation of sustainable, "high-value" employment opportunities (Ireland 2010: 22).

In 2012, the government launched the *Action Plan for Jobs*. This is one of the key policy instruments devised to facilitate and support job creation. It placed an emphasis on enhanced co-ordination and co-operation among government departments and support agencies. Its key goal of job creation was achievable partly through enhanced exporting activity and export-led growth. Within the Action Plan, the government acknowledges the need for targeted initiatives to support specific sectors. It has indicated that it believes the manufacturing sector will be one of the sectors that offer significant job creation potential. It expects the sector to add 20,000 jobs within the next five years. The importance of the sector for the economy is highlighted because of its potential contribution to economic growth. Even though the sector accounts for less than 10% of employment, it is responsible for over 30%

of GDP (Ireland 2012a). While up to date evidence suggests that unemployment is falling and economic growth is recovering, the OECD in a 2014 review of the Action Plan for Jobs, pointed to a greater need to link targets, actions and outcome indicators (OECD 2014).

The Irish government has taken a number of steps to assist firms. One such example is through Enterprise Ireland which is the government agency responsible for the development and growth of Irish enterprises in international markets. Its support of enterprises is focused on their export potential, as well as their job creation potential. It has a series of supports to assist businesses in these areas. Two such supports are the 'Potential Exporters Division' and the 'Job Expansion Fund.' The former is designed to assist enterprises with real growth potential to re-orientate from the domestic to the international market. The latter is designed to help enterprises achieve growth through increased employment (Department of Jobs, Enterprise and Innovation, 2012).

The Industrial Development Authority (IDA)[9] has a stated goal of attracting 50% of investment in Ireland to locations outside of Dublin and Cork between 2010 and 2014 (IDA Ireland, 2010). Regional industrial policy has played a role in Ireland since the 1950's and is another mechanism through which policy makers endeavour to facilitate job creation by enterprises.[10]

As well as efforts to ensure jobs were created and boosting the employment prospects of the unemployed through the *Action Plan for Jobs*, emphasis was also placed on the supply-side of the labour market. *Pathways to Work* was designed to

[9] The IDA supports overseas companies seeking to establish a base in Ireland.
[10] Chapter 3 examines the performance of regions in terms of job flows with respect to manufacturing enterprises.

ensure that new positions and vacancies that arose within enterprises were actually filled by unemployed people. It is essentially a strategy covering the period from 2012-2015. The labour market activation policy of the government was built around five key strands. These strands included ensuring individuals have incentives to take up employment and that these individuals engaged with government agencies to assist them find re-employment. Institutional reform was identified as being required to support labour market activation in an effort to provide a "one-stop-shop" for both labour market activation and benefits support (Ireland 2012b). For example, the National Competitiveness Council (2013)[11] suggested that while a number of labour market activation programmes had been launched, there was a need for a co-ordinated approach to be taken to ensure the unemployed had an awareness of the availability of such schemes and know how to access them. In an effort to address this *Intreo*[12] offices were being established. Other new labour activation programmes were launched to enhance the employment opportunities of unemployed individuals such as *JobBridge.*[13]

A particular emphasis was placed on assisting the long-term unemployed find re-employment. It was recognised that policies were needed to enhance their employability as well as incentivising employers to hire from the pool of unemployed individuals. Employers paid reduced rates of pay-related social

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[11] The National Competitiveness Council reports to the Irish government on important competitiveness issues, providing advice and recommendations on how it can be improved.

[12] Intreo act as the single point of contact for unemployed individuals, providing details on income activation supports, run by the Department of Social Protection.

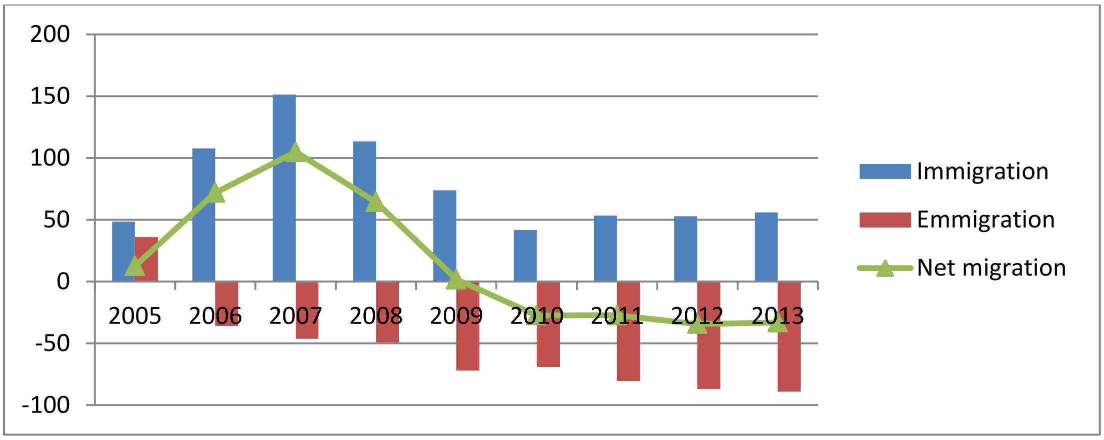
[13] "JobBridge is the National Internship Scheme that provides work experience placements for interns for a 6 or 9 month period. The aim of the National Internship Scheme is to assist in breaking the cycle where jobseekers are unable to get a job without experience, either as new entrants to the labour market after education or training or as unemployed workers wishing to learn new skills". See http://www.jobbridge.ie/

insurance (PRSI)[14] for new employees hired who had been in receipt of social welfare payments for six months or more.[15]

2.4 Migration and the Irish Labour Market

In the face of rising unemployment and wage cuts across both the public and private sector, labour market participants faced a choice about whether to stay in the Irish labour market. Rapid and significant changes occurred between 2005 and 2013 in terms of migration patterns in Ireland. As can be seen from Figure 2.2[16], there was a large inflow of immigrants annually up to 2007 which then declined steadily up to 2010. Barrett (2012) notes that this initial surge in immigration was partly fuelled by the fact that only Ireland, the UK and Sweden offered full access to the labour market to individuals from the new accession member states following European Union (EU) enlargement in 2004.

Figure 2.2: Migration patterns in Ireland 2006-2013



Source: Central Statistics Office, Ireland (2009, 2012, 2015a)

According to Barrett and Kelly (2012), there was an 85% increase in the number of non-nationals aged over 15 years in Ireland between quarter 3 of 2004 and quarter 3 of 2007. Another important factor noted by Barrett (2012) is that Ireland was also

[14] PRSI are payments made by employers and employees to a social insurance fund in Ireland.
[15] The Employer Job (PRSI) Incentive Scheme was introduced in Budget 2010 and ceased for new entrants in 2013.
[16] Emigration figures can include those who previously migrated into Ireland.

experiencing rapid employment and economic growth at this time. This made Ireland an attractive location for those seeking to move outside of their home country. The decline in immigrants from the EU accession states was the largest at 78% between 2006 and 2013. It appears that reduced employment prospects discouraged immigration from these countries to Ireland.

With such positive prospects up to 2008, immigrants may have been confident of their earnings potential in Ireland. However, there is some evidence of a native-immigrant wage gap. It appears that the country of origin of the immigrant worker matters in determining the magnitude of this gap. While Barrett and McCarthy (2007) find that having controlled for education and experience, immigrants in Ireland earn 18% less than native workers, this hides significant heterogeneity among immigrants. Those from English speaking countries experience relatively little, if any, deviations from the wages of natives while those from non-English speaking countries can experience gaps of around 31%. Later work by Barrett et al. (2012) suggests that differences in earnings may be related to difficulties experienced by immigrants in securing a return to their human capital investments. They suggest a possible reason for this could be the failure of employers to recognise immigrants' qualifications. Specifically they find little evidence of a gap at the lower end of the earnings distribution but do find evidence of a native–immigrant gap at the higher end of the earnings distribution.

An interesting feature of the immigrants in Ireland is their level of educational attainment. Evidence from previous Irish studies suggests that immigrants are well educated. Barrett et al. (2006) uses data collected from the 2003 quarter 2 release of the Quarterly National Household Survey in Ireland and reports that while over 50% of immigrants have third level qualifications, around 30% of the native Irish workers do. They point out that this differentiates Ireland from other countries such as the USA where the immigrants have generally been low skilled workers. This evidence has been supported by later work from Barrett and Duffy (2008) who use 2005 data to show that generally, the immigrant population are highly educated. More recent evidence from the CSO (2011) also supports this as seen in Table 2.1 below.

Table 2.1: Educational attainment levels by nationality April – June 2011; 15-64 years

	Country				
Highest level of education attained (%)	**Irish**	**United kingdom**	**Other EU 15**	**Accession States**	**Other**
Primary	11	7	2	5	7
Lower secondary	19	17	5	8	9
Upper secondary	26	22	19	41	21
Post Leaving Cert	12	11	9	15	9
Third Level	32	43	65	31	54

Source: Central Statistics Office, Ireland (2011)

In their Quarterly National Household Survey; Educational Attainment Report (2011), they find that in quarter 2 of 2011, around one third of Irish Nationals between the ages of 15-64 had attained a third level qualification. This was lower than the corresponding figures for UK nationals (43%) and the EU 15 countries (65%) that are usually resident in Ireland. However, it is noted that among 25-34 year olds, Ireland had the highest percentage of people (48%) with a third level qualification among all EU member states.

Emigration increased from Ireland over the period, with the largest number being Irish citizens. While just over 15,000 Irish citizens emigrated in 2006, this increased to over 50,000 in 2013, representing a 233% increase.[17] With the unemployment rate peaking in 2012, it appears that many Irish workers were either unable to secure employment or perhaps not satisfied with their employment prospects and decided to

[17] See Appendix Table 1.4 for further details on migration.

emigrate. While Irish immigrants did return to the Irish labour market, the percentage decrease in those returning between 2006 and 2013 is 17%. It could be argued that the unemployment rate may have been even higher over the period if migration patterns had not changed so significantly.

2.5 Concluding remarks

In this chapter, we have provided an overview of some of the changes in the Irish economy over the period of the study. As noted, economic growth fell significantly, unemployment increased and migration patterns changed markedly with a large increase in emigration and a decrease in immigration. As we have seen, there was a response by policy makers, prioritising an export-led recovery to generate employment and economic growth. Thus this chapter gives an insight into the labour market analysed in the remainder of this thesis.

Chapter 3 : An Analysis of Job Flows in the Irish Economy

3.1: Introduction

As documented in Chapter 2, the Irish economy has experienced dramatic changes over the last decade, with spiralling unemployment and a significant decline in economic growth. In this context, any insights that can be obtained about the labour market and associated job flows are likely to be extremely valuable from a policy perspective. This is achieved through using linked employer-employee data. While not essential for estimating job flows, the dataset utilised in this thesis is large and extensive in coverage of enterprises and associated employment levels.

Focusing only on employment and unemployment levels and associated trends within an economy or sector for example is useful, but it should be acknowledged that it can hide significant heterogeneity. As noted by Konings (1995), differing job creation and job destruction rates can result in the same net employment change and thus may be concealing the degree of volatility or flexibility in the labour market. Focusing on job flows provides an opportunity to conduct more detailed analysis of employment changes over time and across sectors for example. By examining job creation and job destruction rates, we get more detailed information on employment dynamics within the labour market, and at a more disaggregated level also. We know that certain sectors of the economy such as construction have been significantly adversely affected by the onset of the recession in Ireland. While this sector has often been highlighted in discussions as suffering a large decrease in employment, analysis of the rate of job creation and job destruction within other sectors over the period should also be useful in identifying the degree of structural change within sectors of the economy. Such an analysis may identify those sectors or types of enterprises that have a tendency to grow and create jobs over time, as well as those that are more likely to contract.

This research contributes to the existing literature in a number of ways. The first aim of this chapter is to provide a detailed account of job flows in the Irish economy using linked employer-employee data which has not been done before. Initially the chapter focuses on the business economy which comprises of NACE Rev. 2 sectors B-N. The magnitude of job flows is examined and they are considered in the context of international evidence. Comparisons are drawn based on enterprise attributes such as size and sector.

Secondly, this chapter examines how job flows within manufacturing enterprises are affected by an enterprise's level of involvement in international trade. As noted in Chapter 2, the Irish government has identified export-led growth as one of the primary ways of generating employment and economic growth. The chapter seeks to identify if employment growth rates vary across enterprises that are involved in international trade through exporting and importing activity compared to those who are not. Related to this, the impact of exporting and importing activity is also investigated to determine the extent to which such activities are associated with job creation and job destruction. This will arm policy makers with vital information on the relationship between exporting activities and job creation and job destruction in the manufacturing sector. This chapter proceeds as follows. Section 3.2 reviews the literature in relation to job flows, while section 3.3 describes the data and methodology. Section 3.4 details our findings, while section 3.5 concludes.

3.2: Literature Review

In order to gain a greater understanding of labour market flows, this section reviews previous literature and evidence in relation to job flows. We begin by exploring the magnitude of job flows across countries (3.2.1), as well as job flows by industry (3.2.2). We then examine theoretical issues and evidence on the relationship between job flows and firm size (3.2.3) and region (3.2.4) before turning to evidence on job flows and international trade (3.2.5). Section 3.2.6 concludes.

3.2.1 The magnitude of job flows across countries

We begin by re-asserting here that our focus is on job flows. Davis, Haltiwanger & Schuh (1996a) note that the economic factors that affect worker flows, the hiring and separation of workers, can be categorised as either 'demand-side' or 'supply-side.' Demand-side issues reflect the fact that employers can create and destroy a significant number of jobs on a quarterly basis. Supply-side events such as retirement or family relocation can also occur which cause workers to change employment status. This chapter focuses on the demand-side perspective. An examination of job flows can lead to a greater understanding of labour market dynamics. Davis & Haltiwanger (1992) and Lane, Stevens & Burgess (1996) note that looking at the net change in employment only could be misleading when analysing the labour market as there are often high levels of job creation and destruction. A similar point in made by Lawless & Murphy (2008) who highlight that figures on aggregate employment changes can hide significant amounts of job creation and destruction within enterprises, with simultaneous job creation and destruction occurring.

We firstly examine evidence on job flows from the US and Canada before turning to evidence from European countries. Much of the earlier work conducted in the US is attributed to Steven Davis, John Haltiwanger and Scott Schuh. Davis & Haltiwanger (1999) review studies conducted on job flows in the US labour market. It is noted that the studies differ in terms of the period of time covered, the sampling interval used, how the business unit is defined and also the sectors that are covered. But given this, there are still some noteworthy features of the data. For example, the pace at which jobs are created and destroyed is of interest – approximately 10% of jobs are both created and destroyed each year.

Earlier work of Davis & Haltiwanger (1992) examined gross job creation and destruction in the US manufacturing sector between 1972 and 1986. Specifically they measured heterogeneity in employment changes at the level of the establishment. Heterogeneity was measured in terms of gross job creation and job destruction as well as employment reallocation. Their methodology which is described in detail in section 3.3.4 has been used widely by others and forms the basis for the methodology used in this chapter. Briefly, they define job creation by adding employment gains in growing or new establishments and this is weighted by the size of an establishment in a given sector. Job destruction is based on employment losses in declining or exiting establishments within a sector. Equations (3.1) and (3.2) below are adapted from Davis & Haltiwanger (1992: 828).

$$\mathrm{POS}_{st} = \sum_{\mathrm{e} \in \mathrm{E}_{st}:\, \mathrm{g}_{et} > 0} \frac{\mathrm{x}_{et}}{\mathrm{X}_{st}} (\mathrm{g}_{et}) \qquad \textbf{(3.1)}$$

$$\mathrm{NEG}_{st} = \sum_{e \in \mathrm{E}_{st}:\, \mathrm{g}_{et} < 0} \frac{\mathrm{x}_{et}}{\mathrm{X}_{st}} |\mathrm{g}_{et}| \qquad \textbf{(3.2)}$$

POS_{st} is job creation in sector *s* at time *t;* NEG_{st} is job destruction in sector *s* at time *t*. The variable x_{et} captures the size of the firm *e* while X_{st} captures the size of the industry firm *e* belongs to. As outlined by Hijzen et al. (2010: 623), who follow the earlier work of Davis, Haltiwanger & Schuh (1996), employment growth in enterprise *i* between *t-1* and *t* is given by:

$$g_{it} = \frac{(N_{it} - N_{it-1})}{1/2(N_{it} + N_{it-1})} \qquad \textbf{(3.3)}$$

If we divide by the average employment we make sure that g_{it} can only take on values between -2 and +2 for exiters and new entrants respectively.

A key feature of their work is the focus on gross job flows rather than worker flows. They note job flows are concerned with employment changes at the firm level (or industry level) from one period to the next while worker flows reflect movements of workers into and out of jobs at the individual level between one period and the next. While the focus is on measuring these job flows, their link to and potential impact on worker flows is acknowledged. While worker flows may be driven by for example, workers retiring and others being employed into these existing positions, they can also be driven by the destruction of existing jobs and the creation of new job opportunities. They report average gross job creation of 9.2% and gross job destruction of 11.3%. These simultaneously high rates persist when narrowly defined sectors were examined. They report this high rate of job reallocation (the sum of job creation and destruction) is an indicator of the rate at which jobs are reallocated across establishments.

Davis & Haltiwanger (1999) build on their previous work focusing on the measurement of both gross worker and job flows. They note that the absence of timely and complete statistics on worker and job flows is an issue given the importance of having a clear understanding of labour market dynamics from a policy and economic point of view. They focus on the potential of administrative data sources for compiling measures of gross job and worker flows, given that this would be a relatively inexpensive source.

Subsequent work by Davis, Faberman & Haltiwanger (2006) also acknowledges the importance of administrative data and point out that the development of new datasets has led to the emergence of a fuller picture regarding labour market flows in the US. One of these is the Longitudinal Employer Household Dynamics (LEHD) which contains matched employer-employee data. Here the reported rate of job creation and destruction varies depending on the source and the sampling interval of the data. Using the LEHD data, job creation and destruction rates of about 7% and 5.5% are reported between 1993 and 2003 in the US. Also the magnitude of differences in job flow rates across industries is highlighted by the authors, even when these industries are broadly defined. Using Business Employment Dynamics (BED) data from the US, the rates of job creation and destruction in manufacturing are reported to be 4.9% and 5.3% respectively while in the construction sector the corresponding rates are 14.3% and 13.9% between 1990 and 2005.

In another US study, Pinkston & Spletzer (2004) also use data from BED and they find a job creation rate of around 15%. A similar job destruction rate of around 14% is reported. They compare the magnitude of these flows to those found by Davis et al. (1996a) who investigate job flow rates in the US manufacturing sector over the period 1973-1988. Davis et al. (1996a) report lower annual rates of 10.3% and 9.1% for job creation and job destruction respectively over the period. Pinkston & Spletzer (2004) suggest that the most plausible explanation for this is the difference in the sectors covered. While the earlier work of Davis et al. (1996a) focuses on the manufacturing sector, the work of Pinkston & Spletzer (2004) covers all sectors of the economy, not just manufacturing. It also refers to a later time period.

Efforts have also been made to compare the magnitude of job flows in the US to those of Canada by Baldwin, Dunne & Haltiwanger (1998). The US data covers the period 1972-1993 while the Canadian data spans the period 1973-1992. The manufacturing sector is the focus in both countries. The measures used by Davis et al. (1996a) for computing job flows are implemented here for both countries. It is reported that the patterns between both countries are similar over time when examining job creation and destruction, with both job creation and destructions rates of 10% in each country annually.

We now turn our attention to evidence from some European countries, including Ireland. We begin with an Austrian study by Stiglbauer, Stahl, Winter & Zweimuller (2003) who also draw comparisons with the results from studies conducted in the US. Using a large administrative dataset which covers all private sector employees for the period 1978-1998, it is reported that rates are generally comparable in magnitude to those of the US. Over the period it is found that on average, both the job creation and destruction rates were about 9%. Results are also compared to European countries. Job creation is higher than that reported in Germany while it is lower than that of Sweden and Italy. They suggest that the overall pattern with regards to job destruction is similar. A Danish study by Albaek & Sørensen (1998) report a slightly higher rate of job creation and job destruction annually and suggest that on average around 12% of new jobs are created while approximately 11% of jobs are destroyed each year. Thus these results are similar to those of Davis et al. (1996a).

In the UK, Hijzen, Upward & Wright (2010) report the job creation and job destruction rates for the economy and also for the manufacturing and services sectors separately. Using data from an Inter-Departmental Business Register (IDBR) which is a database of all businesses in the UK for the period 1997-2008, the average job creation rate for the economy is approximately 15% while the job destruction rate is around 14%. In earlier work, Blanchflower & Burgess (1996) use data from three waves of the Workplace Industrial Relations Survey in 1980, 1984 and 1990 to investigate job creation and destruction in the UK. Their reported rates are lower than those of Hijzen et al. (2010). They report an increase in the job creation rate from around 3.5% in 1980 to around 5.5% in 1990 across all sectors which are private manufacturing, private services, private sector, public sector, the union sector and the non-union sector. However, overall the job destruction rate also increased slightly from 5.18% to 5.31%. The increase was most pronounced in private services and the public sector.

In an Irish context, some work has been previously conducted on job flows. Lawless & Murphy (2008) examine job creation and destruction in the Irish manufacturing sector for the years 1972 to 2006 using Forfás[18] survey data which includes the Forfás Employment Survey and the Annual Business Survey of Economic Impact. They find that even when the Irish economy was booming during the Celtic Tiger period, there was a 15% job growth rate in expanding firms while there was a 7% job destruction rate in contracting firms. Lawless (2012) updates some of this previous work examining job creation and destruction in Ireland using Forfás survey data from 1972 to 2010 and covers firms engaged in manufacturing and internationally

[18]Forfás was Ireland's policy advisory board for enterprise, trade, science, technology and innovation. In 2014, it was dissolved and its policy research activities were integrated into the Department of Jobs, Enterprise and Innovation. See https://www.djei.ie/en/ for further details.

traded services. Over the period 1972-2006, the average job creation rate was 10% while the average job destruction rate was 8%. However, in 2010 a dramatic shift was noted. The job creation rate fell to below 5% while the job destruction rate increased to 16%.

Other work in relation to Ireland was conducted by Strobl, Walsh & Barry (1998) for the period 1974-1994. They used the same data source used by Lawless & Murphy (2008) and Lawless (2012). Strobl et al. (1998) suggest that the magnitude of the simultaneous creation and destruction of jobs over the period is noteworthy and report an average job creation rate of 8.4% and a job destruction rate of 8.9% over the period. Thus in an Irish context, it is apparent that research conducted to date has used survey data.

In contrast to these Irish studies, administrative data is available in other European countries such as the UK as previously mentioned, and Finland. Ilmakunnas & Maliranta (2003) examine worker and job flows in the Finnish business sector. The data covers practically the entire work force and spans a period in the 1990's when Finland was in a recession. As the recession began, the job creation rate decreased to a low of 9% in 1992, while the job destruction rate increased to around 19% in the same year. However it is noted that by 1994, the gross job flow rates had returned to more normal levels, with both a job creation and destruction rate of around 15%.

In relation to Northern Ireland, Roper (2004) examines job creation and destruction in the manufacturing sector for the years 1973-1993 using data from the Annual Respondents Database (ARD). He reports job creation and job destruction rates are lower when compared to some international results from Ireland, Norway, Denmark, and the UK. This difference appears to be more consistent with regards to job creation rather than job destruction. While noting the difficulty of making comparisons across time because of differences in data sources, timing and coverage, it is noted that the study by Barnes & Haskel (2002) which covers the entire UK uses the same data source as Roper (2004). Roper (2004) suggests that such differences between the two studies may reflect real differences in rates as well as the fact that Barnes & Haskel (2002) compute job flow rates at the establishment level while Roper (2004) uses data at the enterprise level. Further, he notes sectoral differences in data used in previous studies with many such as Strobl et al. (1998) in Ireland and Salvanes (1995) in Norway and in Denmark focusing on the manufacturing sector.

As well as examining job flows and their associated levels, another aspect of job flows discussed in the literature is their volatility and cyclicality. Baldwin et al. (1998) find differences in the variability of job flows. Job destruction displays a greater volatility than job creation. They also note earlier work by Davis & Haltiwanger (1990; 1992), who reported that job destruction in the US manufacturing sector is more sensitive to the business cycle than job creation. This is because the standard deviation of job destruction in the US is 2.8 while it is 1.9 for job creation over the period. In relation to Canada, Baldwin et al. (1998) report a similar pattern but the size of the difference is not as large with the standard deviation of job destruction recorded as 2.6 while that of job creation is 2.1.

Boeri (1996) explores some of the reasons put forward for why we might expect counter-cyclical properties of job turnover. For example, Davis and Haltiwanger (1990) suggest that job creation is a time consuming process. On the other hand, job destruction is not and as a result, it fluctuates more over the business cycle than job creation. Caballero & Hammour (1995) point to the 'cleansing' nature of recessions, drawing on earlier work of Blanchard & Diamond (1989) noting that in such periods a reduction in the job creation rate is unlikely to be enough, necessitating a rise in the magnitude of job destruction. However, Boeri (1996) questions the results from the US where there is statistically significant negative correlation reported between job reallocation and net employment growth. He suggests that these results are not related to the flexibility of the labour market in the US where it may be easier for an employer to fire an employee compared to some European labour markets. He specifically looks at Nordic countries (Denmark, Norway and Sweden), other European countries (France, Germany and Italy), and North America (Canada and United States) and finds that, with the exception of the US, other countries have a positive or statistically insignificant correlation between job reallocation and net employment growth. He suggests that the US results may be a function of the data used. While much of the data from European countries used is from administrative data sources covering manufacturing and services sectors, the US data is drawn from a survey of manufacturers only. On the other hand, Davis & Haltiwanger (1999) suggest that the fact that Boeri finds little difference in the volatility of job flows (job creation and job destruction) may be due to the time period studied and suggest there was little cyclical variation in France or Sweden for example. Boeri (1996) uses data for France for the years 1979 to 1988 and data for Sweden is for 1985 to 1992.

3.2.2 Job flow rates by industry

Gross job flow rates can vary hugely across industries as demonstrated by the OECD (2009). They note that with the exception of Haltiwanger, Scarpetta & Schweiger (2006), there is little evidence on differences in job flows across countries based on comparable cross-country data. They use data from Haltiwanger et al. (2006) and Bartelsman (2008) which is based on data from tax records and national business registers. It is gathered using the same procedures for the countries in question.

They find that enterprise characteristics such as age, industry and firm size affect job flows across nations. In particular it is reported that industry-specific effects account for a greater proportion of the overall variation in job creation rates (44%) than that of the variation in job destruction rates (24%) across countries. Interestingly, they also find a strong correlation across industries between the job creation rate and net employment growth. They interpret this as meaning those industries that are responsible for creating more jobs are also the ones where employment grows more rapidly. However, the opposite does not hold in that they report no relationship between job destruction and a net decrease in employment. This seems to suggest that industry-specific factors are more important determinants of job creation rather than job destruction. This is in contrast with results of Hijzen et al. (2010). While using UK data as opposed to cross-country data used by the OECD (2009), they do not report strong evidence of a correlation between job creation and net employment growth. They do find a strong positive correlation between the job creation and destruction rate.

Sectoral differences are also noted by Lane et al. (1996) in the US. Later work by Baldwin et al. (1998) also analysed the importance of industry as well as year and country effects in an effort to explain differences between the US and Canada. In this case regression analysis is used whereby dependent variables are measures of job flows such as job creation, destruction, reallocation and net employment growth. Country, industry and year are independent variables in these regressions. Interestingly, they report that industry has a high degree of explanatory power in accounting for variations in job creation, job destruction, and job reallocation. Country effects are found to have a very minor role in explaining variations in any of the job flow measures.

This finding regarding the role of industry is not unique to the US economy. For example, a study of both manufacturing and non-manufacturing firms in Taiwan over the period 1987-1997 by Tsou, Liu & Hammitt (2001) reports simultaneous job creation and destruction across sectors and these rates vary across sectors. In the UK, Hijzen et al. (2010) note the importance of the services industry relative to the manufacturing industry in terms of employment, with almost all services sector industries growing while the opposite is the case for manufacturing sectors. Also the gross job reallocation rate varied far less in the manufacturing sector. Across all sectors, a similar pattern is noted as found in the previous papers mentioned – job creation and destruction occurs simultaneously across sectors and the rates vary between sectors. For example, Hijzen et al. (2010) report a job creation rate of around 19% and a job destruction rate of approximately 15% in the construction sector, while the textiles component of the manufacturing sector is creating jobs at a rate of 8.6% and destroying jobs at a rate of 17.4%.

3.2.3 Job flow rates and firm size

As we saw earlier in Chapter 2, much emphasis has been placed on the role that small firms can play in the creation of jobs in Ireland. Here we examine the evidence on the role of small firms in the job creation and destruction process.

In identifying the contribution of small firms to job creation we can go back to the work of Birch (1989) in the US who emphasises the important role they can play in generating employment. However, the actual degree to which small and large firms contribute to job creation and job destruction has not been agreed by researchers. Davis et al. (1996a) were one of the first to suggest their disagreement with the notion that small firms were responsible for the majority of job creation and instead suggest that it is in fact large firms that should be given this credit as "the conventional wisdom rests on fallacious and misleading interpretations of the data" (Davis, et al. 1996a: 62). They emphasise also that both job creation and job destruction figures are higher for small firms, with higher job destruction offsetting this higher job creation. They find that in examining the net employment growth rates, they do not exhibit any strong relationship with firm size. They go on to outline three flaws that they believe contribute to the belief that small firms contribute disproportionately more to job creation. These are now explained below.

They begin with what is termed the size distribution fallacy. They suggest that this fallacy arises as firms can move between size classes from one year to the next. So for example, if a large firm destroys jobs it may be reclassified into the small firm category and therefore may lead researchers to believe that there has been an increase in job creation when in fact it is just due to a large firm shrinking. Barnes & Haskel (2002) note the use of longitudinal data which follows firms through time overcomes this issue. Davidsson, Lindmark & Olofsson (1998) also do not agree with the suggestions of Davis et al. (1996a, 1996b) because they suggest that few studies are affected by this issue. They also point out that any resulting bias arising from this could run in either direction and affect the computation of job creation and destruction rates for both small and large firms. Therefore as noted by Hijzen et al. (2010), there is no reason to suggest that any resulting bias would favour small firms more so than larger firms.

The second issue noted by Davis et al. (1996a: 64) is what they term "netting out reality." This can arise if job creation is reported as a proportion of net rather than gross job creation. So for example, a small firm may have created 20 jobs between year one and year two. Two other firms may have created 140 jobs and destroyed 140 jobs respectively. Thus taking the job creation of small firms as a fraction of net job creation would suggest that they are responsible for 100% of jobs created between one year and the next. However as a fraction of gross job creation, the contribution of small firms would be 20/140 = 14%. But again, as suggested by Davidson et al. (1998) and Hijzen et al. (2010), it is not clear why any resulting bias would distort results in favour of small firms only.

The final issue alluded to by Davis et al. (1996a) is the regression fallacy. It is pointed out that this can arise due to transitory fluctuations in firm employment or by measurement error if it introduces such transitory fluctuations. This fallacy arises as firms are classified into their respective size classes, using the base year employment. Firms that are classified as large in size have a greater likelihood of experiencing recent transitory increase in employment. Thus large firms are more likely to experience a decrease in employment in the following period. On the other hand, small firms are likely to have experienced a transitory decrease in employment and thus have a greater likelihood of experiencing an increase in employment in the following period. They subsequently propose two other measures of firm size. These measures are average firm size which is average employment in each firm over the period and current size which is average employment in the current year and previous year. Davidsson et al. (1998) suggest that while Davis et al. (1996a, 1996b) point out a real problem in relation to the regression fallacy, they question the significance of the impact on reported rates of job creation in small firms. Ultimately, while praising the work of Davis et al. (1996a, 1996b) in terms of their contribution to the debate on the role of small firms and job creation, they suggest that the methodological issues that are highlighted by them are not likely to be of great importance when estimating the role of small firms in relation to job creation. They also take issue with the use of average firm size over the sample period which was proposed by Davis et al. (1996a, 1996b) as a possible solution to the regression fallacy suggesting it is only preferable if all of the changes in size are due to random fluctuations or measurement error. This is because changes may cause a firms' employment to move upwards or downwards and ultimately affect the average firm size estimate.

In Canada Baldwin & Picot (1995) examine how job creation and destruction rates vary between small and large firms in the manufacturing sector. They use a number of employment measures of plant size including average firm employment over the period of the study to aid comparisons with the US data. This average employment method is also used by Roper (2004), as well as the initial employment measure. While the data used only covers firms with >20 employees, it is reported that small firms (20-49 employees) were the only size category to experience a net increase in employment between 1974 and 1993, using either method. However, Baldwin & Picot (1995) also propose a classification whereby size is based on the average size of the firm in the two years preceding the analysis period to overcome problems with the average firm size classification, and this is used by Davidsson et al. (1998) and Hijzen et al. (2010).

In the UK, Hijzen et al. (2010) report that, relative to their share of employment, small firms are responsible for a disproportionate amount of job creation (about 65%) and destruction (about 45%). This is regardless of the chosen firm size measure. An earlier UK study by Blanchflower & Burgess (1996) found a change in the job creation and destruction trend at 200 employees. Firms with less than 200 employees seem to create more than their share of jobs, while establishments with more than 200 employees destroy more than their share of jobs. The share is computed by dividing job creation in a firm size category by the share of employment of firms in that firm size category.

Broersma & Gautier (1997) examine job creation and job destruction in the Dutch manufacturing sector over the period 1978-1991, focusing on both small and large firms. Their data obtained from Netherlands Central Bureau of Statistics allows them to distinguish between rates for continuing firms and those due to entry and exit from the data. In all cases, there is significant heterogeneity across firm size categories. In general, they find that firms with less than 20 employees have the highest rates of both job creation and job destruction and both appear to decline as firm size increases.

Lane et al. (1996) report that small firms (<20 employees) create and destroy jobs at approximately three times the rate of the largest firms. Results from Japan reported by Genda (1998) suggest a similar pattern. Using differing measures of enterprise size at the beginning or end of a year for the period 1991-1995, it is reported that generally the rates of job creation and destruction decline as firm size increases. It is suggested that the importance of small firms in the process of creating new jobs contrasts with results from Davis et al. (1996a). For example in the US, Davis et al. (1996a) report that the share of job creation and destruction in firms with over 100 employees was around 70%. This is in contrast with Japan where figures vary from around 7% to 23% depending on whether establishment or enterprise size measures are used, as well as those of Hijzen et al. (2010) as already outlined.

3.2.3.1 The persistence of job creation and job destruction

While some previous research has suggested that small firms have high rates of job creation relative to their larger counterparts, a question arises as to how likely employment changes are to persist over following periods. So if firm *e* creates 50 new jobs in year *t*, what proportion of those jobs will still be in existence in year *t+1* or year *t+2*? Similarly for a firm that destroys 50 jobs in year *t*, how many of those jobs are likely to reappear in subsequent years? The measure of persistence often used in the literature focuses on the persistence of a newly created or newly destroyed job. [See for example Davis & Haltiwanger (1992), Davis et al. (1996a)]. Hijzen et al. (2010) use the following equation to measure persistence;

$$\text{Persistence}_{e,x} = \frac{\mathrm{N}_{e,t+x} - \mathrm{N}_{e,t-1}}{\mathrm{N}_{e,t} - \mathrm{N}_{e,t-1}} \qquad \textbf{(3.4)}$$

where $0 < \text{persistence}_{e,x} \leq \text{persistence}_{e,x-1} < 1$

In this case, N_e is the level of employment in firm *e*, N_{t+x} is the year under consideration for persistence. As noted by Hijzen et al. (2010) this measure computes the proportion of the change in employment that persists *beyond the initial year* and into year *t+1*, year *t+2* and so on. In using this formula, it is not possible to investigate if an individual who got a job in a certain year still has it in subsequent years. The focus is instead on employment changes at the firm level, rather than on individual level employment changes and tracking individuals through time.

Davis & Haltiwanger (1992) report that changes in employment at the level of the establishment are highly persistent. On average they find that the persistence rate for newly created jobs after one year is around 67% while the corresponding job destruction rate is about 81%. In subsequent work, Davis et al. (1996a) investigate the persistence rate in the US manufacturing sector between 1973 and 1988. They find that the persistence rate for newly created jobs is about 70% after one year, while after two years it is approximately 54%. Similarly for job destruction, a high level of persistence is reported. It is found to be around 82% after one year and a two year persistence rate of 73% is reported. While they find lower rates for persistence using quarterly data over a similar period, they suggest that the use of quarterly data is more likely to be impacted by transitory employment changes that are subsequently reversed, perhaps in the following quarter.

In the UK, Hijzen et al. (2010) also report high one year persistence rates. They find an average one year persistence rate of 75% for job creation and 93% for job destruction. Persistence rates are presented for differing firm size categories. Regarding job creation and job destruction, small firms (0-19 employees) appear to have a higher persistence rate than large firms (5000+ employees). They note that much of the job destruction in small firms is due to exit, therefore this helps explain the high persistence rate. Barnes & Haskel (2002) report lower persistence rates for the manufacturing sector for the period 1981-1990 than Hijzen et al. (2010). For example, Barnes & Haskel (2002) report a one year persistence rate of 57% for job creation and a rate of 47% for job destruction in 1989. Like Hijzen et al. (2010), they report that overall job destruction is more persistent than job creation.

Albaek & Sørensen (1998) examine persistence in the Danish manufacturing sector. Persistence rates for job creation and destruction after one year are reported at 70% and 58% respectively. Here results are compared to Davis et al. (1996a) for the US manufacturing sector. While there are similarities between persistence rates for job creation, it is suggested that job destruction is more persistent in the US. Broersma & Gautier (1997) also examine persistence in the Dutch manufacturing sector focusing on continuing firms. They find that the persistence of job destruction increases with firm size. In relation to job creation, they find that jobs created in small firms are more persistent than jobs created in large firms.

Turning to Austria, Stiglbauer et al. (2003) analyse the persistence of newly created and destroyed jobs. This paper does not focus on persistence across firm size categories but instead focuses on overall levels and also looks at differences across continuing firms and new entrants. They find that job creation and job destruction both display a high degree of persistence. They also compare results to those of Davis et al. (1996a) and find that Austrian rates are slightly higher than those found in the US. Stiglbauer et al. (2003) examine persistence rates for existing firms – contracting or expanding firms – and new entrants separately. Interestingly they find little difference in how stable jobs created in new firms are in comparison to existing firms. For example after 10 years, around 25% of newly created jobs by new entrants are still in existence. In expanding firms the figure is around 29%. As noted by the authors, this is interesting because generally new start-ups would be considered to be relatively unstable when compared to jobs created in continuing firms.

3.2.4 Job flow rates by region in Ireland

Some work has been conducted in Ireland to investigate regional differences in job flows. Meyler & Strobl (2000) examine the impact of industrial policy on job generation. Specifically they look at the impact of industrial policy and support given through the IDA[19] designated areas versus non-designated areas. Such designated areas tended to be the least industrialised and most peripheral parts of Ireland. They report that there was a higher job creation rate within the designated areas in the 1970's with jobs created being more likely to survive, while jobs destroyed had a greater likelihood of being recovered. In identifying the factors that affect job creation and destruction in both designated and non-designated areas, they

[19] The IDA supports overseas companies seeking to establish a base in Ireland.

find that regional industrial policy had a positive effect on job creation in the designated areas and did not have a significant effect on the rate of job destruction between 1973 and 1982.

3.2.5 International trade and job flows

This section outlines the results of recent studies that examine the link between international trade and job flows. As mentioned earlier, there is a strong expectation among Irish policy makers that export-led growth is key to the Irish economic recovery and the creation of jobs.

In the US Davis et al. (1996a) investigate the relationship between international trade and job flows. They use two measures of foreign trade exposure. The first measure is an import penetration ratio which is computed by dividing the imports by the sum of imports and domestic output. The second measure is an export share measure which is a calculated by dividing exports by domestic output. Interestingly they find no evidence of a systematic relationship between their measures of trade exposure and job flows. In reviewing previous literature on job flows and international competition Klein, Schuh & Triest (2003) suggest that the lack of relationship reported between international trade and job flows is due to the nature of their analysis. Davis et al. (1996a) use the averages for job flows and international trade intensity over a fourteen year period. Because different factors determine both, "there is no well-established theoretical or empirical reason for a connection between these two sets of underlying factors that determine long-run averages" (Klein et al. 2003: 22-23). Hence they suggest it is more appropriate to examine changes in exposure to trade intensity and job flows. In this case, the expectation of a relationship between the two variables is appropriate.

Turning to evidence outside of the US, Levinsohn (1999) investigates job creation and job destruction patterns in Chile and links this to the trade orientation and size of the firm. Following significant liberalisation of trade in the country, its impact on employment patterns is examined. The data used is described as a "census" of manufacturing firms as all firms with at least ten employees are included (Levinsohn, 1999: 324). This is a total of 6,665 plants which were taken from eight longitudinal samples and combined to form an unbalanced panel. Levinsohn (1999) follows the approach of Davis & Haltiwanger (1992) for computing job flow rates and reports that, even when job destruction was at its greatest in 1982 at 23% and employment was shrinking at a rate of 18%, there was still job creation occurring at a rate of 5%. These rates are then examined according to whether a firm is an exporter, importer or in the non-tradable group. He uses an OLS regression to estimate the job growth rate and includes year dummies and firm-size dummies. However in addition to these, dummy variables were also included to account for trade orientation. Interaction dummies are included to account for the interaction between trade orientation and year. Here weak evidence is found that the rate of job creation is higher in the export sector when trade was liberalised in Chile.

Hijzen et al. (2010) use similar regression techniques to that of Levinsohn (1999) to explore the impact of exposure to international competition on employment growth rates. They investigate if involvement in international trade can partly account for their observation that job reallocation rates vary across sectors of the UK. They follow the approach of Davis et al. (1996a) to estimate job flows and compute an import penetration ratio and the export share for each industry. Each industry is classified on the basis of its change in import and export intensity respectively. The change is computed between the average of the first three year period which covers the years 1997-1999 and the final three year period of 2006-2008. Industries are assigned to quintiles based on how their import or export intensity changed. A simple regression approach is taken to determine if job creation and job destruction varies significantly across quintiles. Similar to Levinsohn (1999), they control for year and industry fixed effects by including dummy variables in their regression equations for job creation and destruction. Hijzen et al. (2010) find little evidence of a systematic relationship between job creation and the change in import or export behaviour. However, they do find some evidence to support the assertion that job destruction is affected by trade exposure. Industries included in the highest import quintile experience higher rates of job destruction. However, industries that reside in the highest export quintile have the lowest rates of job destruction.

A similar regression approach is adopted by Pisu (2008) in examining job flows and international trade involvement using firm level data from Belgium for the period 1998-2004 in terms of controlling for fixed effects. A simple (six categories) and then detailed (nineteen categories) classification system is used to assign firms according to their type of international activities. Here the employment growth rate is regressed on dummies which represent the trade status and size of the firm. Whether the simple or detailed classification system is used, it is reported that involvement in international markets in some form is associated with a higher employment growth rate. This is particularly true for firms that are just beginning their involvement in international markets.

3.2.6 Conclusion

In this section we explored literature and empirical evidence on job flows. We have seen that job creation and destruction rates can be high and vary across countries. Within countries, sectoral differences can play an important role in understanding the magnitude of job flows and have been attributed with strong explanatory power in explaining job flows. We also noted that the classification of what constitutes a 'small' firm varies across studies. Whether small firms do contribute more to the creation of new jobs, relative to their larger counterparts is at issue. We do find evidence in the literature to support this assertion. With regards to international trade and job flows, the evidence is somewhat limited on the magnitude of the impact of exporting and importing activity on job flows. The measurement of exporting and importing activity is important and can impact results. In response, some studies have utilised a measure of changing export or import intensity rather than average levels to explore the relationship with job creation and job destruction.

3.3: Data & Methodology

This section describes the data used in this chapter and thesis. It also explains in detail the methodology used in the construction of the final panel analysed in this chapter as well as how key job flow measures are computed.

3.3.1 Data sources

The linked employer-employee P35 data used in this chapter (and thesis) is available from the CSO in Ireland. This dataset constructed by the CSO[20] was formed by merging three data sources. These are;

- The P35L data from Revenue Commissioners,
- The Client Record System (CRS) from the Department of Social Protection,
- The Central Business Register (CBR) in the CSO.

As mentioned earlier, an enterprise is defined by the CSO as per EU statistical legislation. It is the smallest combination of legal units that is an organisational unit

[20] See Appendix 12 for details on CSO data access protocols.

producing goods or services, which benefits from a certain degree of autonomy in decision-making, especially for the allocation of its current resources. An enterprise carries out one or more activities at one or more locations (OECD 2016). The P35L data file is the primary source of data which contains information on each registered employment in Ireland for the years 2005 to 2010[21] and so links employee and employer details. A registered employment spell is that which is registered by the employer with the Revenue Commissioners. This data is an administrative source based on data collected by the Revenue Commissioners in Ireland. It contains over two million employee observations in each file annually. It is possible for each worker to have more than one employment record. For example, one person may have more than one job in a given year. As start and end dates associated with each employment record are not available, it is not possible to tell if such jobs are concurrent or consecutive. Table 3.1 sets out the number of enterprises and employment records associated with each year. Thus the number of employment records may be greater than the numbers in employment generated by the CSO from the Quarterly National Household Survey (QNHS), which is the official source of employment and unemployment statistics in Ireland.[22] It is worth noting at this point that the data does not contain a part-time/full-time indicator. It does contain a variable identifying the number of weeks worked associated with an employment record. So if a person worked 40 hours a week for 52 weeks of the year, they would have 52 weeks worked, as would a person who worked for 1 hour a week for 52

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[21] In Chapter 4 we use data from 2005-2011 while in Chapter 5 we use data from 2005-2013.

[22] The QNHS defines a person as being in employment if they worked in the week before the survey for one hour or more for payment or profit, including work on the family farm or business and all persons who had a job but were not at work because of illness, holidays etc. in the week. See http://www.cso.ie/en/releasesandpublications/er/qnhs/quarterlynationalhouseholdsurveyquarter12016/

weeks of the year. The dataset also contains an annual pay variable to identify the pay a person received from an enterprise. This is total taxable pay.[23]

This file contains a person identifier and an enterprise identifier. This facilities its merger with the CRS to assign person-based attributes which are age, gender and nationality. The availability of an enterprise identifier means the file can be merged with the CBR to assign the enterprise-based attributes of the NACE Rev.2 sector it belongs to as well as its legal form.

As mentioned, the available data does not have point in time measurement which means it is not possible to identify the exact start and end date of an employment record. Therefore a methodology where year *t* is compared with year *t-1* is used. This dataset will hereafter be referred to as the P35 dataset and is the primary data source used throughout this thesis.

The second data source used in this chapter is survey data collected through the Census of Industrial Production (CIP) in Ireland for the years 2006 to 2010. This is merged with the P35 dataset and is used in section 3.4.3. The CIP dataset contains over 4,000 enterprise observations per year. According to the CSO (2016h), the CIP is an annual survey sent by the CSO to enterprises with three or more employees, primarily engaged in industrial production and this includes the following NACE economic sectors;

- B - Mining and quarrying
- C - Manufacturing
- D - Electricity, gas, steam and air conditioning supply

[23] Pay is total taxable pay. It is gross pay less employee contributions to health insurance, superannuation, union subscriptions and the travel pass scheme.

- E - Water supply; sewerage waste management and remediation activities

The key variables collected include turnover, exports, purchases, additions to capital assets and sales of capital assets. Of particular interest in this chapter is the percentage of turnover exported variable. The percentage of materials imported is also included as is the region the enterprise is operating in (CSO, 2016h). This is the first time the CIP and P35 datasets have been linked and offers a unique opportunity to examine the impact of export activity on job flows.

3.3.2 Cleaning the data sources

Figure 3.1 provides an overview of how the P35-CIP panel was constructed. The details are now described. Initially each annual P35 data file was examined. There were a number of individually assigned employment records in each file that did not have an associated enterprise number. Therefore it was impossible to identify which enterprise these employment records were associated with. Because of this, these observations were deemed to be un-usable for the subsequent analysis and were removed from the data file.

Figure 3.1: Overview of construction of P35-CIP panel

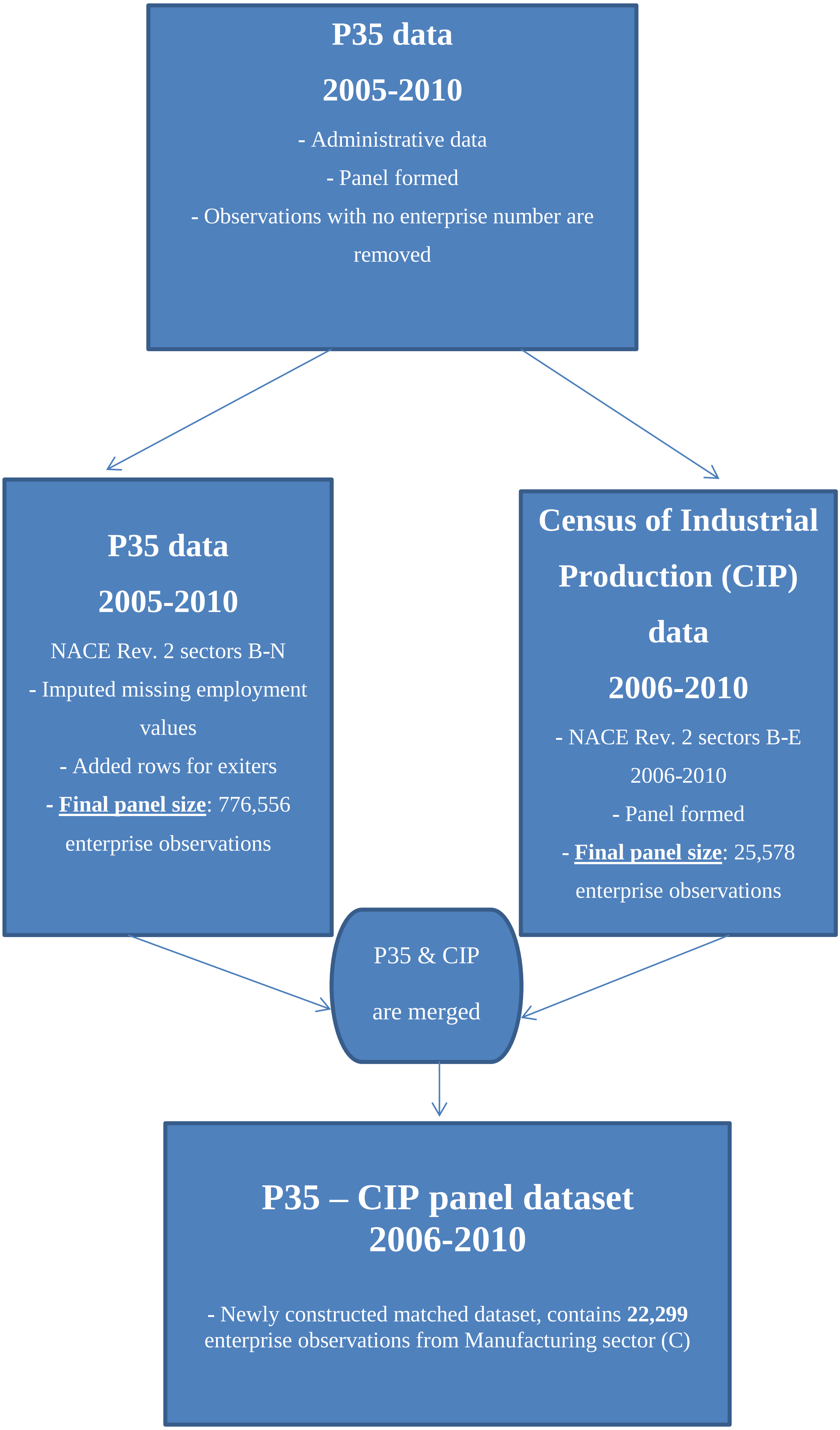


Table 3.1 below details the number of observations that were deleted each year and the remaining number of annual observations. It is important to remember that these deleted observations are person-based employment records as opposed to enterprise based numbers so they represent the number of employment records, not actual enterprises. So while it is possible to identify the number of individually assigned employment records that are removed, it is not possible to identify the number of enterprises that are affected.

Table 3.1: The number of observations removed from data (all NACE sectors)

Year	No. of *employment records*	No. of *employment records* with no enterprise number	No. of remaining *employment records* with enterprise numbers	No. of remaining *individuals* with enterprise numbers	No. of remaining *enterprises* with enterprise numbers
2005	2,659,918	66,494	2,593,424	2,046,661	138,158
2006	2,776,006	51,230	2,724,776	2,161,081	147,028
2007	2,958,235	35,609	2,922,626	2,296,046	156,549
2008	2,834,984	27,614	2,807,370	2,275,552	156,059
2009	2,444,565	20,060	2,424,505	2,067,732	141,640
2010	2,329,216	17,329	2,311,887	1,967,863	138,321

In each annual file, there were some individual observations which had a value greater than 52 for the number of weeks worked. These were subsequently assumed to be due to an administrative error and the number of weeks worked was assumed to be a maximum of 52 per individual. Also the number of individual employment records per enterprise were summed in each year. This gives the number of individually assigned employment records per enterprise in each year. Importantly, this value is used as the enterprise employment value later. At this point, only enterprise level observations are required so one row is retained for each enterprise in each year of the dataset. This means that the dataset is reduced to an enterprise-level dataset as opposed to an individual-level dataset. A panel of enterprises is thus formed for the years 2005 to 2010. At this point it was decided to focus on the Business Economy, specifically sectors B-N. This results in a panel of 689,091 observations across the years 2005-2010.

The data was examined and it was decided that if there was a gap in the data for a particular year for an enterprise, the employment value for that enterprise would be imputed. This was done to capture data for all enterprises that were essentially continuing enterprises but due to a gap in the data, may erroneously be classified as exiters and subsequently as entrants again. This was deemed appropriate as it would be misleading, for example, to classify an enterprise as an exiter if they were clearly present in all years except one. So for example, if an enterprise had an observation in 2006 and there was no record of the enterprise in 2007, but there was a record in 2008 and subsequent years, the employment value is imputed as its exclusion is assumed to be an administrative error. The imputed values are linearly interpolated. In total, 14,826 values were imputed in the panel. Table 3.2 below displays the number of values imputed in each year. It also shows the average size of enterprises with imputed values. As we can see, the average size for enterprises with imputed values is smaller than those without imputed values across all years. A possible reason for this is could be that small enterprise may have not made a return to Revenue, who may have been more active in ensuring compliance from larger enterprises.

Table 3.2: Imputed values and enterprise size

Year	No. of values imputed	Average size of enterprises *with* imputed values	Average size of enterprises with *no* imputed values
2005	0	-	16.9
2006	3,472	11.9	17
2007	3,561	6.4	17
2008	3,254	4.9	16.2
2009	4,539	4.3	14.9
2010	0	-	14.6

The next step was to create variables to identify enterprises that were new entrants or those that exited from the data during the 2005-2010 period. Enterprises are deemed to be new entrants if their first appearance in the dataset occurred in years other than 2005. Similarly an enterprise was deemed to be an exiter in a given year if the final observation for that enterprise was in a year other than 2010. Also an additional row was created for exiters. In this extra row, the employment value was assumed to be 0. This was done to ensure that the employment growth of the enterprise would fluctuate only within the range of +2 for new entrants and -2 for exiters. In total, 72,639 additional rows with zero employment values were created for exiters. This gave a final panel size of 776,556 observations. Table 3.3 below shows the number of enterprises in each year.

Table 3.3: Number of enterprises per year in NACE sectors B-N

Year	Number of enterprises
2005	108,150
2006	127,349
2007	137,660
2008	141,109
2009	136,858
2010	125,430
Total	776,556

3.3.3 The merging of the P35 and CIP data sources

We now explain how the P35 and CIP data sets were merged. As per Appendix Table 2.3, there were 25,578 enterprises in the initial CIP dataset varying from 4,620 in 2006 to 4,782 in 2010. The merging of the P35 and CIP data was facilitated by a common enterprise identifier for each enterprise observation in both datasets. Thus an unbalanced panel is formed. As a result of this, the sample size was reduced considerably as there are a significant number of enterprises that are not covered by the CIP as they belong to a different NACE sector. There are 23,852 matches achieved between the P35 and CIP data.

Initially, one anomaly in the data emerged whereby in 503 cases, an enterprise that was an exiter according to the P35 and so had zero employment had a corresponding survey match. In this case, it was decided to eliminate the data from the CIP match and follow the P35 data which indicated the enterprise had exited.[24]

There were also 267 observations that are correctly coded as exiters in the P35, in the final row which was created by the researcher to identify exiters. By construction, these enterprises correctly could not have a match in the CIP as this final row in the P35 was constructed by the researcher to represent zero employment in the firm and to later capture a growth rate of -2 for exiters. In this case, the merged data was amended to count the rows for these firms as matches in the dataset. Therefore in total, there are 770 exiters in the merged dataset. This change now means there are 24,119 matches in the merged dataset.

So we can see that we did not achieve a match for every one of the 25,578 available CIP observations even though we might anticipate a one-to-one match between the

[24] This judgement was made following discussions with two individuals responsible for the P35 and CIP respectively. Neither provided a useful explanation for this anomaly.

P35 and CIP for each enterprise in each year. From discussions with the CSO, possible reasons were identified for complete one-to-one matches not being achieved between enterprises in both datasets. First, differences may arise because enterprises are born and others die at different points in time within the sample period. For example, an enterprise may die within year *t*, after a CIP survey has been distributed. However the enterprise was in existence at the start of the year *t* and had paid employees. Second, there is an opportunity for an enterprise to apply for an exemption from completing the CIP in a particular year. Third, the CIP covers enterprises with three or more employees while the P35 data covers all enterprises, regardless of size.

As seen from Table 3.4 below, larger firms were more likely to achieve a match in each year from 2006-2010. A possible reason for this is that the CSO are particularly keen on ensuring that larger enterprises respond to the CIP survey and pursue this group to ensure a high response rate.

Table 3.4: Average firm size for matched enterprises

Number of matches achieved	Average enterprise size (no. of employment records)
Enterprise achieves 0 matches (=>in P35 only)	13.03
Enterprise achieves match in 1 year	14.04
Enterprise achieves match in 2 years	28.51
Enterprise achieves match in 3 years	23.71
Enterprise achieves match in 4 years	22.42
Enterprise achieves match in 5 years	67.79

Following discussions with the CSO, concerns were raised regarding confidentially and sectors B, D and E due to the relatively small number of enterprises involved. Therefore, it was decided to remove NACE sectors B, D and E from the analysis. The enterprises in the manufacturing sector (C) were retained. This is not a major limitation as almost 90% of the observations in the CIP are from the manufacturing sector.

As can be seen from Table 3.5 below, the number of manufacturing enterprise observations in the merged CIP-P35 dataset varies from year to year. Over the period 2006-2010, there are 22,299 enterprise observations in the P35-CIP dataset.

Table 3.5: Number of manufacturing enterprise observations in the matched P35-CIP dataset, 2006-2010.

Year	Number of enterprises
2006	4,016
2007	4,894
2008	4,806
2009	4,350
2010	4,233
Total	**22,299**

3.3.4 Methodology

An enterprise level employment growth rate is computed for all enterprises in the P35 data, having formed a panel of all firms for the years 2005 to 2010. This is done prior to merging with the CIP data. This methodology is used in the UK by Hijzen et al. (2010) who follow the work of Davis et al. (1992) in the US. This chapter follows the same approach and draws on the equations used by both which are now described. We begin by computing employment growth g, as per equation 3.3 explained earlier.

To sum the growth of employment across enterprises, a weight is defined. This weight (w_{it}) accounts for the size of the enterprise in calculating the rates of job creation and job destruction for all enterprises. In Equation (3.5), as outlined by Hijzen et al. (2010), ε_{jt} is the set of enterprises in group *j* at time *t* or *t-1*. The grouping *j* could constitute an industrial sector for example.

$$w_{it} = \frac{(N_{it}+N_{it-1})}{\sum_{i\in}\varepsilon_{jt}(N_{it}+N_{it-1})} \quad \textbf{(3.5)}$$

The job creation rate, JC_{it} within a group can be calculated as:

$$\mathrm{JC_{it}} = \sum_{i\epsilon\varepsilon_{jt},g>0} w_{it}\mathrm{g}_{it} \quad \textbf{(3.6)}$$

As noted by Hijzen et al. (2010: 625), this is essentially "employment-weighted employment growth for positive values of g_{it}".

The job destruction rate, JD_{it}, is similarly defined in Equation (3.7) below for values of g_{it} which are negative.

$$\mathrm{JD_{it}} = \sum_{i\epsilon\varepsilon_{jt},g<0} w_{it}|\mathrm{g}_{it}| \quad \textbf{(3.7)}$$

The job creation and destruction rate reflect the reallocation of jobs which influences the reallocation of workers in the economy. The job reallocation rate is defined as the sum of job creation and job destruction in group *j* in Equation (3.8) below. As noted by Davis et al. (1996a) and Hijzen et al. (2010), this link between job flows and worker flows means that the job reallocation rate can be thought of as a 'maximum' amount of worker shifts that are required given the change or reshuffling of job opportunities across sectors.

$$\mathrm{JR} = \mathrm{JC}_{it} + \mathrm{JD}_{it} \quad \textbf{(3.8)}$$

The net job reallocation rate or net employment growth rate is given by the difference between the job creation and job destruction rates as shown in equation

(3.9). This represents the minimum amount of movement of workers required to accommodate the job reallocation.

$$\mathrm{NET} = \mathrm{JC}_{it} - \mathrm{JD}_{it} \quad \textbf{(3.9)}$$

The excess job reallocation rate for a group of enterprises is defined as the difference between JR and NET, as described in equation (3.10).

$$\mathrm{EX} = \mathrm{JR}_{it} - |\mathrm{NET}_{it}| \quad \textbf{(3.10)}$$

It provides a useful measure of offsetting job creation and job destruction within a group of firms. As Hijzen et al. (2010) note, it indicates the number of job changes over and above what is required to accommodate the net employment change given by NET.

3.4: Findings

This section presents the main findings of the descriptive analysis regarding job flow rates. In sections 3.4.1 and 3.4.2 we focus on the P35 dataset (which covers NACE Rev.2 sectors B-N). This gives an overview of the situation in the business economy over the period 2006-2010. Results are presented for the business economy as a whole, for each sector, as well as by enterprise size category. In section 3.4.3 the focus will turn to manufacturing enterprises and the matched P35-CIP data.

3.4.1 Job flow rates in the Irish economy, NACE Rev. 2 sectors B-N

We begin by examining the employment growth rate over the period. As explained in the previous section, the employment growth rate g_{it} ranges between -2 (for exiters) and +2 (for new entrants). Figure 3.2 displays a simple histogram of the employment growth rate. As can be seen, there are a slightly higher number of exiters than new entrants. A large number of enterprises experienced a growth rate of very close to zero.

Figure 3.2: The employment growth rate

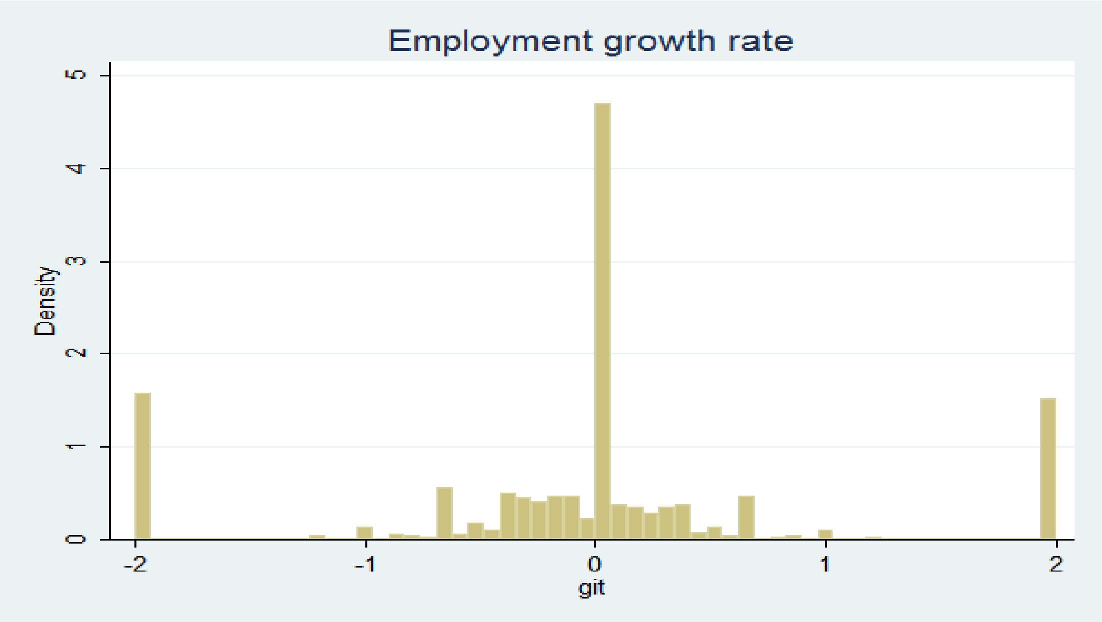


Table 3.6 shows the average job flow measures for NACE sectors B-N over the period 2006-2010. It appears to be a story of two halves, with the years 2006 and 2007 having high rates of job creation relative to job destruction. On the other hand, the years 2008-2010 are periods dominated by high job destruction rates and negative net employment growth. The job creation rate was over 17% in 2006 and this dropped to 11% in 2009.

Table 3.6: Job flow rates in NACE sectors B-N, 2006-2010

Year	Job creation	Job destruction	Job reallocation	Net reallocation	Excess reallocation
2006	0.175	-0.076	0.251	0.099	0.152
2007	0.159	-0.101	0.260	0.058	0.201
2008	0.110	-0.176	0.285	-0.066	0.220
2009	0.110	-0.295	0.405	-0.185	0.220
2010	0.114	-0.193	0.307	-0.080	0.227

The most dramatic shift occurred in terms of job destruction. It stood at almost 8% in 2006 but by 2009 it had increased to almost 30%. The net employment growth figures were positive over the years 2006 and 2007 but turned negative in the later years as a result of a decline in the job creation rate and an increase in the job destruction rate. As outlined in section 3.3.1, job reallocation is the sum of job creation and destruction. Excess reallocation is the difference between job reallocation and net reallocation and measures the amount of job changes over and above what is required to accommodate the net employment change.

3.4.1.1 The cyclicality of job flows

We can also investigate the cyclical dynamics of job flows over the period. A simple correlation between job creation and destruction yields a correlation coefficient of +0.23 (statistically significant at 5% level). While the magnitude of the coefficient is relatively small, it is interesting that it is positive. As observed in Table 3.6, as we approach the onset of the recession in 2008, the job destruction rate increases and the job creation rate falls. However, the cyclical behaviour does not appear to be symmetrical. While job destruction rises dramatically over the period, job creation does not fall to the same degree. We see very little change in the job creation rate between 2008-2010, and even a slight increase in 2010. With regards to volatility and job flows, job destruction displays greater volatility than job creation. This is computed by dividing the variance of job destruction by the variance of job creation over the period which gives a value of 3.01. This ratio confirms greater variance of job destruction relative to job creation. The standard deviation of job creation is 5.3% while for job destruction the value is 9.2%. Davis & Haltiwanger (1999) find that in most of the countries they studied, the variance of job destruction is greater than that of job creation. For example, the variance of job destruction divided by the variance of job creation is 2.04 in the US, 1.49 in Canada, 1.48 in Norway and 2.68 in the Netherlands.

Turning to cyclicality, it is possible to examine the correlations between job flows and the net employment growth rate, assuming that this is an indicator of the business cycle. Beginning with job creation, we find a correlation coefficient of +0.33 between it and net employment growth. So while job creation moves pro-cyclically, it is not a particularly strong relationship (although statistically significant at the 5% level). Previous work by Roper (2004), found a corresponding correlation of +0.80 for manufacturing firms in Northern Ireland, while Strobl et al. (1998) report a slightly higher correlation of +0.87. It is worth noting that Roper's work refers to the manufacturing sector only. With regards to job destruction and the net employment growth rate, we find job destruction moves counter-cyclically, with a correlation coefficient of -0.84 (statistically significant at 5% level). This is quite similar to the earlier work of Strobl et al. (1998) in Ireland (correlation coefficient -0.96) and Roper (2004) for Northern Ireland (correlation coefficient -0.89). For the Finnish business sector, Ilmakunnas and Maliranta (2003) report similarly high correlations over the period 1991-1997.

This evidence shows that Irish enterprises were still creating jobs over the period. Even with the onset of the recession, job creation remained stable between 2008 and 2010. On the other hand, job destruction rose dramatically. So it appears that in Ireland, enterprises do use job destruction as a means of re-organising production when required, rather than reducing the job creation rate. The rise in job destruction is greater than the fall in job creation.

The job reallocation rate increases up to 2009 in Ireland and while it fell slightly in 2010, it remained higher when compared to earlier years. This suggests that it moves counter-cyclically – rising in a recession. This counter-cyclical job reallocation results from the greater variance of job destruction relative to job creation. It suggests much displacement of workers across the economy. Ilmakunnas & Maliranta (2003) cite some theoretical reasons for this phenomenon. One possible explanation refers to that provided by Caballero & Hammour (1994). Essentially it is suggested that less productive firms exit in a recession but when the economy begins to recover, there are start-up costs that may slow down new firms from becoming established and creating new positions. In the Irish case here, it appears that job reallocation does move counter-cyclically with a correlation coefficient of -0.52 (statistically significant at 5% level). Roper (2004) finds a lower correlation of -0.30 for Northern Ireland while Strobl et al. (1998) find a coefficient of -0.61 for Irish manufacturing firms.

Thus our results appear to be closer to those of Davis & Haltiwanger (1999) for the US manufacturing sector, supporting the idea that job reallocation is counter-cyclical. They contrast somewhat with those of Albaek & Sørensen (1998) for Danish manufacturing firms who report a standard deviation of 1.6% for both job creation and job destruction. Therefore they, along with Boeri (1996) as discussed earlier, do not find evidence to support the counter-cyclicality of job reallocation.

It has been suggested by Davis (1998) that it is more appropriate to focus on the correlation between excess job reallocation and net employment growth as a measure of reallocation activity. This is because while the job reallocation measure increases with rising job creation and job destruction, it also increases with rising net employment growth. The measure of excess reallocation used in this chapter removes the net employment growth from the process. Therefore we are left with reallocation in excess of what is required to accommodate the net employment growth. Over the whole period, we see relatively little change in the rate of excess reallocation in Table 3.6 and find a correlation coefficient of -0.38 with net employment growth (statistically significant at 5% level). This suggests that there is still a counter-cyclical relationship between excess reallocation and net employment growth, although the magnitude of the effect is relatively low. The OECD (2009) examine excess job reallocation rates across a number of countries, controlling for industry composition and report that countries with more flexible labour markets due to for example, less employment protection, are more likely to have excess job reallocation rates of above 25%. Such countries mentioned include the United States, Brazil and the UK. On the other hand, European countries including Sweden and Germany have excess job reallocation rates of less than 15%. In Ireland in 2006, the excess reallocation rate was around 15%. However, over the following years it increased to almost 23%.

3.4.1.2 The role of enterprise entry and exit

We now turn our attention to how entry and exit contribute to job creation and job destruction respectively. Table 3.7 breaks the total job creation rates into two groups. The first is job creation caused by enterprise entry and the second is job creation caused by enterprise growth. The job destruction rates are similarly broken down into that caused by exit and decline. Here we observe that the entry of new enterprises accounts for 40%[25] of the job creation on average over the period. On the other hand the exit of enterprises accounts for about 30%[26] of the job destruction on average. The remainder of job destruction is accounted for by shrinking as opposed to exiting enterprises. This suggests that even during this period of economic turbulence in Ireland, new firms were still entering the market and creating new jobs. At the same time, job destruction was increasing considerably and much of this is

[25] Using Table 3.7, this is computed by dividing the total average entrants figure (0.054) by the total average JC figure (0.134).
[26] Using Table 3.7, this is computed by dividing the total average exiters figure (-0.051) by the total average JD figure (-0.168).

attributable to declining enterprises rather than to enterprises that were forced to exit from the market. However it is worth noting that the proportion of job destruction attributable to exiting enterprises increased from 23% in 2006 to 41% in 2010.[27]

Table 3.7: Job creation and destruction; component parts

	Job creation			Job destruction		
Year	**Total**	**Entrants**	**Growth**	**Total**	**Decline**	**Exit**
2006	0.175	0.061	0.114	-0.076	-0.058	-0.018
2007	0.159	0.050	0.109	-0.101	-0.070	-0.031
2008	0.110	0.046	0.064	-0.176	-0.134	-0.042
2009	0.110	0.070	0.040	-0.295	-0.213	-0.082
2010	0.114	0.043	0.071	-0.193	-0.113	-0.080
Average	0.134	0.054	0.080	-0.168	-0.118	-0.051

Next we move to looking at job flows across sectors of the Irish economy.[28] Table 3.8 displays the job creation and destruction rates by NACE economic sector and year. There are big variations in the rates across sectors and years. The most dramatic of the changes occurred in the construction sector (F) where the job creation and destruction rates were about 25% and 11% respectively in 2006, while in 2009 the corresponding rates stood at 8% and 62%. As was the case in Table 3.6 above, the job destruction rate is greater than the job creation rate in many sectors during the 2008-2010 period, while between 2006 and 2007 the job creation rate was greater than the job destruction rate.

[27] Using Table 3.7, this is computed by dividing the total average exiter figure for a given year by the total average JD figure for that year.
[28] Appendix Table 2.1 displays the number of enterprises in sectors B-N for the years 2005-2010.

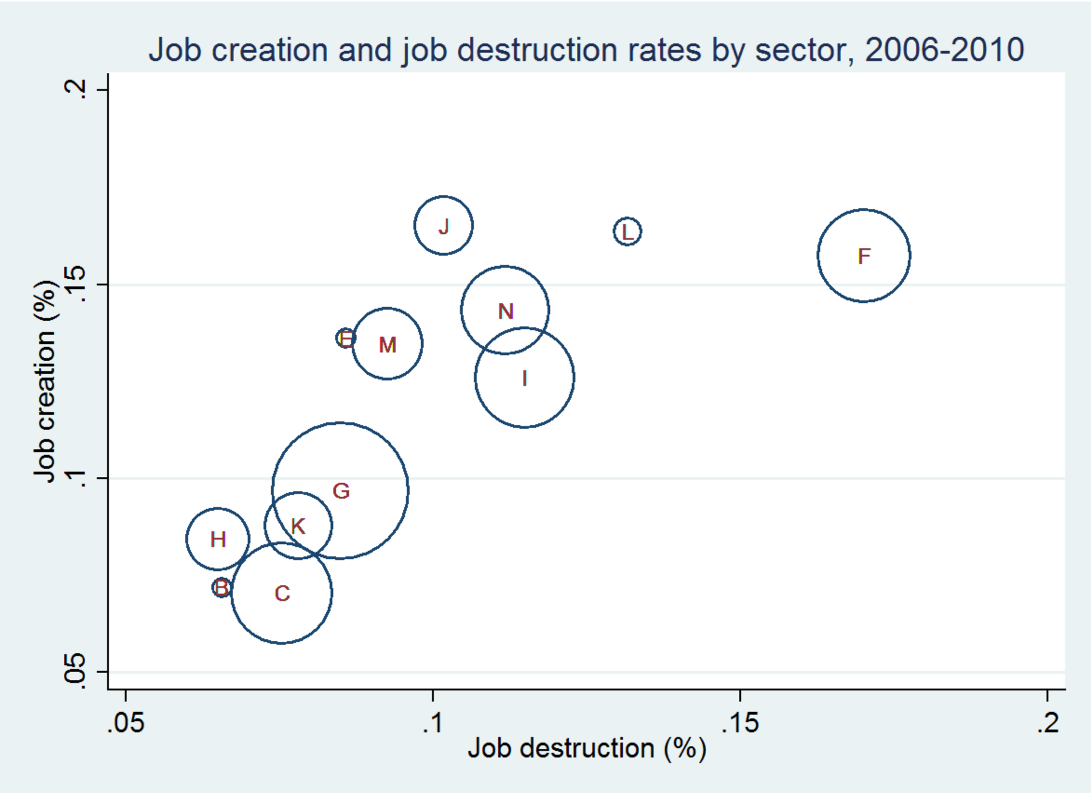
Table 3.8: Job creation and job destruction by NACE sector, 2006-2010

		2006	2007	2008	2009	2010
B. Mining & Quarrying	**JC**	-	-	0.092	0.061	0.028
	JD	-	-	-0.080	-0.273	-0.224
C. Manufacturing	**JC**	0.108	0.089	0.055	0.076	0.028
	JD	-0.065	-0.074	-0.127	-0.232	-0.152
D. Electricity, Gas, Steam & Air Conditioning	**JC**	-	-	-	-	-
	JD	-	-	-	-	-
E. Water supply & sewerage	**JC**	0.196	0.200	0.148	0.080	0.128
	JD	-0.078	-0.066	-0.149	-0.178	-0.166
F. Construction	**JC**	0.250	0.203	0.120	0.085	0.141
	JD	-0.115	-0.180	-0.364	-0.623	-0.470
G. Wholesale & retail trade	**JC**	0.138	0.145	0.087	0.156	0.090
	JD	-0.074	-0.083	-0.122	-0.257	-0.145
H. Transport & storage	**JC**	0.124	0.118	0.107	0.052	0.084
	JD	-0.050	-0.096	-0.087	-0.178	-0.135
I. Accommodation & food service activities	**JC**	0.189	0.173	0.124	0.104	0.138
	JD	-0.102	-0.126	-0.186	-0.327	-0.198
J. Information & Communication	**JC**	0.237	0.186	0.174	0.162	0.154
	JD	-0.087	-0.136	-0.120	-0.265	-0.162
K. Financial & Insurance activities	**JC**	0.136	0.150	0.055	0.049	0.111
	JD	-0.085	-0.109	-0.122	-0.144	-0.072
L. Real Estate Activities	**JC**	0.261	0.205	0.132	0.165	0.179
	JD	-0.102	-0.150	-0.176	-0.379	-0.292
M. Professional, Scientific & Technical services	**JC**	0.211	0.200	0.122	0.105	0.129
	JD	-0.071	-0.087	-0.132	-0.265	-0.204
N. Administrative & Support activities	**JC**	0.182	0.192	0.155	0.137	0.151
	JD	-0.067	-0.076	-0.235	-0.343	-0.297

Note: For confidentiality reasons, results for sector D have been suppressed. Results for 2006 and 2007 for sector B have also been removed for the same reason.

Figure 3.3 follows Hijzen et al. (2010) and plots the job creation and destruction rates for each NACE sector against each other. Many of the sectors that had high job creation rates over the period had similarly high job destruction rates. In some sectors, the job destruction rate has exceeded the job creation rate. The size of each circle in the figure represents the employment level in each sector. The circle representing the construction sector (F) displays the highest rate of job destruction over the period relative to the other sectors. Appendix Table 2.2 shows that over the period, the net reallocation rate was negative across many sectors demonstrating that on average, many of the sectors are declining. Exceptions include water supply and sewerage (E) information and communication sector (I), financial and insurance activities (K) and professional, scientific and technical services (M).

Figure 3.3: Job creation and job destruction rates by sector



Note: For confidentiality reasons, results for sector D Electricity and Gas have been supressed.

3.4.2 Job flows and firm size

This section examines job flows and the firm size category. Following on from the work of Baldwin and Picot (1995), Hijzen et al. (2010) and others, job flows are examined using three different measures of firm size, as used by Hijzen et al. (2010).

- The first measure classifies enterprises by their employment in 2005. As a result, if a firm did not exist in 2005 and entered later, this enterprise is automatically assigned to the smallest firm size group (0-9 employees). As outlined earlier in section 3.2.3, Hijzen et al. (2010) note that this method is likely to be affected by the regression to the mean fallacy as initially highlighted by Davis et al. (1996a).

- The second measure described by Hijzen et al. (2010: 642) as "average current year firm size" classifies enterprises into size categories according to the average of the current and previous year's employment (N_t+N_{t-1}/2). Hijzen et al. (2010) note that because this measure includes current size, a potential weakness arises from the fact that growth or decline of the enterprise affects the chosen size measure.

- The third measure also used by Hijzen et al. (2010: 642), "average previous year firm size" classifies enterprises into size categories using a size measure *prior* to the change in employment. In section 3.2.3, it is outlined that both Davidsson et al. (1998) and Hijzen et al. (2010) use this methodology initially employed by Baldwin & Picot (1995). This helps overcome the problem with the second measure above because now the size measure does not include the current size of the enterprise. Therefore, this is the preferred measure here.

These classifications mean that, according to the first and third definitions, all entrants are assigned to the smallest category because new entrants have, by definition, zero employment in the year before they actually enter. Because of this issue, the analysis is conducted for total job creation and destruction and these shares are subsequently broken down in entry and growth (for job creation) and exit and decline (for job destruction). This is useful to assess the employment growth performance of enterprises.

Table 3.9: **Job creation & job destruction proportions by enterprise size**

		Share of JC			Share of JD		
	Share of employment	**Total**	**Growth**	**Entry**	**Total**	**Decline**	**Exit**
(a)Initial size (N_1)							
0-9	0.252	0.732	0.407	1	0.341	0.275	0.491
10-19	0.084	0.044	0.098	-	0.094	0.098	0.084
20-49	0.125	0.057	0.125	-	0.132	0.143	0.107
50-249	0.209	0.076	0.169	-	0.200	0.231	0.130
>250	0.330	0.091	0.201	-	0.234	0.253	0.188
(b)Average current year firm size (N_t+N_{t-1}/2)							
0-9	0.162	0.282	0.200	0.417	0.259	0.187	0.427
10-19	0.099	0.118	0.123	0.109	0.119	0.123	0.112
20-49	0.143	0.145	0.162	0.117	0.157	0.171	0.126
50-249	0.235	0.211	0.241	0.162	0.221	0.255	0.146
>250	0.360	0.244	0.273	0.195	0.242	0.264	0.190
(c)Average previous year firm size (N_{t-1} + N_{t-2}/2)							
0-9	0.151	0.633	0.313	1	0.201	0.153	0.306
10-19	0.098	0.065	0.122	-	0.115	0.116	0.113
20-49	0.145	0.083	0.156	-	0.159	0.165	0.144
50-249	0.240	0.104	0.195	-	0.240	0.265	0.185
>250	0.365	0.115	0.215	-	0.285	0.300	0.253

The results in Table 3.9 show that the share of employment varies depending on the enterprise size measure used. However, the role of small enterprises with less than 50 employees is fairly consistent. The employment share ranges from 46% using the initial size measure to 39% using the average previous year measure.

The enterprise size measure used does have an impact on the magnitude of the job creation and destruction shares reported. Using the initial size measure we see that small enterprises (<50 employees) account for 83% of job creation and 57% of job destruction. It should be recalled that this is likely to be inflated due to the fact that entrants are automatically assigned to the smallest size category. However even just focusing on existing enterprises, we still see that small enterprises account for a greater fraction of jobs created relative to large enterprises with over 250 employees. Using the second measure of enterprise size, ‘average current year firm size,’ we can see that small enterprises account for about 55% of job creation and 54% of job destruction. Using the third measure we see that small enterprises accounted for 78% of the jobs created and 48% of job destruction. Our evidence suggests that small enterprises account for a greater proportion of job creation than their employment share. It appears that a large amount of job turnover is attributable to small enterprises, particularly micro-firms with less than 10 employees.

3.4.2.1 Persistence and job flows

This section examines the persistence of job creation and destruction by year and by enterprise size category. This may be important if there are significant differences in how long a newly created position lasts for depending on whether it is in a small or large enterprise.

We begin by exploring persistence by year. The persistence measure used here is that which is described earlier in equation (3.4). Using this method allows the calculation of the proportion of a positive change (job creation) or negative change (job destruction) in employment that persists through time. The measure can only take on a value between 0 and 1. This is because it represents the proportion of jobs created (or destroyed) in year t that are still in existence (or destroyed) in $t+n$. Therefore by definition, the measure cannot exceed 1 (or 100%) as the maximum proportion of jobs that are created (or destroyed) in t and still in existence in $t+n$ is 1 (or 100%).

Here in Table 3.10 we can see that 64% of the jobs created in 2006 still existed in 2007 *(t+1)*. This falls to 18% in 2010 *(t+4)*. In 2008, we can see that just 40% of jobs created still existed the following year. Higher persistence rates are seen with regards to job destruction. This may be due to exiting enterprises which results in a permanent decrease in employment. Overall persistence rates for job destruction are slower to decline than those of job creation.

Table 3.10: Persistence of job creation and destruction by year

Persistence of jobs created at year *t*				
Year (*t*)	***t*+1**	***t*+2**	***t*+3**	***t*+4**
2006	0.640	0.430	0.259	0.185
2007	0.523	0.273	0.187	-
2008	0.400	0.253	-	-
2009	0.536	-	-	-
2010	-	-	-	-
Persistence of jobs destroyed at year *t*				
Year (*t*)	***t*+1**	***t*+2**	***t*+3**	***t*+4**
2006	0.702	0.594	0.536	0.479
2007	0.807	0.733	0.664	-
2008	0.900	0.823	-	-
2009	0.853	-	-	-
2010	-	-	-	-

Next we turn to the persistence of job creation and destruction by enterprise size category, in line with Hijzen et al. (2010). Table 3.11 shows that the persistence of job creation varies little by firm size category. Enterprises with 250+ employees have the highest job creation persistence rates. But overall there is little difference between small (<50) and large (250+) enterprises. Job destruction is more persistent in larger enterprises.

Table 3.11: Persistence of job creation and destruction and firm size category

Persistence of jobs created at year *t*				
No. of employees	***t*+1**	***t*+2**	***t*+3**	***t*+4**
0-9	0.547	0.316	0.173	0.076
10-19	0.496	0.279	0.154	0.076
20-49	0.497	0.276	0.142	0.070
50-249	0.505	0.279	0.141	0.074
250+	0.581	0.341	0.194	0.110
Persistence of jobs destroyed at year *t*				
No. of employees	***t*+1**	***t*+2**	***t*+3**	***t*+4**
0-9	0.825	0.657	0.436	0.199
10-19	0.819	0.700	0.536	0.314
20-49	0.839	0.742	0.585	0.360
50-249	0.865	0.787	0.644	0.426
250+	0.865	0.796	0.642	0.421

3.4.3 Job flow rates in manufacturing sectors

This section analyses results obtained having merged the P35 and CIP data files. The results presented here refer specifically to the manufacturing sector (C).

3.4.3.1 Job flow rates of all manufacturing firms

Table 3.12 below presents the job flow rates in this sector based on those enterprises included in the CIP-P35 panel of manufacturing enterprises. A similar pattern can be seen here as was observed for NACE sectors B-N regarding the difference between the first two years and the latter three years. The job creation rate exceeded the job destruction rate in 2006 and 2007 and the net employment growth was positive. However, this changed in 2008 and in 2009 we can see that the job destruction rate is four times greater than the job creation rate. Net employment growth is negative in the years 2008-2010.

Table 3.12: Job flow rates in the manufacturing sector, 2006-2010

Year	Job creation	Job destruction	Job reallocation	Net reallocation	Excess reallocation
2006	0.105	-0.048	0.154	0.057	0.097
2007	0.119	-0.090	0.209	0.029	0.180
2008	0.043	-0.098	0.141	-0.054	0.087
2009	0.049	-0.190	0.239	-0.141	0.098
2010	0.060	-0.117	0.177	-0.058	0.119

In Table 3.13 below, we present total job creation by enterprise entry and growth. The job destruction rates are similarly broken down into that caused by exit and decline.

Table 3.13: Job creation and destruction; component parts

	Job creation			Job destruction		
Year	**Total**	**Growth**	**Entrants**	**Total**	**Decline**	**Exit**
2006	0.105	0.073	0.032	-0.048	-0.048	0
2007	0.119	0.060	0.058	-0.090	-0.047	-0.043
2008	0.043	0.031	0.012	-0.098	-0.089	-0.008
2009	0.049	0.025	0.041	-0.190	-0.148	-0.042
2010	0.060	0.057	0.024	-0.117	-0.093	-0.024
Average	0.0752	0.0492	0.0334	-0.1086	-0.085	-0.0234

Here we can see that the entry of new enterprises explains 44%[29] of the job creation. This is higher than when NACE sectors B-N were considered in Table 3.7. On the other hand the exit of enterprises accounts for around 21%[30] of the job destruction on average. The remainder of job destruction is explained by shrinking as opposed to exiting enterprises. This pattern is similar to that reported for all firms in Table 3.7. However here we see that on average the contribution of entrants to job creation is

[29] Using Table 3.13, this is computed by dividing the total average entrants figure (0.0334) by the total average JC figure (0.0752)
[30] Using Table 3.13, this is computed by dividing the total average exiters figure (-0.0234) by the total average JD figure (-0.1086)

higher, while the contribution of exiters to job destruction is lower when we examine manufacturing only in comparison to all NACE sectors B-N.

3.4.3.2 Job flow rates of manufacturing enterprises by sub-sector

Next we examine the job flow rates by manufacturing sub-sectors and year. The manufacturing sector is split into 13 subsectors. This gives an indication of the relative performance of the various subsectors with respect to their job flows. The sectoral classifications are shown in Table 3.14 below.

Table 3.14: Manufacturing sub-sectors

1.	Manufacture of food products, beverages and tobacco
2.	Manufacture of textiles and wearing apparel leather and related products
3.	Manufacture of wood, wood products except furniture; manufacture of straw and plaiting materials
4.	Manufacture of paper and paper products; printing and re-production of recorded media
5.	Manufacture of coke and petroleum products ; Manufacture of chemical and chemical products; basic pharmaceutical products and preparations
6.	Manufacture of rubber and plastic products
7.	Manufacture of other non-metallic mineral products
8.	Manufacture of basic metals and fabricated metal products, except machinery and equipment
9.	Manufacture of computer, electronic and optical products, electrical equipment
10.	Manufacture of machinery and equipment
11.	Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment
12.	Manufacture of furniture and other manufacturing
13.	Repair and installation of machinery and equipment

Job creation and destruction rates by sub-sector and year are shown in Appendix Table 2.4. As with the NACE sectors B-N, we can see that significant changes occur over the period studied. In 2006, all of the manufacturing sectors displayed positive net employment growth. Particularly, sector 5 which incorporates the pharmaceutical sector had a high rate of job creation at 12% and a job destruction rate of less than 3%, while the manufacture of non-metallic mineral products sector (7) had an even higher job creation rate at over 15% and a job destruction rate of less than 3%. By 2010, both have experienced a decline in job creation and an increase in job destruction, the increase in job destruction being greater in sector (7). The pharmaceutical sector (5) has maintained lower rates of job destruction over the period, when compared to others.

3.4.3.3 Job flow rates of manufacturing firms by region

We now examine job flow rates by geographic region. As there is no location identifier in the P35 data, this can only be done for the merged P35-CIP panel. We can see below that Ireland is divided into eight regional authority areas. Table 3.15 shows the job creation and destruction rates by region and year. We can see that in 2006 and 2007, each region was creating more jobs than it was destroying. However, this began to change and in 2009 a big shift had taken place which saw a job creation rate of 3% and destruction rate of 17% in Dublin. The West appears to be the region worst affected in 2009 with job creation and destruction rates of 2% and almost 30% respectively.

Table 3.15: Job flow rates in the manufacturing sector by region and year

Regional Authority Area		2006	2007	2008	2009	2010
1. Border	JC	0.101	0.104	0.046	0.030	0.077
	JD	-0.046	-0.052	-0.114	-0.166	-0.102
2. Dublin	JC	0.122	0.067	0.037	0.027	0.039
	JD	-0.049	-0.058	-0.104	-0.172	-0.117
3. Mid-East	JC	0.088	0.071	0.033	0.015	0.034
	JD	-0.041	-0.068	-0.106	-0.152	-0.029
4. Midlands	JC	0.079	0.088	0.137	0.029	0.062
	JD	-0.041	-0.087	-0.083	-0.180	-0.116
5. Mid-West	JC	0.057	0.111	0.030	0.031	0.042
	JD	-0.041	-0.086	-0.068	-0.378	-0.152
6. South-East	JC	0.069	0.074	0.051	0.086	0.057
	JD	-0.039	-0.078	-0.099	-0.159	-0.088
7. South-West	JC	0.171	0.060	0.042	0.053	0.021
	JD	-0.057	-0.084	-0.074	-0.151	-0.294
8. West	JC	0.078	0.070	0.027	0.022	0.113
	JD	-0.042	-0.065	-0.105	-0.294	-0.068

3.4.3.4 Job flow rates of manufacturing enterprises & international trade

This next section presents some descriptive information on enterprises in the P35-CIP panel and their involvement in international trade. The measure of exports used here is the reported percentage of turnover exported by each enterprise. The import measure is the percentage of materials imported by the enterprise.

Previous research by Biscourp and Kramarz (2007) analyses the link between export activity, import activity and employment in manufacturing firms in France. As is the case in this thesis, they use firm level data to measure exports and imports. With regards to imports, they suggest that two differing employment outcomes may result from increasing imports. Switching suppliers from local producers to less expensive foreign suppliers for intermediate goods may positively affect employment. However, substituting the production of goods internally with imports may have a negative effect on employment. They find that firms importing final goods tend to destroy more jobs than those importing only intermediate inputs. While we cannot distinguish between imports of intermediates and final goods in our data, we still explore its relationship with job creation and job destruction.

Regarding exporting activity, Biscourp and Kramarz (2007) note that it seems to be that growth in employment is associated with growth in exports, citing evidence from Bernard and Jensen (1999:1) that "good firms become exporters."

Firstly we can see from Table 3.16 that there is a relatively even split between enterprises that report being an exporter or not in a given year. It is interesting to note that in 2010, there is an increase in the number of enterprises who report some exporting activity and a decrease in the number of enterprises who do not export. With regards to imports, it can be seen that over the years 2006-2009, more enterprises reported importing some materials rather than not importing any materials. However, in 2010 we can see that those reporting they do not import has increased and there is a relatively even split between those who do and do not import.

Also noteworthy are the mean employment figures. Average employment is higher in enterprises that do engage with international markets through importing and/or exporting. Mean employment in general has declined over the period in all enterprises, falling from about 60 employees in 2006 to 42 employees in 2010. It is observed also that the standard deviation of employment is quite high and almost four times mean employment in some cases. This suggests that enterprise size is widely distributed and so there is significant enterprise-level heterogeneity.

Table 3.16: Irish manufacturing employment and trade status, 2006-2010

	Trade status	No. of enterprises	Mean employment	Standard deviation	Minimum	Maximum
2006	**All**	4,016	59.54	203.99	1	6,365
	Exporter – Yes	1,833	94.76	244.48	1	4,981
	Exporter – No	1,823	25.81	47.46	1	661
	Importer – Yes	2,307	81.48	218.17	1	4,981
	Importer – No	1,349	24.30	63.36	1	1,352
2007	**All**	4,894	50.04	174.91	0	5,902
	Exporter – Yes	2,281	80.33	216.57	0	4,342
	Exporter – No	2,417	22.36	41.70	0	592
	Importer – Yes	2,890	69.64	193.37	0	4,342
	Importer – No	1,808	19.93	48.84	0	1,144
2008	**All**	4,806	45.86	160.97	0	5,247
	Exporter – Yes	2,276	74.34	225.64	0	5,247
	Exporter – No	2,421	20.75	45.52	0	986
	Importer – Yes	2,965	62.30	195.94	0	5,247
	Importer – No	1,732	20.05	69.93	0	2,313
2009	**All**	4,350	43.01	136.67	0	3,353
	Exporter – Yes	2,147	68.10	186.92	0	3,353
	Exporter – No	2,190	18.59	40.42	0	3,353
	Importer – Yes	2,743	57.18	167.17	0	3,353
	Importer – No	1,594	18.87	44.15	0	547
2010	**All**	4,233	42.05	134.41	0	3,007
	Exporter – Yes	2,756	52.73	162.92	0	3,007
	Exporter – No	1,477	22.14	40.57	0	478
	Importer – Yes	2,181	68.69	181.09	0	3,007
	Importer – No	2,052	13.75	29.42	0	480

Note: Figures for importers and exporters may not sum to the total number of enterprises ("All") as the export/import figure may be missing for some enterprises.

Table 3.17 below shows the mean annual employment growth rate for exporters and non-exporters, as well as for all enterprises. Employment growth, computed as a change in employment between one year and the next is divided by average employment over the period. The figure is therefore constrained to range between -2 for exiters and +2 for new entrants. Employment growth was positive in 2006 and 2007. The figure was lower for exporters relative to non-exporters during this time. Over the period 2008-2010, we can see that the employment growth rate is negative for all enterprises. However, the value is not as low for the exporters when compared to the non-exporters over these years. It would appear that in 2010, the employment growth rate had started to recover slightly, particularly for exporters.

Table 3.17: Manufacturing employment growth rates by year and export status, 2006-2010

		All enterprises	Exporter – Yes	Exporter – No
2006	**Mean**	0.104	0.086	0.111
	Std Dev	0.449	0.411	0.439
	Frequency	4,016	1,833	1,823
2007	**Mean**	0.052	0.032	0.051
	Std Dev	0.480	0.460	0.469
	Frequency	4,894	2,281	2,417
2008	**Mean**	-0.038	-0.034	-0.074
	Std Dev	0.562	0.552	0.519
	Frequency	4,806	2,276	2,421
2009	**Mean**	-0.241	-0.226	-0.256
	Std Dev	0.523	0.513	0.526
	Frequency	4,350	2,147	2,190
2010	**Mean**	-0.179	-0.139	-0.254
	Std Dev	0.520	0.478	0.585
	Frequency	4,233	2,756	1,477

The employment growth rate is examined by import status in Table 3.18. In contrast to the previous table, here we observe that enterprises who engage in some import activity perform less well in terms of employment growth generally, when compared to those who do not import. In 2006 and 2007, importers have a lower employment growth rate than non-importers. Between 2009 and 2010, the employment growth of importers is also lower. The year 2008 however shows a different trend. While employment growth was negative for both importers and non-importers, it was lower for non-importers.

Table 3.18: Manufacturing employment growth rates by year and import status, 2006-2010

		All firms	Importer – Yes	Importer – No
2006	**Mean**	0.104	0.086	0.120
	Std Dev	0.449	0.400	0.467
	Frequency	4,016	2,307	1,349
2007	**Mean**	0.052	0.039	0.046
	Std Dev	0.480	0.465	0.464
	Frequency	4,894	2,890	1,808
2008	**Mean**	-0.038	-0.039	-0.081
	Std Dev	0.562	0.553	0.539
	Frequency	4,806	2,965	1,732
2009	**Mean**	-0.241	-0.246	-0.232
	Std Dev	0.523	0.522	0.516
	Frequency	4,350	2,743	1,594
2010	**Mean**	-0.179	-0.184	-0.174
	Std Dev	0.520	0.526	0.514
	Frequency	4,233	2,181	2,052

Overall, we have seen that the job creation and destruction rates have varied across sectors and over time in the Irish economy. Focusing specifically on the manufacturing sector above, we have highlighted some differences for exporters and importers. As outlined in section 3.2.5, some studies such as that by Levinsohn (1999) and Pisu (2008) have focused on the possible link between international trade involvement and job flows. Given the important role that exporting firms are expected to play in the Irish economic recovery, the manufacturing sector is examined to identify the relationship between export ~~and import~~ activity and job flows.

We begin by disaggregating the manufacturing sector into 13 different subsectors as set out in Table 3.14. Enterprises who do engage in some export or import activity (ie non-zero exports or imports) were identified and then split into quintiles based on the *level* of their exports (the percentage of turnover exported) and imports (the percentage of raw materials imported).[31] Both Hijzen et al. (2010) and Levinsohn (1999) used quintiles to measure exports and imports in their regressions. One benefit of splitting continuous variables like exports and imports into quintiles is that it helps avoid the assumption that there is a linear relationship between the export/import variables and the employment growth rate. For example, there may be a different effect on employment growth (dependent variable) from a small change in exports (independent variable) if exports are at a low level rather than a higher level. To assess the role of international trade activity in explaining job creation and destruction, regression analysis is used. To control for fixed effects, industry and time dummies are included. The benefit of such an approach is that it allows for heterogeneity among the industrial sectors because each is allowed to have its own intercept value. It is also important to control for time effects here as we know that over the period, job creation generally declined while job destruction increased.

[31] The non-exporters and non-importers are the reference categories excluded from the regressions.

Following the work of Levinsohn (1999) and Hijzen et al. (2010), we use an OLS regression. The regression is weighted by that given in equation (3.5) earlier.

$$\mathbf{g}_{it}^{+} = \boldsymbol{\alpha} + \sum_{q=1}^{5} \boldsymbol{\beta}_q \boldsymbol{EX}_{qit} + \sum_{q=1}^{4} \boldsymbol{\delta}_q \boldsymbol{IMP}_{qit} + \boldsymbol{\gamma}_t + \boldsymbol{z}_{it} + \boldsymbol{\varepsilon}_{it} \qquad \textbf{(3.11)}$$

Above, g_{it}^{+} is the employment growth rate value for enterprises experiencing positive employment growth, or job creation, where $g_{it} > 0$. Job destruction is similarly computed by defining the employment growth rate, g_{it}^{-} as equal to the employment growth rate g_{it} for those enterprises where $g_{it} < 0$. In the case of negative values for job destruction, the absolute value was used to aid interpretations of the coefficients. The variables EX_{qit} and IMP_{qit} are dummy variables to capture export and import intensity quintiles respectively that an enterprise belongs to.[32] When creating quintiles (five groups), quartiles (four groups) were created for the imports variable. This is due to a large number of enterprises reporting a high level of imports. While there are around 2,600 observations in the first three quartiles, quartile 4 contains 5,220 observations. These enterprises have reported imports of raw materials of 90% or above. This large number of observations reporting a high level of imports contributes to the creation of four rather than five groupings. The variables γ_t and z_{it} are vectors of dummy variables to capture industry and time fixed effects respectively. Therefore estimates of β_q and δ_q can be used to determine if job creation and job destruction differs significantly across export and import quintiles.

Table 3.19 reports our results for the level of export and import activity respectively. It seems that trade exposure, through export and import activity, generally has a

[32] Details of the export and import quintiles/quartiles are available in Appendix Table 2.5.

negative effect on job creation. It appears that having the highest level of exports is associated with a statistically significant decrease in job creation. The magnitude of the effect is relatively small. Other export level coefficients are not statistically significant. All importing activity is associated with a decrease in the job creation rate, although only levels 2 and 3 are statistically significant.

Table 3.19: Job creation, job destruction and level of trade intensity

	Job creation Coefficients	**Job destruction** Coefficients
β_1	-0.00931	-0.0193***
	(0.00576)	(0.00668)
β_2	0.00697	0.000562
	(0.00646)	(0.00749)
β_3	-0.00795	-0.0110
	(0.00632)	(0.00733)
β_4	0.000311	-0.0327***
	(0.00520)	(0.00604)
β_5	-0.0229***	-0.0144***
	(0.00476)	(0.00553)
δ_1	-0.00451	-0.0231***
	(0.00573)	(0.00665)
δ_2	-0.0190***	-0.0252***
	(0.00530)	(0.00615)
δ_3	-0.0154***	-0.0394***
	(0.00499)	(0.00578)
δ_4	-0.00178	0.0198***
	(0.00525)	(0.00608)
α	0.126***	0.0452***
	(0.00585)	(0.00679)
Observations	21,621	21,621
Fstat	16.76	67.04
Prob > F	0.000	0.000
R-squared	0.020	0.075

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regarding the level of trade activity and job destruction, the results generally suggest that being involved in exporting and importing activity reduces job destruction.

Beginning with exporting level, being an exporter reduces job destruction. The exception to this is the second export intensity level which is positive but insignificant. For import levels we again see that being an importer has a negative and significant effect on job destruction, except for enterprises with the highest level of imports. Here we see that importing a large percentage of materials has a positive and significant impact on job destruction. So results suggest that involvement in international trade does reduce job destruction, except for enterprises who import the majority of their materials.

However as noted earlier, Klein et al. (2003) have cautioned on expecting a relationship between the *level* of trade intensity and the turnover of jobs. Instead it is suggested that it may be more appropriate to examine the *changes* in trade intensity. Because of this a regression is also now used to test if changes in the intensity of exporting and importing activity affect job flows. The dependent variable is the employment growth variable g_{it}, as explained previously. Initially we identify if there was a change in export activity from one year to the next for each enterprise. Enterprises were then classified into three mutually exclusive groups as either being:

- A *non-exporter* in both years;
- An exporter who experienced *a change* in trade intensity (*ExpQ1-ExpQ5*);
- An exporter who *did not* experience a change (*EX*).

To capture importing activity enterprises were classified in a similar way;

- A *non-importer* in both years;
- An importer who experienced *a change* in trade intensity (*ImpQ1-ImpQ5*);
- An importer who *did not* experience a change (*IMP*).

Of enterprises that did experience a change in intensity, these were split into export intensity quintiles. These quintiles are essentially quintiles of the changes in export intensity. The change in intensity variable can range between -100 and +100, where -100 represents an enterprise that experienced a 100% decline in exporting activity, while +100 represents a 100% increase in such activity. The regression then included a series of dummy variables to capture whether a particular enterprise is in a given change in export intensity quintile. Import activity was treated in the same way as exporting activity above and details are available in Appendix Table 2.6. As this shows, the first two export and import intensity quintiles capture enterprises that have experienced a *decrease* in export and import intensity. Therefore, these lower quintiles represent enterprises that have experienced a fall in intensity. Time and industry fixed effects were also included as before. Regression equation (3.12) below was used which is similar to equation (3.11) but modified to include variable EX_{it} representing no change in exports and IMP_{it} representing no change in imports. The change in export and change in import intensity quintiles are represented by the variables EXQ_{qit} and $IMPQ_{qit}$ respectively. As before, γ_t and z_{it} are vectors of dummy variables to capture industry and time fixed effects respectively. Therefore estimates of β_q and δ_q can be used to determine if job creation and job destruction differs significantly across export and import intensity quintiles.

$$\boldsymbol{g_{it}^{+} = \alpha + \lambda EX_{it} + \sum_{q=1}^{5} \beta_q EXQ_{qit} + \sigma IMP_{it} + \sum_{q=1}^{5} \delta_q IMPQ_{qit} + \gamma_t + z_{it} + \varepsilon_{it}} \qquad \textbf{(3.12)}$$

Table 3.20 reports our results. Beginning with job creation, we see that the magnitude of the effect of changing export and import intensity is small and not all quintiles are significant. Focusing on exports, we see that most of the coefficients are negative except for quintile 5 (Q5). It is worth noting again that the first two quintiles represent a decrease in export intensity, while quintiles 3 and 4 account for small increases in export intensity.[33] So it appears that a decrease in export intensity (Q1 & Q2) or a small increase in export intensity (Q3 and Q4) is associated with lower job creation. However the magnitude of the effects decreases as the change in export intensity increases from Q1 to Q4. Then we see a positive effect for those in the top quintile (Q5), representing those who experience the largest positive change in export intensity. Enterprises in the highest export change intensity quintile have higher and significant rates of job creation.

Turning to imports, we can see that all coefficients are negative, with quintiles 2-4 being significant. The magnitude of the negative effect on job creation reduces for enterprises in higher import intensity quintiles. As with export intensity, quintiles 1 and 2 represent a decrease in importing activity.

Moving to job destruction, we see that enterprises that are in the lower and higher export intensity quintiles have lower rates of job destruction. The exception to this is those enterprises in quintile 3 (Q3), which represents a small positive increase in export intensity. So it appears those experiencing declining or increasing changes in export activity are associated with a lower rate of job destruction, while those in quintile 3 (Q3) have higher rates of job destruction. With regards to imports, again we see a negative relationship. Any change in import intensity appears to reduce job destruction. Enterprises in the middle quintile experience the largest effect and we see that magnitude of the effect declines as we move to higher quintiles, as changing import intensity increases.

[33] See Appendix Table 2.6 for details.

Table 3.20: Job creation, job destruction and change in trade intensity

	Job creation Coefficients	Job destruction Coefficients
λ	-0.00874***	-0.0339***
	(0.00261)	(0.00609)
β_1	-0.0113***	-0.00487
	(0.00377)	(0.00881)
β_2	-0.0104***	-0.0416***
	(0.00333)	(0.00778)
β_3	-0.0109***	0.0400***
	(0.00330)	(0.00772)
β_4	-0.00194	-0.0395***
	(0.00381)	(0.00891)
β_5	0.0121***	-0.0179*
	(0.00455)	(0.0106)
σ	-0.0164***	-0.0108
	(0.00301)	(0.00703)
δ_1	-0.00181	-0.0265***
	(0.00432)	(0.0101)
δ_2	-0.0189***	-0.0152*
	(0.00354)	(0.00828)
δ_3	-0.0148***	-0.0524***
	(0.00356)	(0.00832)
δ_4	-0.0113***	-0.0387***
	(0.00366)	(0.00856)
δ_5	-0.00522	-0.0284***
	(0.00392)	(0.00915)
α	0.0847***	0.0491***
	(0.00337)	(0.00788)
Observations	15,114	15,114
Fstat	20.13	49.37
Prob > F	0.000	0.000
R-squared	0.036	0.084

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Levinsohn (1999) finds weak evidence that job creation is higher in the export sector in Chile following the liberalisation of trade. Pisu (2008) also finds that involvement in international markets is associated with higher employment growth rates in Belgium. Results for the Irish manufacturing sector presented here suggest that there is a positive association between export intensity and job creation for those in the top quintile only. Results suggest a negative effect on job creation for the lower change in export intensity quintiles and for all change in import intensity quintiles. Regarding job destruction however, we do find support for the assertion that involvement in international trade reduces it. However, it should be noted in both cases that the magnitude of the effect is small. These findings are somewhat similar to Hijzen et al. (2010) regarding export activity rather than import activity. They find that industries in the highest import quintile have higher rates of job destruction while those in the highest export quintile have lower rates of job destruction. They also report little evidence of a "systematic relationship between job creation rates and the change in trade exposure" for UK industries (Hijzen et al. 2010: 635).

Regarding import activity, we find a negative relationship between changing intensity and job destruction. Increases in intensity reduce job destruction, although the magnitude of the effect is small. It may be that these imports represent intermediate goods rather than final goods, although this cannot be stated definitively.

3.5. Concluding remarks

This chapter uses the P35 dataset, a newly available Irish administrative data from the CSO, to examine how job flows have changed over the turbulent economic period of 2006-2010 for NACE sectors B-N. This P35 dataset is then merged with survey data from the Census of Industrial Production (CIP) to analyse the relationship between job flows and international trade involvement.

We see that over the period in NACE sectors B-N, there was a dramatic increase in job destruction and decrease in job creation. The construction sector was most adversely impacted. Regarding enterprise size, evidence suggests that a large amount of job creation and destruction is attributable to small enterprises, particularly micro-enterprises with less than 10 employees. Turning to persistence, we find little difference in persistence rates of job flows between small and large enterprises. There is some evidence that job destruction rates appear to be more persistent in larger enterprises (250+ employees).

Moving to the merged P35-CIP data, we observe a similar pattern in job flow rates in the manufacturing sub-sectors to that of NACE sectors B-N. From 2008-2010, we see an increase in the job destruction rate and a decline in the job creation rate. The West of Ireland appears to have suffered most with a job destruction rate of nearly 30% in 2009 in the manufacturing sub-sectors.

We also examine the role of involvement in international trade with respect to employment growth rates. We begin with a descriptive analysis and observe that there was a roughly even number of enterprises who do and do not engage in international trade through exporting and importing activity. Examining employment growth rates for exporters and importers revealed differing results. While the employment growth rate was negative over the period 2008-2010 it is less negative for the exporters when compared to the non-exporters over these years, possibly suggesting that exporters were less adversely impacted in terms of employment growth. However, when examining whether enterprises imported or not, we see that enterprises who engage in some import activity perform less well in terms of employment growth in general when compared do those who do not import.

Regression results suggest that the magnitude of the effect of involvement in international trade on job creation and destruction rates is relatively small. Export intensity quintiles appear to have a negative impact on job creation, with the exception of the highest quintile which has a positive effect. A similar negative impact across quintiles is reported for import intensity. However, we find some evidence that those experiencing either a lower or higher change in export intensity are associated with lower rates of job destruction. Likewise, a change in import intensity appears to reduce job destruction.

Chapter 4 : The Impact of Displacement on the Earnings of Workers

4.1: Introduction

Ireland has experienced dramatic changes in its economic environment over the last ten years. As documented in Chapter 2, with the slowdown in economic growth and the onset of the financial crisis in 2008, the business environment which employers and employees operate in has changed dramatically. The unemployment rate increased from approximately 4% in 2005 to around 14% in 2011 (The World Bank, 2016). Many of these unemployed individuals are likely to have involuntarily separated from their employers during this time. Also, as reported in Chapter 3, job destruction increased particularly in 2009. In the labour market, enterprises are also constantly entering or exiting, growing or declining. In this context, workers who lose their jobs may face significant adjustment costs. These include the prospect of long spells of unemployment and for those who find a new job, they may have lower wages than in their previous job.

The purpose of this chapter is for the first time in Ireland, to estimate the earnings losses of workers who become displaced from their employment. This research uses the extensive and relatively new linked employer-employee P35 dataset available from the CSO for the period 2005-2011. The uniqueness of this dataset stems from the fact that it covers virtually all employees in the public and private sector in Ireland, consisting of around two million person observations per year. This chapter aims to add to the existing literature in a number of ways. Firstly, it examines the impact of displacement on the earnings of workers. We focus on two displacement events – both closure and mass-layoff. Relatedly, we examine if the sector an individual finds re-employment in after displacement impacts on their earnings losses. From a policy perspective this chapter is significant. Given the large number of workers who are unemployed, this research helps to identify if particular groups of workers, such as older workers, are at greater risk of displacement and if they suffer greater earnings losses once they re-enter employment compared to other groups. Also as the Irish economy grew in the late 1990's and early 2000's, many workers migrated there from other countries. This research offers a unique opportunity to identify the differential impact of displacement on earnings for Irish versus non-national workers.

Secondly, we identify which workers are at the highest risk of displacement based on both individual and enterprise-level characteristics. Individual characteristics include gender, age and nationality, while the enterprise-level characteristics included are the NACE Rev. 2 economic sector of the enterprise and enterprise size.

A noteworthy feature of the data used in this thesis is that displaced individuals may leave the dataset and never re-appear within the analysis period. Their exit means they are no longer in employment and we do not know the reason for this. It may be that they have emigrated.

This chapter proceeds as follows. Section 4.2 reviews the literature in relation to displacement and the income or earnings losses associated with such events in various countries. Section 4.3 describes the data and the methodology used in this study while section 4.4 describes the results and section 4.5 concludes the chapter.

4.2: Literature Review

In this section we review the available literature regarding displacement and associated earnings losses. While much of the work conducted on the topic relates to the United Sates, there has also been work undertaken in a number of European countries. The earnings losses associated with displacement are the focus of this chapter. However, we begin this section by firstly identifying what constitutes a displacement event and focusing on issues arising from the use of varying definitions of the incidence of displacement and the displacement rate. Section 4.2.4 reviews evidence on displacement and earnings. Studies conducted in the US indicate that displacement is associated with a negative impact on earnings in both the long-term and the shorter term. In contrast, Huttunen, Møen & Salvanes (2011) note that fewer European studies have been undertaken and results from these have been less conclusive on the size of the impact of displacement on earnings.

4.2.1 The definition and incidence of job displacement

Much work has been undertaken on the incidence of job displacement. One of the main obstacles preventing meaningful cross-country comparisons is the lack of a single definition of job displacement. As noted by Stevens, Crosslin & Lane (1994), estimated earnings losses are sensitive to the definition of displacement adopted. A contributory factor to this is that displacement can be defined using survey data or administrative data sources. As well as definitions being self-defined by survey respondents or firm defined, the incidence of job displacement can be measured differently, with some studies focusing on displacement due to mass-layoffs only and others investigating displacements due to both firm closure and mass-layoffs.

In the US, many studies investigating displacement and earnings losses have used data from the Displaced Workers Survey (DWS) administered by the Bureau of Labor Statistics. Examples include the work of Podgursky (1992), Carrington (1993) and Kletzer (1998). The DWS survey began in 1984 and was distributed at two year intervals with the January Current Population Survey (CPS). "Specifically, these surveys ask workers if in the past five years they have '*lost or left a job because of a plant closing, an employer going out of business, a layoff from which [they were] not recalled or other similar reason*" (Farber, Hall & Pencavel 1993: 73). Thus we can see that this definition does not allow for a distinction to be drawn between displacement due to mass-layoff or closure. However, previous work from Gibbons & Katz (1991) does find support for the assertion that the post-displacement wages of displaced workers may be influenced by the cause of displacement. It is suggested that when firms have some degree of discretion regarding who is selected to be laid off, the labour market – including future employers – can make an inference that such workers are of lower ability. Specifically they find that earnings of white-collar workers displaced due to a mass-layoff event are significantly lower than those displaced due to a closure event.

Kletzer (1998) discusses earlier work in relation to job displacement, and relies on the previous work of Farber, Haltiwanger & Abraham (1997). Again DWS survey data is used for the period 1984-1996 and displacement is deemed to have occurred if workers involuntarily separate from their jobs. She focuses on issues such as the incidence of job displacement, the characteristics of displaced workers in comparison to other unemployed workers and the impact of displacement on a worker's earnings. She cites the work of Farber et al. (1997) describing displacement rates. The displacement rate is computed by "dividing the number of workers who have lost at least one job by the number of workers 'at risk' of losing a job during the relevant time period" (Kletzer, 1998: 117). This 'at risk' group is computed based on the number of individuals in employment at the time the DWS survey was distributed. Earlier work by Farber et al. (1993) also used DWS data and so use an analogous displacement definition to measure the incidence of displacement. They find that women have a lower incidence of job loss when compared to men (6.2% versus 7.8%). They also examine the rates of job loss by education. They find a strong negative relationship between the two variables. This is supported by findings presented by Kletzer (1998) that workers with a lower level of education are more likely to be displaced compared to workers who have attained a higher level of education.

The OECD (2013) has attempted to overcome this issue of varying definitions by investigating the incidence of job displacement across fourteen countries, with an attempt made to use common definitions and sample restrictions. Some countries used matched worker-firm data, generally from administrative data sources (eg taxation files) and others use survey data. Firm defined job displacements, usually from administrative data sources, are defined as "job separations from firms that, from one year to the next, experience an absolute reduction in employment of five employees or more and a relative reduction in employment of 30% or more (mass dismissal) or that cease to operate (firm closure)" (OECD, 2013: 6).

When survey data is used in the OECD (2013) study, a self-defined measure is used. Displacement is deemed to have occurred when the reasons for leaving a job are economic or if a person is dismissed for reasons such as they were unable to do the job – dismissal for cause[34]. As pointed out by the OECD (2013), the reasons that constitute a displacement vary from one country to another which hinders comparability across countries. One of the advantages of administrative data, as cited by the OECD (2013), is that because administrative data usually involve larger samples, it tends to lead to more accurate measures of the effect on wages and

[34] The OECD (2013) suggests they include dismissal for cause their displacement definition because in an number of countries included in the study, it is not possible to distinguish between those dismissed for economic reasons and dismissal for cause.

earnings after displacement. On the other hand, self-defined displacement is usually measured using data gathered from survey data sources – either household or cross-sectional. Such surveys could gather detailed information on workers. However, the sample size is smaller and since information is self-reported, there may be problems with bias. Other sample restrictions imposed in the OECD (2013) study are that workers must have one year tenure with the same employer, firms with less than ten employees in the year before displacement are excluded, only workers between the ages of 20-64 are included, while those who work in some public sector roles are omitted.[35] Also, those who were employed in multiple jobs prior to displacement are excluded and those with a single job are retained. It was not possible to implement all restrictions in all countries due to the nature of the data.

Displacement rates are computed for the various countries from 2000-2008 and 2009-2010. These time periods are chosen to capture the effect of the economic downturn. These rates are computed by calculating the number of employees aged 20-64 who are displaced between one year and the next as a fraction of the total number of employees aged 20-64 (OECD 2013). It is reported that there are large differences across countries and between the two time periods selected. A note of caution is added here by the authors who suggest that in spite of their efforts to use common definitions and sample restrictions across countries, there is still a doubt as to whether meaningful comparisons can be made across countries. However, overall rates are relatively low, varying between 1.5% and 7% over the entire period. In all countries examined, except the United Kingdom, the impact of the recession can be seen with higher displacement rates.

[35] "Those who work in public administration, defence, for private households or international organisations are also excluded" (OECD, 2013: 7).

4.2.2 Industry and job displacement

A feature of the work on displacement has been to examine the incidence of displacement by the sector or industry of employment. While the incidence of displacement may increase, this is not necessarily uniformly spread across all sectors of the economy. Turning to evidence from the US, Podgursky (1992) report that one of the more interesting findings is that while manufacturing and goods producing industries are still responsible for a large proportion of job displacement, there is a trend of displacement events shifting away from manufacturing towards service producing industries such as retail trade and services. His findings regarding this shifting trend are supported by the work of Farber et al. (1993) who find that while the probability of job loss in manufacturing declined by 4% between 1982-83 and 1990-91, a 4% rise was noted in finance, insurance and real estate over the same period. They cite this as evidence of an increased incidence of job loss in non-goods producing industries. Kletzer (1998) relies on previous estimates produced in Farber et al. (1997) and supports Podgursky's findings that job loss has declined in manufacturing and increased in some services sectors, particularly from 1985 onwards.

4.2.3 Displacement and worker characteristics

It is possible that displacement rates may vary according to demographic characteristics such as age and gender. The OECD (2013) attempt to identify workers that are at the highest risk of displacement across countries. They find that initially displacement rates for male workers are higher than those for females in most countries. However, once they control for factors such as the industry, occupation and contract type, males do not have a greater likelihood of being displaced relative to females. In the US, Kletzer (1998) shows that females have a displacement rate of 15.7% while males have a displacement rate of around 16.4% over the study period.

It appears that older workers and younger workers have a greater risk of being displaced in many countries. The OECD (2013) find that younger workers in the 20-24 age category have a greater risk of displacement compared to prime aged workers (35-44 years) in Sweden, Finland, Denmark and Germany even when controls are included for worker and job characteristics. However in the US and Portugal the opposite is reported; younger workers are at a lower risk of displacement. With regards to older workers aged between 55 and 64, in the majority of countries, they are found to be at higher risk of displacement compared to prime aged workers. Not surprisingly, those who have less than a secondary level of education are at a greater displacement risk. The effect has increased with the onset of the recession in 2008.

4.2.4 The impact of displacement on earnings of workers

We now turn to empirical evidence on the impact of displacement on earnings. Evidence from the US is examined with regards to their results and also the methods used. Research in the field has evolved in the methodological approach taken, given the availability of administrative data sources. We begin with evidence from the US. Findings from European studies are then examined.

4.2.4.1 The earnings of displaced workers in the United States

Much of the work on the impact of displacement on earnings has originated in the US. Ruhm (1991) notes that at the time, while work had been conducted examining the impact of permanent lay-offs, little work had been done on the duration associated with labour market adjustments regarding a displaced workers' employment and wages. He reported that displaced workers experience a considerable and long lasting impact on their wages. Others in the US reporting similar findings regarding earnings losses include Jacobson, LaLonde & Sullivan (1993). Their paper is regarded as one of the more influential papers in the area for a number of reasons related to their data and the methodology they employed as explained below. Their paper focuses on the earnings losses of displaced, high tenure workers in the state of Pennsylvania using administrative data for the period 1974-1986. Displaced workers are followed for around thirteen years after they are displaced. Given the importance of the Jacobson et al. (1993) paper, we begin our examination of US studies by exploring its methodology and key results.

In an effort to capture changes across workers over time, Jacobson et al. (1993) pool the data for displaced workers for the years 1980-1986. Dummy variables D_{it} are constructed to capture the number of quarters (*k*) before or after a person is displaced. It equals one if displaced and zero otherwise. As per equation 4.1, they regress earnings on these dummies and other variables to control for time varying and fixed characteristics.

$$y_{it=} \propto_i + \ \gamma_t + \ x_{it}\,\beta + \sum_{k \geq -m} D_{it}^k\ \delta_k + \ \varepsilon_{it} \tag{4.1}$$

In equation (4.1) above, taken from Jacobson et al. (1993: 693), δ_k is designed to capture the effect of displacement on earnings *k* quarters after displacement actually happened. Jacobson et al. (1993) explain that the variable y_{it}, represents the earnings of individual *i* at time *t*. The variable x_{it} captures the time-varying and observed characteristics of workers. Here, due to the information available, this vector is limited to interactions between age and sex. Age squared is also included. The $\propto_i$ term is described by Jacobson et al. (2003: 693) as a "fixed effect" which captures the impact of permanent differneces among individuals in relation to both observed and unobserved traits or characteristics. They then alter the model as per equation 4.2 to account for a number of other specifications which include worker-specific time trends, $\omega_i t$ (Jacobson et al. 1993: 694).

$$y_{it} = \propto_i + \omega_i t + \gamma_t + x_{it}\beta + \sum_{k \geq -m} D_{it}^k \delta_k + \varepsilon_{it} \tag{4.2}$$

They report that workers displaced due to mass-layoff experience on average a 25% reduction in income compared to the non-displaced workers in the control group, even six years after the separation event. They note that this is more likely to be attributed to loss of earnings rather than a spell of unemployment. They arrive at this determination having excluded workers with long unemployment spells post-displacement from the sample. So while quarterly unemployment rates are lower than expected in the year after displacement, they are not very different in later periods. Also they show that displaced workers' earnings had begun to diverge from their expected levels around three years prior to separation. It is also worth noting here that the paper focuses on high tenure workers. To be included in the sample, workers must have had at least six years of tenure at the start of 1980. As Hijzen et al. (2010: 245) point out, it would be reasonable to expect that such workers could experience greater income losses relative to a random sample of workers.

The econometric approach used by Jacobson et al. (1993) is closely followed by Stevens (1997) to investigate the long-term impact on wages and earnings losses of displaced workers in the USA from 1968-88 using the Panel Study of Income Dynamics. The sample size is relatively small at 1,606 workers, 441 of whom experience displacement during the sample period. The sample is dominated by males as only household heads are permitted to answer. A fixed effects estimator is used in an effort to control for unobserved worker characteristics that may be correlated with displacement. Like Jacobson et al. (1993), it is recognised that there is a possibility that displaced workers may have unobserved characteristics that reduce their wage growth as well as wage level. Stevens (1997) reports that the inclusion of worker-specific time trends makes little difference to results in explaining annual earnings and hourly wage changes. This result is different from those reported by Jacobson et al. (1993) who find that when they control for worker-specific time trends, the estimated losses from displacement are slightly larger. Jacobson et al. (1993) suggest that this is evidence against the notion that employers displace workers who have more slowly growing earnings. Other US papers which have exploited administrative data sources and use this fixed-effects approach include Couch, Jolly & Placzek (2009). They estimate earnings losses of older displaced workers (aged 40 and older) for Connecticut between 1993 and 2004. They find that earnings losses for displaced workers increase monotonically with age.

The development of large administrative data sets has facilitated the use of other econometric techniques in estimating the impact of displacement on earnings. Moving on from before-and-after type studies associated with the DWS, Couch & Placzek (2010) set out to measure the earnings losses of displaced workers in Connecticut over the twelve year period from 1993-2004 and initially employ the methods used by Jacobson et al. (1993) which involve using a fixed effects and time trend estimator. They then extend their work to use matching estimators. Matching, or propensity score[36] matching, is another method for controlling for individual heterogeneity that has been used in more recent studies when estimating the cost of displacement. This method involves estimating propensity scores for the displaced (treatment) group and matching them to a person in the non-displaced (control) group with the same propensity to be displaced. The propensity scores are computed based on a given set of characteristics, prior to the displacement event, and can be estimated by a probit or logit. Couch & Placzek (2010) also compute a differenced estimator having matched individuals based on their propensity score. Due to the volatility of employment in small firms, they exclude firms with less than 50 employees.

They find that in the quarter directly following displacement through mass-layoff, workers' earnings fall by 32-33%. This is in comparison to a reported immediate loss of 40% by Jacobson et al. (1993). Measuring earnings losses six years later for those displaced due to mass-layoff, Couch & Placzek (2010) report earning losses of 13-15% while Jacobson et al. (1993) report an estimated loss of 25%. These results from Couch & Placzek (2010) are generated using the same fixed effects estimation methods as used by Jacobson et al. (1993) and suggest that these results provide evidence in support of their view that results obtained for the state of Pennsylvania reflect the time period covered in the study and capture the effects of adverse economic conditions. With regards to results from Couch & Placzek (2010) having implemented propensity score matching methods, they report similar findings to their fixed effects estimator – those displaced following a mass-layoff event saw a 12% reduction in their earnings after six years.

[36] According to Rosenbaum & Rubin (1983: 41) suggest "The propensity score is the conditional probability of assignment to a particular treatment given a vector of observed covariates."

The receipt of unemployment insurance (UI) is an important indicator of long-term losses associated with displacement in the US. Couch & Placzek (2010) find that in both their study and the Pennsylvanian study, there are no longer-term losses for those who separate from their job and do *not* collect UI benefits. As they note, this has important policy implications; those who do become displaced should be assisted to find employment as quickly as possible. Thus this negates the need to apply for UI benefits.

Kletzer (1998) also examines the impact of displacement on earnings in the short term and long term. Citing evidence from Farber et al. (1997), it is reported that between 1981 and 1995, post displacement earnings, measured on a weekly basis were 13% lower than what workers had been earning prior to being displaced. However, it is pointed out that such findings mask a high degree of heterogeneity. While some workers who were displaced experienced earnings losses of 25%, there was a larger group of workers (30-40%), who experienced an increase in their post-displacement earnings.

While the work of Jacobson et al. (1993) is recognised as being a seminal contribution, others have identified some possible limitations associated with their work. We now explore some of the strengths and limitations identified.

Jacobson et al. (1993) exploit administrative data to study displacement, unlike other US studies that use survey data from the Displaced Workers Survey (DWS). As noted earlier, the OECD (2013) suggest one of the advantages of using administrative data over survey data is that it tends to give a more accurate measure of the effect of displacement on subsequent earnings. While more detailed information on worker characteristics may be obtainable through survey data, the sample size tends to be smaller than is available using administrative data and since survey responses are self-reported, there may be problems with bias.

A second strength of the work of Jacobson et al. (1993) is their use of a control group to assess earnings losses. This approach is intended to capture how wages of workers would have changed, if they had not been displaced from their job. This was an important feature of their work as it meant that they no longer relied on the use of before-and-after type studies which did not use a control group. These studies included for example, Podgursky & Swaim (1987). Such studies using DWS survey data compare the work income of individuals before and after they are displaced and do not account for how earnings *would* have grown *if* displacement had not occurred. This limitation is noted by Kletzer (1998). The use of a control group therefore allows for the earnings of the non-displaced or control group of workers to be differenced from those earnings of the displaced group and according to Farber et al. (1993) this is the only way of accurately identifying any adverse impact on earnings as a result of displacement. A similar point is noted by the OECD (2013) who highlight that the difference-in-differences approach utilised by Jacobson et al. (1993) has been widely used in other studies measuring the earnings losses associated with displacement.

A possible limitation of the work of Jacobson et al. (1993), which the authors themselves acknowledge, is that the demographic information of workers is limited to gender and date of birth. Clearly other factors could impact on the earnings losses of displaced workers. Because of this, they employ econometric techniques that account for the unobserved heterogeneity in the data arising from the lack of other worker characteristics as set out in Equations 4.1 and 4.2. This is done to reduce potential bias when estimating the earnings losses of employees. Also the displacement measure used does not distinguish between workers displaced as a result of a mass-layoff or a closure event. A mass-layoff event is deemed to have occurred if firms have downsized by 30% or more below the maximum level in the 1970's. This figure then includes workers who have been displaced due to both mass-layoff events and firm closure.

While the paper by Jacobson et al. (1993) is recognised as being a seminal contribution, others such as Couch & Placzek (2010) have raised questions about the applicability of Jacobson et al.'s (1993) results in other settings. They question the generalizability of the results given that the period covered was characterised by high unemployment and conducted in the state of Pennsylvania which was reliant on manufacturing. Given this, they suggest that findings may not be applicable to areas where there is a greater reliance on the services sector as opposed to industrialised sectors. However they do note that the use of administrative data is important as it reduced problems such as recall bias inherent in the use of survey data.

Another noteworthy feature of Jacobson et al. (1993) is that they construct their sample to ensure it consists of high tenure workers. They exclude workers who have less than six years of tenure in their jobs prior to displacement. Podgursky (1992) also cited this as a difference with regards to how the US Bureau of Labour Statistics construct their sample of displaced workers as they remove individuals with less than three years tenure in the job they were displaced from. He notes that not excluding displaced workers from the sample on the basis of tenure has the benefit of not eroding the sample size and allows for a greater level of disaggregation. Jacobson et al. (1993) justify their approach by suggesting that such high tenure workers are likely to have accrued a certain amount of human capital specific to the firm, and are therefore at a higher risk of experiencing earnings losses.

As mentioned earlier, this point is noted by Hijzen et al. (2010) who suggest this may have impacted the magnitude of earnings losses reported by Jacobson et al. (1993). It may have biased their estimates upwards because workers with such high tenure could be expected to experience greater losses if displaced.

4.2.4.2 The earnings of displaced workers in Europe

It appears evidence from the US supports the assertion that displacement has a negative and lasting impact on earnings. While less work has been undertaken in Europe in analysing job displacement, Huttunen et al. (2011) assert that the available evidence from Europe suggests that while those displaced may experience smaller earnings losses than their US counterparts, their unemployment spell following displacement is likely to be longer. They question the robustness of previous studies due to varying data sources and samples used, as well as definitions of displacement. We now move to results from European studies. The methodology used as well as results are outlined and comparisons are drawn with US studies.

We begin with the work of Couch (2001) in Germany who follows the estimation procedure used by Jacobson et al. (1993) to analyse the earnings differences for displaced and non-displaced workers and find that in the year of displacement, workers experience a 13.5% reduction in their earnings, relative to their pre-displacement earnings. He uses data from the German Socio-Economic Panel for the years 1988-1996. However over the following two years, the size of the losses decrease to 6.5% of their pre-displacement earnings. These losses appear to be lower than those cited by US studies such as Jacobson et al. (1993) and Stevens (1997).

Hijzen et al. (2010) examine the income losses faced by displaced workers in the UK. A key attribute of this work is the use of matched worker-firm data. The dataset allows workers to be followed for up to nine years after the displacement event. Data on workers is also available for the period before they were displaced and covers the period 1994-2003. Like Couch & Placzek (2010), they initially follow the methods of Jacobson et al. (1993). As well as using a difference-in-differences approach and regression, Hijzen et al. (2010) also go on to use propensity score matching. Their sample includes workers displaced due to both mass-layoff and firm closure. A feature of their work is that they construct five different samples which are analysed. These samples differ for example in how the control group is constructed, tenure of employees before displacement, as well as how periods of non-employment are treated. They report that the income losses in the five year period following displacement are lower for workers who are displaced from firms that experience a mass-layoff (14-25%) relative to those who are displaced due to firm closure (18-35%). In contrast with the results of Jacobson et al. (1993), they find that income losses of displaced workers are largely driven by spells of non-employment experienced by displaced workers. They find less support for the suggestion by Jacobson et al. (1993) that earnings losses were associated with lower earnings or wages. This finding is supported by other European studies below.

Like Hijzen et al. (2010), the data source used by Carnerio & Portugal (2006) to analyse earnings losses of displaced workers following a firm closure in Portugal in 1994, 1995 and 1996 is also matched worker-firm data from the 'Quadros Pessoal' survey.[37] They construct a treatment and control group to analyse displacement. The fixed effects model used to estimate earnings losses is based on that formulated

[37] This is annual survey of all firms that have paid employees in Portugal and is administered by the Ministry of Employment.

by Jacobson et al. (1993). They find that, even four years after displacement, earnings are approximately 10-12% below what would be expected for women and men respectively. Like Hijzen et al. (2010), they find that those who are displaced and experience unemployment spells are more adversely affected and experience an additional wage penalty. Thus it appears that finding re-employment quickly is important.

This idea is also supported by Huttunen et al. (2011) who find that displaced Norwegian workers who stay in the labour force experience a 3% reduction in earnings, relative to their non-displaced counter-parts after seven years. Similarly, evidence from Burda & Mertens (2001) find that displaced German workers who are subsequently re-employed do not see a large reduction in the growth of their wages, with male workers who are displaced in 1986 and re-employed in 1987 experiencing a decrease in wage growth of under 4%, relative to a group in continuous employment. They use self-reported displacement status from the German Socioeconomic Panel for the years 1985-1994. Their sample is split into earnings quartiles and they find that those in the upper three quartiles experience wage growth losses of 17%, which they point out is comparable to estimates from the US. However, they also note that a large proportion of displacement in Germany occurs towards the lower bound of the wage distribution. Here they find such displaced workers may actually experience slightly positive growth of 2%.

As this shows, much of the recent work on displacement has exploited the availability of new administrative data sources. This is also the case with Eliason & Storrie (2006) who examine the longer-term impact of displacement in Sweden. They specifically focus on displacement due to firm closure in 1987 and follow the displaced to assess the effect of displacement on their employment status and earnings in subsequent years, as well as the incidence of "insured unemployment"[38] (Eliason & Storrie 2006: 842) This would include those in employment training programmes. In recognition of the fact that it is desirable to measure how the outcomes of those displaced would have changed if they had not been displaced, they employ propensity score matching techniques. Propensity scores are estimated based on a large number of individual-specific and establishment-specific factors using a logistic regression. Displaced workers were then matched based on the propensity score to the nearest non-displaced worker. They note that results suggest that establishment-specific factors have greater explanatory power when examining displacement risk from closure relative to individual factors related to employment such as tenure and experience.

While there is an employment probability differential of about 7% in the year of displacement for displaced relative to non-displaced workers, they find that this decreases to 2-3% over the following three years. They find less of a recovery in earnings compared to employment probability. Importantly they note the influence of wider macroeconomic conditions on the prospects of displaced workers. Swedish workers displaced in 1987 initially had relatively good prospects of securing re-employment as the country was experiencing very low unemployment levels of 1.5% in 1989 (Eliason & Storrie 2006). However following this, GDP fell and unemployment increased to 8% by 1993. Displaced workers are vulnerable to macroeconomic conditions which can have an impact on both their employment prospects in the labour market and subsequent earnings differentials. The initial recovery in employment prospects and earnings of displaced workers was actually reversed as the recession took hold in Sweden in the early 1990's.

[38] The authors note this captures those in receipt of unemployment benefits, including those classified as part-time unemployed and those in relevant labour market training programmes.

4.2.4.3 Earnings losses and variations across workers; gender, tenure and age in the US and Europe

Given that displaced workers may experience significant and persistent earnings losses, Jacobson et al. (1993) seek to determine if these losses are affected by certain worker characteristics, particularly age and gender. Their model allows the pattern of earnings losses among workers to differ in terms of their decline prior to displacement (dip), the average loss in earnings over the subsequent six quarters (drop), and the rate at which earnings recovered after displacement (recovery) (Jacobson et al. 1993). Beginning with gender, while results initially suggest that men's earnings decline by more than women's on a quarterly basis, it is shown that once variables such as age, industry and firm size are controlled for, any difference in earnings losses between men and women disappear. Interestingly, another study in the US by Couch & Placzek (2010) report similar findings showing that women and men experience a similar monetary loss five years after displacement, although it is pointed out that because women's earnings prior to displacement were lower than men's, this meant that they experienced a greater earnings loss in percentage terms. In the UK Hijzen et al. (2010) find that displaced men experience greater earnings losses than displaced women. This contrasts with the above US studies.

Hijzen et al. (2010) also explore the effect of tenure on earnings losses. A sample of all displaced workers is taken, without imposing the same restriction on tenure as Jacobson et al. (1993) noted earlier. A direct measure of tenure is not available in the UK. However, it is possible to determine if a person was in the same position a year earlier. They report that those with higher tenure experience greater losses having become displaced. This is in line with results from the US and Jacobson et al. (1993).

Some of the literature on displacement has also examined how the impact on earnings varies with the age of the individual. As noted by Eliason & Storrie (2006), a number of reasons may explain why the earnings of older workers could be more negatively impacted post-displacement relative to those of younger workers. For example, older workers may have accumulated long tenure within a firm and have a high level of firm-specific capital. If this person is displaced, such skills may not be of value to a new employer. This is also noted by Couch et al. (2009) who point to the work of Becker (1962) and the finding that firm-specific skills of workers can be an important factor in explaining wages of individuals. From a policy perspective, Couch et al. (2009) note that workers displaced due to events such as the closure of their employer suffer a cost, even though external factors are responsible for a firm closure for example. Therefore, the examination of the earnings losses of displaced workers provides an opportunity to examine this aspect of the cost of firm closure.

As noted by Ichino et al. (2007) both demand-side and supply-side issues can impact differentially by age upon the employment opportunities faced by displaced workers. An example cited of a demand effect is whereby a worker may experience changes in their level of productivity as they get older.[39] A supply effect could occur if a worker was willing to lower their reservation wage and this could be significant in explaining their employment prospects. Alternatively, older workers may be less patient when engaging in a job search and so may be willing to accept a lower wage if it means securing re-employment more rapidly (Ichino et al. 2007). They suggest that the magnitude of such demand and supply effects may assist in explaining the employment rates of younger and older workers.

[39] As noted by Ichino et al. (2007), human capital theory predicts that the age-productivity profile of workers would be concave, due to the possibility of skills becoming obsolete as the worker ages or a reduced incentive to invest in human capital and training.

Work has been conducted in both the US and Europe on the earnings losses of displaced older workers. In general, studies do seem to support the idea that older workers suffer greater earnings losses. For example, Chan & Stevens (1999) find that half of workers who are aged 50 and over and displaced, experience a wage loss of 19% relative to their pre-displacement earnings. They point out that there may be two opposing effects occurring for those older workers who become displaced. Firstly, lower wages for displaced workers seeking re-employment may reduce their incentive to work. Secondly, displaced workers may have had to spend savings or deplete assets due to the displacement event and subsequent unemployment spell. Therefore, for these individuals, they may be more likely to delay retirement. Interestingly they find that men are more likely to be affected by the second scenario above while women are more likely to be affected by the first. They find that those aged over 50 who become displaced do seem to find re-employment quickly – between 70-75% for women and men respectively. However, they note that such workers have an increased likelihood of exiting from their job within the following two years when compared to non-displaced individuals. But as time passes, they report that such displaced individuals have a reduced likelihood of ceasing work, relative to the non-displaced. This could be because such workers may have depleted their savings or investments due to the displacement event and are conscious of the need to rebuild these as retirement approaches (Chan & Stevens, 1999).

Couch (1998) finds a large effect for displaced workers aged between 51-60 years who experienced a decrease in earnings of between 30%-39% in the year following their displacement. Later work by Couch et al. (2009) on displaced workers aged 40 and over find that earnings losses increase as age increases. They also find that earnings recover faster for younger workers. Couch & Placzek (2010) continue their work in an effort to identify any variations in earnings following displacement related to other factors such as age or the industry a worker is employed in. Focusing on earnings changes five years after being displaced in a mass-layoff event, it is reported that older workers (those born in the 1950's) see a reduction in their annual earnings of about $10,000.[40] This is more than double the expected losses of younger workers.

These results from the US support those of Hijzen et al. (2010) for the UK who find that older workers are adversely affected by displacement. Over a five year post-displacement period, older workers lose almost 40% of the income they were earning prior to displacement per year. For younger workers the figure is lower at 32%. These results contrast with the earlier results of Jacobson et al. (1993) where workers are grouped into categories based on the decade they were born; either 1930's, 1940's or 1950's. They attach less significance to the role that age plays with regards to explaining earnings losses of displaced workers. They report that in general the earnings of younger workers recover at a faster rate than those of older workers. Five years after the displacement event, earnings losses of the oldest workers are about $522 more than the earnings losses of younger workers. Overall, they conclude that displaced workers' earnings losses do not have a great dependence on the workers' age. This conclusion of Jacobson et al. (1993) appears to be different to the results of later studies.

4.2.4.4 Displacement, industry and earnings losses

Research that has been conducted regarding earnings losses of displaced workers has also considered the role of industry. Firstly, losses may be affected by the industry a

[40] The authors have converted wages to real 2000 values using a Consumer Price Index.

worker is initially employed in and subsequently becomes displaced from. Secondly, earnings losses of the displaced may be affected by the industry or sector that they find re-employment in. Here the evidence from the US and Europe is reviewed.

In the US, Carrington (1993) explores the role that re-employment of a displaced worker in a different industry can play with regards to the magnitude of earnings losses. Their sample is restricted to include male workers between the age of 21 and 63 years and is drawn from the years 1984, 1986 and 1988. This leads to a sample size of 8,689 displaced workers. He includes tenure and experience as control variables in a regression to identify earnings losses. In an effort to examine the impact of switching industries, a dummy variable is included to capture if the worker changed occupation and moved to a different one-digit industry. He also interacts this dummy variable with experience and tenure. Results suggest that the losses of displaced workers are much lower for those who find re-employment in a similar type of business. He goes on to show that the losses for those who switch industry or occupation are persistent, even when controls are added to capture the conditions in the local labour market.

These findings are supported by the later work of Stevens (1997) who reports that workers who are displaced from their industry appear to suffer long-term reductions in their earnings (-24%). For those displaced but who do not switch industry, earnings recover quickly. However, she does note this does not automatically imply that there is causation between switching industry following displacement and a loss of earnings. It is suggested that losses of displaced workers may have been even greater had such workers remained in their original sector of employment.

The findings of Jacobson et al. (1993) support the findings of the previously mentioned studies and suggest that displaced workers who secure re-employment in the same industry may experience smaller earnings losses. One of the reasons for this is related to specialised, industry-specific skills that employees may have attained over their period of employment. If these skills are industry-specific and their loss translates into earnings losses for workers, the industry or sector of re-employment for displaced workers may be an indicator of earnings losses. To investigate this, they examine the earnings losses of displaced workers who find re-employment either (i) in the same sector, (ii) in the same sector but a different industry or (iii) in a different sector. With regards to industry, the classification used simply refers to either manufacturing or non-manufacturing. In general, they find similar results across each of the three categories above for displaced workers in both manufacturing and non-manufacturing. So it would seem that being displaced from one industry or the other does not lead to differences in earnings losses in percentage terms. Those who move to a completely new sector seem to suffer the greatest loss. For example, displaced workers from the manufacturing sector who subsequently find re-employment in non-manufacturing have losses amounting to 38% of their pre-displacement earnings. A slightly lower figure of 33% is reported for those displaced workers in non-manufacturing and who find re-employment in manufacturing. The authors do note that the actual number of displaced workers involved is relatively small.

These findings for the US are also supported by the later work of Couch & Placzek (2010) and Couch et al. (2009). Using a very similar breakdown as Jacobson et al. (1993), Couch & Placzek (2010) find that those who moved to a new sector to find re-employment following displacement suffered the largest earnings losses of the three categories. Re-employment in the same sector would seem to play an important role in minimising earnings losses after displacement. This finding is echoed in the work of Couch et al. (2009) who analyse the earnings losses of older displaced workers. Industrial sectors were classified as either manufacturing or non-manufacturing. Displaced workers who stayed within the exact same sector experienced the smallest earnings losses six years post displacement. Losses[41] were in the range of $1,211 (manufacturing) to $1,655 (non-manufacturing). Those falling into category (ii) experienced even greater losses of $3,767 (manufacturing) and $3,607 (non-manufacturing). Finally, those moving from manufacturing to non-manufacturing experienced losses of $5,551 and those moving from non-manufacturing to manufacturing incurred losses of $3,651. It is noted that when explaining earnings losses of displaced workers, firm-specific skills may be more important for workers from the manufacturing sector, as suggested by previous research [eg Carrington (1993)].

A number of European studies investigating the impact of displacement on earnings have also examined the role that industry plays in earnings losses. Burda & Mertens (2001) find similar results in Germany with regards to the negative impact of switching industries and wage growth. In analysing wage growth, the sample is split into quartiles. Firstly they report that workers displaced and later re-called to the same firm who are in the upper three quartiles of the wage growth distribution have higher wages when compared to workers who are not recalled to their previous employer. They also report that after 1988, workers who move to a different industry after displacement experience lower wage growth compared to those who

[41] The authors note amounts are in 2000 constant dollars.

do not switch following displacement. It is suggested by Burda & Mertens (2001) that this could be seen as evidence of industry-specific human capital.

Results from Portugal confirm the findings from both Europe and the US cited previously. Carnerio & Portugal (2006) report that those displaced who secure re-employment in the same industry do not suffer the same magnitude of earnings losses as those who switch to another industry. They also look at gender differences with regards to industry switchers and find that women who switch industry experience a greater earnings loss than men (13.1% compared to 6.2%). An interesting feature of their work is that they attempt to identify the contribution of (i) job tenure, (ii) unemployment and (iii) switching industry to the earnings losses of displaced men and women relative to non-displaced men and women in Portugal. For both men and women it appears that three years after job displacement, job tenure is the most important factor in explaining 12% of the earnings differential that exists between displaced workers and those who are not displaced. Switching industry is less important in explaining the difference. For men, it explains between 14-24% of the above earnings gap, while for women it explains 16-31% of the earnings gap.

In the UK, Hijzen et al. (2010) also examine the role of industry in explaining displacement costs across individuals. They suggest that their sample may be more representative than that of Jacobson et al. (1993) as they use a random sample of displaced workers, whereas the sample used by Jacobson et al. (1993) only includes high tenure workers as previously outlined. Here they do not examine the impact of switching industry but do report the losses associated with displacement from either manufacturing or services. They find that the losses associated with displacement from the manufacturing sector are slightly greater than those associated with displacement from the services sector.

4.2.5 Conclusion

Here we have examined literature and empirical evidence in relation to displacement. Earlier studies used survey data to estimate displacement effects, but later studies have exploited the availability of administrative data. This has facilitated the use of more advanced methods of estimating earnings losses by for example, combining matching techniques with difference-in-differences estimators.

While much work has been pioneered and conducted in the US, evidence from Europe is also available. These European studies have generally reported smaller earnings losses for those displaced. However, it is worth noting that the duration of the unemployment spell may matter in explaining these losses. While Jacobson et al. (1993) suggest that this is not important, Hijzen et al. (2010) suggest it is key in accounting for the magnitude of losses.

The reported evidence suggests older workers appear to be particularly adversely impacted by displacement and experience large earnings losses. We have also seen that being re-employed within the same sector is important for displaced workers in order to minimise earnings losses. Those who find employment in a new sector following displacement experience greater earnings losses compared to those who do not switch sectors.

4.3: Data and methodology

In this section we provide an overview of how the cohorts were constructed (4.3.1) as well as the implementation of propensity score matching (4.3.2) and finally we outline our estimation methodology (4.3.3).

4.3.1 Overview of data and construction of cohorts

We begin by describing the dataset used and details of how the panels for the closure and mass-layoff samples are constructed. The data used is the P35 dataset available from the CSO.[42] The available data covers the years 2005-2011. A panel was created using each annual data file. A separate panel is created for the closure group and mass-layoff groups respectively. The panel construction process was very similar for both – the key difference being the use of a closure or mass-layoff identifier. The objective here is to create separate annual datasets or cohorts of displaced and non-displaced workers.

Employment is computed for each enterprise in each year, based on the number of individually assigned employment records attached to the enterprise. As is the case with many administrative data sets, such as the New Earnings Survey (NES) in the UK, the P35 data does not record the reason for an individual separating from their job. So we cannot definitively identify whether a separation is voluntary or involuntary. As a consequence, we use the P35 data to define the displacement events. Closure and mass-layoff events are defined as below:

- An enterprise is identified as having closed if its final year in the data was not 2011. An employee is identified as being displaced due to a closure event if their employer at time *t* no longer exists at *t+1*.

[42] Further details on the dataset are also provided in Chapter 3.

- An individual is identified as having experienced a mass-layoff event if they leave their current employer following a decrease in employment at that enterprise of 30% or more between *t* and *t+1*.

Based on these definitions, the mass-layoff sample does not include firm closures. To measure the change in employment in the mass-layoff sample, the enterprise had to be in existence at *t+1*. Therefore the mass-layoff sample does not include those in the closure sample. It is however possible for a enterprise to experience a mass-layoff at time *t* and a closure event at *t+n,* where *n>=1*. An example below in Table 4.1 illustrates this point. Here the enterprise experiences a decrease in employment of 50% between 2006 and 2007. Therefore a mass-layoff event is deemed to have occurred in this enterprise in 2006. Later we see that 2008 is the last year this enterprise appears in the dataset. There are no observations for 2009-2011 and so it is clear that a closure event does not incorporate a mass-layoff event.

Table 4.1: An example of displacement events

Year	Enterprise ID	Employment	Last year	Employment change (%)	Closure	Mass-layoff
2005	16	300	N	0	0	0
2006	16	300	N	0	0	1
2007	16	150	N	-50	0	0
2008	16	150	Y	0	1	0

While we retain all enterprises in the closure sample, we impose an enterprise size restriction in the mass-layoff sample. Enterprises with less than 50 employees are excluded from the sample.[43] Otherwise, an enterprise with 6 employees at time *t* and

[43] As a robustness check, we also conducted analysis on the mass-layoff sample, without imposing this restriction. The findings are presented in Appendix 4. We see that estimated earnings losses are less than those of the restricted sample. We believe that this provides evidence to support the use of the restricted sample as the unrestricted sample may include far more voluntary separations - possibly to higher paying jobs which may reduce the magnitude of earnings losses.

4 employees at time *t+1* could be identified as experiencing a mass-layoff event. Given that our interest here is in those workers displaced involuntarily, we impose this restriction. This is consistent with previous studies such as Jacobson et al. (1993) and Couch & Placzek (2010).

An indicator is constructed to identify employees with one job in a given year for which they worked more than 30 weeks. The data does not include a full-time/part-time indicator.[44] It does include the number of weeks a person worked in each year. However, a person who worked just 1 hour in a week is classified as working for 1 week, the same as a person who worked 40 hours a week over 5 days. By focusing on employees with just one job in the relevant year and who worked more than 30 weeks, we are likely to capture those most affected by a displacement event as they would have only had one job and been working for a large part of the year. This is a key indicator for identifying the treatment and control groups. While such workers may have more than one job in other years, those identified as being treated or untreated in a given cohort can only have one job. So for example, the “2006 displaced (treated) group” comprises of the group who conform to this criteria of having a single job, are working more than 30 weeks and experience displacement in 2006, while the “2006 non-displaced (control) group” comprises of the group who conform to the criteria of having a single job, are working more than 30 weeks and do not experience displacement in 2006. As there is no direct measure of tenure available, we do not attempt to impose restrictions on the sample based on tenure. This is in line with the work of Podgursky (1992) who does not exclude displaced workers on the basis of tenure from their sample, which has the benefits of not

[44]According to Central Statistics Office, Ireland (2015b), the number of those in part-time employment as a percentage of those in employment increased from 17% in quarter 1 2005 to 25% in quarter 1 of 2011.

eroding the sample size and allows for a greater level of disaggregation when analysing the data.

If an individual was not in employment in a given year, there would be no observation or row for that person in that year. To form a balanced panel, the dataset is expanded to include a row for each individual in each year. In the situation where the individual was not in employment, the new row contains only the individual's identification number, age, gender and nationality. Then in each year, a dummy variable is constructed to identify if the person is in the treatment (displaced due to either closure or mass-layoff) or control (non-displaced) group.

A limitation of the data is that it is not possible to identify the order of the job spells for each individual because there are no start and end dates recorded with each employment record. So if a person has more than one employment record in a year, we do not know whether such jobs were concurrent or consecutive or the length of the gap between them, if any. Therefore, in order to form a balanced panel and retain one row per individual per year, it was necessary to decide how to treat such observations. It was decided to retain the record and associated enterprise number where the individual worked the greatest number of weeks. This was done in an effort to retain the enterprise record associated with a workers main job as well as to give a true reflection of the employment earnings of such workers. Given the goal of the chapter is to estimate earnings losses, such an approach is important. In an effort to retain information on pay[45] and weeks worked, their pay and weeks worked are summed and represented in the single employment record for that year which is retained, before the other is dropped from the panel.

[45] As explained in Chapter 3, pay is total taxable pay. It is deflated using the Consumer Price Index [Base year=2011].

For each individual, the following key variables are retained;

- Age of employee
- Gender
- Nationality of employee
- Annual pay received by employee
- Weeks worked
- NACE Rev.2 sector of the enterprise
- A displacement dummy

This process is repeated for each year or cohort. Within each cohort, we identify our treatment group (displaced due to either closure or mass-layoff) and our control group (non-displaced). For example, the 2005 treatment group consists of those who experienced a displacement (either closure or mass-layoff) between 2005 and 2006, while the control group are those who did not experience a displacement between 2005 and 2006.

To facilitate our estimation procedure, a relative time variable is constructed. This variable is a measure of time relative to the displacement event, *t*. For example, *t=0* in 2005 for those in the 2005 treatment and control groups. This relative time variable allows for the analysis of displacement events across time. In this way, for all those displaced, the displacement event is deemed to have occurred at *t=0*. Thus within each cohort, there are 7 relative time observations covering the years 2005-2011. For example, if a person was displaced in 2007 *(t=0)*, their employment records are available for *t=-1*, or 2006 and *t=-2*, 2005. We also have an observation for this person at *t=1* (2008), *t=2* (2009), *t=3*, (2010) and *t=4* (2011). If this person secured re-employment elsewhere, the record will include an enterprise identifier, NACE Rev.2 sector, the weeks worked and the pay the individual received. If there was no employment record for this person in a year, they will be identified as having missing values for the following variables; weeks worked, enterprise identifier and

NACE Rev.2 code. An example is seen in Table 4.2. This Irish male worker (id=6) was displaced (D=1) in 2007 (*t=0*) at the age of 38 from enterprise 22 in sector F and so is in the 2007 cohort. This person was unemployed in 2008 and 2009 and secured re-employment in enterprise 57 in 2010.

Table 4.2: Example of displaced person and associated variables

Year	Relative time	Cohort	Person ID	Enterprise ID	Displaced (D)	Pay (€)	Age	Gender	Nationality	NACE sector
2005	-2	2007	6	22	1	50,000	36	M	IRE	F
2006	-1	2007	6	22	1	51,000	37	M	IRE	F
2007	0	2007	6	22	1	52,000	38	M	IRE	F
2008	1	2007	6	.	1	0	39	M	IRE	.
2009	2	2007	6	.	1	0	40	M	IRE	.
2010	3	2007	6	57	1	48,000	41	M	IRE	G
2011	4	2007	6	57	1	48,000	42	M	IRE	G

Having constructed an employee-based panel for each cohort, each of the files for the cohorts 2005-2011 are saved. Within each cohort we have identified our treatment and controls groups. Displaced workers are matched within each cohort with non-displaced workers. Section 4.3.2 explains the choice and implementation of matching procedure used in the analysis. Once this matching procedure below is conducted within each cohort, the matched cohorts are stacked. This results in 6 cohorts (2005-2010)[46] of treatment and control groups which are followed from *t=-5* to *t=+6*, or 12 time periods. Ultimately as noted by Hijzen et al. (2010: 248), this enables the estimation of the pooled effect of the displacement event at each time period *t*, across each year of displacement.

4.3.2 Matching procedure

As discussed earlier, the paper by Jacobson et al. (1993) was influential in the analysis of the earnings losses of displaced workers for a couple of reasons. Firstly, they exploited administrative data (as used in this thesis) and secondly, this

[46] While we have data for 2011, it is not possible to define displacement events given that it is the final year.

facilitated the move from before-and-after type studies such as Podgursky & Swaim (1987) to the use of a control group to measure the earnings losses. Since then, matching methods have been used in numerous studies to estimate treatment effects, in which displacement is the treatment event [eg Couch & Placzek (2010) for the US; Hijzen et al. (2010) for the UK]. Individuals could be split into a treatment group who are displaced workers and untreated or control group who are not displaced. The basic problem in measuring the impact of a treatment such as displacement on employment prospects or earnings is that the outcome is observable for an individual in either the treatment or control group, but never both. If we assume D_i measures treatment and equals 1 if the individual i is subject to the treatment and zero otherwise, the outcome for each individual is measured as $\mathrm{Y_i(D)}$. The effect of the treatment could be measured as;

$$\tau_{\mathrm{i}} = \mathrm{Y_i}(1) - \mathrm{Y_i}(0) \tag{4.3}$$

Ideally we would like to know how the outcome for those who were in the treatment group would have been affected if they had not been subject to the treatment. But for a given individual it is not possible to observe both $\mathrm{Y_i}(1)$ and $\mathrm{Y_i}(0)$.

One possible suggestion could be to assume that the mean outcome for the control group is applicable to the treatment group. However, this gives rise to potential selection bias problems. Those who are displaced may have different characteristics to those who are not displaced which may ultimately affect their prospects in the labour market. In this case, factors that affect the treatment are also likely to impact on the outcome variable. One method to overcome this is through matching. This matching process involves pairing those in the treatment group with those in the control group who have similar observable characteristics (Dehejia & Wahba, 2002).

In this chapter, we examine the incidence of displacement. Those who are displaced and in the treatment group may have different characteristics to those who are not displaced and in the control group, and these characteristics may be related to subsequent displacement and an associated impact on earnings.

4.3.2.1 Propensity Score Matching

One way of matching is to use propensity scores. Rosenbaum & Rubin (1983: 41) suggest "The propensity score is the conditional probability of assignment to a particular treatment given a vector of observed covariates." An option here is to match displaced individuals with non-displaced individuals who have similar characteristics or attributes prior to the displacement event and so have a similar propensity to be displaced.

The individual-level variables used in the matching process in this chapter are a person's age, age squared, gender and nationality. Regarding nationality, individuals were spilt into groups. These groups are Irish nationals, UK and Northern Ireland, Western Europe, Eastern Europe, Asia and finally the rest of the world.

We also have information on enterprise characteristics which are used in the matching procedure. These include firm size and the NACE Rev.2 sector an enterprise belongs to.[47] Regarding NACE Rev.2 sector, four categories were created. The first includes NACE sectors A-F, group 2 contains sectors G-U (excluding K, M, N, O, P, Q), group 3 covers sectors K, M and N, while group 4 covers sectors O, P, and Q. Enterprise size category is also used. As noted by Hijzen et al. (2010: 253), such pre-displacement firm characteristics could prove to "be important if selection is non-random with respect to firm types."

[47] See Appendix Table 5.1 for further details.

Displaced individuals are matched with non-displaced individuals within each cohort for the years 2005-2010.[48] It was decided to match displaced individuals with non-displaced individuals within the same cohort. This was done in an effort to maximise the potential success of matching in identifying the impact of displacement on earnings, given the relatively short span of available data. It is also important to acknowledge that a relatively limited set individual characteristics is available here, namely age, gender and nationality of the worker. Others such as Hijzen et al. (2010) have matched on pre-displacement characteristics such as the wage and firm size at *t=-4*. They do not include measures from *t=-3* to *t=0* in order to allow for genuine pre-displacement effects that may occur. Unfortunately, given the duration of the available data, this was not possible and matching was implemented within each cohort. However, we do include firm size and NACE sector as mentioned above. While we acknowledge the somewhat limited set of characteristics used in the matching procedure, they are similar to some of the variables available to and used by Hijzen et al. (2010) in their UK study.[49] In an effort to offset the limited set of characteristics, we use propensity score matching and difference-in-differences to estimate losses. To construct an accurate counter-factual – what would have happened to displaced workers if they had not been displaced, we use a control group. While propensity score matching allows us to control for unobserved worker heterogeneity, difference-in-differneces allows us to accurately measure the difference between the displaced and non-displaced group in their before and after difference in income. As noted by Jacobson et al. (1993), another option to estimate earnings losses would be to compare earnings of the displaced before and after the displacement event. However, this does not accurately capture what would have

[48] Propensity score matching is implemented using the *psmatch2* command in STATA 11. This is a user-written command by Leuven & Sianesi (2003).
[49] Hijzen et al. (2010) also have details on occupation and union coverage.

happened to earnings if the worker had not been displaced (Keltzer, 1999). A difference-in-differences framework, used in conjunction with propensity score matching helps overcome this and so improves accuracy of estimated earnings losses.

Regarding estimating the propensity scores, Caliendo & Kopeninig (2005) note that little advice is available when selecting an appropriate functional form. However, logit and probit models are typically used when the treatment case is binary. Both tend to produce similar results. In this chapter a probit model is used.

The next decision to be taken concerns the matching procedure to be used once the propensity scores have been computed. Nearest-neighbour matching is one of the most straightforward matching procedures. A unit in the displaced group is matched with a unit in the non-displaced group which has the closest propensity score. This type of matching can take place with and without replacement. Dehejia & Wahba (2002) point out that an advantage of matching with replacement is that each treated observation can be matched to the nearest untreated observation, even if it has been used in the matching process already, thus reducing bias. However, given the large sample size used in this chapter, it was determined that matching without replacement would not adversely cause bias and that it would be possible to match displaced with non-displaced individuals with a very close propensity score.[50]

To ensure the closeness of the propensity score match, a caliper was used. This overcomes the problem that may arise if the nearest neighbour in the control group

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[50]Hijzen et al. (2010) also use nearest neighbour propensity score matching without replacement. Depending on the sampling restrictions used in that study, sample size for the displaced workers varied between 1,311 and 6,775 individuals while the control group consisted of between 168,682 and 341,570 individuals.
Eliason & Storrie (2006) use nearest neighbour matching *with* replacement and propensity score matching. Here a sample of 4,397 displaced and 115,696 non-displaced workers were used. Thus the size of the control group may have influenced their decision to match with replacement.

that a treated person is matched with is far away in terms of propensity score. Thus the caliper acts as an allowable range within which a match can be made. The main objective here is to improve the quality of the match. One of the issues with the use of a caliper as noted by Smith & Todd (2005) is that prior to the matching process, it is difficult to determine an appropriate tolerance level. In this chapter, a caliper of 0.001 and 0.002[51] was used in the closure and mass-layoff samples respectively, thus giving greater confidence in the quality of matches achieved. Caliendo & Kopeinig (2005) note the suggestion of Smith (2000) that asymptotically, all propensity score matching estimators should give the same results because as the size of the sample increases, the estimators become closer to comparing matches which are exactly the same. With the large sample size in this study, such an observation is important.

4.3.2.2 Assessing Common Support

In conducting propensity score matching, it is necessary to investigate the common support in relation to the matching procedure. This is done to ensure that given the set of covariates X in the model, it is not possible to perfectly predict being in either the treatment or control group. So for each value of X there should be treated and control observations. Essentially we want to ensure we are comparing comparable people (Eliason & Storrie, 2006). This means ensuring that there is enough overlap between the treatment and control groups to allow for comparability. Heckman, Lalonde & Smith (1999) describe this as ensuring that individuals with the same X values should have some positive probability of being in either the treatment or control group.[52] We can produce a histogram of the propensity score for the treatment and control groups. This is a visual representation of the extent to which

[51] A slightly higher caliper was used in the mass-layoff sample as the lower caliper of 0.001 was resulting in an inability to find matches in a number of cases.
[52] In this chapter, this was assessed using the *psgraph* command in STATA 11.

the distributions of the propensity scores in the treatment and control groups overlap. By examining the resulting histograms we see that the treatment and control groups have a similar range of propensity scores and therefore it is suggested that there is enough overlap between the displaced and non-displaced groups to make reasonable comparisons.[53] It was determined that there was no common support problem. Given the size of the potential control group, this is not surprising. This evidence of overlap is a positive result and implies that the distribution of the X covariates for displaced and non-displaced workers overlap.

4.3.2.3 Assessing Balance and the quality of matches

Balancing tests[54] are performed to ascertain the extent of differences that remain after matching between the treatment and control groups. We are essentially comparing the situation before and after matching to determine if there are any differences remaining after conditioning on the propensity score (Caliendo & Kopeinig, 2005).

In attempting to establish the displacement effect, we can gain confidence in the propensity score method by checking the results of the balance tests. We wish to ensure that in estimating the displacement effect, conditional on the propensity score, the two outcomes of (i) the wages of the displaced and (ii) the wages of the non-displaced are independent of the actual displacement event. Assuming independence conditional on the observables, the X covariates should be balanced between the displaced and non-displaced groups. If it is found that there is a lack of balance, this may point to a misspecification in the propensity score matching model used.

[53] The graphs generated for each sample and cohort are available in Appendix Table 6.1 and Appendix Table 6.2.

[54] This can be implemented using *pstest* in STATA 11.

Rosenbaum & Rubin (1983) and more recently Dehejia & Wahba (2002), have emphasised the importance of checking that the balancing condition is satisfied.

There are a number of options to assess the balancing property and the impact of matching on the characteristics of individuals in the data. One option is to examine the bias or standardised difference for all of the X covariates used in the propensity score matching model. It is calculated as the difference in means between the treatment and control group for each X covariate such as age, divided by the average variance in the age variable for the treatment and control groups. Ideally, the standardised difference will be low because this points to a greater degree of similarity between the treatment and control groups, given the set of X covariates included. Girma & Gorg (2007) follow Rosenbaum & Rubin (1985) in suggesting that a value of 20 is large enough to be considered a serious problem. Caliendo & Kopeinig (2005) note that there is no formal criterion on how to assess the size of the bias, but suggest that a decrease in bias below 3-5% is seen as successful. Here we find that in the matched samples, the percentage bias is close to zero and the percentage bias reduction is generally over 90%.[55]

Another approach to balance testing involves using t-tests to compare the mean of the X covariates before and after the matching procedure. One might expect that before matching statistically significant differences may exist between the treatment and control groups on their observable characteristics. However, after matching we would expect balance in the X covariates and that there would be no significant difference remaining across the treatment and control groups. Therefore we would expect a large reduction in the number of t-tests which indicate the presence of such

[55] See Appendix Table 6.1 and Appendix Table 6.2 for details.

statistically significant differences. This was the case in Hijzen et al. (2010) who report that their matching procedure removed almost all of the differences between the treatment and control groups for both the closure and mass-layoff samples.

Our results of the balancing tests suggest that matching on the observable characteristics has been useful. The results of the t-tests for the closure and mass-layoff samples are presented in Table 4.3. We can see that in the unmatched data, the treatment and the control group are different in terms of their observable characteristics as denoted by the significant t-test results for variables. However, it is clear that after matching, all of these differences have been removed in each cohort.

Table 4.3: Results of Balancing Tests

Cohort	Closure sample		Mass Layoff sample	
	Unmatched	Matched	Unmatched	Matched
2005	15/15	0/15	10/12	0/12
2006	15/15	0/15	10/12	0/12
2007	14/15	0/15	11/12	0/12
2008	12/15	0/15	11/12	0/12
2009	12/15	0/15	11/12	0/12
2010	14/15	0/15	11/12	0/12

Note: Each cell of the table denotes the fraction of t-tests that are significant (at the 5%) level in the mean between the displaced and non-displaced groups.

A final measure is the pseudo-R^2. This measure denotes how well the X covariates explain the probability of participation in the treatment and control group. It would be expected that matching would eliminate any systematic differences in the distribution of the covariates between both the treatment and control groups and so the pseudo-R^2 should be relatively low (Caliendo & Kopeinig 2005). In all cases here, the pseudo-R^2 in the matched sample is zero.[55]

The results of the propensity score matching for the closure sample are presented in Appendix Table 7.1. This shows the conditional probability of being a displaced worker in a given year. The results are estimated using a probit model. The dependent variable used here is a displacement dummy taking on a value of 1 if the individual is displaced and 0 otherwise. The variables used to predict the probability of displacement are age, age squared, gender, nationality group, NACE Rev.2 group and enterprise size category group. The estimation results for the closure sample across the years 2005-2010 indicate that in the years 2005, and 2007-2009, being male was positively associated with displacement. Age is generally negatively associated with displacement. Turning to sector dummies,[56] we see that in general, being in Nace groups 1-3 increases the probability of displacement relative to Nace group 4. Similarly for enterprise size[57] we see that being in smaller firms increases the probability of displacement relative to those in the largest firm size category of 250+ employees. Finally, nationality dummies[58] are generally negative, with many insignificant in earlier years indicating that being in these nationality groups may decrease the probability of displacement relative to the 'Rest of the world' group.

Moving to the mass-layoff sample,[59] we examine the conditional probability of a worker being displaced due to a mass-layoff event. Nace sector dummies are positive and significant and so being in groups 1-3 increases the predicted probability of displacement due to mass-layoff, relative to the base group of Nace group 4. The gender variable is positive and significant between 2007-2010 suggesting that being male has a positive effect on the probability of displacement. Unlike the closure sample, many of the nationality variables are positively related to the displacement probability in the mass-layoff sample suggesting that some groups are more likely to be displaced relative to the 'Rest of the World' group. The Irish

[56] The omitted NACE dummy is group 4.
[57] The omitted firm size category dummy is "250+ employees."
[58] The omitted nationality grouping is "Rest of the world."
[59] See Appendix Table 7.2 for detailed results.

worker nationality dummy is negative in all years and significantly related to the displacement probability in four of the six years, relative to the 'Rest of the world' group. Finally the enterprise size dummy is negative in earlier years and positive in later years, although not always statistically significant, suggesting a decreased probability of displacement in earlier years followed by an increased probability of displacement in later years, relative to the enterprise size group of 250+ employees. Table 4.4 displays the number of displaced workers before and after the implementation of the propensity score matching. As can be seen, the matching procedure resulted in all of displaced workers being matched successfully with a non-displaced worker in each cohort.

Table 4.4: The number of displaced workers in the before and after matching

Year	Number of displaced workers			
	Closure sample		Mass-layoff sample	
	Before matching	After matching	Before matching	After matching
2005	10,221	10,221	1,979	1,979
2006	14,120	14,120	2,270	2,270
2007	20,516	20,516	3,005	3,005
2008	45,258	45,258	8,079	8,079
2009	32,452	32,452	4,656	4,656
2010	29,963	29,963	2,232	2,232

4.3.3 Estimation methodology

Following the matching cohorts are stacked, resulting in 6 cohorts which are followed from $t=-5$ to $t=+6$, or 12 time periods. We now turn to the estimation of the effect of displacement for the closure and mass-layoff samples respectively.

Earlier we explained how individuals were allocated to treatment and control groups. We wish to measure the earnings losses of those individuals in the displaced or treatment group. We are endeavouring to establish what would have happened to their earnings on average if they had not been displaced. We could simply examine the earnings of workers before and after the displacement event but as noted by Kletzer (1998) earlier, this does not take into account how earnings would have changed if the displacement event had not occurred.

Having a control group facilitates the more accurate measurement of counter-factual income. It is important to note that both a closure and mass-layoff event may be non-random. As noted in the literature,[60] those who experience a mass-layoff event are unlikely to have been selected at random – they may have been specifically selected by their employer. In the case of a closure event being signalled well in advance of the event, employees with good opportunities in the labour market may choose to leave in advance of the closure. Given that non-random assignment to the treatment and control group may be a feature of the data, it is possible that there is an associated permanent unobserved component of income that may be impacted. Therefore, a difference-in-differences estimate can be used as was the case in Jacobson et al.'s (1993) influential paper described earlier. As noted by Hijzen et al. (2010: 252), this method captures the difference between the displaced (treated) and non-displaced (control) groups "in their before-after difference in income."

In estimating counter-factual income, the choice of the pre-displacement period is important. For example, Hijzen et al. (2010) choose the average differences in income of the treatment and control group between periods $t=-4$ and $t=-8$. They do this in an effort to capture the permanent unobserved income component as mentioned earlier. If we select a time period closer to the displacement event, we risk picking up some genuine pre-displacement fall in earnings. While we acknowledge this risk, unfortunately with the time-span of the existing dataset, it is

[60] See Hijzen et al. (2010), von Wachter & Bender (2006) , Gibbons & Katz (1991).

not possible to select this exact base period. However, our base period is t=-5 and it is suggested that this is sufficiently in advance of the displacement event.

As mentioned earlier, we have incorporated a relative time variable in each cohort. Having stacked all cohorts, this facilitates the estimation of the pooled effect of displacement, at each relative time period. We proceed by creating an interaction term between our dummy variable which identifies if a person was displaced or not and our relative time variable within each cohort. The coefficient on this variable, δ^k, is our difference-in-differences estimate of the earnings losses of the treatment group. Equation 4.4 below is drawn from Hijzen et al. (2010).

$$y_{it} = \propto_i + \sum_{k=-5}^{6} \gamma^k \ T_{it}^k + \sum_{k=-5}^{6} \delta^k D_{it} * T_{it}^k + \varepsilon_{it} \qquad \textbf{(4.4)}$$

Here y_{it} is the earnings of worker[61] i at time t. Each T_{it}^k is a dummy variable which is equal to one if t=k and zero otherwise. $\propto_{\mathbf{i}}$ is intended to account for an individual unobserved income component or individual 'fixed' effect. $\mathrm{D_i}$ is our displacement dummy which is equal to one if the person is displaced and zero otherwise.[62] This regression equation is used separately in both the closure and mass-layoff samples, where displacement represents a closure event in the closure sample or mass-layoff event in the mass-layoff sample.

We now proceed to present our findings in section 4.4.

[61] Pay is deflated using the Consumer Price Index [Base year=2011].
[62] As it is possible for individuals to be in more than one cohort, the standard errors are clustered using the individual identifier number.

4.4: Findings

This section describes the main findings regarding the impact of displacement on individuals. Before estimating earnings losses, we begin by briefly exploring the numbers displaced and the associated displacement rates (4.4.1). Further details are available in Appendix 3. Section 4.4.2 explores the impact of displacement on workers with respect to their probability of employment and crucially, their earnings losses are estimated in section 4.4.3.

4.4.1 Displacement rates in the closure and mass-layoff samples

We begin by identifying the displacement rate and follow the definition used by the OECD (2013). The displacement rate is calculated as the number of those displaced in a given cohort as a proportion of all employment records in that cohort. The numbers reflect the numbers displaced and total employment records prior to the implementation of the propensity score matching described earlier.

Table 4.5 and Table 4.6 display the numbers displaced due to firm closure and mass-layoff over the period. As we can see, the numbers displaced have increased considerably over the period, peaking in 2008 with 45,258 and 8,079 workers displaced in the closure and mass-layoff samples respectively. It is important to recall that the mass-layoff sample excludes enterprises with less than 50 employees, while the closure sample includes all enterprises and their employees.

Table 4.5: Displacement numbers, employment records and displacement rate for 2005-2010 (Closure)

Year	Number displaced	Total employment records	Displacement %
2005	10,221	1,301,122	0.8%
2006	14,120	1,353,178	1.0%
2007	20,516	1,439,831	1.4%
2008	45,258	1,477,869	3.1%
2009	32,452	1,391,772	2.3%
2010	29,963	1,376,848	2.2%

At the same time, the number of employment records was increasing up to 2008 and then decreased subsequently. While at the lower end of the scale, these results are within the range found by the OECD (2013) who reported rates of between 1.5% and 7%. In most countries, the impact of the recession was visible with higher displacement rates in the period 2009-2010 relative to 2000-2008. This is broadly in line with the Irish evidence here although the spike in Irish displacement rates occurs in 2008. In the mass-layoff sample in Table 4.6, we observe that fewer workers are displaced each year, resulting in a lower displacement rate in each year.

Table 4.6: Displacement numbers, employment records and displacement rate for 2005-2010 (Mass-Layoff 30%)

Year	Number displaced	Total employment records	Displacement %
2005	1,979	812,302	0.24%
2006	2,270	840,841	0.27%
2007	3,005	893,760	0.34%
2008	8,079	935,248	0.86%
2009	4,656	928,486	0.50%
2010	2,232	898,055	0.25%

The numbers displaced are broken down by gender in Table 4.7 and Table 4.8 below. The number and percentage of displaced males are generally greater than females. These results are in line with those of Kletzer (1998) in the US who reports that females have a lower displacement rate than men. Again 2008 stands out as the year with the greatest number of displacements for males and females in both the closure and mass-layoff samples.

Table 4.7: Displacement numbers, employment records and displacement rate by gender for 2005-2010 (Closure)

Year	Males			Females		
	Number displaced	Total employment records	Displacement %	Number displaced	Total employment records	Displacement %
2005	6,528	700,869	0.9%	3,693	600,253	0.6%
2006	8,485	738,326	1.1%	5,635	614,852	0.9%
2007	14,203	778,790	1.8%	6,313	661,041	1.0%
2008	27,007	787,478	3.4%	18,251	690,391	2.6%
2009	19,033	722,777	2.6%	13,419	668,995	2.0%
2010	17,711	687,694	2.6%	12,252	689,154	1.8%

Table 4.8: Displacement numbers, employment records and displacement rate by gender for 2005-2010 (Mass-Layoff 30%)

Year	Males			Females		
	Number displaced	Total employment records	Displacement %	Number displaced	Total employment records	Displacement %
2005	1,096	399,376	0.3%	833	412,926	0.2%
2006	1,054	417,796	0.3%	1,216	423,045	0.3%
2007	1,978	435,849	0.5%	1,027	457,911	0.2%
2008	5,376	453,262	1.2%	2,703	481,986	0.6%
2009	3,141	440,156	0.7%	1,515	488,330	0.3%
2010	1,404	421,507	0.3%	828	476,548	0.2%

4.4.2 The probability of employment and displacement

We now move to analysis of the matched closure and mass-layoff groups using the matching procedure as described in section 4.3.2. Displaced individuals were matched with non-displaced individuals with a similar propensity to be displaced. As described, this was done separately for both the closure and mass-layoff samples in an attempt to identify the impact of a displacement event on those affected. Particularly here we focus on the probability of a displaced worker finding re-employment relative to their non-displaced counter-parts, as well as the impact on their earnings. We begin by examining the pooled data for all years, before later splitting the cohorts and examining the experience of displaced workers before and after 2008 in section 4.4.3.5.

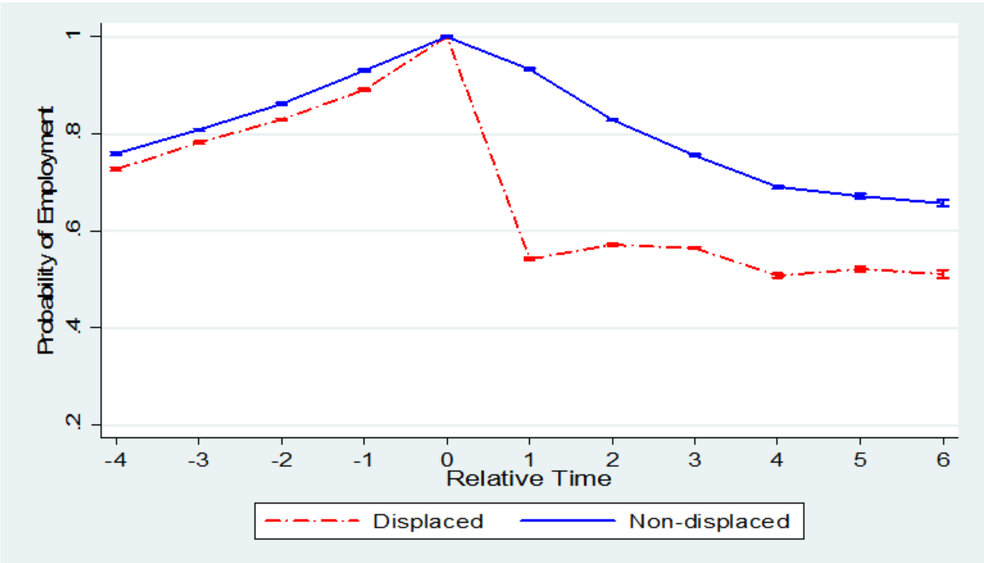
An employment dummy variable, Emp_{it} is constructed which equals one if an individual is in employment and zero otherwise. Each T_{it}^{k} is a dummy variable which is equal to one if t=k and zero otherwise. This is essentially the relative time variable described earlier. Equation (4.5) below is estimated separately for the treatment and control groups and so it is possible to identify the pooled effect of displacement on the probability of employment at each value of t across all years of displacement.

$$Emp_{it} = \sum_{k=-5}^{6} \gamma^{k}\, T_{it}^{k} + \varepsilon_{it} \qquad \textbf{(4.5)}$$

The probability of employment, γ^{k}, and associated confidence intervals for displaced and non-displaced workers are depicted in Figure 4.1.[63] As we can see, displaced workers have a much lower probability of employment relative to those who are not displaced.

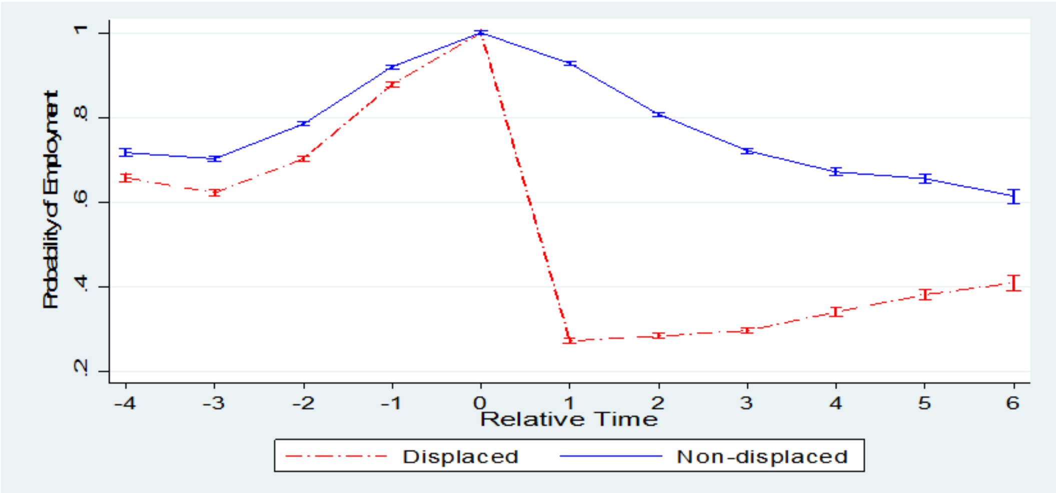
Figure 4.1: Probability of employment of displaced and non-displaced workers

a) Closure



[63] See Appendix Table 8.1 for regression output.

b) Mass-Layoff



We observe that those displaced as a result of a mass-layoff have a lower probability of employment in the period after displacement compared to those who are displaced as a result of an enterprise closure. Workers displaced due to enterprise closure have a 54% probability of being in employment at *t=1*, while those displaced following a mass-layoff have a 27% probability. So it appears that the type of displacement event matters in explaining the employment prospects of displaced workers in Ireland. We will return to this issue again, as subsequent evidence appears to support the idea that the type of displacement event also plays a role in determining the post-displacement earnings experience of workers.

It is noteworthy that displaced workers in both the closure and mass-layoff samples do not experience a large recovery in their probability of employment. With this in mind, we look at the level of attrition of displaced workers from the sample. We can see in Table 4.9 that as time progresses, the rate of attrition from the sample increases, as those in earlier cohorts have a longer time-span to find re-employment. However, we do see that the mass-layoff group have a higher rate of attrition. For example, 49% of those displaced due to a mass-layoff in 2006 never re-appear in employment compared to 23% of those displaced due to closure. It is possible that some of these individuals have emigrated but we cannot say this definitively.

Table 4.9: Numbers and % of displaced workers who do not reappear in the sample

Year	Closure			Mass Layoff		
	No. of displaced who never reappear in panel	No. of displaced workers	% of displaced workers who never re-appear	No. of displaced who never reappear in panel	No. of displaced workers	% of displaced workers who never re-appear
2005	2,149	10,221	**21%**	535	1,979	**27%**
2006	3,183	14,120	**23%**	1,112	2,270	**49%**
2007	7,046	20,516	**34%**	1,850	3,005	**62%**
2008	13,465	45,258	**30%**	5,385	8,079	**67%**
2009	13,407	32,452	**41%**	3,387	4,656	**73%**
2010	13,834	29,963	**46%**	1,418	2,232	**64%**

If we look at the attrition by nationality, we find that in the closure sample it is Irish workers who constitute the greatest number workers who do not re-appear in the data following displacement. In the mass-layoff sample, there is a more even split between Irish and non-Irish workers and attrition from the sample in 2007 and 2008, with both groups being almost equal in terms of numbers who do not re-appear after displacement. While we can only speculate, it is possible that many workers, both Irish and non-Irish may have emigrated. This is in line with earlier evidence presented in chapter 2.

Table 4.10: Numbers of displaced workers who do not reappear in the sample by nationality

Year	Closure		Mass-Layoff	
	Irish	Non-Irish	Irish	Non-Irish
2005	1,792	357	412	123
2006	2,145	768	863	249
2007	4,924	2,122	919	931
2008	10,061	3,404	2,951	2,434
2009	10,090	3,317	2,591	769
2010	10,898	2,963	1,063	355

With regards to age, we do find evidence that a greater number of younger workers in the 26-45 age groups exit from the sample following displacement in both the closure and mass-layoff samples, compared to other age categories, as evidenced in Table 4.11 below. So it does appear that the attrition of younger workers from the sample increases with the onset of the recession around 2008.

Table 4.11: Numbers of displaced workers who do not reappear in the sample by age category

Year	16-25 years Number	26-35 years Number	36-45 years Number	46-55 years Number	56-64 years Number	65 years+ Number
Closure						
2005	243	515	538	366	315	172
2006	400	799	763	556	446	219
2007	1,137	2,096	1,643	1,206	666	298
2008	1,955	3,957	3,190	2,227	1,544	592
2009	1,871	3,866	3,300	2,367	1,456	547
2010	1,753	3,865	3,459	2,544	1,617	596
Mass-layoff						
2005	130	155	-	-	-	-
2006	180	321	256	1950	-	-
2007	442	733	309	215	-	-
2008	1,294	2,181	934	521	371	455
2009	376	1,145	771	618	-	-
2010	206	488	366	211	-	-

Note: Some figures are suppressed for confidentially reasons.

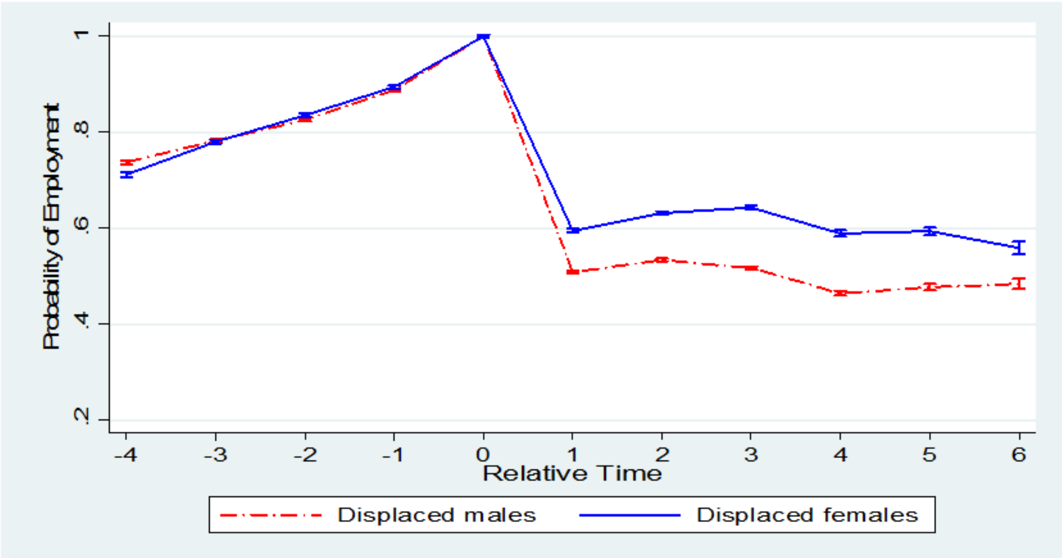
To determine if there are gender differences arising regarding the probability of employment, we examine the experience of males versus females. These are displayed in Figure 4.2 below.[64] We see a similar trend here – those displaced as a result of a mass-layoff have a lower probability of employment. However, there are

[64] See Appendix Table 8.2 for regression output.

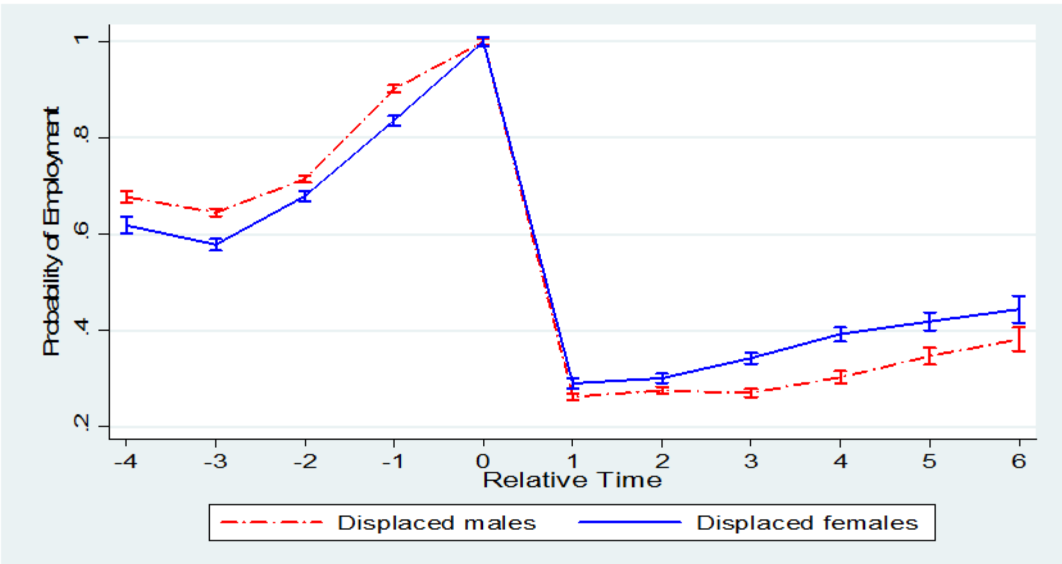
differences between males and females. We observe that displaced males have a lower probability of employment relative to displaced females. Over the time period considered here, these differences persist.

Figure 4.2: The probability of employment of displaced males and females workers

a) Closure



b) Mass Layoff



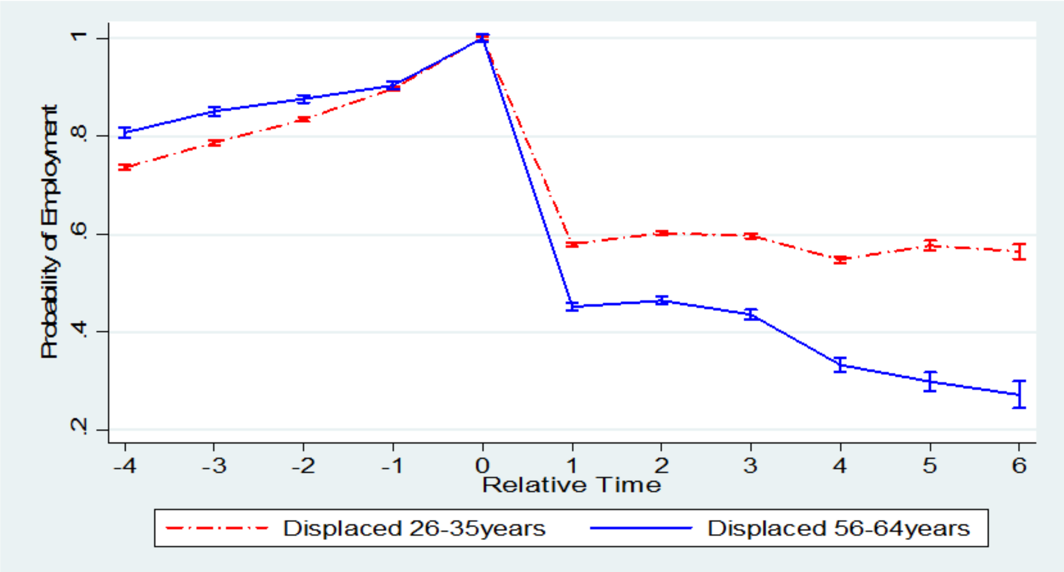
It is possible that the probability of employment may be impacted by other individual characteristics such as the age of the worker and their nationality. Older workers, with higher tenure and firm-specific capital may find it more difficult to secure re-employment following a displacement event compared to non-displaced workers. Figure 4.3 below examines the probability of employment for those aged 26-35 and displaced compared to those aged 56-64 years for both samples.[65] In both samples we see that the probability of re-employment for those aged 56-64 years is lower than that of younger workers. It is also clear that those older workers displaced due to a mass-layoff event experience a much lower probability of employment after a displacement event. For example at $t=1$, those aged 56-64 years in the mass-layoff sample have a probability of re-employment of 18% compared to 46% for those displaced following an enterprise closure.

For both samples, the probability of employment does not recover to the pre-displacement level and older workers in the closure sample experience a declining trend after displacement. In the mass-layoff sample, the probability of employment of older workers hovers around 20% in the post-displacement years. However as we move further from the displacement event, it is clear that the confidence intervals around the estimates widen, suggesting greater variation in the experience of displaced workers. It appears displaced workers of all ages may face greater competition in securing re-employment, although it appears that older displaced workers face an even greater challenge.

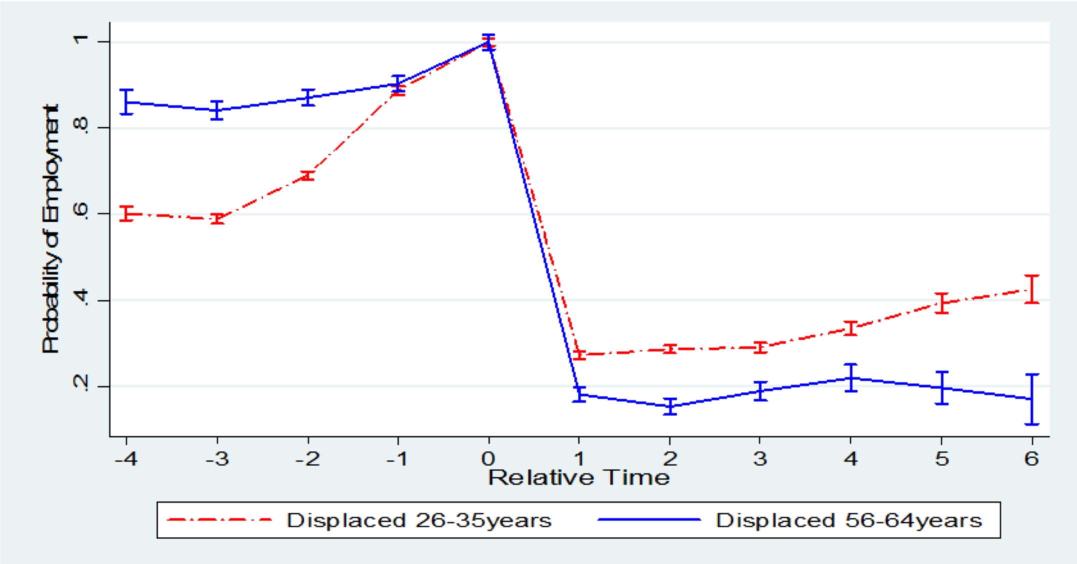
[65] See Appendix Table 8.3 for regression output.

Figure 4.3: The probability of employment of displaced 26-35 year olds and displaced 56-64 year olds

a) Closure



b) Mass Layoff

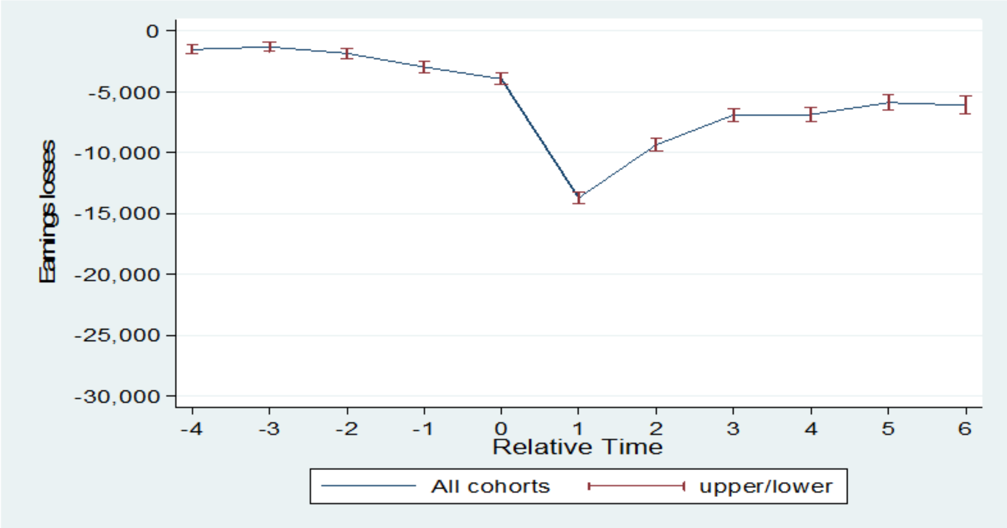


4.4.3 Earnings losses and displacement

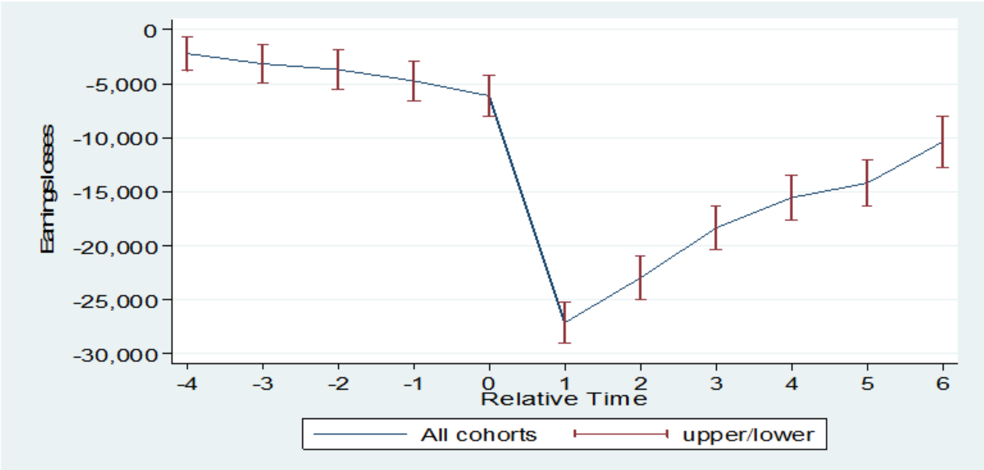
As highlighted in section 4.2.4, much of the previous work on displacement has examined the impact of displacement on workers' subsequent earnings. Here we investigate the impact of displacement due to closure and mass-layoff events on workers' employment earnings. In order to further investigate the impact of displacement on earnings, we estimate equation (4.4) described earlier. The resulting difference-in-differences estimates and associated confidence intervals are graphed below.

Figure 4.4: The earnings losses of displaced workers

a) Closure



b) Mass Layoff



Looking at the entire period in Figure 4.4,[66] the mass-layoff sample does appear to experience greater earnings losses relative to the closure sample. While displaced workers in the closure sample experience losses of around €13,500 at *t=1*, those in the mass-layoff sample experience earnings losses of just over €27,000 at *t=1*. This represents losses of 36% and 69% for the closure and mass-layoff samples

[66] The associated regression output is in Appendix Table 8.4.

respectively, relative to their earnings immediately before displacement at *t=0*. Although earnings do recover for both samples, they do not reach their pre-displacement level in the time period considered.

This evidence of smaller losses for the closure group is consistent with the theory and evidence provided by Gibbons & Katz (1991). They suggest that if firms have discretion over who is selected for layoff, as they would in a mass-layoff event as opposed to a closure event, the market will assume that those who are subject to layoff are of lower ability. Because of this, those displaced through mass-layoff may receive a lower post-displacement wage, relative to the closure group. Those affected by the closure are different because all employees are let go and thus a negative signal is not sent to the market, as is the case with the mass-layoff event. Evidence from the Irish labour market presented here would seem to support this theory.

However, these results differ somewhat from those of Hijzen et al. (2010) who report lower income losses for the mass-layoff group relative to the closure group in the UK. While the time period post-displacement in this chapter is limited to six periods, it appears that displaced workers are adversely impacted, particularly those in the mass-layoff sample, with earnings not recovering to their pre-displacement level in the six time periods after displacement. This contrasts with Huttunen et al. (2011) and Burda & Mertens (2001) who both find little impact on the post-displacement earnings or wage growth of workers.[67]

[67] The earnings losses of displaced workers were also estimated with the inclusion of cohort dummies. Results are presented in Appendix Table 8.5 and Appendix Figure 8.1. As this shows, their inclusion has very little impact on estimated losses.

In both samples, we see evidence of a dip in the pre-displacement earnings or an Ashenfelter's 'dip' (Ashenfelter 1978). This is particularly true in the mass-layoff sample. Ashenfelter (1978) found that wages of participants in training programmes had a tendency to decline in the period before they entered a training programme. In the context of this study, such a dip would be identified by a decrease in the pre-displacement earnings of the displaced group. This could be explained by enterprises implementing a shorter working week or cutting back on overtime in an effort to cut costs. A potential consequence of such a dip is that difference-in-differences estimates may understate the impact of displacement on the earnings losses of displaced workers.

A possible way of avoiding this is to do as Hijzen et al. (2010) have done and choose a base period which is well in advance of the displacement event and prior to a dip occurring. Given the limited number of years that data was available for in this study, such an approach was not possible. However, while we acknowledge the potential for over-estimation of earnings losses, we feel that the magnitude of the dip is relatively small, particularly in the closure sample and proceed with our estimation. Also, given the large sample and the use of propensity score matching, this helps ensure close matching between treatment and control groups.

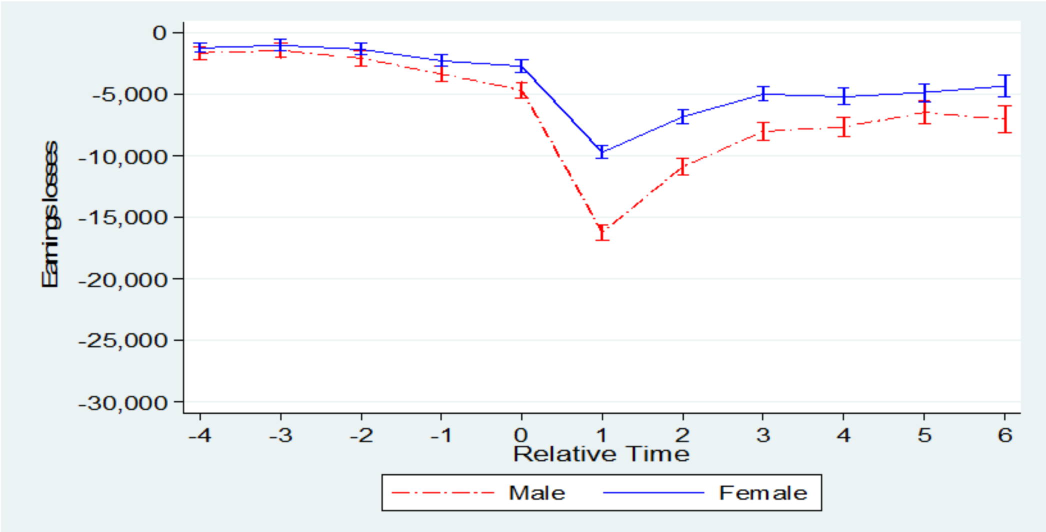
4.4.3.1 Displacement and earnings losses – individual characteristics

We further explore the earnings losses by looking at differences associated with gender, age and nationality. This is done using equation (4.4) and splitting the closure and mass-layoff samples by gender, age and nationality respectively. Percentage losses relative to the base period of $t=0$ immediately prior to displacement are reported in parentheses.

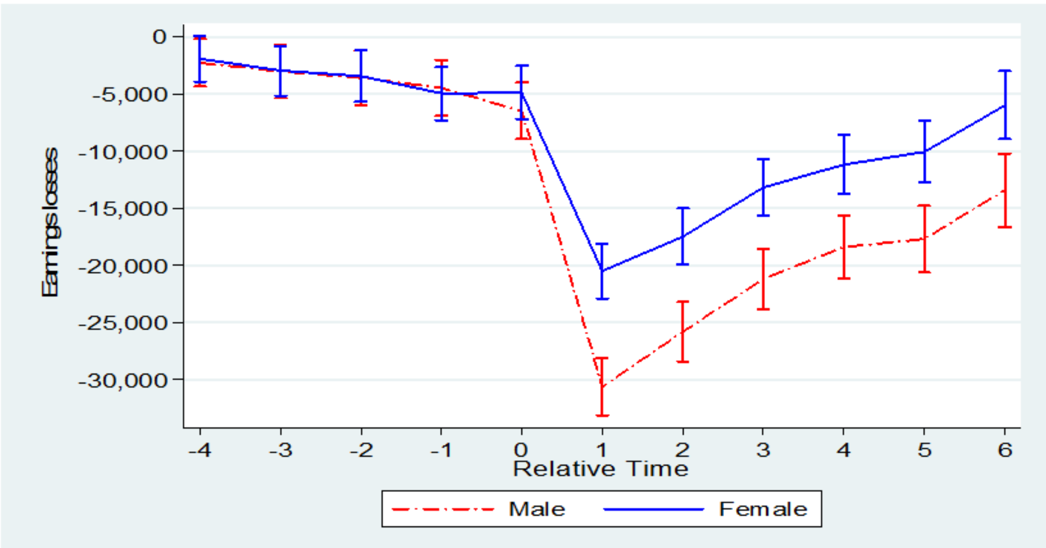
Beginning with gender, males appear to experience a greater earnings loss compared to females in both samples in Figure 4.5.[68] In the closure sample, males experience a loss of just over €16,200 (38%) with females experiencing a loss of just under €10,000 (32%) at *t=1*, relative to the previous period. However in the mass-layoff sample, displaced males experience a loss of over €30,000 (70%) at *t=1* with the corresponding figure for females standing at just over €20,000 (68%).

Figure 4.5: Earnings losses of displaced workers and gender

a) Closure



b) Mass Layoff



[68] See Appendix Table 8.6 for regression output.

This is consistent with evidence from Hijzen et al. (2010) who report that displaced men experience greater earnings losses when compared to displaced women. As mentioned earlier, this finding is different to some of the results presented for the US. Couch & Placzek (2010) suggest that five years after displacement, men and women experience similar losses. It is possible in the Irish case that men were displaced from sectors such as construction, traditionally male-dominated, which were more adversely affected by the downturn and thus experienced larger earnings losses immediately after displacement. As reported in Chapter 2, this sector alone experienced a decrease in employment of almost 163,000 workers between 2007 and 2011.[69] Consistent with earlier observations, both males and females in the mass-layoff group experience greater earnings losses than those in the closure sample.

Turning to age, empirical work in both the US and Europe does suggest that older workers experience a greater earnings loss in comparison to younger workers. It is possible for example, that older workers have been working with one employer for a long period of time and acquired significant firm-specific capital which may be of little value to a potential new employer after displacement. In the US, Couch (1998) finds that older workers aged 51-60 years experience a loss of 30-39% in the year after displacement. In the UK, Hijzen et al. (2010) report that, examining a five year post displacement period, displaced workers experience a loss of 40% relative to what they were earning the year before the displacement event.

Figure 4.6 and Figure 4.7 below show the earnings losses associated with each age category.[70] We generally observe that the younger categories experience smaller earnings losses when compared to older age categories. As previously, the mass-

[69] See Appendix Table 1.1 for further details.
[70] See Appendix Table 8.8 and Appendix Table 8.8.

layoff group display greater losses immediately after displacement. For example, while 54-64 year olds in the closure sample experience a loss of around €15,000 (37%), those in the mass-layoff group experience a loss of almost €29,000 (69%) at *t=1*. The losses for the closure sample are very similar to those of Couch (1998), while again we see that the mass-layoff sample is more adversely impacted. We do observe wider confidence intervals in the mass-layoff sample, attributable to the smaller sample size.

Figure 4.6: Earnings losses of displaced workers and age category (closure)

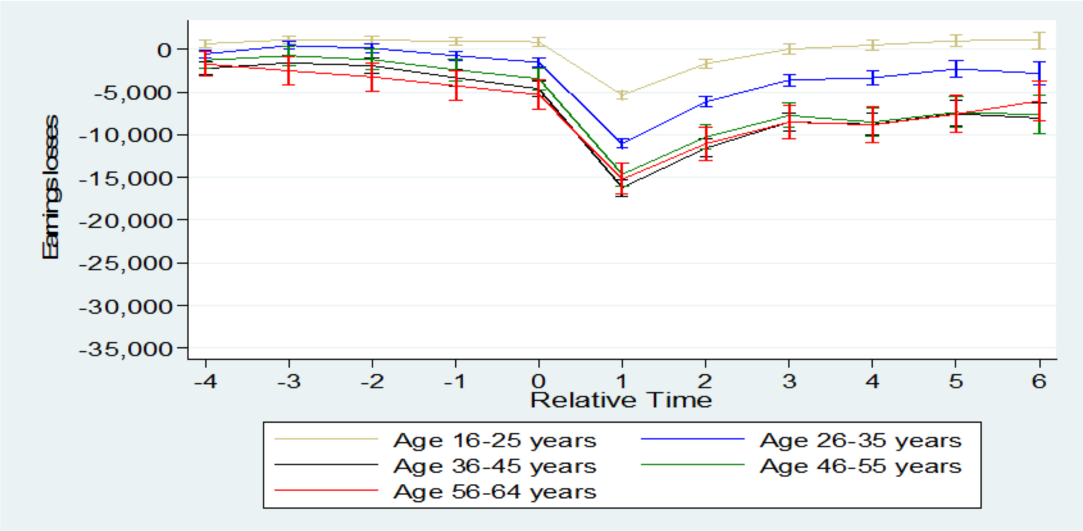
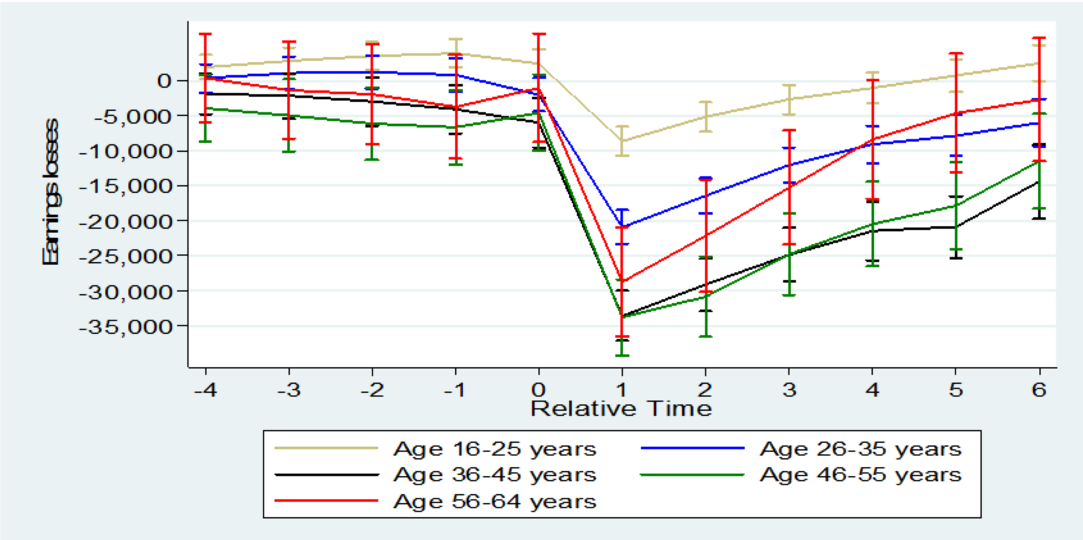
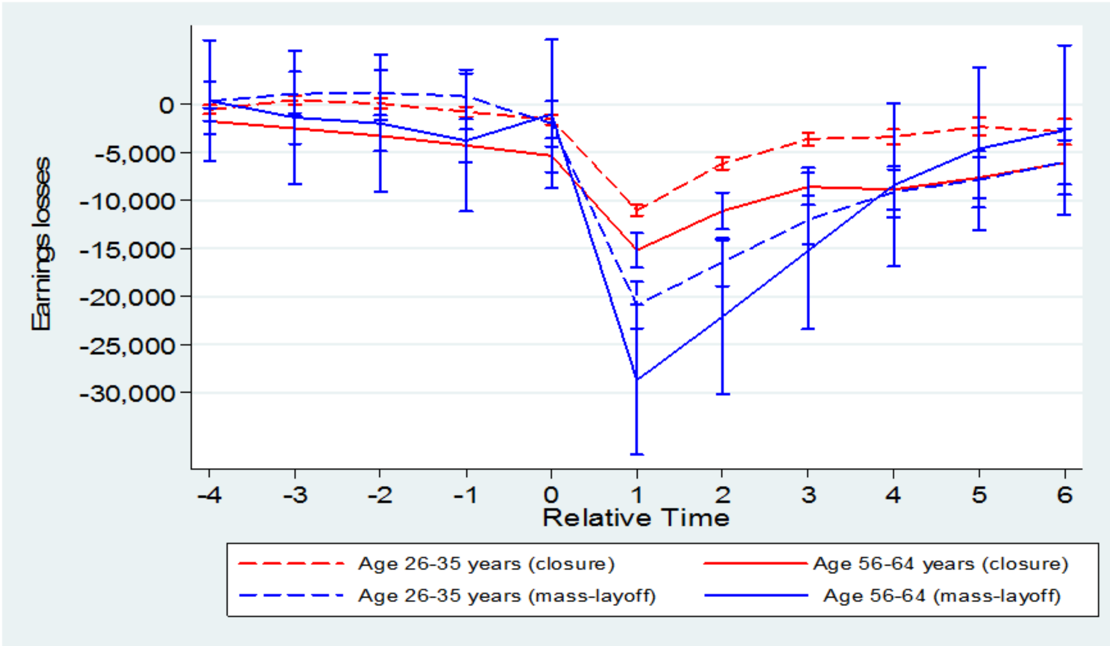


Figure 4.7: Earnings losses of displaced workers and age category (mass-layoff)



The losses of older workers are also displayed in Figure 4.8 and compared to the losses of younger displaced workers. As already noted older workers, especially those displaced as result of a mass-layoff are particularly adversely impacted immediately after displacement with losses of 69%, although they do show signs of recovery, albeit with wide variation.

Figure 4.8: Earnings losses of displaced workers aged 26-35 and 56-64 years



Younger workers displaced due to closure appear to suffer the smallest losses representing a 34% fall in earnings in the period after displacement and recover quickly. This contrasts with a 68% loss for such workers displaced due to a mass-layoff. At *t=6*, the earnings losses of these workers in the closure sample are approaching their pre-displacement level.

This supports the work of Couch et al. (2010) who find that earnings recover faster for younger workers. In our case this appears to be true, particularly for those displaced due to closure. As seen in Figure 4.3 earlier, younger displaced workers also have a higher probability of employment compared to older displaced workers.

We also investigate the role of nationality with respect to earnings losses. We begin by examining the average age of Irish and non-Irish workers. As we can see in Table 4.12 below, displaced Irish workers are four years older than non-Irish workers in the closure sample and six years older than non-Irish workers in the mass-layoff sample. The average age of displaced Irish workers is the same in both samples while non-Irish displaced workers are slightly younger in the mass-layoff sample.

Table 4.12: Average age for displaced workers in each cohort

Nationality & Displacement event	Cohort						
	2005	2006	2007	2008	2009	2010	2011
Closure							
Displaced Non-Irish	31	32	33	34	35	36	37
Displaced Irish	35	36	37	38	39	40	41
Mass-Layoff							
Displaced Non-Irish	29	30	31	32	33	34	35
Displaced Irish	35	36	37	38	39	40	41

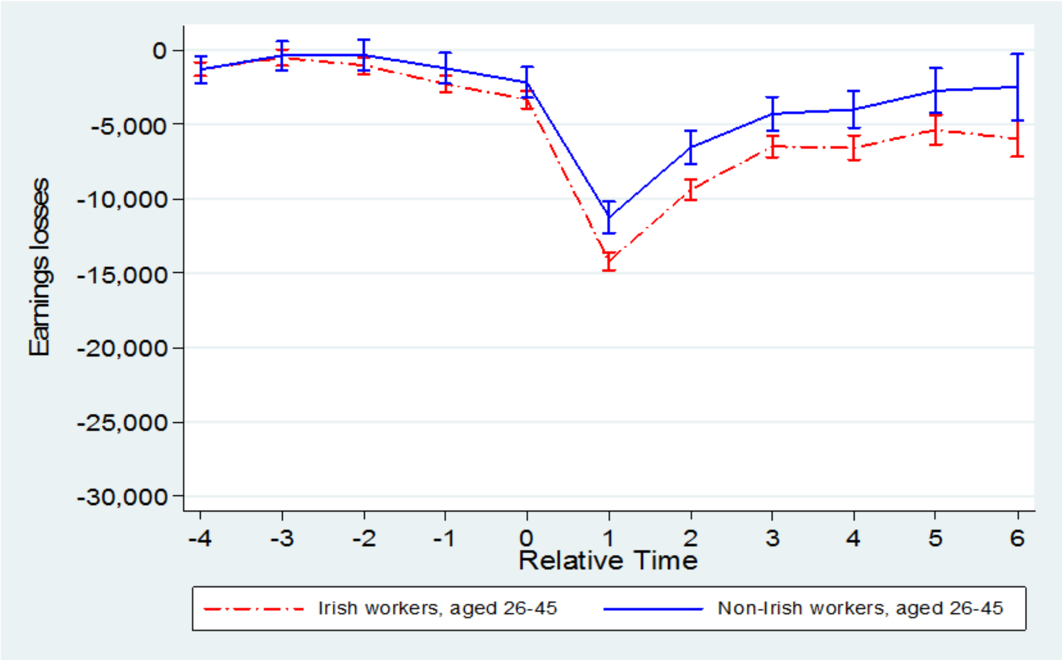
In examining the losses of such workers, and in light of their average age, we focus on those aged 26-45 years. In Figure 4.9[71] we observe that the losses of those in the closure sample are less than those in the mass-layoff sample following displacement. In the mass-layoff sample, these losses represent a 70% fall in earnings for Irish workers and a 68% fall for non-Irish workers, relative to their earnings immediately before displacement. On the other hand in the closure sample, we observe smaller percentage losses for Irish workers. Irish workers displaced as a result of closure experience losses of 34%, while non-Irish workers see earnings fall by 37% in the period after displacement. The confidence intervals associated with the losses of non-Irish workers are wider. As noted, the mass-layoff sample size is considerably

[71] See Appendix Table 8.10 for regression output.

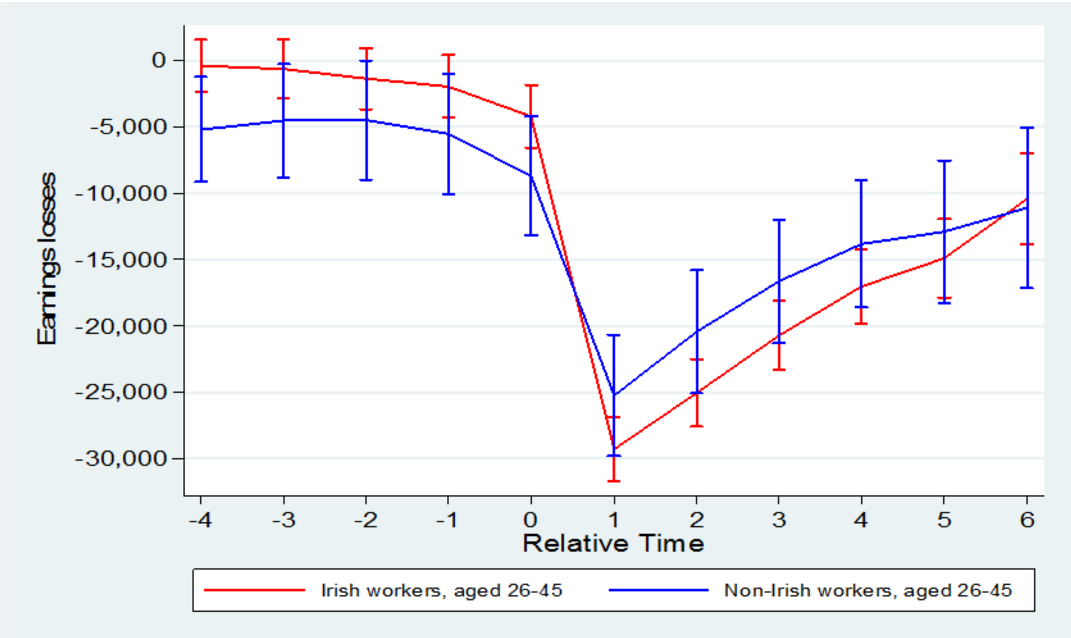
smaller than that of the closure sample. Overall, the magnitude of the losses is similar for both nationality groups but the trend of mass-layoff workers experiencing greater losses is continued.

Figure 4.9: Earnings losses of displaced Irish and non-Irish workers

a) Closure b) Mass Layoff



b) Mass Layoff



Next we explore the losses of displaced workers who find re-employment in the same sector they were displaced from and those who were displaced and move to a new sector of employment, relative to those who are not displaced. We do this for both the closure and mass-layoff samples. As noted earlier, evidence from the US from Jacobson et al. (1993), Couch et al. (2009) and Couch & Placzek (2010), as well as Burda & Mertens (2001) in Europe suggests that finding re-employment in a different sector after displacement can have a negative impact on subsequent earnings relative to those who stay within the same sector to secure re-employment. Displaced workers are identified as being either (i) industry switchers, (ii) industry stayers or (iii) unemployed. A worker is deemed to be an industry switcher if the industrial classification of the enterprise they secure re-employment in after displacement is different to the industrial classification of the enterprise they were displaced from. The first employment record following displacement is identified, which allows for the possibility that an individual may have an intervening unemployment spell. A worker is classified as unemployed if there is no employment record in all periods following displacement.

To identify the earnings losses of displaced industry switchers and stayers, earnings y_{it} is regressed on a series of interaction terms as per the equation (4.6). Specifically, $Dswitch_{it}$ is a dummy variable equal to one if an individual is displaced and finds employment in another sector, and zero otherwise. The next variable of $Dstay_{it}$ is a dummy variable equal to one if an individual is displaced and stays in the same sector after displacement, and zero otherwise. The variable $NoDswitch_{it}$ is a dummy variable and equal to one if an individual is not displaced and switches sectors and zero otherwise. Finally, $Unemp_{it}$ is another dummy variable equal to one if a person is unemployed in all periods following displacement, and zero otherwise.

The γ^k coefficient represents the earnings of non-displaced workers who stay employed in the same industry. Therefore, all earnings losses (or increases) described are relative to this group of workers.

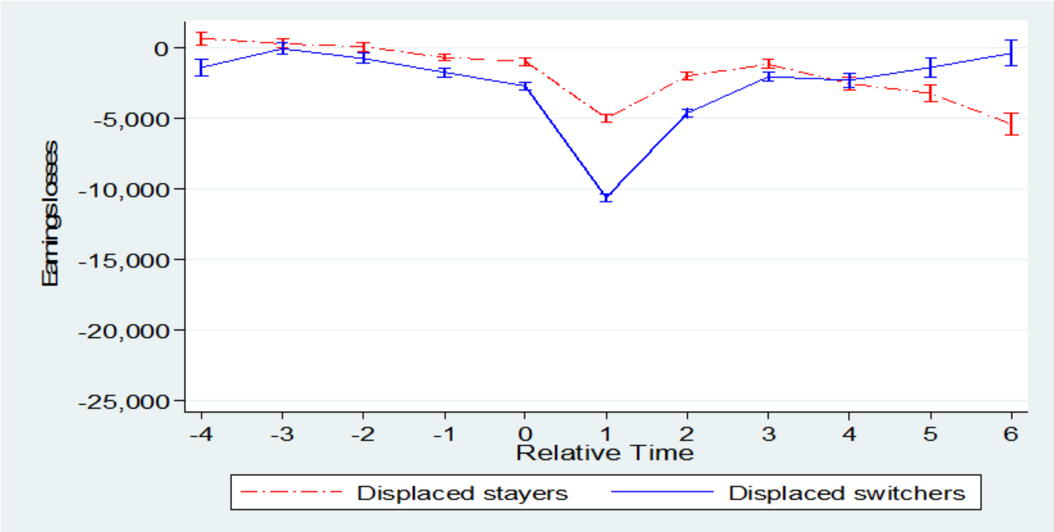
$$\boldsymbol{y_{it}} = \sum_{k=-5}^{6} \gamma^k \ T_{it}^k + \sum_{k=-5}^{6} \delta^k \, Dswitch_{it} * T_{it}^k + \sum_{k=-5}^{6} \alpha^k \, Dstay_{it} * T_{it}^k + \sum_{k=-5}^{6} \beta^k \, NoDswitch_{it} * T_{it}^k + \sum_{k=-5}^{6} \sigma^k \, Unemp_{it} * T_{it}^k + \ \varepsilon_{it} \quad \textbf{(4.6)}$$

Firstly we observe in Figure 4.10[72] that all displaced workers suffer large losses but the losses are greater for those who switch industry. Secondly as noted previously, it appears that the mass-layoff group suffer a greater penalty, with losses of over €23,000 (53%) at *t=1* for those who switch to another industry. This is in comparison to losses of around €10,000 (36%) at *t=1* for the group of workers from the closure sample who switch to another industry. Displaced workers who stay in the same industry after displacement experience losses of 13% and 26% respectively in the closure and mass-layoff samples at *t=1*.

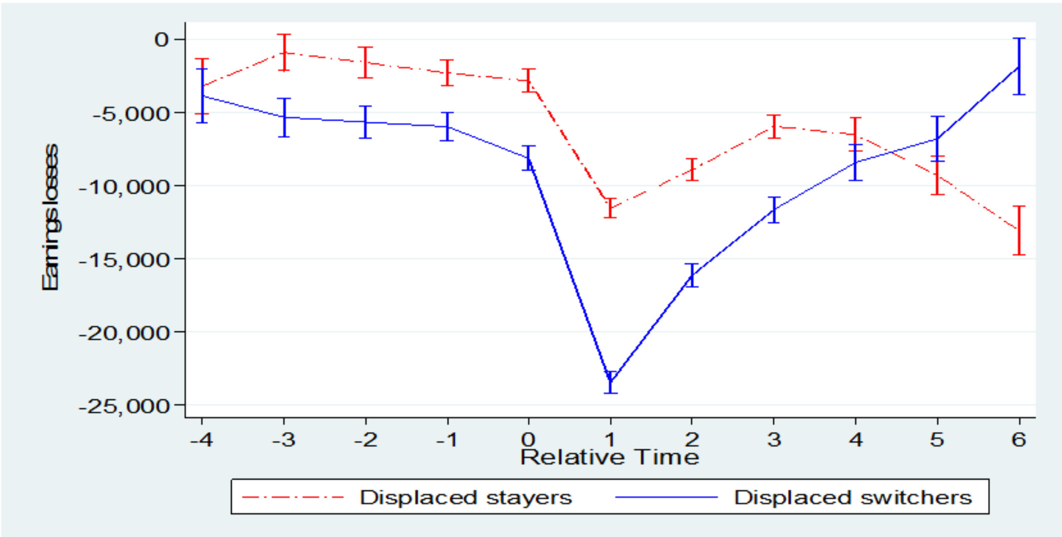
[72] See Appendix Table 8.10 for regression output.

Figure 4.10: The earnings changes of displaced workers who switch or stay in the same sector following displacement

a) Closure



b) Mass Layoff

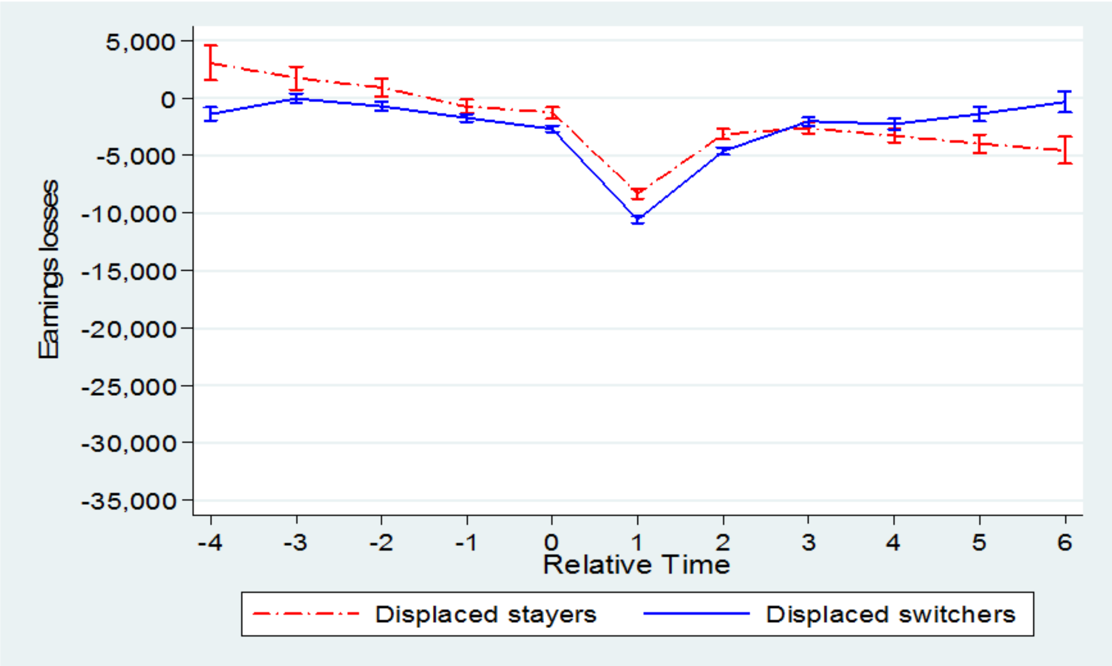


This trend of greater losses for the group of displaced switchers from the mass-layoff sample versus displaced switchers from the closure sample continues in the periods after displacement. Both closure and particularly the mass-layoff switchers appear to experience losses prior to the displacement event, which is generally not the case for the displaced stayers. Interestingly, we observe that the earnings losses of the displaced switchers do recover quickly and at *t=5* they actually appear to have smaller losses that the displaced stayers, although we do note the widening confidence intervals for both sets of workers in both samples.

As we observed earlier in Chapter 2, the construction sector was particularly adversely impacted by the economic recession in the period under investigation. In particular we observed a large decrease in employment over the period as well as a decrease in earnings. We now explore the earnings of those who were displaced from the construction sector either due to a closure or mass-layoff event in Figure 4.11.[73] Equation (4.6) is used and this time the sample includes only those from the construction sector.

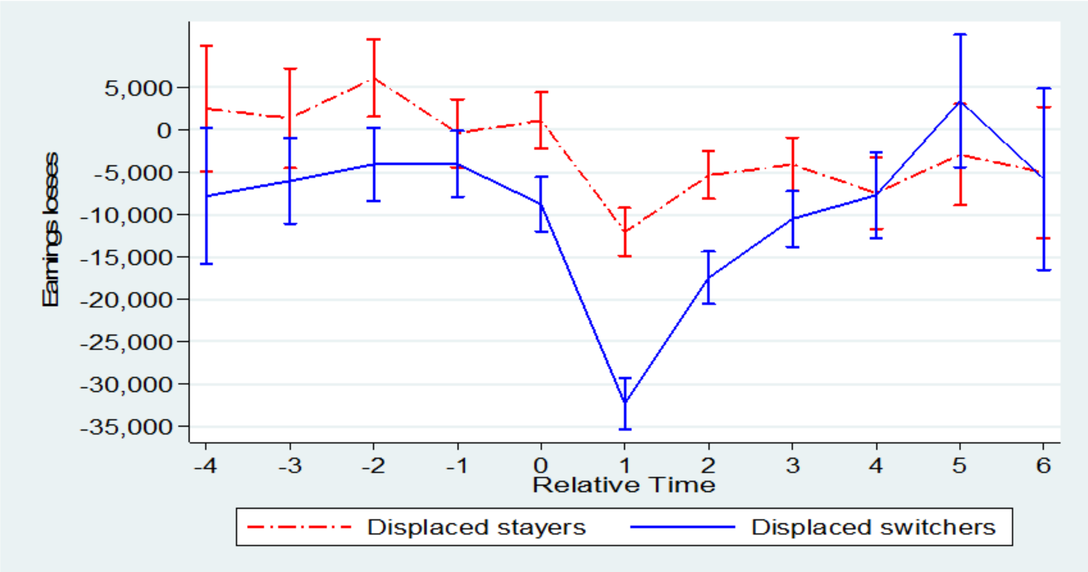
Figure 4.11: The earnings changes of displaced workers in the construction sector (F) who switch or stay in this sector following displacement relative to non-displaced stayers

a) Closure



[73] See Appendix Table 8.11 for regression output.

b) Mass Layoff

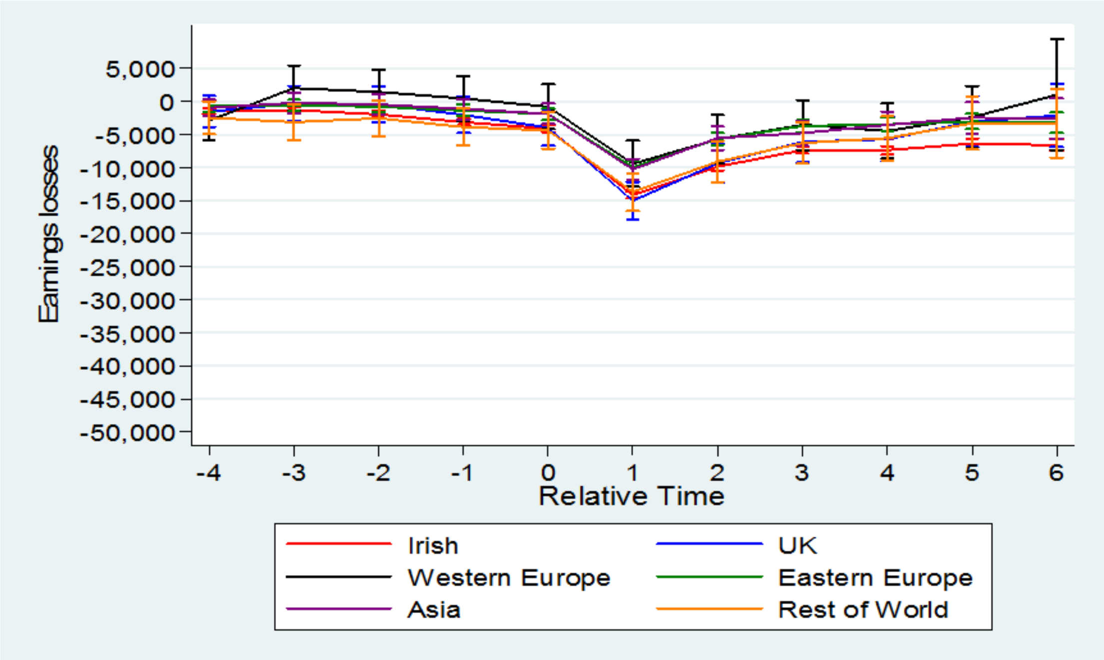


Again we can see that both displacement events cause large losses for workers. As was the case earlier, displaced switchers who move to another sector either as a result of closure or mass-layoff suffer greater losses (54% and 83% respectively) relative to those who are displaced and secure re-employment in the same sector in the period following displacement (43% closure and 44% mass-layoff). Interestingly we observe in the closure sample that displaced industry switchers experience a recovery in their earnings and from *t=3* their earnings losses are smaller than those who stayed within the construction sector. We note a similar trend in the mass-layoff sample. While the mass-layoff group of switchers experience losses of over €30,000 (83%) at *t=1*, earnings appear to recover and losses are less than those who stay in that sector, although after *t=4*, results are not statistically significant.

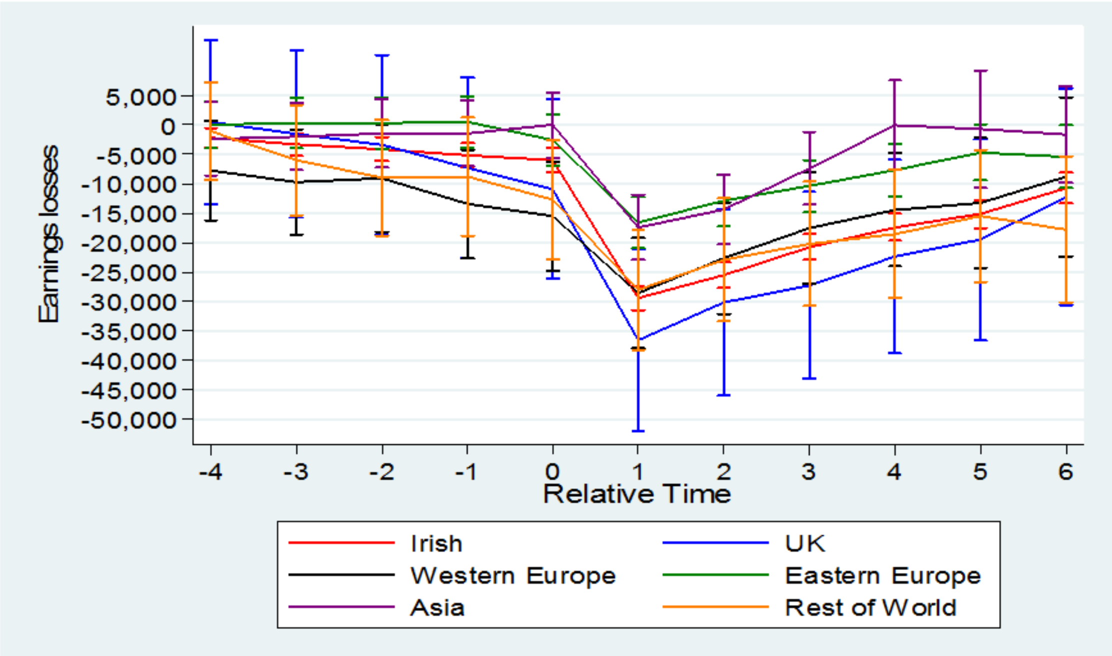
We also examine the earnings losses by nationality for workers. Both the closure and mass-layoff samples are split into nationality groupings and equation (4.4) is applied as before. In Figure 4.12 below we see in general across nationalities, those displaced due to mass-layoff experience greater earnings losses.[74]

Figure 4.12: Earnings losses of displaced workers and nationality

a) Closure



b) Mass Layoff



[74] See Appendix Table 8.12 for regression output.

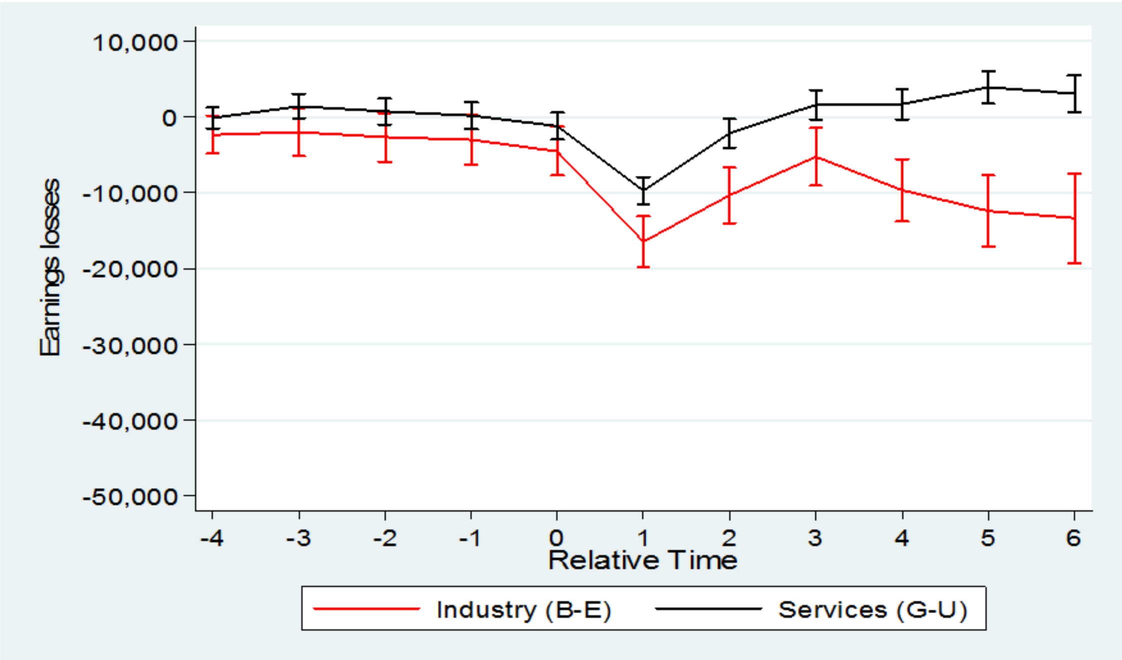
Exploring nationality groups, we see evidence of a greater negative effect on the earnings of the displaced in the mass-layoff sample. Irish workers, the largest group in the sample, experience losses of 36% following a closure event and 70% in the period following a mass-layoff event. The largest percentage losses are experienced by the group of Eastern European workers in the mass-layoff sample who see a fall in earnings of 80% after displacement. The variation in losses is greater in the mass-layoff sample.

4.4.3.2 Displacement and earnings losses – enterprise characteristics

We now examine more closely the earnings losses with regards to industry in Figure 4.13.[75] Broad sectoral groups are examined – NACE sectors (B-E) are in one grouping while the services sectors (G-U) are in another.

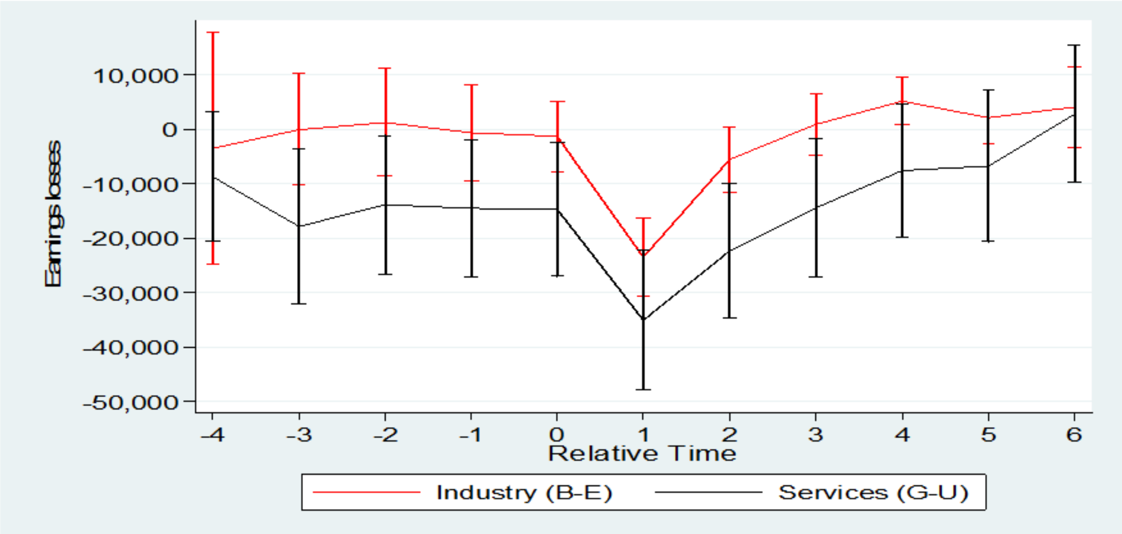
Figure 4.13: Earnings of displaced workers and sector of employment at displacement

a) Closure



[75] See Appendix Table 8.13 for regression output.

b) Mass Layoff



Beginning with the closure sample and the services sector (G-U) we see earnings losses of just under €10,000 (33%) in the time period following displacement, while those in the industry (B-E) group experience losses of over €16,000 (35%). Earnings losses appear to recover quickly and even surpass their pre-displacement level for those in services sector (G-U). The confidence intervals associated with the services sector are also narrower than industry sectors. For the industrial sectors (B-E), an initial recovery is not sustained and begins to fall again after *t=3*.

Turning to the mass-layoff sample, we observe greater losses, as well as greater variability in losses relative to the closure sample. As highlighted earlier, the mass-layoff sample is smaller. However, we do see a different trend by sectoral grouping here with those in the services sector experiencing greater losses than the industry (B-E) group (75% and 65% respectively). As noted earlier, Hijzen et al. (2010) report that the losses of those displaced from the services sector are slightly greater than the losses of those displaced from manufacturing. Our results for the mass-layoff sample are similar. On the other hand in the closure sample, those displaced from the services sectors experience smaller losses relative to those displaced from the industry sectors (B-E). So it appears workers in the services (G-U) sector are less adversely impacted by displacement due to closure rather than mass-layoff.

4.4.3.3 Earnings losses and unemployment

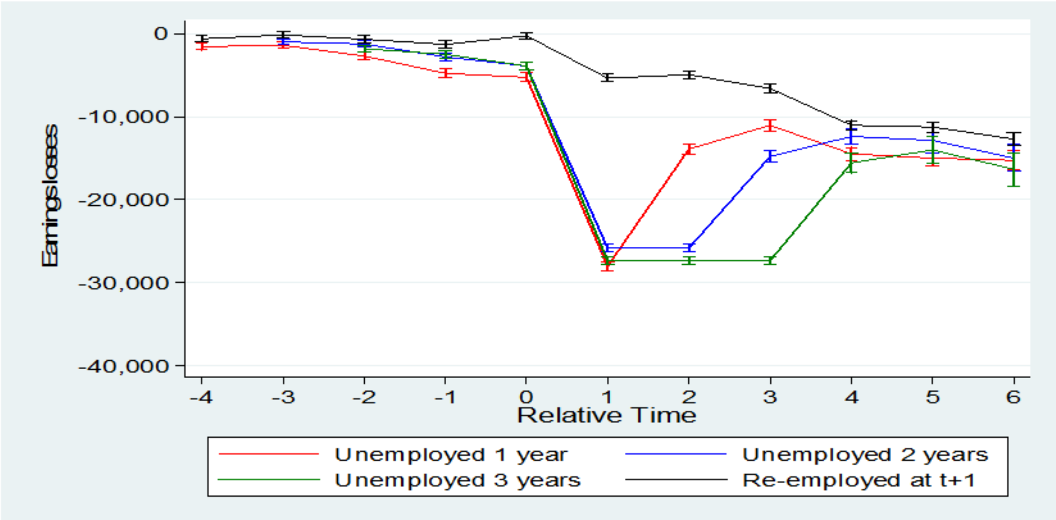
It is possible that the reported earnings losses are driven by non-employment spells. We have assumed income of zero for out-of-work periods for displaced workers.[76] This is in line with the work of Jacobson et al. (1993). We spilt both samples based on their post displacement employment status. Specifically displaced workers are grouped into seven categories. These are those re-employed in the year after displacement and six further groups representing those unemployed for between one and six periods after displacement. Non-displaced workers are split into two groups – one representing those who are in continuous employment and another representing those who do experience an unemployment spell.[77] Relative time dummies are also created for each of the above groups. Pay is then regressed on each group above and the associated relative time dummies, with the exclusion of the control group – workers who are not displaced and have no employment gap.[78]

In both samples we see in Figure 4.14 that those who are re-employed immediately in the period after displacement suffer the smallest earnings losses. This result seems to support that of Hijzen et al. (2010) who suggest that income losses are largely driven by spells of non-employment. However, we do see evidence here of declining losses for this group as time progresses. Our results here generally point to a recovery in earnings for those who are displaced, but particularly in the mass-layoff sample we note the widening confidence intervals as time progresses.

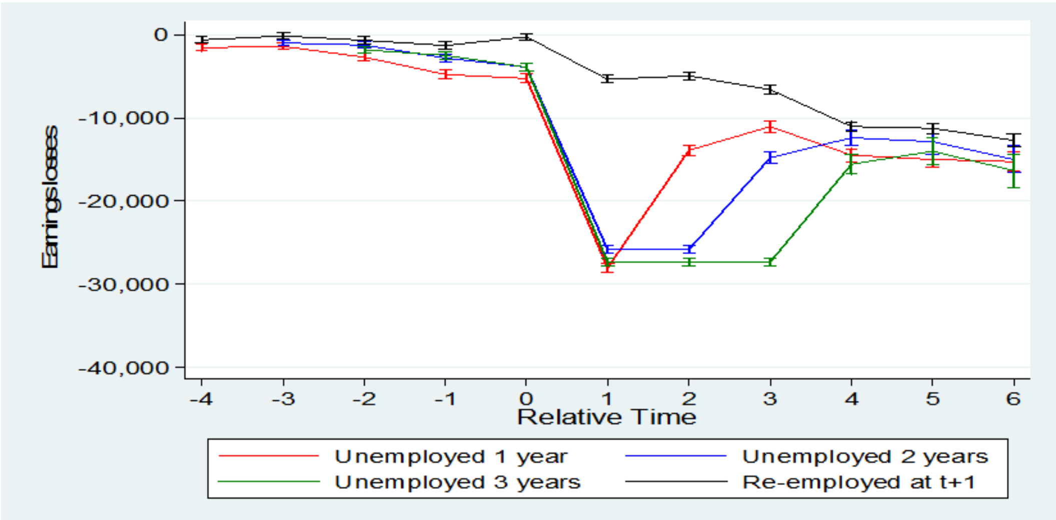
[76] While this due to non-employment, it is also possible that this is due to sample attrition due to immigration for example.
[77] For clarity, four groups are included in Figure 4.14.
[78] See Appendix Table 8.14 for full regression output. The standard errors are clustered using the individual identifier number.

Figure 4.14: Earnings losses and unemployment spell

a) Closure



b) Mass Layoff



4.4.3.4 Test for pooling

At this stage, it was decided to investigate if pooling all of the cohorts for analysis was appropriate. Given the large increase in the number of displacements in 2008 in both the closure and mass-layoff samples, it is possible that a structural break may have occurred here and so pooling the data for all cohorts from 2005-2010 may not be ideal. Thus a likelihood ratio (LR) test of the null hypothesis that there is no change or structural break is conducted against the alternative that there is a structural break.[79] In this case, the full pooled model is tested against the *pre 2008* periods (2005, 2006, 2007 cohorts) and the *post 2008* period (2008, 2009 and 2010 cohorts). The results of the LR provide evidence *against* the null hypothesis and so we continue the analysis by splitting the sample into these two time periods.

4.4.3.5 Earnings losses and displacement pre and post 2008

Before the onset of the recession, workers who lost their jobs had more of an opportunity to find re-employment. This is certainly the case for workers who experience a displacement due to a closure event. As before in equation 4.5, the probability of employment is estimated by regressing an employment dummy on a relative time variable for both the displaced and non-displaced groups in both the closure and mass-layoff samples respectively. As seen in Table 4.13[80] there is less of a difference in the probability of employment in the initial time periods after displacement in the closure sample. We see that at $t=1$ and $t=2$, those displaced before 2008 have a slightly higher probability of employment compared to those displaced after 2008. However for those displaced after 2008, we see the trend is increasing, and by $t=3$, the probability of employment is almost 60%.

[79] See Appendix Table 9.1 and Appendix Table 9.2 for LR test results.
[80] See Appendix Table 10.1 for regression output.

Table 4.13: The probability of employment for the closure sample

Relative time	Closure pre 2008	Closure post 2008
t=-4	-	0.727
t=-3	-	0.782
t=-2	-	0.849
t=-1	0.832	0.910
t=0	1	1
t=1	0.563	0.534
t=2	0.574	0.570
t=3	0.535	0.594
t=4	0.508	-
t=5	0.522	-
t=6	0.511	-

Note: All coefficients are significant at the 1% level.

Turning to the mass-layoff sample, the probability of employment for those displaced before 2008 is around 35% in the year following displacement at *t=1* as seen in Table 4.14.[81] For those displaced in the post 2008 group, the probability of employment is just over 23% at *t=1*. It appears those displaced in the later cohorts may have found it increasingly difficult to find re-employment.

Table 4.14: The probability of employment for the mass-layoff sample

Relative time	Mass-Layoff pre 2008	Mass-Layoff post 2008
t=-4	-	0.658
t=-3	-	0.622
t=-2	-	0.726
t=-1	0.823	0.898
t=0	1	1
t=1	0.353	0.233
t=2	0.360	0.242
t=3	0.361	0.241
t=4	0.341	-
t=5	0.382	-
t=6	0.409	-

Note: All coefficients are significant at the 1% level.

[81] See Appendix Table 10.2 for regression output.

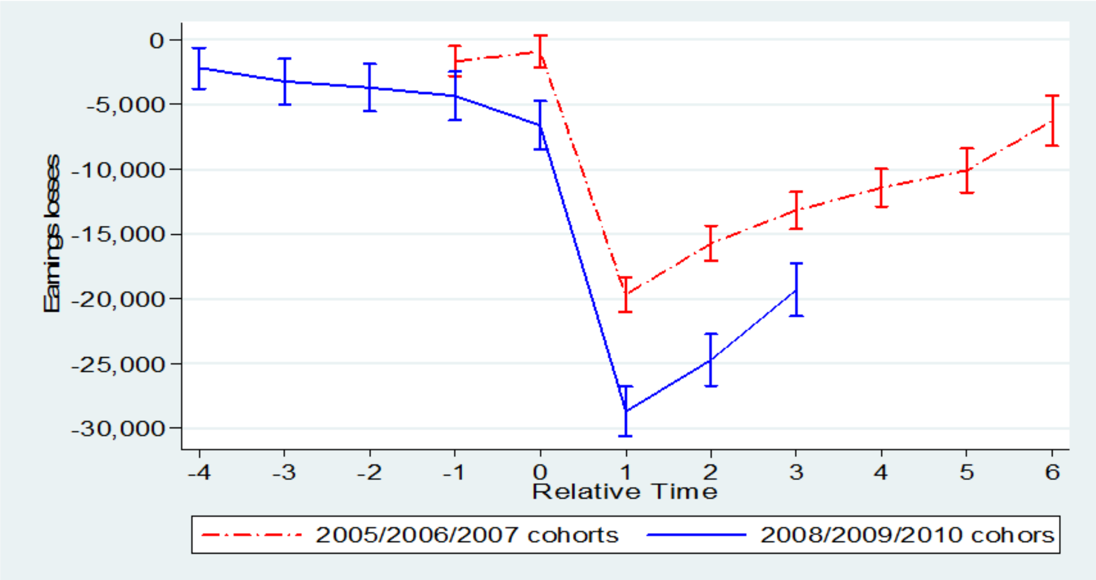
In estimating earnings losses,[82] we find the same continuing trend – the mass-layoff sample experience greater losses than those in the closure sample. Examining earnings losses of those displaced pre 2008 and post 2008 in both samples in Figure 4.15,[83] we observe little difference in earnings losses at *t=1* for the closure sample. Earnings losses pre 2008 are around €12,000 (40%) compared to roughly €13,000 (35%) for the post 2008 group. So it appears those who experience displacement due to closure before 2008 have slightly greater losses in percentage terms relative to their pre-displacement level.

Figure 4.15: Earnings losses of displaced workers pre and post 2008

a) Closure

[82] Equation 4.4 is used and the sample is split into two periods.
[83] See Appendix Table 10.3 for regression output.

b) Mass Layoff



However, we see that workers displaced due to mass-layoff pre 2008 experience loss of around €20,000 (63%) compared to almost €29,000 (72%) for those displaced after 2008. As evidenced in Table 4.13 and Table 4.14, those displaced pre 2008 generally experienced a higher probability of employment and this was most obvious in the mass-layoff sample. Those displaced as a result of a mass-layoff post 2008 appear to suffer the largest earnings losses.

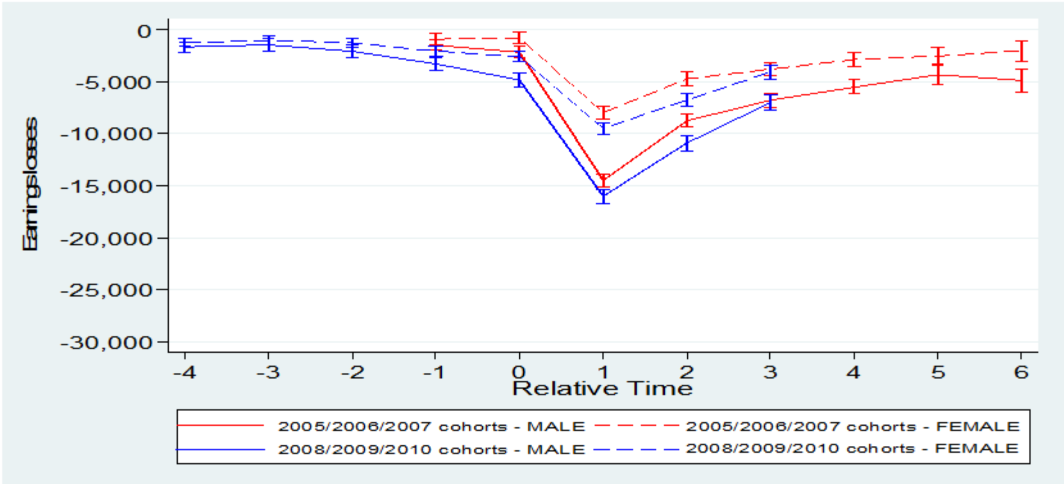
To examine gender differences in earnings losses pre and post 2008, the basic equation (4.4) is again used and altered to split samples by gender and pre and post 2008. As we see in Figure 4.16[84], those displaced following a mass-layoff suffer the greatest earnings losses compared to those in the closure sample. Also, male workers appear to suffer a greater fall in earnings relative to female workers. In the post 2008 period, males and females in the mass-layoff sample experience losses of 72% and 73% respectively, while those males and females in the closure sample have estimated losses of 37% and 31% respectively. Generally, male workers are

[84] See Appendix Table 10.4 for regression output.

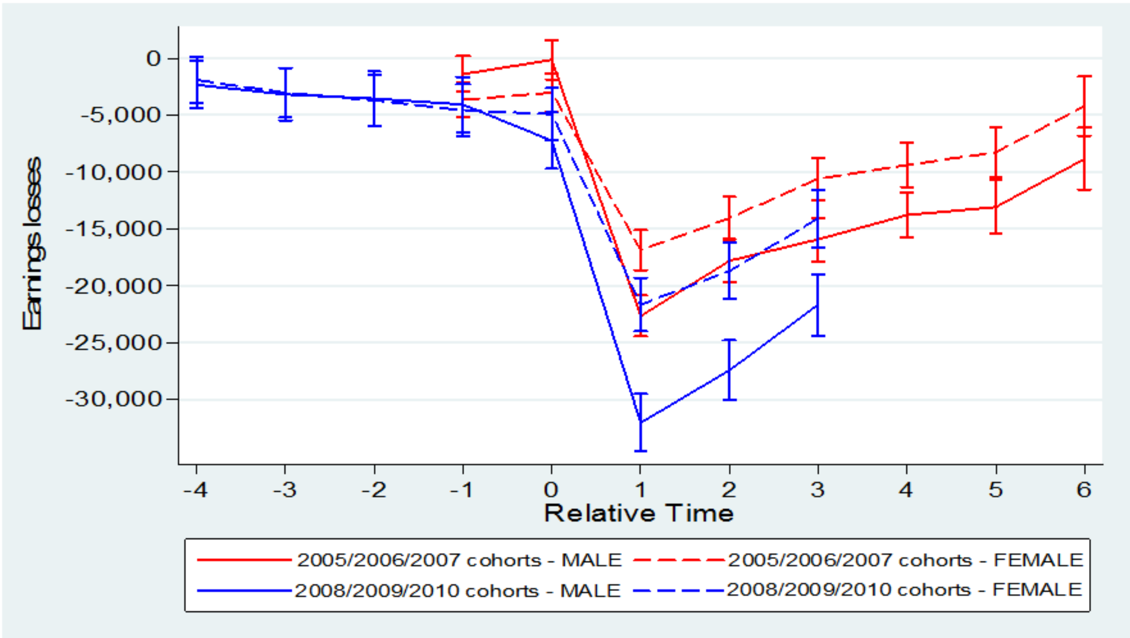
most adversely affected and experience greater percentage losses except those in the post 2008 mass-layoff group, where female earnings losses are one percentage point greater as cited previously.

Figure 4.16: Earnings losses of displaced workers and gender; pre and post 2008

a) Closure



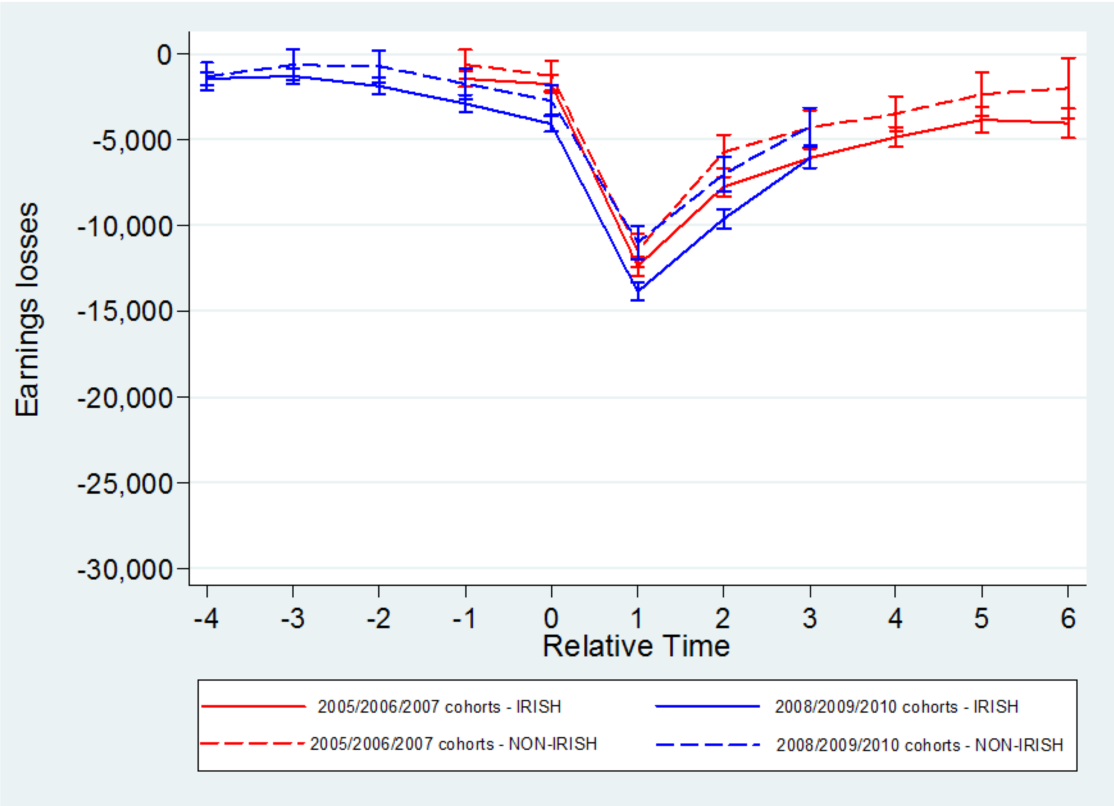
b) Mass Layoff



As observed earlier, earnings losses of displaced workers differed by nationality. Here we examine those losses pre and post 2008. Consistent with earlier observations, Figure 4.17[85] shows that the mass-layoff group again suffer the greatest wage penalty. Both Irish and non-Irish workers suffer greater losses than their closure counterparts. In particular we see that that Irish workers displaced after 2008 due to mass-layoff suffer the largest earnings losses at *t=1*. In the closure sample, we see that it is Irish workers, pre and post 2008 that suffer the greatest losses.

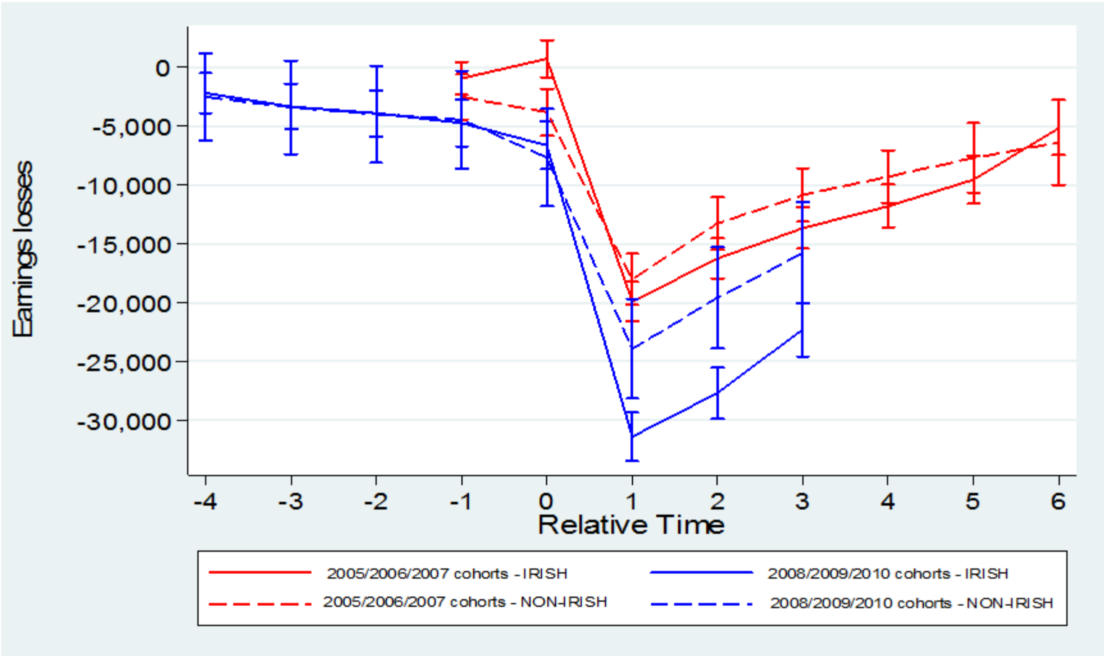
Figure 4.17: Earnings losses of displaced workers and nationality; pre and post 2008

a) Closure



[85] See Appendix Table 10.5 for regression output.

b) Mass Layoff



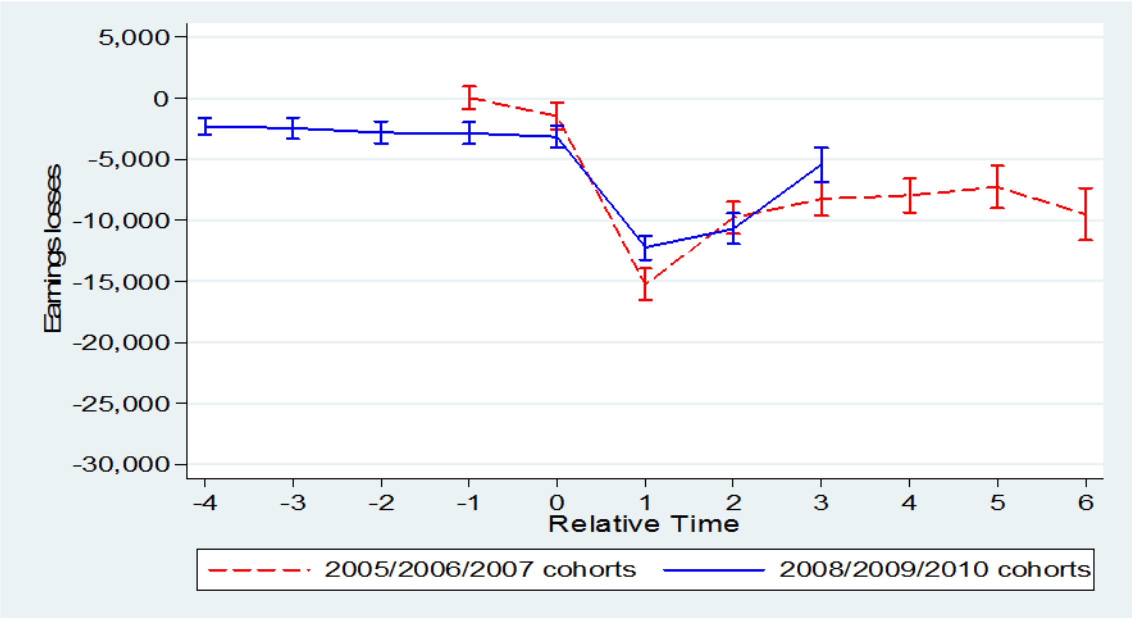
Earlier in Chapter 2 we observed that the manufacturing sector in Ireland was one of the few sectors to experience wage growth over the period 2008 to 2011. Here we examine the fate of those displaced in that sector in Figure 4.18.[86] In the closure sample, those displaced before 2008 experience a slightly larger fall in earnings at *t=1* relative to those displaced after 2008 at *t=1*. It also appears that the earnings of this group are somewhat slower to recover and at *t=3*, the losses of the pre 2008 group are slightly greater than those displaced in the post 2008 group. However, in the mass-layoff group, those displaced after 2008 see a greater fall in their earnings after displacement from the manufacturing sector. The magnitude of the losses of the mass-layoff group is greater when compared to the closure sample. Interpreting these losses as percentage losses between *t=0* and *t=1*, those displaced due to closure before 2008 experience a 47% fall in earnings, compared to 25% for those displaced after 2008. On the other hand, the losses of those in the post 2008 mass-

[86] See Appendix Table 10.6 for regression output.

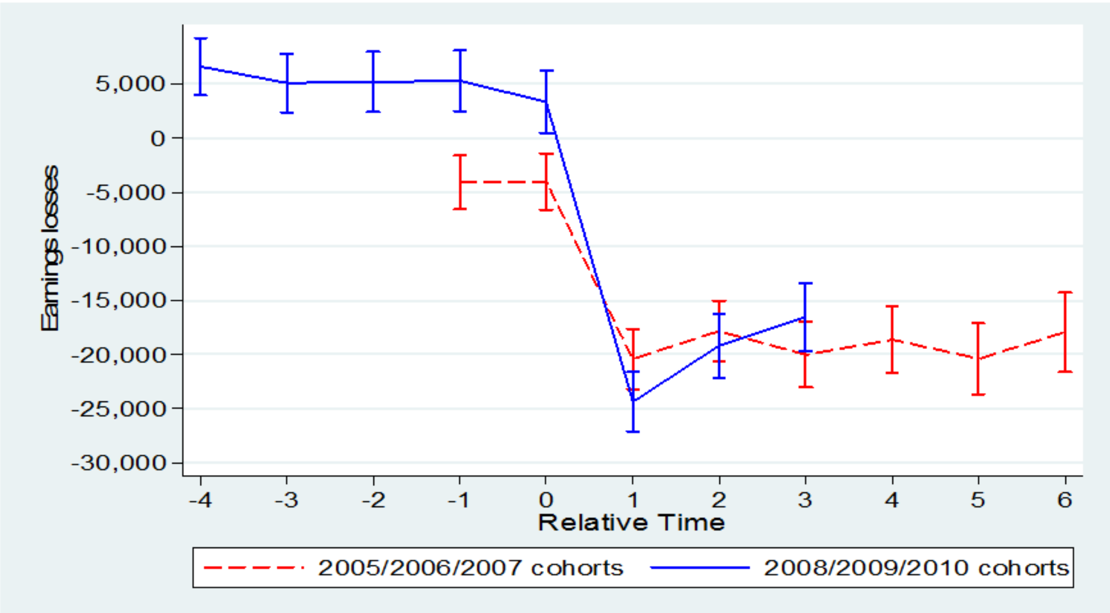
layoff group represent an 81% fall in earnings from period $t=0$ to $t=1$. Those in the pre 2008 group experienced smaller losses of 54%.

Figure 4.18: Earnings losses of displaced manufacturing workers; pre & post 2008

a) Closure



b) Mass Layoff



4. 5: Concluding remarks

We examined the displacement experience of workers in Ireland for those who experience a mass-layoff event or a closure event in the period 2005-2011 using the P35 linked employer-employee dataset. This large dataset facilitates the successful matching of displaced individuals in a treatment group with non-displaced workers in a control group. We use propensity score matching to achieve this.

We find that those who are displaced following a mass-layoff are more adversely impacted in terms of their earnings losses relative to those displaced following an enterprise closure. This suggests that an unfavourable information signal may be sent to the market regarding workers displaced through a mass-layoff event. At the same time, this was a period of severe economic turbulence which made securing re-employment in a comparable paying job more challenging for all displaced workers, but particularly it seems for the mass-layoff group. Also for the displaced, securing re-employment quickly is important. When we explore the earnings losses of those before and after 2008, we can see evidence of the impact of the recession in the greater earnings losses for those displaced after 2008, in both samples. Now the magnitude of the losses for those in the mass-layoff sample is even greater. In both cases, earnings losses appear to persist for a long period after displacement.

It appears that earnings losses vary depending on whether an individual secures employment in the same sector that they have been displaced from, with those switching to a new sector experiencing a larger wage penalty. While suffering greater losses than those who stayed within the same sector, it is interesting to note that after $t=5$, the earnings losses of switchers are actually less than those who were displaced and secured re-employment in the same sector. It is possible that individuals displaced in the 2005 cohort were facing into a very different labour market in 2006 to secure re-employment, compared to those displaced in later years. As evidenced earlier in Chapter 2, unemployment in Ireland was less than 5% in 2005 which facilitated mobility across sectors for those searching for re-employment, possibly without suffering a large wage penalty.

We do find evidence that older workers also experience greater losses when compared to younger workers. They also have a lower probability of employment. Such findings are consistent with those of Couch et al. (2009) who report that earnings losses increase as age increases. We also see that earnings do recover faster for younger workers particularly for those in the closure sample. This is not surprising given that we saw younger workers have a higher probability of employment after displacement. If such losses are related to lack of skills or training, there is a role for government to address these issues.

Male workers are more likely to experience greater earnings losses compared to female workers. We know that the male dominated construction sector (F) was adversely impacted by the recession, with increased enterprise deaths and reduced employment, as observed in Chapter 2. From a policy perspective, ensuring adequate skills provision for such workers would seem to be vital, given that we might expect more of these workers required to switch to another sector to secure re-employment.

Chapter 5 : Is there Evidence of Monopsony in the Irish Labour Market?

5.1 Introduction

In this chapter we estimate the wage elasticity of labour supply to the firm in the Irish labour market. Under the assumption of perfect competition, the labour supply curve to the firm is horizontal i.e. perfectly elastic. It implies employers possess little wage setting power and are constrained to pay workers the prevailing wage in the market. A decrease in wages would result in the employer losing all their workers. Whether this is an accurate assertion can be tested by estimating the labour supply elasticity to the firm. In contrast to the perfectly competitive situation, monopsonistic competition would suggest the labour supply curve to the firm is not perfectly elastic, and so employers possess a degree of wage setting power. In fact, monopsonistic discrimination could occur if employers are able to distinguish between groups with different labour supply elasticities and so exploit their market power by paying those with lower elasticities lower wages.

This chapter makes a number of distinct contributions to the literature. Firstly, we build on previous work and use linked employer-employee data and survival analysis to estimate the firm level[87] labour supply elasticities in the Irish labour market. In doing so we exploit the P35 dataset from 2005-2013. This dataset is highly valuable given its coverage of all employees in Ireland and this is a key strength in comparison to other studies. This is the first time such work has been conducted in Ireland using such an extensive administrative data source. In fact, there are few studies conducted in the area that use administrative data for any country. Notable

[87] As described in Chapter 1, the P35 data contains information on enterprises. We use the word 'firm' rather than enterprise here, in line with previous literature in the area.

exceptions are Hirsch & Jahn (2015) who study native-immigrant wage differentials in Germany and Hirsch, Schank & Schnabel (2010) who use the same German data source to estimate gender differences in labour supply elasticities. However the dataset used in this chapter is much larger, with over 1.9 million individuals included in the final panel, in comparison to approximately 300,000 in both German papers. Crucially for the period the data is available for, we can distinguish between separations to employment and non-employment as well as recruitment from employment and non-employment.

Secondly, this research offers a unique insight into the relevance of monopsonistic discrimination in the Irish labour market. We examine the role of monopsonistic discrimination in explaining differences in the pay of native and immigrant workers in the Irish labour market. As mentioned, previous work by Hirsch & Jahn (2015) has investigated the usefulness of monopsonistic discrimination in explaining native-immigrant wage differentials in Germany. Here we focus on the Irish labour market during a turbulent economic period which saw positive net migration between 2005 and 2008 and negative net migration between 2009 and 2013 (CSO 2014a). Separately we also estimate male and female firm level labour supply elasticities to explore the role of monopsonistic discrimination in explaining male and female wage differentials.

The next section (5.2) explores literature and theoretical issues in relation to monopsony and also whether this as a useful tool for examining the native-immigrant wage differentials as well as gender differentials in Ireland. Section 5.3 and 5.4 detail the methodology and data respectively, while section 5.5 presents our findings. Finally, section 5.6 concludes the chapter.

5.2 Literature Review

The classical view of monopsony is the 'one company town' where there is one employer and a large number of workers to supply labour. As noted by Hirsch et al. (2010) early work in the area of monopsony by Robinson (1933) assumed monopsony power existed in this sense of a single employer. This single employer then had a significant wage setting power. This employer had the ability to set wages that were lower than the marginal productivity of the workers. The elasticity of labour supply to the firm was important because "the more inelastic the labour supply, the lower are wages relative to productivity" Barth & Dale-Olsen (2009: 589). This implies that employers can exploit market power by paying lower wages to groups with more inelastic labour supply. Because there are relatively few examples, if any, of this is the modern world, the applicability of the traditional monopsony model is questionable, when considering wage differences among workers in the labour market.

More recent work by Manning (2003) and others has extended and developed the traditional view of monopsony to a new or 'dynamic' monopsony model which allows for employers to have significant power, even when there are numerous firms competing for employees. The model is referred to as 'dynamic' by Boal & Ransom (1997) and Manning (2003) due to constantly changing nature of the labour market. Their monopsony model allows for more than one employer, or a large number of small employers, who each face an upward sloping labour supply curve. In light of this assertion regarding the labour supply curve, it is necessary to consider the sources of monopsony power that allow employers to manipulate wages and why labour markets may not be perfectly competitive. These are preferences and search frictions. Bhaskar & To (1999: 191) outline a model of monopsonistic competition that allows workers to have different preferences over the non-monetary aspects of the job, which they refer to as allowing for "horizontal job differentiation." So for example, some workers may have a preference to work in a particular location. The fact that workers take both the wage and non-wage aspects of the job into consideration gives some wage setting power to employers.

Additionally, monopsony power can be derived from search frictions in the labour market and these are outlined by Manning (2003) who as mentioned is credited to a large extent with developing the dynamic monopsony model. His model is described in section 5.3. He makes two assumptions which "can be stated very simply: there are important frictions in the labour market; employers set wages" (Manning, 2003: 3). Ultimately these frictions give the employer a degree of market power - this allows them to have some degree of power when setting wages. He notes the identification of these frictions begins with the work of Robinson (1933). Such frictions essentially arise from three sources; heterogeneous preferences of workers, search frictions and mobility costs. For example, workers may not have information on potential employers, workers may have preferences for non-financial components such as medical insurance to form part of their remuneration package or workers may not be geographically mobile and seek employment in a particular location. In any case such frictions, or elasticity inhibiting factors, will result in employers possessing a degree of monopsony power as a result of the firm labour supply curve not being infinitely elastic. Profit maximizing employers may exploit this power and pay lower wages to workers with low labour supply elasticities to the firm. Clearly, it must be possible for employers to distinguish between these groups (for example, men versus women; natives versus immigrants). If one group has a lower labour supply elasticity relative to another, it may be possible for employers to set lower wages for this group.

It is worth noting that while the existence of an upward sloping labour supply curve to the firm due to search frictions supports the idea of firms having wage setting power, it does not automatically imply that they use it. They may be "unable to take full advantage of it because of the institutions and environment in which it operates." (Ransom & Oaxaca 2010: 283) For example, minimum wage laws and equal pay legislation restrict the wage setting power of firms. However, Ransom & Oaxaca (2010) describe a situation where it is plausible to imagine that firms do have scope to exert some monopsony power in the context of male and female workers by assigning female workers to lower paying jobs.

Such search frictions as described above are also a key feature of Burdett & Mortensen's (1998) model which Manning (2003: 36) describes as "a general equilibrium version of the dynamic monopsony model." In exploring differences in labour supply elasticities between men and women, both Barth & Dale-Olsen (2009) and Ransom & Oaxaca (2010) use this Burdett & Mortensen (1998) model. It allows for the estimation of labour supply elasticities to the firm by estimating the separation rate elasticity to employment with respect to the wage. In their model, employees search for jobs and will leave their current employer if the wage on offer at another employer is higher. Thus the wage rate plays a crucial role – by adjusting it, employers can influence the rate employees separate from their employer and how successful they are at attracting new recruits. Specifically, a wage increase leads to less separations and the firm also finds it easier to recruit. However, this approach only considers the elasticity of separations to employment and recruitment from employment in other firms. It does not allow for separations to non-employment and recruitment from non-employment to be sensitive to the wage. As noted by Ransom & Oaxaca (2010: 270) “Since both separation to and hires from unemployment are inelastic with respect to the wage, the only sources of elasticity of the firm’s labor supply are job-to-job moves.” This is a restrictive assumption and Manning (2003) builds on the model of Burdett & Mortensen (1998) in an effort to incorporate the fact that transitions related to non-employment may also be sensitive to the wage.

In many previous papers it has not been possible to allow for both separations and recruitment from non-employment to be responsive to the wage, due to the nature of the available data. As noted by Ransom & Oaxaca (2010: 271) “Unfortunately, the more sophisticated models he suggests require much more detailed data than is available to us.” Therefore the ability to include both transitions to and from employment and non-employment is a key advantage of this chapter. Few studies have been able to follow the extensions to Manning’s (2003) search model which allow for such wage responsive transitions with respect to non-employment, with notable exceptions being Hirsch et al. (2010) and Hirsch & Jahn (2015) for Germany as well as Booth & Katic (2011) for Australia.

As we proceed, it is important to note that the focus here is on the labour supply elasticity at the firm level, as opposed to the market level. At the market level, the labour supply curve captures the decision to supply labour to the market or not. But as Hirsch et al. (2010: 292) point out, “From the perspective of a single firm, however, it does not matter whether an individual supplies labor generally, but whether he or she supplies it to this firm or not.” In the model of monopsonistic discrimination it is the firm level labour supply elasticity that matters. Another added dimension to this is that individuals making decisions to supply labour to a given firm, rather than to the market, could be coming from employment as well as non-employment. Therefore it is reasonable to expect that the labour supply elasticity at the firm level is likely to be different to the labour supply elasticity at the market level. This idea has been supported by previous empirical studies. For example, there are a number of studies which have shown that female labour supply is more elastic than males at the market level [see Heckman (1993) and Blundell & Macurdy (1999)]. However, this is not necessarily the case at the firm level. We now explore findings from previous studies which estimate the labour supply elasticity to the firm of different groups, specifically males versus females and natives versus immigrants.

5.2.1 Gender and labour supply elasticities

The new monopsony model allows for employers to possess some wage setting power. In exploring the gender pay gap, Robinson (1933) demonstrated that if an employer is a monopsonist, it is profitable from their perspective to pay different wages to male and female workers even though they may be equally productive, provided their labour supply elasticities differ. While the assumption of a monopsonist as a single employer is restrictive, the new monopsony model allowing for more than one employer has renewed interest in the applicability of monopsony in explaining the gender pay gap.

Manning (2003: 195) identifies that when explaining wages of workers, "the monopsonistic approach to labour markets adds other factors to the list of possible determinants of wages." These factors are the rate at which workers transition in the labour market and the reservation wage. The key implication of this, he notes, is that equally productive male and female workers may experience wage differentials if their labour market transition rates are not equal.

A number of papers have recently investigated the usefulness of monopsonistic discrimination as a means of understanding the gender pay gap [see Hirsch et al. (2010) for Germany, Ransom & Oaxaca (2010) for the USA, Barth & Dale-Olsen (2009) for Norway]. These papers find that the labour supply elasticity of females at the firm level is less elastic than that of males. As noted earlier, the work of Ransom & Oaxaca (2010) for the USA and Barth & Dale-Olsen (2009) for Norway make more restrictive assumptions than Hirsch et al. (2010). The US study uses less extensive data covering one retail firm which had between 54-61 stores over the period 1976-1986. Both the Norwegian and German studies use administrative data. These steeper labour supply curves may enable firms to exercise discrimination in their wage setting practices, paying different wages to males and females. Such lower labour supply elasticity for female workers at the firm level could arise for a number of reasons, such as "different preferences over the non-wage characteristics of the job and a higher degree of immobility" (Hirsch et al. 2010: 292). For example, the location of the firm or the ability to work part-time may be more highly valued by female employees relative to males and so gives employers a degree of wage setting power. These results contrast with earlier work by Manning (2003) who did not find differences in the firm labour supply elasticities of male and female workers. He used four survey data sets, two from the US and two from the United Kingdom (UK).[88]

5.2.2 Native-immigrant wage elasticities

Another aim of this chapter is to investigate if monopsony explains some of the native-immigrant wage differential in Ireland. There has been little empirical work

[88] The US datasets used are the Panel Study of Income Dynamics (PSID) and National Longitudinal Survey of Youth (NLSY), while the UK datasets are the British Household Panel Survey (BHPS) and Labour Force Survey (LFS).

conducted which examines the labour supply elasticities of native and immigrant workers to determine the role of monopsonistic discrimination in explaining any of the native-immigrant wage gap. One notable exception to this is the work conducted by Hirsch & Jahn (2015) who use linked employer-employee data to examine if there is monopsonistic discrimination against immigrants in Germany. Their main finding is that there are differences in the labour supply elasticities of native and immigrant workers. Having controlled for unobserved heterogeneity, immigrants have a lower labour supply elasticity than German workers. Also, evidence suggests that when human capital and workplace differences are controlled for, immigrant workers earn less than German workers. They come to the conclusion that monopsonistic discrimination explains "the entire unexplained native-immigrant wage differential" (Hirsch & Jahn, 2015: 501).

A useful feature of their work is their exploration of the reasons why such a wage differential may exist. These include differences in human capital among native versus immigrant workers, discrimination against immigrants, the inability of potential employers to assess productivity differences between native and immigrant workers and finally, employers may possess a higher degree of monopsony power over immigrant rather than native workers (Hirsch & Jahn, 2015). The usefulness of the monopsonistic discrimination model for explaining native-immigrant wage differentials rests on the existence of differences in labour supply elasticities of the two groups. Both Dale-Olsen, Roed & Schone (2014) and Hirsch & Jahn (2015) explore reasons why one might expect immigrants to have a lower labour supply elasticity than native workers. For example, immigrant workers may lack proficiency in the language of the country they move to, or they may lack knowledge of local employers or institutions and organisations which could help them secure employment. Dale-Olsen et al. (2014: 5) specifically refer to "chain migration." Essentially this means that immigrant workers are more likely to move to locations where other immigrants from their home country may have moved to, or to "form enclaves" (Hirsch & Jahn 2015: 504). This behaviour limits the geographic mobility of workers in their host country. These examples could potentially enable employers to engage in monopsonistic discrimination and pay immigrant workers lower wages relative to native workers.

While we have highlighted reasons why you may expect immigrant workers to supply labour less elastically to the firm, it is also reasonable to expect that immigrants might actually have a higher labour supply elasticity to the firm than native workers. Again both Dale-Olsen et al. (2014) and Hirsch & Jahn (2015) explore this possibility. It may be that immigrant workers are in fact more mobile than native workers. Given that they have already moved from their home country, and possibly family and friends, there is good reason to believe that this mobility will mean that they may be guided to locate to areas with better employment opportunities or wages within their host country. A study in the USA by Borjas (2001) finds that wages and employment opportunities do in fact guide immigrants when choosing where to locate in their host country. Particularly he finds that "new immigrants who have particular skills to offer are more likely to reside in those states that happen to offer the highest wages for those skills" (Borjas 2001: 118). It is also possible that immigrant workers could actually be more concerned about the pecuniary rather than non-pecuniary aspects of the job which may limit employer monopsony power. For example, immigrant workers may initially plan on staying in the host country for a pre-defined amount of time and be primarily concerned about maximizing their earnings before returning to their host country, rather than receiving fringe benefits or perks associated with their job, as an alternative to pecuniary rewards. Thus as noted by Hirsch & Jahn (2015), it is not immediately obvious whether the labour supply elasticities of immigrants to the firm will be greater than or less than the labour elasticities of native workers.

5.2.3 Conclusion

Here we have examined literature and empirical evidence in relation to monopsony in the labour market. Manning (2003) is credited to a large extent with extending the traditional view of monopsony to allow for many employers to compete for workers. Monopsony power can arise as a result of frictions in the labour market. These frictions which may inhibit labour supply elasticity mean that employers possess a degree of monopsony power, which may be exploited by paying lower wages to workers with low labour supply elasticities to the firm.

Previous studies have explored the usefulness of monopsonistic discrimination in explaining the gender pay gap as well as native-immigrant wage elasticities. Hirsch et al. (2010) and others have reported that the labour supply elasticity of females at the firm level is less elastic than that of males. This contrasts with the earlier work of Manning (2003) who did not find differences in the firm labour supply elasticities of males and females. In relation to monopsonistic discrimination and immigrants, it is not immediately apparent from a theoretical point of view whether immigrant workers would supply labour more or less elastically to the firm relative to native workers. Hirsch & Jahn (2015) do find that immigrants have a lower labour supply elasticity to the firm compared to German workers.

5.3 Methodology

Our starting point for estimating the firm level labour supply elasticities draws on the work of Manning (2003) where he sets out his model of 'dynamic' monopsony. His underlying model has been used and refined by others including Hirsch et al. (2010) and Ransom & Oaxaca (2010) who examine gender pay differences, Hirsch et al. (2013) examine the cyclicality of employers' monopsony power and Hirsch & Jahn (2015) explore the existence of employers' monopsonistic discrimination of immigrant versus native workers. Given the importance of Manning's work, and that it is also used in this chapter, his model is described now, drawing on Manning (2003: 96-104).

His work begins with the recognition that the supply of labour to the firm is related to the recruits to the firm (R) and the separation rate (S) of employees from the firm. Importantly, recruitment and separation are a function of the wage, (*w)*. It is assumed that the rate at which workers leave the firm (s) depends negatively on the wage paid by the firm and the number of workers recruited by the firm (R) is positively related to the wage paid. The firm's employment this period (N_t) is therefore related to its employment in the last period, the wage, the recruitment rate and the separation rate as below;

$$N_t = [1 - s(w_t)]N_{t-1} + R(w_t) \quad \textbf{(5.1)}$$

Therefore, the wage has a direct impact on the labour supply to the firm and the firm can use the wage to influence this supply. The steady state, which implies total separations from the firm must equal total recruits to the firm, is thus;

$$N(w) = \frac{R(w)}{s(w)} \quad \textbf{(5.2)}$$

From equation (5.2) above we can derive the long run firm level labour supply elasticity below as;

$$\varepsilon_{N(w)} = \varepsilon_{R(w)} - \varepsilon_{s(w)} \quad \textbf{(5.3)}$$

The work of Manning (2003) incorporates some of the earlier work of Burdett & Mortensen (1998), which according to Hirsch & Jahn (2012: 7) "can be thought of as a dynamic equilibrium model of monopsonistic competition." The model implies that firms recruit workers from other employers who pay lower wages and in this way, the recruits hired by one employer are the separators from another employer. Manning (2003: 97) has demonstrated that the recruitment elasticity ($\varepsilon_{R(w)}$) is the negative of the separation elasticity ($\varepsilon_{s(w)}$), implying that the labour supply elasticity is twice the separation rate elasticity, as below.

$$\varepsilon_{N(w)} = -2\varepsilon_{s(w)} \quad \textbf{(5.4)}$$

Using the above equation is helpful as it shows that you only require knowledge of the separation rate elasticity to estimate the labour supply elasticity of the firm. Because of this, it has been used in a number of studies, including Barth & Dale-Olsen (2009) and Ransom & Oaxaca (2010). However, it is useful to be able to distinguish between moves to and from employment and moves to and from non-employment. At the same time, the assumption is made that such transitions, including those to and from non-employment, are related to the wage. As Hirsch et al. (2012) note, this is a plausible assumption. For example, a worker on a low wage may believe they are better off leaving their job, being unemployed and receiving unemployment benefit/insurance. By identifying separations to employment (ε_{Sw}^{e})

and non-employment (ε_{Sw}^{n}), and the share of separations to employment (θ_S) as well as recruits from employment (ε_{Rw}^{e}) and non-employment (ε_{Rw}^{n}), and the share of recruits from employment (θ_R), Manning (2003) suggests the labour supply elasticity of the firm can be estimated as below;

$$\varepsilon_{N(w)} = \theta_R \varepsilon_{Rw}^{e} + (1-\theta_R)\varepsilon_{Rw}^{n} - \theta_S \varepsilon_{Sw}^{e} - (1-\theta_S)\varepsilon_{Sw}^{n} \qquad \textbf{(5.5)}$$

Clearly, the use of this equation is dependent on having appropriate data to measure the components as identified above. Such an approach has been used by Hirsch et al. (2010). Booth & Katic (2011: 361) also follow equation (5.5) but make some further simplifying assumptions;

$$\varepsilon_{Sw}^{e} = -\varepsilon_{Rw}^{e} \qquad \textbf{(5.6)}$$

$$\varepsilon_{Sw}^{n} = -\varepsilon_{Rw}^{n} \qquad \textbf{(5.7)}$$

$$\theta_R = \theta_S \qquad \textbf{(5.8)}$$

Given the data available in this current study, it is not necessary to make the assumptions above in equations (5.6)-(5.7) and this study will follow the approach of Hirsch et al. (2010), in only incorporating equation (5.8) above. As they note, "In the steady state, the share of recruits from employment and the share of separations to employment must be the same." (Hirsch et al. 2010: 298) Therefore we define;

$$\theta = \theta_R = \theta_S. \qquad \textbf{(5.9)}$$

Manning (2003: 100) has shown that "the estimated co-efficient of the log wage $\hat{\beta}_w$ can be used to obtain an estimate of (ε_{Rw}^{n}) from $(\hat{\varepsilon}_{Rw}^{e})$ by subtracting $\hat{\beta}_w$ from the latter." (Hirsch et al. 2010: 298) Using this along with equation (5.9) means the long run labour supply elasticity of the firm can be estimated as:

$$\varepsilon_{N(w)} = -(1+\theta)\hat{\beta}_w^e - (1-\theta)(\hat{\beta}_w^n + \hat{\beta}_w) \qquad \textbf{(5.10)}$$

As noted by Hirsch et al. (2010), $\widehat{(\beta_w^e}\,)$ gives an approximate estimate of (ε_{Sw}^{e}), the separation rate elasticity to employment while $(\hat{\beta}_w^n)$ gives an approximate estimate of (ε_{Sw}^{n}), the separation rate elasticity to non-employment. $\hat{\beta}_w$, the estimated coefficient of log wage, can be used as an approximate estimate of $(\hat{\varepsilon}_{Rw}^{e})$, the recruitment rate elasticity from employment.

We will follow a similar procedure as Manning (2003) and Hirsch et al. (2010) for estimating equation (5.10). This involves a number of steps as set out by Hirsch et al. (2010);

1. Estimate the separation rate elasticity to employment and non-employment separately to obtain the associated wage elasticities;
2. Use a logit model to estimate the probability that a hire comes from employment;
3. Determine the share of recruits from employment and separations to employment, or θ above;
4. These estimates can be combined as per equation (5.10) to give an estimate of the long run labour supply elasticity of the firm.

We follow Hirsch et al. (2010) as we begin with a given number of workers, *W* (numbered *w=1,....W*) and *N* employment spells (*i=1,....N*) who work for *K* firms (*k=1,....K*). It is possible for one worker to have more than one spell in the data. One row per spell is retained in the data. In this way, there is no issue with time-varying covariates. We have a vector of covariates per spell related to the worker or the firm characteristics, denoted by x. These are the age of the worker, their gender and nationality. The NACE Rev. 2 sector of the firm is also included. Finally, the natural logarithm of the real average weekly wage[89] per spell is included for each spell. We model the instantaneous separation rate to employment and non-employment respectively, of the *i*-th spell at time *t*, conditional on x_i from two separate hazard rate models.

In the present study, the baseline hazard is assumed to follow the Weibull distribution. As noted by Røed and Zhang (2002) the Weibull model has been extensively used in other studies that analyse unemployment duration.

The Weibull implies that the hazard distribution follows the form:

$$\lambda(t) = \gamma p t^{p-1} \quad \textbf{(5.11)}$$

The Weibull model is flexible because it allows for the hazard to monotonically increase or decrease. This is monotonically increasing if $p > 1$ and monotonically decreasing if $p < 1$, where $\lambda(t)$is the hazard rate, γ= the hazard and p= the shape parameter. We model the separation rate to non-employment below as:

$$s^n = \exp(x_i'\beta)\,\gamma p t^{p-1} \quad \textbf{(5.12)}$$

[89] The wage is deflated using the Consumer Price Index [Base year =2011].

where x_i is a vector of individual and firm characteristics. Since the natural logarithm of the real wage is included as an explanatory variable also, its coefficient $\hat{\beta}_w^n$ gives an approximate measure of the separation rate elasticity to non-employment. We follow Manning (2003) and Hirsch et al. (2010) in assuming that the separation rate to non-employment and employment are independent. Therefore two estimations are employed – one for separations to non-employment and one for separations to employment. The separation to non-employment estimation is conducted using the whole sample, while when estimating the separation rate to employment we remove spells that enter non-employment before estimation. Thus given that a worker has not entered non-employment, then the individual can either remain in the same job or move to a new one. Thus the sample is restricted to those in employment only. This follows the method of Manning (2003) who restricts the sample when estimating separations to employment to workers who are in continuous employment.

We also estimate the wage elasticity of the share of recruits hired from employment as a logit model. The dependent variable is a binary variable taking on a value of one if the recruit comes from employment and zero otherwise. We use the same vector of independent variables as before, including the natural log of real average wage over the spell.

$$\Pr[y_i = 1|x_i] = x'_i\beta \qquad \textbf{(5.13)}$$

The final estimate needed to compute the firm-level labour supply elasticity is the share of recruits hired from employment as a proportion of all recruits.

5.4 Data

The P35 data used here is for the years 2005-2013. The unique coverage of the data allows for the construction of measures to identify movement into and out of employment. A key feature of the data is that it is possible to differentiate between transitions that represent movements from one job to another and those that are transitions from a job to non-employment and vice-versa. Given that the data covers virtually all employees in Ireland, it provides a unique opportunity to observe labour market movements of workers and estimate wage elasticities. For each employment record we have the following variables; a firm and person identification number, the year of employment, the number of weeks a person worked at the firm, the pay they received in that year, the person's age, gender and nationality, the NACE Rev.2 sector of the firm and its legal form.

While the size of this dataset is its unique selling point, it does pose some challenges. The data does not contain an indicator of whether a person is working full-time or part-time. Therefore, it was not possible to just retain all full-time employees as was done by Hirsch et al. (2010). Individuals who held multiple jobs within a given year also pose a challenge. It is not immediately identifiable whether job spells are concurrent or consecutive and we attempt to identify a person's main job in a given year, if they had multiple jobs. We are therefore focusing on those with a high attachment to the labour market, as was the approach essentially followed by Hirsch et al. (2010). Therefore a new variable was created to capture the total number of weeks a person worked in a given year. If a person had just one job, this was the same as the weeks worked variable. However, if they had more than one job, this new variable captures the total number of weeks worked. A restriction was imposed on the data whereby an employment record was removed if it represented employment of less than 26 weeks and the person had a total number of weeks worked in that year of over 52 weeks. For example, in the table below, the employment record for person 1 in enterprise 32 is eliminated in 2006 for this reason. However, it is important to note that this was only done in cases where an employment record did not have the same enterprise number in the preceding or following year. This approach was taken to ensure that short employment spells that were part of genuine transitions were not removed. We can see below[90] that both employment records for person 3 in 2006 are retained.

Table 5.1: Example of treatment of multiple record data

Year	Person ID	Enterprise ID	Weeks	Weeks Total
2006	1	30	52	67
~~2006~~	~~1~~	~~32~~	~~15~~	~~67~~
2007	1	30	52	52
2008	1	30	52	52
2006	3	121	36	58
2006	3	142	22	58
2007	3	142	52	52
2008	3	142	52	52
2009	3	142	52	52

Also, if people had multiple employment records in a year which meant that employment spells overlapped, the spell with the largest number of weeks worked is retained. Again this is done in an effort to retain the dominant job spell for an individual. A spell variable is also constructed to identify the employment spell, while another is used to ensure the employment order within the spell is correct. We can see in Table 5.2 below[91] that the employment of person 9 in enterprise 113 is identified as their first employment spell while their time in employment in

[90] This is for illustrative purposes only and is not actual data.
[91] This is for illustrative purposes only and is not actual data.

enterprise 155 is identified as spell 2. The order of the years within the respective spells are identified by the employment order variable.

Table 5.2: Identifying spell and employment order

Year	Person ID	Enterprise ID	Weeks	Weeks Total	Spell	Employment order
2006	9	113	42	42	1	1
2007	9	113	52	52	1	2
2008	9	113	30	52	1	3
2008	9	155	22	52	2	1
2009	9	155	52	52	2	2
2010	9	155	52	52	2	3

5.4.1 Constructing the sample

Having sorted the data into a useable form, key separation and recruitment variables are constructed. These are;

- Separations to employment
- Separations to non-employment
- Hiring from employment
- Hiring from non-employment

While it is possible to identify when a person moves to another job, if there is no employment record in the following year it is assumed the person is in "non-employment." There are many possible explanations for this. It could be that the person is unemployed and seeking employment, that they chose to leave the labour market, emigrated from the country, or that that they are deceased and so on. It is not possible to make a definitive statement regarding their labour market status, given the information in the dataset. All we can say is that they are not in paid employment for an enterprise – we can only speculate as to the reason why.

The data does not identify the start and end date of an employment record. We construct an identifier to capture the beginning and end of a job spell with an enterprise. To identify the start and end of a spell we begin by identifying the initial year that a person begins employment with an enterprise. So a person may begin one job in 2006 and another job in 2009 for example. We identify the order of these spells as 1 and 2 respectively. We then identify the beginning of a spell as the first observation *within* a given spell, while the end of a spell is identified as the final observation *within* that given spell. For example, an individual would be deemed to be separating to non-employment if they were at the end of a job spell and they work less than 50 weeks in that year. Or if the final employment record for a person occurs in a year before 2013, for example in 2008, this person is said to separate to non-employment. A tenure variable is constructed to identify the number of weeks worked within a spell and this is our key duration measure. Table 5.3 contains two examples.

In Table 5.3[92] Person 1 is working with enterprise 22 until 2010 and then moves to employment in enterprise 63. The spell with enterprise 22 is identified as spell 1 while the spell with enterprise 63 is identified as spell 2, beginning in 2011 and ending in 2013. Since 2013 is the final year of the data, this is identified as the 'end.' There is no employment record for person 2 in 2005. They appear in the data for the first time in 2006. They are identified as being hired from non-employment in 2006 and work with that enterprise until 2008. There is no employment record for this person in 2009, so they are identified as separating to non-employment in 2008. The person is then hired from non-employment by firm 19 in 2010, their second employment spell. This is the last employment record for this person so they are identified as separating to non-employment in 2010.

[92] This is for illustrative purposes only and is not actual data.

Table 5.3: Example of employment records and key transition variables

Year	Person id	Enterprise id	Begin	End	Spell	Total Weeks	Separation to_emp	Separation to non-emp	Hiring from_emp	Hiring from non-emp
2006	1	22	1	0	1	18	0	0	0	1
2007	1	22	0	0	1	52	0	0	0	0
2008	1	22	0	0	1	56	0	0	0	0
2009	1	22	0	0	1	52	0	0	0	0
2010	1	22	0	1	1	52	1	0	0	0
2011	1	63	1	0	2	52	0	0	1	0
2012	1	63	0	0	2	45	0	0	0	0
2013	1	63	0	1	2	52	0	0	0	0
2006	2	14	1	0	1	40	0	0	0	1
2007	2	14	0	0	1	42	0	0	0	0
2008	2	14	0	1	1	3	0	1	0	0
2010	2	19	1	1	2	35	0	1	0	1

At this stage, there are 3,300,156 individuals in the dataset. Without yet making any further adjustments to the panel, we have the following number of transitions over the period 2005-2013:

Table 5.4: The number of transitions for the period 2005-2013

Transition type	Total
Separations to employment	**907,218**
Separations to non-employment	**4,678,176**
Hirings from employment	**907,218**
Hirings from non-employment	**3,821,506**

As observed in Table 5.4 the number of transitions to and from non-employment is quite high relative to the transition to and from employment. Approximately one third of the hirings from non-employment represent individuals who appear in the data for the first time. This could be a young person entering the labour market for the first time or a person who has immigrated to the country.

It is possible to identify these new entrants who are classified as transitioning from non-employment by their nationality. Table 5.5 below shows a simple breakdown of

Irish versus non-Irish workers over the period. We see that 2006 and 2007 saw large numbers of individuals appearing in the data for the first time. Both groups decline significantly with the onset of the recession. For the non-Irish group in 2009, numbers of new entrants had decreased by 77% compared to 2006.

Table 5.5: Those from non-employment in panel for first time by nationality

Year	Irish	Non-Irish
2006	179,133	158,166
2007	127,575	149,824
2008	82,100	92,229
2009	48,409	37,094
2010	50,104	35,792
2011	58,123	36,489
2012	62,351	40,566
2013	63,080	42,858
TOTAL	**670,875**	**593,018**

As outlined earlier, it was not possible to keep only those in full-time employment in the data. All individuals, regardless of age are included in the data. The youngest workers are aged 16 years old. Younger workers may still be in education and may take up employment for short periods or take up seasonal work. Therefore, these workers are likely to move into and out of employment relatively often. Given the objective of this chapter is to investigate if there is evidence of monopsony in the Irish labour market through estimating wage elasticities, a restriction is imposed to only include employment records for those aged 21-55. Other papers have imposed similar restrictions. For example, Hirsch et al. (2010) keep only workers aged 16-55. The upper limit is chosen to ensure that transitions to non-employment are not due to a person retiring early. Booth & Katic (2010) and Hirsch & Jahn (2015) use the same upper limit of 55 years. Their lower bounds are 25 years and 18 years respectively. By imposing this restriction, we endeavour to ensure that the sample includes individuals with a high attachment to the labour market. Therefore, an employment spell is removed from the data if the worker is less than 21 years at the start of the spell, or more than 55 years at the end of the spell. This results in 2,677,485 observations being removed from the data.

We follow Hirsch & Jahn (2015) in excluding workers who transition due to closing and down-sizing plants. In our data, as in theirs, we are unable to distinguish between voluntary and involuntary separations. Therefore by omitting downsizing and closing enterprises, we are more likely to capture voluntary separations. A firm is deemed to have closed if the final record for a firm is not 2013. A mass-layoff is deemed to have occurred in a firm if employment decreased by 30% or more from one year to the next. As a result, 444,881 observations are removed.

The removal of closing and downsizing plants, as well as retaining individuals aged between 21-55 years of age results in a sample size of 9,670,360 observations spanning nine years.

As the next step in creating the panel, left censored and some unusable observations were removed. A spell may be left censored if an event occurred before a subject was under observation. In our case, this could mean that a person in employment in 2005 (the first year of available data) could have experienced a transition to employment or from unemployment before 2005. Therefore these observations are removed. Also, partial years at the end of a spell may be censored and so these are also removed.

The final step in constructing the panel was to collapse the data to keep one row or observation per spell. A wage variable was constructed to represent the average weekly wage over the spell.[93] It was therefore possible for each person to have more than one row if they had multiple spells. The final dataset consists of 1,936,048 *individuals* representing 3,611,390 *spells*. Thus the mean number of spells per individuals is 1.87 (SD=1.25). Given that it is possible for one person to experience multiple spells, the number of spells is greater than the number of individuals in the dataset.

Table 5.6: The number of spells and individuals

No. of spells	No. of individuals	Percent	Cumulative Percent
1	1,020,228	52.7	52.7
2	498,783	25.76	78.46
3	229,762	11.87	90.33
4	104,224	5.38	95.71
5	45,938	2.37	98.08
6	20,288	1.05	99.13
> **6**	16,825	0.46	99.59
TOTAL	1,936,048	0.04	100

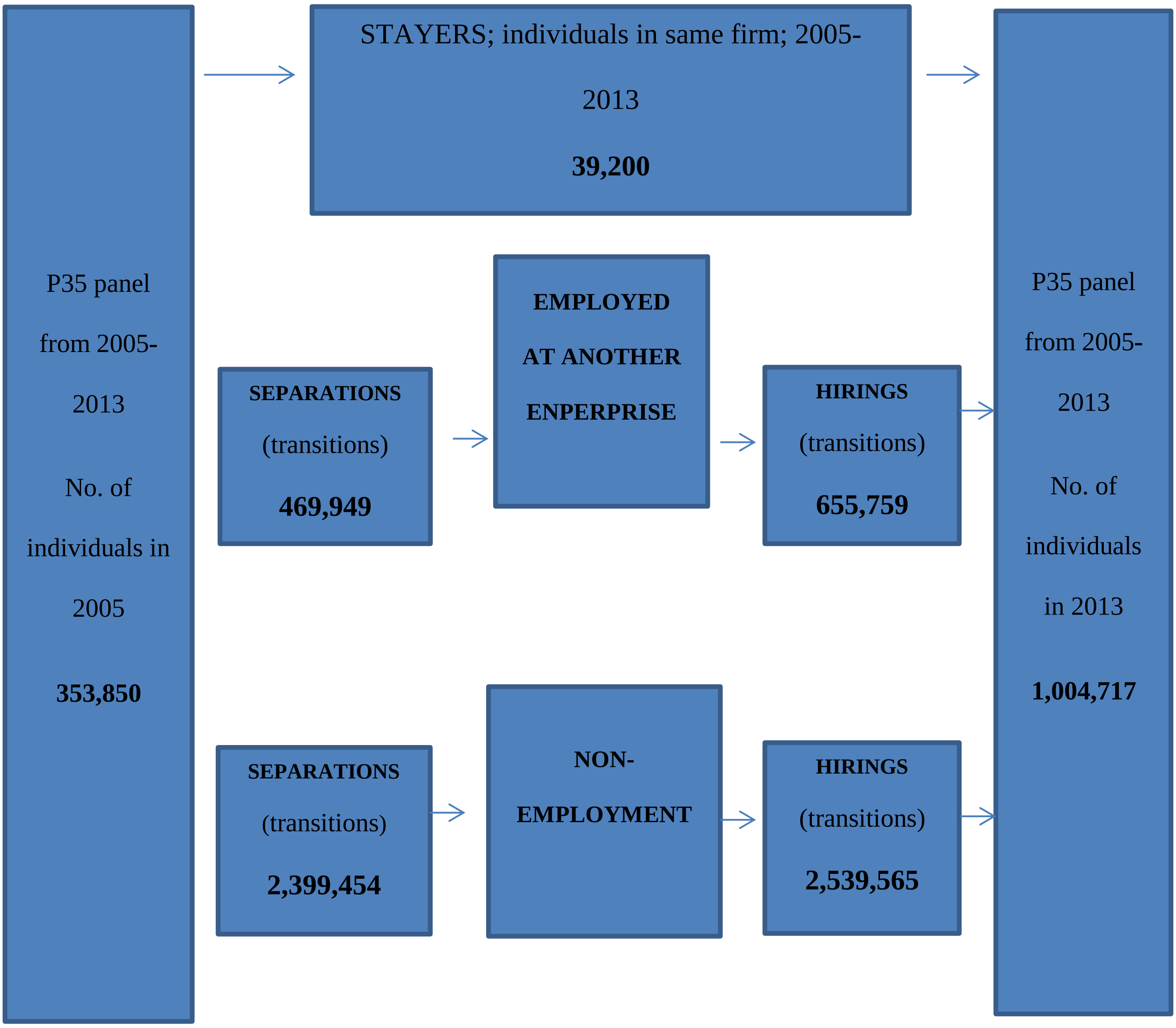
As can be seen from Table 5.6, 90% of workers had 3 spells or less over the period, with less than 1% having more than 6 spells. Figure 5.1 below details the number of transitions in the panel for all workers over the period 2005-2013. As observed, there are 353,850 workers[94] in the dataset in 2005, while there are just over one million individuals in the panel in 2013. The final sample included 39,200 ‘stayers’. These are workers who remained in employment with the same firm from 2005 to 2013. As noted earlier, it is not possible to determine why a person is not in employment and therefore we examine transitions via non-employment. We can see

[93] Wage was divided by weeks per spell. The wage is then logged. While we know the number of weeks a person worked per year, we do not know how many days/hours they worked within that week.

[94] There were 616,264 *individuals* excluded when left censored observations were removed from the sample.

that a high number of the separations and hirings taking place are via non-employment, while much less take place via employment.

Figure 5.1: **The transitions of workers**



5.4.2 Investigating non-employment durations

Given the relatively high numbers of transitions via non-employment compared to others such as Hirsch et al. (2010) for Germany, it was decided to investigate non-employment duration further. Table 5.7 shows the average non-employment duration of workers in the panel. Around 6% of workers who experience a non-employment spell experience a non-employment duration of less than 4 weeks, while 36% of workers experience a non-employment duration of 52 weeks or more.

Table 5.7: Non-employment durations

Non-employment duration	Percentage (%)
< 1 month	5.80
>= 1 month & < 3 months	11.20
> =3 months & < 6 months	13.28
> =6 months & < 1 year	33.91
1 year +	35.81

This can be compared to OECD data on unemployment durations for Ireland. The table below shows these durations for Ireland over the period 2005-2013. We see that the unemployment durations of less than one month have decreased from 9% in 2005 to 4% in 2013. On the other hand, the percentage of those unemployed for one year or more has increased from 33% in 2005 to 61% in 2013.

Table 5.8 : Unemployment durations for Ireland

Year & Duration	2005	2006	2007	2008	2009	2010	2011	2012	2013
	Percentage (%)								
< 1 month	9	23	9	8	8	4	4	4	4
> 1 month & < 3 months	24	10	24	26	20	12	10	10	10
> 3 months & < 6 months	18	7	19	20	20	14	11	11	11
> 6 months & < 1 year	17	18	18	19	24	21	16	14	14
1 year +	33	32	30	27	29	49	59	62	61

Source: OECD (2015)[95]

Therefore it appears that our reported non-employment durations are broadly in line with those of the OECD.

Other evidence also suggests that there has been an increase in the number of temporary employment contracts, as opposed to permanent contracts. Table 5.9 shows that the percentage of people in temporary employment (as a percentage of all

[95] No explanation is offered by the OECD (2015) for the high figure reported for <1 month in 2006

in employment) in Ireland has increased from 3.7% in 2005 to around 10% in 2013. If we look at younger workers in particular, we see that this group has experienced an increase in those employed on a temporary basis, with just over 33% of this age group being in temporary employment in 2013.

Table 5.9: Incidence of permanent & temporary employment in Ireland

YEAR	2005	2006	2007	2008	2009	2010	2011	2012	2013
ALL PERSONS									
Share of *permanent* employment	96.3	94	91.5	91.4	91.2	90.4	89.8	89.8	90
Share of *temporary* employment	3.7	6	8.5	8.6	8.8	9.6	10.2	10.2	10
AGED 15-24									
Share of *permanent* employment	88.4	84.9	78.8	78	75.4	69.9	66.2	65.1	66.9
Share of *temporary* employment	11.6	15.1	21.2	22	24.6	30.1	33.8	34.9	33.1

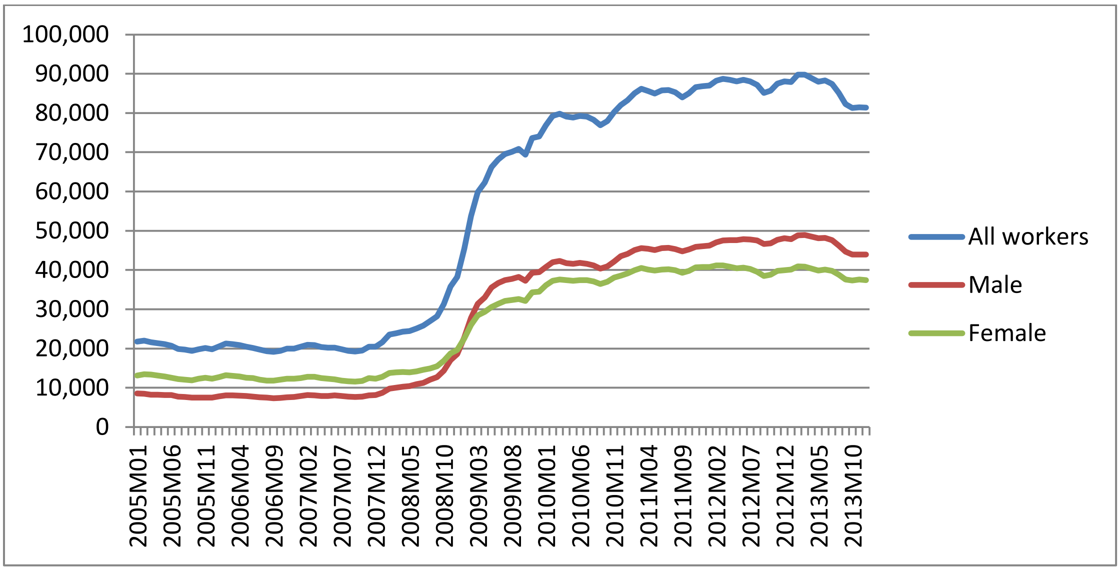
Source: Central Statistics Office, Ireland (2016g)

Further evidence from the CSO (2016j) shows that of those who are in temporary employment, the numbers reporting the reason as '*could not find a permanent job*' has increased from 28.4% in Q1 of 2009 to 77.2% in Q2 of 2013. This big increase suggests that many workers have to accept temporary employment and this is contributing to the high number of transitions to and from non-employment, as observed in Table 5.4.

These figures are supported by data from the Live Register[96] in Ireland which shows the large jump in casual and part-time workers as displayed in Figure 5.2. Such workers could be captured in the data used in this thesis as those experiencing multiple job spells, possibly with short duration.

[96]The Live Register is used to provide a monthly series of the numbers of people registering for Unemployment Assistance/Benefit or for various other statutory entitlements at local offices of the Department of Social Protection. The Live Register is not designed to measure unemployment. It includes part-time workers (those who work up to three days a week) and seasonal and casual workers entitled to Jobseeker's Benefit (JB) or Jobseeker's Allowance (JA) (CSO, 2016i).

Figure 5.2: Number of casual & part-time workers, 2005-2013[97]



Source: CSO (2016e)

At the same time as this large increase occurred, we can see in Table 5.10 that the length of time someone is on the Live Register can be quite short.

Table 5.10: Live Register unemployment durations ('000's)

	Bi –annual results								
Duration	**2009 H1**	**2009 H2**	**2010 H1**	**2010 H2**	**2011 H1**	**2011 H2**	**2012 H1**	**2012 H2**	**2013 H1**
<3 months	**169**	**160**	**156**	**151**	**150**	**149**	**142**	**143**	**138**
>= 3 & < 6 months	74	72	65	56	49	45	43	40	39
>=6 & < 12 months	70	93	94	76	71	57	61	49	54
=1 year +	71	87	117	148	169	180	184	188	186
>= 1 & < 2 years	34	43	63	78	79	68	59	55	52
>=2 & < 3 years	12	15	21	31	43	53	53	45	38
>=3 years +	25	29	33	39	47	58	72	88	96
TOTAL	454	500	550	577	609	610	614	608	604
Under 3 months as % of total	37%	32%	28%	26%	25%	24%	23%	24%	23%

Source: Central Statistics Office, Ireland (2016f)

For example, we see that between 2009 and 2013, the percentage of those registering for unemployment assistance/benefit for less than 3 months varied between 37% in

[97] Casual work is work in which You are normally employed for periods of less than a week; The number of days and the days of the week you work varies with the level of activity in the business; and; have no assurance of being re-employed in the job when a period of employment ends. See http://www.citizensinformationboard.ie/downloads/relate/relate_2011_11.pdf for further details.

2009 to 23% in 2013. This helps in our understanding of why the number of transitions via non-employment may be high.

5.4.3 The transitions of Irish and non-Irish workers

Next we disaggregate the data presented in Figure 5.1 to show the transitions for Irish and non-Irish workers in Figure 5.3 and Figure 5.4. All workers and their spells are coded as being either Irish or non-Irish based on their reported nationality. We have 1,231,039 Irish workers and 708,062 non-Irish workers in the panel over the period 2005-2013.[98] There are 2,336,718 and 1,274,672 spells associated with Irish and non-Irish workers respectively. As before, left censored observations were removed from the panel. This contributes to the relatively low number of individuals in the sample in 2005 for both Irish and non-Irish workers.

We see that relative to the number of individuals in both samples in 2013, non-Irish workers experience a greater number of transitions via non-employment. The mean number of spells per Irish worker is 1.89 and is 1.80 for non-Irish workers.

[98] This gives a total number of people as 1,939,101, which is 3,053 more than reported earlier. This increased number is due to non-Irish workers changing nationality during the period, so that while initially identified as non-Irish in one spell, the same person could be identified as Irish in a later spell. Nationality is self-reported.

Figure 5.3: The transitions of Irish workers

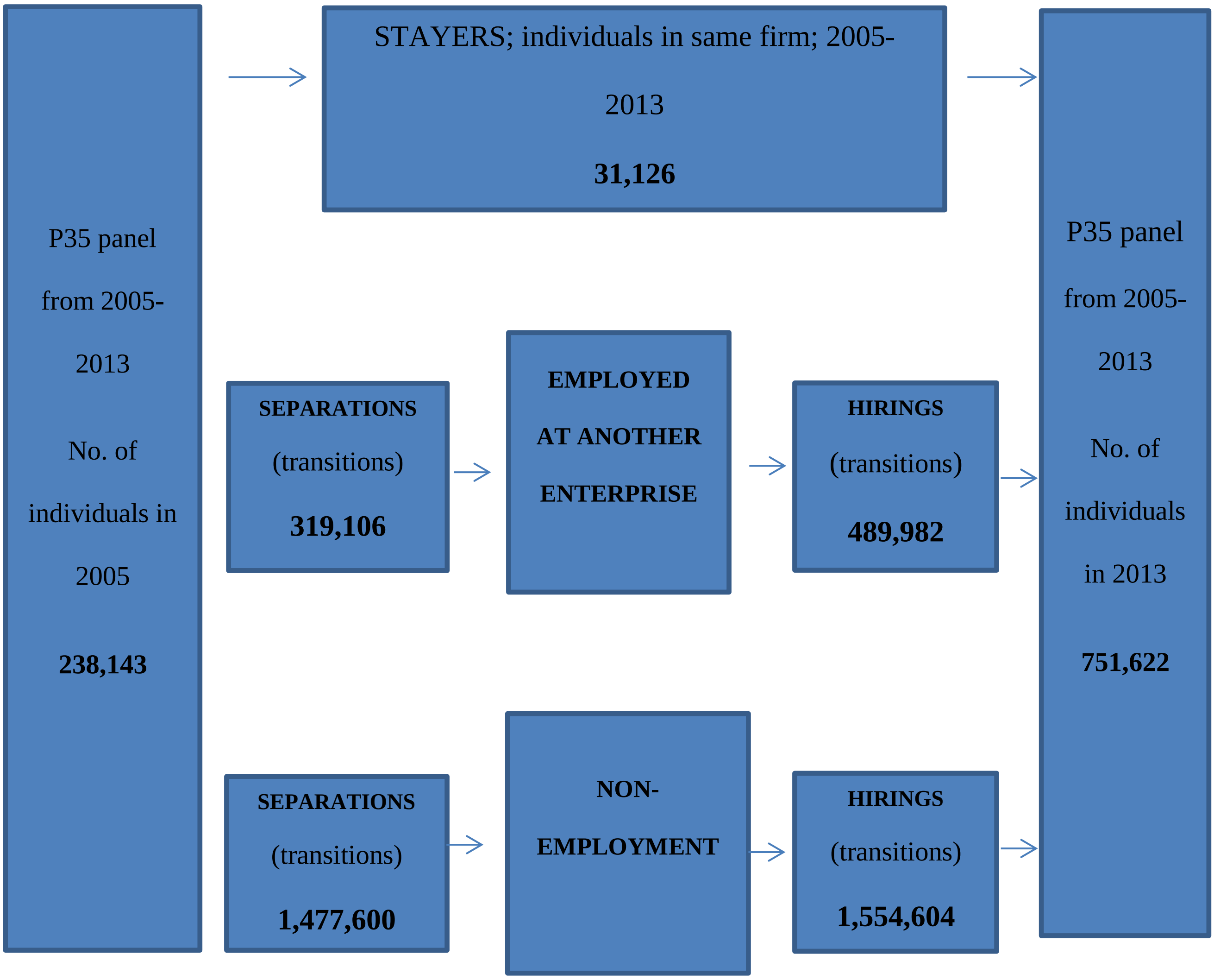
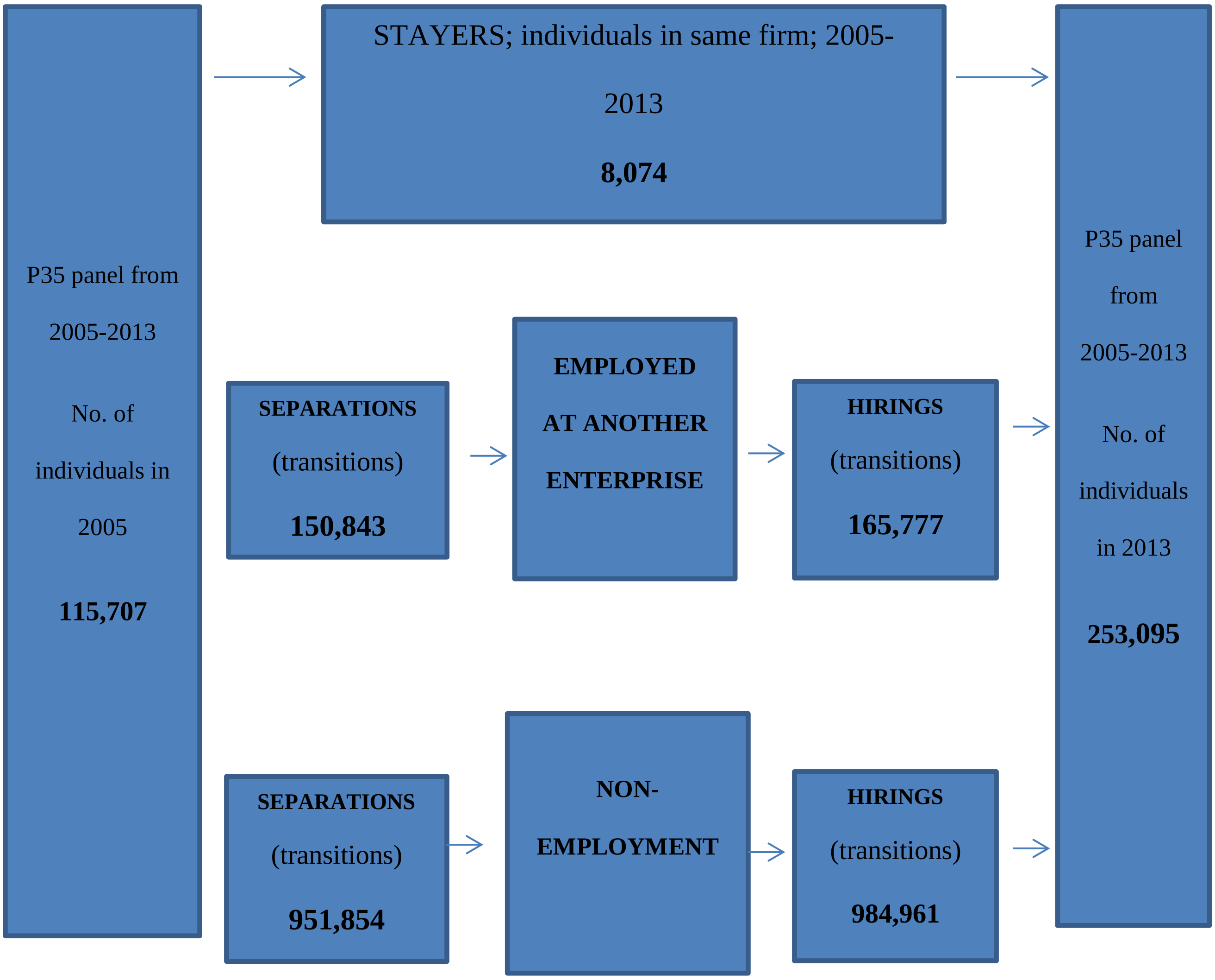


Figure 5.4: The transitions of non-Irish workers



5.5 Findings

To estimate labour supply elasticities at the firm level, thereby determining whether monopsonistic discrimination can provide an explanation of a native-immigrant wage differential, as well as male versus female differences, we use the econometric approach outlined earlier. We do this initially for all workers, then for Irish and non-Irish workers (5.5.6) and finally for male and female workers (5.5.7). We fit Weibull hazard models for the instantaneous separation rates to employment and non-employment. By including the logged real average weekly wage per spell in these estimations we arrive at estimates of the separation rate elasticities to employment and non-employment. We also estimate a logit model for the probability that an individual is hired from employment to obtain their wage elasticity. Finally, we calculate the proportion of recruits from employment. These estimates are then inserted into equation (5.10) to arrive at an estimate of the firm-level labour supply elasticity. We include the same covariates in all estimations. These include a gender dummy variable, age at the start of the spell, nationality group[99] and the economic sector[100] the enterprise belongs to.

In estimating the elasticities we include both worker and firm characteristics as described above. These variables are included in an effort to control for differneces across workers and firms which may help explain wage variations across workers and firms. Hirsch et al. (2010) also include establishment and worker controls. With their more detailed information on workers and enterprises, a rich set of control variables are included. Thus this may help enhance the accuracy of the elasticity estimates. We therefore proceed by using the NACE sector as a control variable. While the inclusion of establishment size was considered, Hirsch et al. (2010) note that in dynamic monopsony models, such as those of Burdett & Mortensen (1998), the use of enterprise size as a control variable should not matter as it can be increased by paying higher wages. Hirsch et al. (2010) find that their original results are robust to its inclusion.

[99] Nationality is grouped into six categories. The purpose is to create groups that are broadly similar in terms of geographic location of country of origin. These groups are Ireland, UK & Northern Ireland, Western Europe, Eastern Europe, Asia and the Rest of the World.

[100] NACE Rev.2 sectors are grouped into 6 categories. The purpose is to create groups that are broadly similar in terms industrial sector of employment. These groups are Agriculture (A), Industry (B-E), Construction (F), Business Economy services (G-N), Public sector (O, P, Q) and Other Activities (R, S, T, U and unknown).

We note that Manning (2003) does not control for "firm-specific determinants of transition behaviour" due to the nature of the available data being individual or household based (Hirsch et al. 2010: 298). Also, Ransom & Oaxaca (2010) do not include firm-specific controls in their estimations.

Having considered using firm fixed effects, we firstly note the lack of use of this approach in the literature and secondly that our data in this thesis is essentially short in years and wide in terms of firm observations. Therefore there was the potential that that such an econometric approach could bias results. The availability of additional years of data would make such an approach more feasible.

5.5.1 Transitions to employment (all workers)

We begin by estimating the separation rate elasticity to employment for all workers as described in Figure 5.1. We follow Manning (2003) and Hirsch et al. (2010) and only include spells that do not end in non-employment in the estimation. This reduces the number of spells included in the analysis to 1,211,936, which includes 469,949 failures.

The primary effect of interest is the impact of the wage on the separation rate to employment. Therefore we have included the log of the real average weekly wage over the spell as an explanatory variable. We would expect that there would be a negative effect– the higher the wage paid, the lower the separation rate.

Other variables may also influence the separation rate to employment. The age of the worker may have an effect. The age of the workers at the start of the spell is also included as an explanatory variable. If we ascribe to the view that there are search frictions in the labour market and that workers accumulate human capital as they get older, we would anticipate that older workers may be in better paying jobs and are less likely to leave their job when compared to younger workers. As a result, we may expect that there is a negative relationship between age and the separation rate to employment.

Gender may also play a role. One could argue that women have a lower attachment to the labour market. In a study of job mobility in the Irish labour market, Bergin (2009) sets out two possible scenarios. In the Barron et al. (1993) model, workers differ in their attachment to the labour market. For those who are less attached, they may take jobs that involve less training, and as a result, have less to lose by moving jobs so possibly are more mobile. On the other hand, it could be that women are more constrained by non-market issues and so are less mobile than men, and less likely to move between jobs. A similar point is made by Hirsch et al. (2010) who note that job moves by females may be more associated with non-pecuniary aspects of the job.

We also include sectoral and nationality dummies as outlined already. This allows us to determine if any particular sector or nationality grouping is more or less likely to separate to employment.

Estimations of the elasticity of separation are displayed in Table 5.11.[101] They show that the relationship between the log weekly wage and the separation rate to employment is negative and significant – the higher the wage, the lower the separation rate. A 1% fall in the wage is associated with an increase in separations to employment of 0.377%.

Other results also confirm with our priors. We see that age has a negative and significant effect as predicted. The gender dummy is positive and significant

[101] Detailed output is available in Appendix Table 11.1.

implying that being male is positively associated with moving to another job. Each nationality dummy has a negative relationship with the transition to employment variable except the third group, 'Western Europe' which is positive. This implies that relative to the 'Rest of the World' base group, the 'Western Europe' group of workers are more likely to separate to employment, while the other groups are less likely to separate to employment. NACE sector group coefficients for 'Construction' and the 'Business Economy' are positive, implying that these groups are more likely to separate to employment relative to the base category of 'Other activities.'

Appendix Table 11.1 reports the results of a Wald test which tests if the hazard is constant or not. The test statistic is -99.6 and is significant at the 1% level. Therefore we can reject the hypothesis that the hazard is constant at this level. The shape parameter p = +0.907. As p<1, it implies the hazard is monotonically decreasing. This result is supported by the survival graph and cumulative hazard curve in Appendix Figure 11.1.

5.5.2 Transitions to non-employment (all workers)

Estimates of the elasticity of separations to non-employment are displayed in Table 5.11[102] with detailed results are available in Appendix Table 11.1.

Again estimation is conducted by fitting a Weibull hazard model for the separation rate to non-employment. This time we do not restrict our sample and so include all 3,611,390 observations in the estimation which includes 2,399,454 failures, as shown in Figure 5.1. As before, the key variable of interest is the impact of the wage

[102] In presenting our results, we follow the work of Hirsch et al. (2010) and Hirsch & Jahn (2015).

on the separation rate elasticity to non-employment. All the variables included in the model are the same as outlined in 5.5.1.

As with the transition to employment, we expect the effect of the wage variable to be negative – the higher the wage, the lower is the separation rate to non-employment. We would anticipate similar effects for age. As a worker gets older, it's more likely that they will achieve a better job match and so would be less likely to leave and enter non-employment. On the other hand, Hirsch et al. (2010) point out that older workers who are considering retirement may be offered attractive retirement options or may be drawn by generous welfare payments for older workers.[103]

The estimated coefficients generally have the expected signs. The wage variable is negative and significant suggesting that the higher the wage, the lower the separation rate to non-employment. Specifically, a 1% fall in the wage is associated with an increase in separations to non-employment of 0.715%. As before, age is negative – as a person gets older, the separation rate to non-employment decreases. Male workers display an increasing likelihood of separating to non-employment relative to female workers. Regarding nationality, as with transitions to employment, we see that relative to the 'Rest of the World' group, the 'Western Europe' group is more likely to transit to non-employment, while other groups are less likely to do so. Turning to sector, we see that individuals in the construction sector are more likely to transition to non-employment relative to those in the 'Other activities' group, with other groups less likely to do so.

The Wald test statistic is -648.57, therefore we can reject the hypothesis that the hazard is constant at the 1% level. If we look at the shape parameter *p*, we see it has

[103] We have attempted to mitigate this risk by restricting the sample to workers less than 55 at the end of their employment spell.

a value of +0.74 which is <1. As before, this implies the hazard is monotonically decreasing. Parametric graphs are displayed in Appendix Figure 11.2.

5.5.3 Hiring from employment (all workers)

We now turn to hiring from employment and fit a logit model for the probability that a hire comes from employment. Full results are displayed in Appendix Table 11.1 while the coefficient on log wages is displayed in Table 5.11. Here we would expect a positive coefficient – the higher the wage, the higher the probability that a hire would be recruited from employment. So firms that pay higher wages find it easier to recruit. Manning (2003: 104) points out that "This implies that the wage elasticity of recruits from employment is higher than the wage elasticity of recruits from non-employment."

We observe that the relationship between the log wage and the hiring from employment variable is positive and statistically significant at the 1% level. A 1% increase in wages is associated with a 0.995% increase in hirings from employment. Males are less likely to be hired from employment relative to females. We see that with the exception of the 'Public Sector' group, all other groups are less likely to be hired from employment than the reference group of 'Other activities.'

5.5.4 Obtaining estimates of the labour supply elasticities

By combining the results discussed above we can obtain an estimate for the long-run wage elasticity of the firm using equation (5.10). One final calculation is needed – the share of recruits from employment is computed as a ratio of the number of all recruits from employment divided by the number all recruits. This gives a share of 0.205. Hirsch et al. (2010) assume that in the steady state, the share of recruits from employment equals the share of separations to employment. We compute the share of separations to employment as 0.164. Given the small differences between these shares, we opt to use share of recruits from employment, as is consistent with Manning (2003), Hirsch et al. (2010) and Hirsch & Jahn (2015).

Table 5.11: Estimating the long-run wage elasticity of labour supply to the firm

Parameter & Results	
Elasticity of separations to employment ($\hat{\beta}_w^e$)	-0.377*** (0.002)
Elasticity of separations to non-employment ($\widehat{\beta_w^n}$)	-0.715*** (0.001)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\hat{\beta}_w$)	0.995*** (0.002)
Share of recruits from employment (θ)	0.205
Estimated wage elasticity of firms labour supply	**0.231**

Note: Estimated coefficients are taken from Appendix Table 11.1.
Standard errors are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The estimated wage elasticity of the firms' labour supply is obtained according to Equation (5.10).

As we can see from Table 5.11, the estimated labour supply for all workers is low at 0.231. This would suggest the Irish labour market is not perfectly competitive and the labour supply curve to a single firm is not infinitely elastic. Our results here suggest that labour supply curve to a firm is in fact inelastic or upward sloping as would be predicted by the 'new' monopsony literature.

5.5.5 Discussion

In an effort to put our results in context compared to other studies, Table 5.12 reproduces Booth & Katic (2011: Table 4) which compares the separation and labour supply elasticities of the United States, the United Kingdom and Australia. The results for the US and UK are drawn from Manning (2003).

Table 5.12: Estimates from previous studies

Parameter & Results	Country				
	United States (US)		United Kingdom (UK)		Australia (AUS)
	PSID	**NLSY**	**BHPS**	**LFS**	**HILDA**
Elasticity of separations to employment	0.867	0.359	0.631	0.529	0.376
Elasticity of separations to non-employment	0.892	0.850	0.632	0.578	0.282
Share of separations to employment	0.620	0.78	0.63	0.56	0.77
Elasticity of labour supply curve	**1.38**	**0.68**	**0.75**	**0.75**	**0.709**

Note: The authors choose to omit the negative sign from the separation elasticities to aid comparisons

It is worth noting that the share of recruits from employment in our sample is lower than estimates obtained for other countries. This is due to the high number of transitions via non-employment in the sample, which was investigated earlier. For example, Manning (2003) reports shares of between 0.56 and 0.78 for datasets under consideration from the US and UK. In Australia, Booth & Katic (2011) report a share of 0.77. For Germany, Hirsch et al. (2010) find share figures of 0.525 and 0.579 for males and females respectively. It seems that in the Irish labour market transitions via non-employment are more common, as outlined in section 5.4.2, and this contributes to a relatively lower reported share (θ) figure of 0.205. This relatively low share and overall elasticity, along with the evidence presented when investigating non-employment durations in 5.4.2 would seem to suggest that the Irish labour market is somewhat unique when compared to others. Our overall elasticity of labour supply to the firm figure of 0.231 suggests that employers do in fact possess a degree of monopsony power.

5.5.6 Elasticity of labour supply of Irish versus non-Irish workers

We now turn to the issue of investigating monopsonistic discrimination against immigrants in Ireland. We take the same approach as before except this time we split the sample in two – Irish and non-Irish workers. All estimations are obtained assuming a Weibull distribution as before with the same set of explanatory variables. Summary results are displayed in Table 5.13.[104]

Table 5.13: Estimating the long-run wage elasticity of labour supply to the firm of Irish and Non-Irish workers

Parameter & Results	Nationality: Irish workers	Nationality: Non-Irish workers
Elasticity of separations to employment $(\hat{\beta}_w^e)$	-0.358*** (0.003)	-0.427*** (0.005)
Elasticity of separations to non-employment $(\widehat{\beta_w^n})$	-0.711*** (0.002)	-0.709*** (0.002)
Estimated coefficient of log wage in logit model for probability hire comes from employment $(\hat{\beta}_w)$	1.046*** (0.003)	0.827*** (0.005)
Share of recruits from employment $(\boldsymbol{\theta})$	0.240	0.144
Estimated wage elasticity of firms labour supply	**0.189**	**0.387**

Note: Estimated coefficients are taken from Appendix Table 11.2.
Standard errors are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The estimated wage elasticity of the firms' labour supply is obtained according to Equation (5.10).

We begin as before by examining the separation rate to employment and non-employment for Irish and non-Irish workers. It is clear that non-Irish workers are more sensitive to wages when shifting to employment, while Irish workers are more sensitive to the wage when shifting to non-employment. Specifically, a 1% fall in the wage is associated with a 0.427% and 0.358% increase in separations to employment for non-Irish and Irish workers respectively, and the difference is statistically significant at the 1% level. For separations to non-employment, a 1% fall in the wage will result in a 0.711% increase in the separations for Irish workers, and 0.709% for non-Irish workers. Again, this difference is statistically significant at the 1% level. Overall the evidence suggests that there is not a large separation response to a change in wages. This is interesting, as it suggests that there are other

[104] Detailed results are available in Appendix Table 11.2.

factors that are tying workers to firms. This is in line with what is suggested by Manning (2003) in relation to monopsony – there are frictions in the labour market which mean if an employer cuts wages, workers will not necessarily be induced to leave. Therefore the employer has market power arising from these frictions.

We also observe that the probability a hire comes from employment increases with the wage offered as expected, with the wage coefficient higher for Irish workers, and the difference is statistically significant at the 1% level. This may be due to non-Irish workers being newly arrived in the country and so more likely to be coming from non-employment.

Finally, it is possible to compute the estimated wage elasticity to the firm and we find a lower elasticity for Irish workers (0.189) relative to non-Irish workers (0.387). It is possible that immigrants could be more driven by pecuniary considerations than Irish workers. Given that these workers have made the decision to travel to and work in Ireland, they are a mobile group. As mentioned earlier, search frictions and mobility costs limit elasticity. But for this group, moving location in search of a higher paying job may not be so problematic. On the other hand, the mobility of Irish workers may be inhibited by social and family considerations. This reduced mobility may enhance the monopsony power of employers with regards to wage setting for Irish workers, relative to non-Irish workers.

In order to investigate this differential further, it was decided to disaggregate the immigrant group into regional categories. These are UK & Northern Ireland, Western Europe, Eastern Europe, Asia and the Rest of the World. Summary results are displayed in Table 5.14. Additional rows have been added to display the elasticity ranking and also the mean age of the workers in each nationality grouping.

As can be seen, Eastern European and Western European workers have the highest elasticities. We also see that the average age of workers in these groups is lower than the other groups. Such younger workers are possibly less tied to a location and are more driven by pecuniary considerations. On the other hand, Irish workers or those from the UK & Northern Ireland are older. This could imply that they are more likely to have a family or put down roots in a particular location. As a result, employers may be able to exert a greater degree of monopsony power over those groups.

Table 5.14: Estimating the long-run wage elasticity of labour supply to the firm by nationality group

	NATIONALITY					
Parameter & Results	**Irish**	**UK & NI**	**Western Europe**	**Eastern Europe**	**Asia**	**Rest of World**
Elasticity of separations to employment $(\widehat{\beta}_w^e)$	-0.358*** (0.003)	-0.280*** (0.013)	-0.724*** (0.017)	-0.616*** (0.009)	-0.318*** (0.016)	-0.302*** (0.012)
Elasticity of separations to non-employment $(\widehat{\beta}_w^n)$	-0.711*** (0.002)	-0.585*** (0.005)	-0.858*** (0.007)	-0.812*** (0.004)	-0.702*** (0.007)	-0.619*** (0.005)
Estimated coefficient of log wage in logit model for probability hire comes from employment $(\widehat{\beta}_w)$	1.046*** (0.003)	0.751*** (0.011)	0.934*** (0.012)	1.091*** (0.009)	0.628*** (0.012)	0.731*** (0.010)
Share of recruits from employment $(\boldsymbol{\theta})$	0.240	0.173	0.146	0.131	0.217	0.126
Estimated wage elasticity of firms labour supply	**0.189**	**0.191**	**0.765**	**0.454**	**0.329**	**0.242**
Elasticity ranking (highest to lowest)	**6**	**5**	**1**	**2**	**3**	**4**
Mean Age	**32.0**	**35.5**	**29.9**	**29.7**	**30.5**	**31.5**

Note: Estimated coefficients are taken from Appendix Table 11.3.
Standard errors are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The estimated wage elasticity of the firms' labour supply is obtained according to Equation (5.10).

Table 5.15 further examines how elasticity changes with age for workers of all nationalities. The youngest cohort of workers has the highest labour supply elasticity and we see that this generally declines with age. We observe that the 36-45 and 46-55 age groups have the lowest labour supply elasticities. This is in line with the suggestion earlier that as workers get older, they may become less mobile, possibly due to family commitments.

Table 5.15: Estimating the long-run wage elasticity of labour supply to the firm by age category

Parameter & Results	AGE categories (years) 21-25	26-35	36-45	46-55
Elasticity of separations to employment $(\widehat{\beta}_w^e)$	-0.668*** (0.006)	-0.330*** (0.004)	-0.221*** (0.006)	-0.304*** (0.008)
Elasticity of separations to non-employment $(\widehat{\beta}_w^n)$	-0.836*** (0.003)	-0.757*** (0.002)	-0.578*** (0.003)	-0.495*** (0.003)
Estimated coefficient of log wage in logit model for probability hire comes from employment $(\widehat{\beta}_w)$	0.951*** (0.006)	1.096*** (0.004)	0.872*** (0.004)	0.822*** (0.006)
Share of recruits from employment $(\boldsymbol{\theta})$	0.139	0.236	0.237	0.225
Estimated wage elasticity of firms labour supply	**0.662**	**0.149**	**0.049**	**0.119**
Elasticity ranking (highest to lowest)	**1**	**2**	**4**	**3**

Note: Estimated coefficients are taken from Appendix Table 11.4.
Standard errors are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The estimated wage elasticity of the firms' labour supply is obtained according to Equation (5.10).

We disaggregate by both nationality groups and age in Table 5.16. This shows the importance of both age and nationality in explaining elasticity differences across workers. For prime aged workers in age categories 2 and 3, we note that Irish workers have lower labour supply elasticities relative to workers from the UK & Northern Ireland, Western Europe and Eastern Europe. This suggests that employers possess a higher degree of monopsony power over Irish workers. The results support our earlier suggestions that Irish workers may be less mobile compared to those of other nationalities. In general we see that the youngest age cohort has the highest labour supply elasticities within each group, suggesting a higher degree of mobility. The highest elasticity is reported for the Asian grouping and we see that the Irish group has a lower elasticity when compared to all other groups.

Table 5.16: Estimating the long-run wage elasticity of labour supply to the firm by nationality & age group

IRELAND	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\beta}_w^e$)	-0.639*** (0.007)	-.272*** (0.005)	-0.246*** (0.006)	-0.334*** (0.009)
Elasticity of separations to non-employment ($\widehat{\beta}_w^n$)	-0.820*** (0.003)	-0.756*** (0.003)	-0.583*** (0.003)	-0.513*** (0.004)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\beta}_w$)	0.970*** (0.006)	1.20*** (0.005)	0.908*** (0.005)	0.873*** (0.007)
Share of recruits from employment (θ)	0.160	0.284	0.271	0.253
Estimated wage elasticity of firms labour supply	**0.615**	**0.031**	**0.076**	**0.150**
Elasticity ranking (highest to lowest)	**1**	**3**	**4**	**2**
United Kingdom & Northern Ireland	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\beta}_w^e$)	-0.568*** (0.045)	-0.286*** (0.022)	-0.251*** (0.021)	-0.259*** (0.033)
Elasticity of separations to non-employment ($\widehat{\beta}_w^n$)	-0.773*** (0.016)	-0.654*** (0.009)	-0.531*** (0.009)	-0.418*** (0.012)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\beta}_w$)	0.786*** (0.048)	0.827*** (0.019)	0.696*** (0.017)	0.619*** (0.024)
Share of recruits from employment (θ)	0.085	0.191	0.194	0.174
Estimated wage elasticity of firms labour supply	**0.604**	**0.201**	**0.167**	**0.138**
Elasticity ranking (highest to lowest)	**1**	**2**	**3**	**4**
Western Europe	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\beta}_w^e$)	-1.02*** (0.046)	-0.761*** (0.024)	-0.508*** (0.032)	-0.460*** (0.063)
Elasticity of separations to non-employment ($\widehat{\beta}_w^n$)	-0.988*** (0.013)	-0.906*** (0.010)	-0.620*** (0.014)	-0.430*** (0.024)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\beta}_w$)	1.340*** (0.041)	1.030*** (0.017)	0.651*** (0.022)	0.424*** (0.042)
Share of recruits from employment (θ)	0.068	0.178	0.189	0.152
Estimated wage elasticity of firms labour supply	**0.760**	**0.795**	**0.579**	**0.535**
Elasticity ranking (highest to lowest)	**2**	**1**	**3**	**4**

Table 5.16 continued: Estimating the long-run wage elasticity of labour supply to the firm by nationality & age group continued

Eastern Europe	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\beta}_w^e$)	-0.853*** (0.020)	-0.563*** (0.013)	-0.348*** (0.027)	-0.236*** (0.045)
Elasticity of separations to non-employment ($\widehat{\beta}_w^n$)	-0.967*** (0.008)	-0.813*** (0.006)	-0.619*** (0.010)	-0.498*** (0.016)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\beta}_w$)	1.12*** (0.021)	1.13*** (0.013)	0.828*** (0.024)	0.642*** (0.038)
Share of recruits from employment (θ)	0.099	0.162	0.118	0.092
Estimated wage elasticity of firms labour supply	**0.800**	**0.389**	**0.205**	**0.127**
Elasticity ranking (highest to lowest)	**1**	**2**	**3**	**4**
ASIA	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\beta}_w^e$)	-0.791*** (0.035)	-0.376*** (0.022)	0.371*** (0.036)	0.307*** (0.073)
Elasticity of separations to non-employment ($\widehat{\beta}_w^n$)	-0.841*** (0.015)	-0.750*** (0.010)	-0.496*** (0.016)	-0.293*** (0.034)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\beta}_w$)	0.499*** (0.030)	0.611*** (0.017)	0.746*** (0.026)	0.592*** (0.051)
Share of recruits from employment (θ)	0.169	0.226	0.255	0.241
Estimated wage elasticity of firms labour supply	**1.209**	**0.569**	**-0.652**	**-0.608**
Elasticity ranking (highest to lowest)	**1**	**2**	**3**	**4**
Rest of the World	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\beta}_w^e$)	-0.746*** (0.033)	-0.336*** (0.017)	-0.135*** (0.022)	-0.164*** (0.049)
Elasticity of separations to non-employment ($\widehat{\beta}_w^n$)	-0.726*** (0.010)	-0.643*** (0.007)	-0.556*** (0.009)	-0.381*** (0.018)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\beta}_w$)	0.672*** (0.032)	0.743*** (0.015)	0.791*** (0.018)	0.483*** (0.033)
Share of recruits from employment (θ)	0.070	0.131	0.173	0.155
Estimated wage elasticity of firms labour supply	**0.848**	**0.293**	**-0.036**	**0.103**
Elasticity ranking (highest to lowest)	**1**	**2**	**4**	**3**

Note: Estimated coefficients are taken from Appendix Table 11.5
Standard errors are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The estimated wage elasticity of the firms' labour supply is obtained according to Equation (5.10).

5.5.7 Elasticity of labour supply of male and female workers

We now turn our attention to gender differences within our sample. As discussed earlier, previous work in the area by Hirsch et al. (2010) and Barth & Dale-Olsen (2009) have examined whether there are differences in the firm level labour supply elasticities of males and females. Hirsch et al. (2010) suggest that for females, job transitions may be less motivated by monetary considerations and they may have stronger preferences over the non-wage characteristics of the job, such as where the job is located – how close the job is to home for example.

The summary results are presented in Table 5.17 for all male and female workers in the sample. If we look at the elasticity of separations, we observe that females' separations to employment are more sensitive to the wage than male separations and the differences are statistically significant at the 1% level. On the other hand, male workers are more sensitive to the wage when shifting to non-employment than female workers, and again differneces are statistically significant at the 1% level. Hirsch et al. (2010) suggest that if monopsonistic discrimination is an important part of explaining a gender pay gap then females would be expected to have a lower separation rate elasticity to employment than males and so less responsive to wage changes. Clearly we do not find evidence of this, with our results suggesting that monetary considerations have a greater influence on a female's decision to separate to employment than for males. Our findings are however in line with Booth and Katic (2011) for Australia.

On the other hand, we find that male separations to non-employment are more sensitive to the wage than female separations, and although the difference is not large it is statistically significant at the 1% level. Our findings regarding the separation rate to non-employment are again in line with Booth and Katic (2011) for

Australia, and also for Hirsch et al. (2010) for Germany and Manning (2003) for the UK. Overall we find that female labour supply to the firm is more elastic than the labour supply of males.

Table 5.17: Estimating the long-run wage elasticity of labour supply to the firm by gender

Parameter & Results	Gender Males	Gender Females
Elasticity of separations to employment $(\widehat{\beta}_w^e)$	-0.362*** (0.004)	-0.415 *** (0.004)
Elasticity of separations to non-employment $(\widehat{\beta_w^n})$	-0.735*** (0.002)	-0.721*** (0.002)
Estimated coefficient of log wage in logit model for probability hire comes from employment $(\widehat{\beta}_w)$	0.985 *** (0.003)	1.02 *** (0.003)
Share of recruits from employment $(\boldsymbol{\theta})$	0.188	0.225
Estimated wage elasticity of firms labour supply	**0.227**	**0.277**

Note: Estimated coefficients are taken from Appendix Table 11.6
Standard errors are shown in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
The estimated wage elasticity of the firms' labour supply is obtained according to Equation (5.10).

It is also possible that the labour supply elasticities of men and women may differ by the age of the workers. You might expect that very young males and females are equally mobile with little difference in their responsiveness to wages. But as workers get older, it could be suggested that all workers may become less mobile due to family commitments for example and so monetary considerations may be less important. Older women may be concerned by the proximity of child care. In the case of male workers, they are less likely to have experienced interruptions to their labour supply, while females' tenure may be more affected by child care responsibilities. Summary results are presented in Table 5.18.[105] Barth & Dale-Olsen (2009: 593) suggest "A prerequisite for the theory of monopsonistic

[105] Detailed results are available in Appendix Table 11.7.

discrimination to provide a reasonable explanation for the gender wage gap is that worker turnover of women is less sensitive to wages than that of men's worker turnover." We find evidence to support this only for workers up to the age of 35.

Table 5.18: Estimating the long-run wage elasticity of labour supply to the firm by gender & age category

MALE	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\boldsymbol{\beta}}^{e}_{w}$)	-0.714*** (0.009)	-0.355*** (0.006)	-0.137*** (0.008)	-0.198*** (0.012)
Elasticity of separations to non-employment ($\widehat{\boldsymbol{\beta}}^{n}_{w}$)	-0.826*** (0.004)	-0.803*** (0.003)	-0.595*** (0.004)	-0.489*** (0.005)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\boldsymbol{\beta}}_{w}$)	0.959*** (0.009)	1.11*** (0.006)	0.859*** (0.006)	0.706*** (0.008)
Share of recruits from employment ($\boldsymbol{\theta}$)	0.117	0.212	0.231	0.199
Estimated wage elasticity of firms labour supply	**0.680**	**0.188**	**-0.034**	**0.068**
Elasticity ranking (highest to lowest)	**1 1**	**2 4**	**4 8**	**3 7**
FEMALE	Age categories			
Parameter & Results	**21-25**	**26-35**	**36-45**	**46-55**
Elasticity of separations to employment ($\widehat{\boldsymbol{\beta}}^{e}_{w}$)	-0.644*** (0.007)	-0.308*** (0.006)	-0.302*** (0.008)	-0.396*** (0.011)
Elasticity of separations to non-employment ($\widehat{\boldsymbol{\beta}}^{n}_{w}$)	-0.848*** (0.003)	-0.721*** (0.003)	-0.566*** (0.004)	-0.548*** (0.005)
Estimated coefficient of log wage in logit model for probability hire comes from employment ($\widehat{\boldsymbol{\beta}}_{w}$)	0.954*** (0.008)	1.09*** (0.005)	0.889*** (0.022)	0.954*** (0.009)
Share of recruits from employment ($\boldsymbol{\theta}$)	0.160	0.264	0.244	0.253
Estimated wage elasticity of firms labour supply	**0.658**	**0.118**	**0.132**	**0.193**
Elasticity ranking (highest to lowest)	**1 2**	**4 6**	**3 5**	**2 3**

Note: Estimated coefficients are taken from Appendix Table 11.7
Standard errors are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The estimated wage elasticity of the firms' labour supply is obtained according to Equation (5.10).
The ranking in black is the within males and female groups respectively, the numbers in red are the overall ranking across males and females.

Looking at Table 5.18 above, we observe that men have higher labour supply elasticities to the firm in the 21-25 & 26-34 age groups. On the other hand, females supply labour less elastically, although the magnitude of the differences between groups is small. However, all differences are statistically significant at the 1% level. These results are in line with Hirsch et al. (2010) suggesting that women may be less mobile.

However, in higher age categories we see a reversal with women having higher elasticities. Now it appears that men may be *less* mobile than women.

Table 5.19: The real mean weekly wage for males and females

	Age categories & Mean wage per spell (€)			
	21-25	**26-35**	**36-45**	**46-55**
Males	415.74 (0.399)	579.93 (0.570)	744.82 (1.992)	762.11 (4.779)
Females	361.67 (0.311)	491.43 (0.520)	496.41 (1.502)	455.94 (2.295)
Difference	**54.07**	**88.50**	**248.41**	**306.18**

Note: Standard errors are in parentheses.

If we look at Table 5.19, we see that across all age categories, men earn a higher mean weekly wage than women. Initially this difference is relatively low at €54 in the youngest age category. However, this increases to around €306 in the oldest age category. These higher wages for the male group may suggest they could be the primary earner in households with a male and female. So while males have a higher weekly wage per spell than females, we saw in Table 5.17 that they supply labour less elastically than females, possibly suggesting males are less driven by pecuniary considerations. Earlier work in Ireland by McGuinness, Kelly, Callnan, & O'Connell (2009) finds a gender wage gap of around 8% when education, labour market experience, and firm and job characteristics are controlled for. Without controls, the gap was around 22%.

Conversely, females have a lower mean wage per spell than males and have a higher wage elasticity to the firm. It may be that the lower relative wages of the female workers make monetary considerations more important to them when considering their labour supply decisions and contribute to a higher degree of mobility relative to their male counterparts. As pointed out by Hirsch et al. (2010: 292) "profit-maximising firms may take advantage of gender specific differences in supply elasticities by exercising pay discrimination, that is, paying different wages to women and men, ceteris paribus." The lower supply elasticity of male workers would imply employers potentially have the power to engage in monopsonistic discrimination against older men.

It is important to note that, as Ransom & Oaxaca (2010) point out, while a low labour supply elasticity to the firm suggests that firms may possess wage setting power, it does not mean that they are able to exercise it. Clearly there are constraints on their wage setting power such as minimum wage laws and anti-discrimination laws for example. So "The firm faces an upward-sloping labor supply curve – it has market power due to market frictions – but is unable to take full advantage of it because of the institutions and environment in which it operates" (Ransom & Oaxaca 2010: 283). While the power to assign workers fulfilling the same role a different salary is constrained, it may be possible to assign workers to lower paying roles. While not formally testing this, Ransom & Oaxaca (2010) suggest that if male workers had a higher separation elasticity with respect to the wage, assigning them to higher paying jobs (and assigning women to lower paying jobs, given they have a lower separation rate elasticity) could be an optimal strategy in an effort to reduce turnover costs without altering the wage bill. This explanation could plausibly be applied to workers up to the age of 35 in our study. For older age categories, generally we see separation rate elasticities are greater for female workers and they experience lower wages per spell.

5.6 Concluding remarks

In this chapter we explore the labour supply elasticities of workers in the Irish labour market. In doing so, we follow the literature on new monopsony as extending by Manning (2003) and others. In this new dynamic model of monopsony, the power of the firm to set wages is related to the labour supply elasticity at the level of the firm. Through focusing on the responsiveness of labour market transitions to the wage, it is possible to estimate the labour supply elasticity to the firm. This would not have been possible without the use of the P35 data which covers all employees in the Irish economy which allowed the estimation of wage elasticities to and from non-employment as well as to and from employment. We are thus able to construct a panel containing almost two million individuals over the period 2005-2013 which was analysed using methods of survival analysis.

Overall we find that the estimated labour supply elasticities to the firm are relatively low. This implies that elasticity is not infinite as suggested by perfect competition, and so employers may possess a degree of monopsony power in wage setting.

In exploring the elasticities further, we divide the population into native and immigrant workers and separately, male and female workers. We find that native Irish workers have a lower labour supply elasticity to the firm (0.189) than non-native workers (0.387). This contrasts with the evidence of Hirsch & Jahn (2015) who find that immigrants in Germany supply labour less elastically than native workers. Thus we find evidence of more severe frictions for Irish relative to immigrant workers in Ireland. As suggested earlier, Irish workers may be inherently less mobile than their immigrant counterparts and this lack of mobility potentially gives employers greater monopsony power over native workers. In Chapter 2 we observed that non-Irish workers had a high level of third level educational attainment in almost all cases, suggesting that immigrant workers in Ireland are well educated and so are possibly driven by pecuniary considerations, and seeking a return on their human capital investment. The fact that they have left their native country and secured employment in the Irish labour market shows that the immigrants are a mobile group and this may be contributing to their higher labour supply elasticity.

In the case of gender, we find that females supply their labour slightly more elastically (0.276) than male workers (0.227). However, differences do emerge when we split the data and look at different age categories. Up to the age of 35 we see that males supply labour more elastically than females but this is reversed for workers over the age of 35. For older male workers, family considerations might act as a mobility-inhibiting factor. We saw evidence that male workers earn more than female workers per employment spell and this gap increases with age.

Chapter 6 : Conclusion

6.1 Summary of the thesis

The purpose of this thesis was to examine the Irish labour market over a turbulent economic period. Specifically we investigated issues related to both the demand-side and supply-side of the labour market. In order to gain an understanding of the Irish labour market and provide an overview of the time period of 2005-2013, Chapter 2 documented evidence regarding unemployment, earnings and migration. We observed that unemployment increased significantly, accompanied by a sharp decline in economic growth. As the economic crisis evolved, migration patterns shifted, with an increase in emigration and decrease in immigration. While many sectors experienced declining earnings, others such as Industry sectors (B-E) experienced an increase in earnings.

In addition, we noted some of the policy responses to the changing economic circumstances. Of particular relevance here was the emphasis placed on the role of exporting activity in potentially contributing to improved employment and economic growth. This contextualises part of the analysis in Chapter 3.

In Chapter 3 we focused on job flows in the Irish labour market. We initially concentrated on enterprises in NACE Rev.2 sectors B-N and found that the period of 2006-2010 could be sub-divided into two sub-periods, characterised by very different trends in terms of job flows. Earlier years up to 2007 were associated with higher rates of job creation relative to job destruction. From 2008 onwards, we observed that job destruction was greater than job creation. Certain sectors, such as construction, saw a large increase in their job destruction rate over the period. In light of the discussion in the literature regarding the role of small firms in job creation and destruction, we also examined this. When we compare the Irish labour market with international evidence on jobs flows, we note the key differentiating feature is the dramatic rise in job destruction that occurred in the Irish labour market in 2009. At the same time, even with rising unemployment and job destruction, we still see that enterprises were creating jobs. So while the labour market was experiencing great turbulence, job creation remained somewhat resilient. We find evidence that, as in the US, job reallocation is counter-cyclical. Interestingly, this contrasts somewhat with some of the evidence presented earlier from other European countries [*eg* Albaek & Sorensen (1998)].

We found that small firms accounted for a greater proportion of job creation and job destruction than their employment share would imply. This highlights the importance of small firms in an Irish context and is in line with UK evidence presented by Hijzen et al. (2010).

We then turned our focus to the manufacturing sector to estimate the impact of international trade activity (exporting and importing activity) on job creation and job destruction. To do this, we merged the P35 linked employer-employee data with the CIP survey data. Descriptive evidence points to higher mean employment for those engaged in international trade. While employment growth was generally negative over the period, it was less negative for those who export and import, compared to non-exporters and non-importers. Estimates obtained from regressions suggest that there was a positive association between export intensity and job creation and this exists only for those in the top quintile. For lower quintiles 1 and 2 which represented those enterprises experiencing declining trade intensity, our findings pointed to a negative effect on job creation. Turning to job destruction however, we did find some support for the suggestion that exporting and importing activity reduces it. However, it should be noted in the case of both exports and imports, that the magnitude of the effect was small. Thus the Irish labour market appears to be somewhat similar to other labour markets, such as the UK where Hijzen et al. (2010) find a small effect of international trade on job flows.

In Chapter 4 we turned our attention to workers in the labour market. Specifically, we estimated the impact of displacement on the earnings of workers. We noted earlier in Chapter 2 that there was a large increase in unemployment during the period of the study and so many of these workers may have found it challenging to secure re-employment. We identified two displacement events – closure and mass-layoff. The extensive P35 dataset allowed for the implementation of propensity score matching to match displaced with non-displaced workers.

Our difference-in-differences estimates suggested large losses for displaced workers. This contrasts somewhat with other labour markets. In particular we found that the type of displacement event matters. Those displaced due to a mass-layoff experience a greater fall in earnings compared to those who are displaced due to a closure event. This contrasts with results for the UK reported by Hijzen et al. (2010) who found that those displaced due to a closure experience greater losses. Male workers experienced greater losses as did older workers. We also provided estimates of the losses of those who either switch sectors or stay in the same sector after displacement and found that those who switch sectors to find employment after displacement suffer greater losses. This finding is similar to evidence from other labour markets highlighted in section 4.2.

In Chapter 5 we focused on the wage elasticity of labour supply to the firm. Through obtaining an estimate of this, it is possible to determine if there is evidence of monopsony in the labour market. The methodology employed was based on survival analysis and the available data contributed to our ability to identify transitions to and from employment as well as transitions to and from non-employment. We also provided elasticity estimates to investigate the relevance of monopsonistic discrimination in explaining pay gaps between native and immigrant workers, as well as between males and females.

We find that the labour supply elasticity to the firm is 0.231. This suggests that the labour supply to the firm is not perfectly competitive and is characterised by an upward sloping labour supply curve. This figure is low relative to some of the evidence cited earlier from Manning (2003) and Hirsch et al. (2010) for example. However, in the Irish labour market, we noted that many a workers appear to transition via non-employment. In investigating non-employment durations, we found that many non-employed workers experience short non-employment spells. Particularly we noted evidence from the CSO (2016e) which demonstrated the large increase in part-time and casual workers over the period of investigation. This dramatic increase coincides with the onset of the recession in 2008 and would appear to be a rather unique feature of the labour market. It suggests a changing labour market in which employers may be less inclined to offer full-time positions and instead are relying more on part-time contracts to fill vacancies.

Next we investigated differences in labour supply elasticities across groups of workers. We found a lower elasticity for Irish workers (0.189) relative to non-Irish workers (0.387) and suggested this may be due to mobility differences between the groups. We suggested that the non-Irish group may be more mobile in the search for work and so are more driven by monetary considerations. This in turn limits the monopsony power of employers. With regards to gender, we found that male workers have slightly lower labour supply elasticity to the firm compared to their female counterparts. This contrasted with previous studies and could imply females are more mobile and more driven by monetary considerations than males. In an effort to explore this further we examined the estimates by age and gender. While there was little differences between estimates for younger groups, older male workers have lower labour supply elasticities to the firm. We suggested family considerations could act as mobility inhibiting factors for these older male workers, giving employers some degree of monopsony power.

6.2 Contributions to the literature

This thesis has contributed to several strands of the literature related to labour markets. In each chapter, one of the important contributions was to provide Irish evidence. In fact to the best of our knowledge, Chapters 4 and 5 constituted a first in the Irish literature. While work has been conducted on job flows in Ireland previously, Chapter 3 was the first to examine job flows using this linked employer-employee data. It was also the first to match the P35 and CIP data sources and estimate the impact of international trade on job flows. However, in the remainder of this section we will highlight contributions to the international literature.

The work in Chapter 3 is one of the first to examine job flows with such a large linked employer-employee dataset. Many of the earlier studies identified in section 3.2 used survey data and focused specifically on the manufacturing sector. We are thus adding to empirical evidence on the magnitude of job flows as well as issues such as the contribution of small versus large firms to job flows. As outlined, there is not consensus in the literature on the contribution of small and large firms to job flows. Our results point to an important role for small firms in the job creation and destruction processes. They account for a greater proportion of job creation and job destruction than their employment share.

Secondly, this chapter contributes to the existing body of knowledge examining the relationship between international trade and job flows. While data here is limited to the manufacturing sector, the data coverage is extensive within that sector.

Chapter 4 has contributed to the literature and empirical evidence on the impact of displacement on the earnings of workers. Again here the data used is a unique feature of our work. Also while many previous studies such as Jacobson et al. (1993) and Couch & Placzek (2010) focus on mass-layoff events only, we analyse closure events also. This is important as we found the type of displacement event matters in explaining earnings losses post-displacement. We found larger losses for those displaced due to a mass-layoff event.

Secondly, our methodology employs propensity score matching and difference-in-differences to estimate the earnings losses of displaced workers, building on the approach of Couch & Placzek (2010) for example. While some previous studies used survey data [see Podgursky (1992), Carrington (1993) and Kletzer (1998)], the availability of administrative data has allowed for the application of such matching techniques. Our approach here is enhanced by the size and coverage of our dataset which to our knowledge, is unique and a first in the literature.

Chapter 5 contributes to the relatively recent work on the role of monopsony in explaining the elasticity of labour supply to the firm. To the best of our knowledge, we are the first to use such an extensive linked employer-employee dataset. A limitation of some previous studies was the inability to estimate transitions to and from employment as well as transitions to and from non-employment. We overcome this with our data and employ the methodology of survival analysis to estimate the wage elasticity of labour supply to the firm.

This chapter also contributes to the recent attempts to investigate if monopsonistic discrimination can play a role in explaining native-immigrant wage differentials as well as gender wage differentials. Our results contrast with previous findings of Hirsch & et al. (2010) and Hirsch & Jahn (2015) with regards to native-immigrant labour supply elasticities and male-female labour supply elasticities respectively. In the case of immigrants we suggested that this group has demonstrated their mobility in the act of immigrating to Ireland, and this could act as an explanation for reduced monopsony power of employers in their treatment of immigrants relative to native workers. Turning to gender, we suggested that age matters when exploring gender differneces in labour supply elasticities. While females had a higher labour supply elasticity than males in general, our results changed when we broke down by age and gender. Up to the age of 35 years, males supply labour more elastically than females. But after 35 years, this trend is reversed.

6.3 Policy implications

There are several policy implications that arise from this thesis. In Chapter 3 we provide evidence on job flows across sectors. This gives policy makers an insight into which sectors have had a tendency to grow and create jobs and those which have contracted. Those workers who lose employment in sectors with negative employment growth may find it more difficult to secure re-employment in the same sector. Thus, it identifies workers who may benefit from skills conversion programmes. Ensuring an adequate talent pool for those sectors with positive net employment growth is important.

We also provide evidence on the role of small firms with regards to their job creation potential. We observed that they account for a larger fraction of job creation and job destruction that their employment share would imply. This would seem to suggest that support offered to small firms is warranted. For example the *Action Plan for Jobs* referred to in Chapter 2, places an emphasis on supporting small and medium size enterprises to create employment.

In Chapter 2 we outlined how policy makers have advocated the potential of export-led growth to lead to increased employment after the economic crisis which began in 2008. In Chapter 3, we provided some evidence related to the manufacturing sector and the impact of export intensity on job creation and job destruction over the period 2006-2010. We found that only the highest export intensity quintile was associated with higher rates of job creation. Lower intensity quintiles, representing decreasing exporting activity, were associated with lower job creation. Overall, the magnitude of the effect on job creation across quintiles was small. There is evidence that lower and higher export intensity was associated with lower rates of job destruction. Thus it is possible that the measures in the *Action Plan for Jobs* to support and enhance exporting activity of Irish enterprises could help to strengthen the relationship between exporting activity and job creation.

The research in Chapter 4 has implications for support and assistance offered to displaced workers. Firstly, we saw that those displaced due to a mass-layoff experienced greater earnings losses that those displaced following a closure event. We suggested that this could be related to a negative signal relayed to future employers, given that such workers had been ‘selected’ by their employers. This may warrant greater engagement with such workers to assist in their employment search post-displacement.

Furthermore, this chapter highlighted the adverse effects on those who are displaced and securing re-employment in another sector. We observed that this group of 'switchers' experienced greater losses that those 'stayers' who secured re-employment in the same sector. This may be because such switchers lack the required human capital and skills in their new sector of employment. Thus there is a role for ensuring these workers have access to information and supports to facilitate good skills matches between employers and employees. From Chapter 2 we know that many of those who became unemployed were from the construction sector and so these workers had little opportunity to find re-employment within this sector during the time period.

In Chapter 5 we found that the estimates of the wage elasticity of labour supply to the firm are relatively low and are not infinitely elastic as would be expected if the labour market was perfectly competitive. This has implications for policy makers if they model labour markets on the assumption that they are perfectly competitive. For example, we know the predicted effects of a minimum wage on employment imply a positive effect if a monopsonistic labour market is assumed, or a negative effect if a perfectly competitive labour market is assumed. Thus we see that the predicted effects of policy intervention could be misleading if the incorrect assumption is made about the labour market.

6.4 Directions for future research

Although this thesis has shed light on several important topics in the labour market, there are many directions that future related work could take.

With the available data, is possible to explore the earnings of workers in relation to the legal form of the enterprise. Specifically the data records whether an enterprise is a branch of a foreign company or not. Thus it would be possible to explore wage differences across domestic firms and those that are a branch of a foreign company. This has been explored in the literature by Heyman et al. (2007) for example.

The addition of further annual observations and variables to this dataset would expand its applicability to other areas of the labour market research as well as to the areas under investigation here. For example in Chapter 3, the time period in question is relatively short and covers a period of severe economic turbulence. Thus a longer data set would also capture the potential impact of measures in the *Action Plan for Jobs* to support exporters and potential exporters.

A longer data set would also be beneficial in relation to the other work conducted in this thesis. For example in Chapter 3, we investigated the relationship between export-growth in the manufacturing sector only. A broader study across sectors would be useful to make more wide-scale assertions.

In terms of estimating earnings losses, a longer dataset would allow us to follow the approach of Hijzen et al. (2010) and select a base period for measuring income losses a number of periods before the displacement event. With the relatively short data span here, it was not possible to take such an approach. In Chapter 5, more annual observations would mean capturing more spells of employment and non-employment, as well as associated labour market transitions.

The availability of additional variables would further enhance the dataset and analysis of job flows. For example, we do not know the age of the enterprise. There is much discussion in the job flows literature on the importance of enterprise size versus age effects. Lawless (2013) has investigated this in an Irish context using survey data and found that enterprise age may be more important than size in explaining the contribution to job creations rates. Other variables which would provide opportunities for further research include education, tenure of workers as well as ownership information in relation to the enterprise. These could all assist in further exploring earnings losses associated with displacement in the labour market, as well as exploring monopsony in the labour market.

In estimating earnings losses associated with displacement, it could be possible to incorporate unemployment assistance into the analysis. This is somewhat complicated by the fact that the level of benefits is dependent on time in employment and the number of dependent children for example. If it was possible to identify employee tenure, we could obtain another estimate of earnings losses. This has been done previously in the literature [see Hijzen et al. (2010) for example].

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Appendix 1 : Data tables for Chapter 2

Appendix Table 1.1: **Seasonally adjusted series of persons aged 15 years employed and classified by NACE Rev.2 Economic Sector ('000's)**

NACE Rev.2 Economic Sector	Quarter and Year								
	Q1 2005	**Q1 2006**	**Q1 2007**	**Q1 2008**	**Q1 2009**	**Q1 2010**	**Q1 2011**	**Q1 2012**	**Q1 2013**
Agriculture, forestry and fishing (A)	110.6	111.7	109.6	118.3	104.3	82.5	85.4	82.3	97.9
Industry (B-E)	296.4	289.7	305.1	286.6	269.6	248.3	240.9	237.2	238.0
Construction	226.7	248.8	272.5	258.0	184.4	131.8	109.5	104.2	97.2
Wholesale and retail trade; repair of motor vehicles and motorcycles (G)	266.2	285.0	297.4	319.5	292.1	275.9	271.9	271.8	274.9
Transportation and storage (H)	92.3	93.3	93.8	94.7	94.7	93.4	94.3	90.0	88.6
Accommodation and food service activities (I)	114.2	119.2	135.9	134.4	125.1	133.2	112.6	119.8	122.8
Information and communication (J)	64.2	70.5	66.8	72.2	73.6	76.3	73.0	79.2	78.3
Financial, insurance and real estate activities (K-L)	90.7	93.3	101.4	105.9	105.8	105.5	100.7	101.9	100.5
Professional, scientific and technical activities (M)	97.0	103.9	108.5	112.0	105.0	103.2	103.7	98.1	104.2
Administrative and support service activities (N)	68.5	73.4	74.7	84.4	69.4	62.6	66.2	63.9	60.9
Public administration and defence; compulsory social security (O)	93.4	104.4	102.6	104.4	106.8	105.8	105.2	100.0	95.6
Education (P)	121.5	134.3	141.1	138.4	149.9	146.8	146.7	144.7	145.3
Human health and social work activities (Q)	186.5	194.1	213.8	223.6	225.5	236.5	237.1	241.7	249.6
Other NACE activities (R-U)	90.5	90.7	95.9	99.7	98.4	93.8	99.6	98.4	99.6
Unemployed	**84.1**	**94.6**	**101.8**	**114.9**	**231.8**	**286.7**	**311.3**	**325.3**	**294.4**

Appendix Table 1.2: Percentage of Enterprise deaths (as % of active enterprises)

NACE Rev.2 Economic Sector Year					
	2006	**2007**	**2008**	**2009**	**2010**
Industry (B to E)	3%	5%	6%	9%	7%
Mining and quarrying (B)	-	-	6%	-	-
Manufacturing (C)	3%	5%	6%	9%	7%
Electricity, gas, steam and air conditioning supply (D)	-	-	7%	-	-
Water supply, sewerage, waste management and remediation activities (E)	3%	6%	6%	10%	7%
Construction (F)	6%	10%	15%	16%	11%
Wholesale and retail trade, repair of motor vehicles and motorcycles (G)	4%	5%	6%	9%	7%
Transportation and storage (H)	5%	6%	8%	11%	8%
Accommodation and food service activities (I)	6%	6%	7%	10%	8%
Information and communication (J)	7%	7%	9%	11%	9%
Financial and insurance activities excluding activities of holding companies (K-642)	4%	6%	7%	9%	6%
Real estate activities (L)	7%	7%	8%	10%	8%
Professional, scientific and technical activities (M)	4%	6%	7%	10%	8%
Administrative and support service activities (N)	4%	6%	8%	11%	7%
Annual Average across sectors	5%	6%	7%	10%	8%

Source: Central Statistics Office, 2016a

Note: “-“ figures are unavailable for confidentiality reasons

Appendix Table 1.3: **Average Weekly Earnings (Seasonally Adjusted) (Euro) by Type of Economic Sector NACE Rev 2 and Quarter**

NACE Rev.2 Economic Sector	Quarter and Year						
	2008Q1	**2009Q1**	**2010Q1**	**2011Q1**	**2012Q1**	**2013Q1**	**% Δ**
All NACE economic sectors	705.08	709.59	691.42	689.96	692.67	691.62	-2%
Mining and quarrying (B)	907.86	817.58	828.56	870.08	918.76	921.33	1%
Manufacturing (C)	742.52	781.81	773.39	775.11	782.84	788.28	6%
Construction (F)	737.9	772.18	742.14	684.32	674.4	658.97	-11%
Wholesale and retail trade; repair of motor vehicles and motorcycles (G)	513.28	505.11	496.23	502.11	514.32	523.86	2%
Transportation and storage (H)	770.22	750.07	696.15	725.31	719.98	734.6	-5%
Accommodation and food service activities (I)	349.53	343.03	332.39	324.59	316.36	306.65	-12%
Information and communication (J)	944.2	948.64	919.15	951.74	976.57	1027.88	9%
Financial and insurance activities (K)	1120.63	992.29	1027.84	1034.46	1011.76	1033.9	-8%
Real estate activities (L)	763.69	677.15	577.15	537.32	626.7	597.26	-22%
Professional, scientific and technical activities (M)	786.26	823.24	830.73	718.09	831.39	802.95	2%
Administrative and support service activities (N)	501.71	492.15	482.56	485.42	486.07	501.47	0%
Public administration and defence; compulsory social security (O)	961.73	981.97	930.15	908.62	925.12	933.6	-3%
Education (P)	849.66	894.57	855.46	852.44	856.25	828.1	-3%
Human health and social work activities (Q)	730.37	756.34	721.56	730.17	721	695.53	-5%
Arts, entertainment and recreation (R)	459.11	463.69	467.43	407.49	450.06	496.79	8%
Other service activities (S)	547.22	506.52	465.95	452.17	501.32	484.26	-12%
Industry (B to E)	780.84	809.25	801.51	798.75	816.77	816.36	5%
Electricity, water supply and waste management (D,E)	1152.26	1181.08	1128.55	1086.98	1074.21	**1069.57**	-7%
Financial, insurance and real estate activities (K,L)	978.4	946.92	1003.45	993.25	982.05	985.72	1%
Arts, entertainment, recreation and other service activities (R,S)	484.66	469.82	454.62	420.31	468.45	**483.24**	0%

Source: (Central Statistics Office, Ireland 2016b)

Appendix Table 1.4: Immigration and Emigration by Nationality, 2006-2013[106]

Nationality	Year 000's 2006	2007	2008	2009	2010	2011	2012	2013	% change 2006-2013
					Immigration				
Irish	18.9	30.7	23.8	23	17.9	19.6	20.6	15.7	**-17%**
UK	9.9	4.3	6.8	3.9	2.5	4.1	2.2	4.9	**-51%**
Rest of EU 15	12.7	11.8	9.6	11.5	6.2	7.1	7.2	7.4	**-42%**
EU 13[107]	49.9	85.3	54.7	21.5	9.3	10.1	10.4	10.9	**-78%**
Rest of World	16.4	19	18.6	14.1	6.0	12.4	12.4	17.1	**4%**
TOTAL	107.8	151.1	113.5	73.7	41.8	53.3	52.7	55.9	**-48%**
					Emigration				
Irish	15.3	12.9	13.1	19.2	28.9	42.0	46.5	50.9	**233%**
UK	2.2	3.7	3.7	3.9	3.0	4.6	3.5	3.9	**77%**
Rest of EU 15	5.1	8.9	6.0	7.4	9.0	10.2	11.2	9.9	**94%**
EU 13[107]	7.2	12.6	17.2	30.5	19.0	13.9	14.8	14.0	**94%**
Rest of World	6.2	8.2	9	11.0	9.3	9.9	11.1	10.3	**66%**
TOTAL	**36.0**	**46.3**	**49.2**	**72.0**	**69.2**	**80.6**	**87.1**	**89.0**	**147%**

[106] Source: (Central Statistics Office, Ireland 2012; Central Statistics Office, Ireland 2015a)
Note 1: Rest of EU15 (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxemburg, Netherlands, Spain, Sweden, Portugal)
Note 2: Figures for 2012/2013 are preliminary

[107] EU 13 includes 10 countries that joined 1/5/04 (Cyprus, Czech Republic, Estonia, Hungry, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia); Bulgaria, Romania who joined 1/1/07 and Croatia who joined 1/7/13.
Figures for 2006-2009 are based on EU 12 (ie (EU13 minus Croatia)

Appendix 2 : Data tables and results for Chapter 3

Appendix Table 2.1: NACE Rev. 2 sectors B-N and number of enterprises, 2005-2010

NACE economic sector	2005	2006	2007	2008	2009	2010
B. Mining & Quarrying	241	266	291	312	307	280
C. Manufacturing	8,221	9,105	9,591	9,762	9,565	8,965
D. Electricity, Gas, Steam & Air Conditioning	56	64	70	81	100	114
E. Water supply, sewerage	406	466	542	592	582	584
F. Construction	28,429	35,088	38,502	38,124	33,372	25,718
G. Wholesale & Retail Trade	26,549	29,995	31,548	32,400	32,243	31,200
H. Transport & Storage	5,272	6,086	6,586	6,808	6,764	6,410
I. Accommodation & Food service	11,131	12,916	13,494	13,848	13,941	13,694
J. Information & Communication	4,595	5,589	6,215	6,552	6,584	6,444
K. Financial & Insurance activities	2,718	3,145	3,425	3,668	3,986	3,914
L. Real Estate activities	2,631	3,230	3,547	3,690	3,727	3,533
M. Professional, Scientific & Technical services	12,698	15,107	16,792	17,824	18,232	17,654
N. Administrative & Support activities	5,203	6,292	7,057	7,448	7,455	6,920

Appendix Table 2.2: Mean job flow rates by NACE Rev2 sector

NACE economic sector	Job creation	Job destruction	Job reallocation	Net reallocation	Excess reallocation
B. Mining & Quarrying (1)	0.076	-0.106	0.182	-0.030	0.152
C. Manufacturing (2)	0.087	-0.132	0.219	-0.045	0.175
D. Electricity, Gas, Steam & Air Conditioning (3)	-	-	-	-	-
E. Water supply, sewerage (4)	0.152	-0.126	0.278	0.027	0.251
F. Construction (5)	0.168	-0.300	0.467	-0.130	0.336
G. Wholesale & Retail Trade (6)	0.116	-0.127	0.244	-0.010	0.233
H. Transport & Storage (7)	0.099	-0.106	0.205	-0.007	0.199
I. Accommodation & Food service activities (8)	0.150	-0.178	0.327	-0.028	0.299
J. Information & Communication (9)	0.191	-0.163	0.354	0.027	0.327
K. Financial & Insurance activities (10)	0.105	-0.094	0.199	0.011	0.187
L. Real Estate activities (11)	0.192	-0.214	0.405	-0.022	0.384
M. Professional, Scientific & Technical services (12)	0.154	-0.150	0.304	0.004	0.300
N. Administrative & Support activities (13)	0.180	-0.184	0.364	-0.004	0.360

Note: *For confidentiality reasons, results for sector D have been supressed.*

Appendix Table 2.3: Number of enterprise observations in the CIP, 2006-2010.

Year	Number of enterprises
2006	4,620
2007	5,558
2008	5,589
2009	5,029
2010	4,782
Total	**25,578**

Appendix Table 2.4: Job creation and job destruction by manufacturing subsector, 2006-2010

Manufacturing sub-sector		2006	2007	2008	2009	2010
1.	**JC**	0.079	0.092	0.068	0.039	0.068
	JD	-0.057	-0.048	-0.071	-0.130	-0.052
2.	**JC**	0.108	0.072	0.047	0.031	0.051
	JD	-0.061	-0.080	-0.092	-0.173	-0.122
3.	**JC**	0.106	0.052	0.043	0.014	0.036
	JD	-0.045	-0.076	-0.201	-0.376	-0.159
4.	**JC**	0.065	0.076	0.047	0.015	0.046
	JD	-0.072	-0.082	-0.075	-0.134	-0.112
5.	**JC**	0.123	0.048	0.027	0.135	0.030
	JD	-0.023	-0.027	-0.040	-0.093	-0.097
6.	**JC**	0.117	0.115	0.034	0.020	0.054
	JD	-0.065	-0.077	-0.154	-0.241	-0.130
7.	**JC**	0.156	0.085	0.054	0.008	0.012
	JD	-0.023	-0.037	-0.122	-0.363	-0.248
8.	**JC**	0.127	0.109	0.067	0.054	0.050
	JD	-0.069	-0.062	-0.126	-0.260	-0.216
9.	**JC**	0.087	0.173	0.015	0.065	0.110
	JD	-0.053	-0.082	-0.096	-0.651	-0.118
10.	**JC**	0.098	0.092	0.044	0.045	0.056
	JD	-0.040	-0.038	-0.085	-0.020	-0.181
11.	**JC**	0.068	0.029	0.112	0.005	0.037
	JD	-0.017	-0.227	-0.054	-0.136	-0.069
12.	**JC**	0.072	0.076	0.036	0.063	0.070
	JD	-0.043	-0.098	-0.080	-0.273	-0.112
13.	**JC**	0.284	0.122	0.069	0.030	0.063
	JD	-0.044	-0.041	-0.081	-0.177	-0.123

Appendix Table 2.5: The level of trade intensity quintiles

Variable	N	Mean	Std. Dev.	Min	Max
Export Δ level 1	2,476	4.209	2.684	1	9
Export Δ level 2	2,208	14.86	3.2288	10	20
Export Δ level 3	2,132	29.37	6.2449	21	42
Export Δ level 4	2,270	66.15	13.905	43	90
Export Δ level 5	2,207	98.61	2.3574	91	100
Import Δ level 1	2,671	5.966	3.872	1	14
Import Δ level 2	2,595	28.080	9.1264	15	47
Import Δ level 3	2,600	70.575	13.035	48	90
Import Δ level 4	5,220	99.528	1.5431	91	100

Appendix Table 2.6: The change in trade intensity quintiles

Variable	N	Mean	Std. Dev.	Min	Max
Export Δ intensity 1	974	-32.714	29.041	100	-7
Export Δ intensity 2	1,044	-2.685	1.649	-6	-1
Export Δ intensity 3	881	2.099	1.094	1	4
Export Δ intensity 4	856	10.241	3.852	5	16
Export Δ intensity 5	874	39.628	25.418	17	100
Import Δ intensity 1	1,237	-72.216	29.486	-100	-22
Import Δ intensity 2	1,365	-9.240	5.340	-21	-3
Import Δ intensity 3	1,252	0.472	1.723	-2	3
Import Δ intensity 4	1,112	9.021	4.132	4	18
Import Δ intensity 5	1,219	57.416	27.683	19	100

Appendix 3 : Displacement, individual and firm characteristics

Here we provide some details on displacement rates by worker and firm characteristics. As appropriate, we refer to previous empirical evidence

- **Displacement and age**

The displacement rate is also computed for age categories. This is potential useful in identifying if particular age groups are at greater risk of displacement. Individuals are divided to age categories below;

- Category 1: 16-25 years old
- Category 2: 26-35 years old
- Category 3: 36-45 years old
- Category 4: 46-55 years old
- Category 5: 56-64 years old
- Category 6: 65 + years old

Appendix Table 3.1: Displacement number and rates by age category, 2006-2010 (Closure)

Year	1: 16-25 years		2: 26-35 years		3: 36-45 years		4: 46-55 years		5: 56-64 years		6: 65 years+	
	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate
2005	2,185	**1.0%**	3,100	**0.8%**	2,372	**0.7%**	1,494	**0.6%**	844	**0.7%**	226	**1.7%**
2006	2,892	**1.4%**	4,485	**1.1%**	3,194	**1.0%**	2,144	**0.9%**	1,122	**0.9%**	283	**2.0%**
2007	4,271	**2.0%**	6,727	**1.5%**	4,775	**1.4%**	2,940	**1.1%**	1,395	**1.0%**	408	**2.7%**
2008	6,677	**3.2%**	14,587	**3.1%**	11,452	**3.2%**	7,559	**2.7%**	4,039	**2.8%**	944	**5.8%**
2009	5,109	**2.8%**	10,221	**2.3%**	8,022	**2.3%**	5,465	**2.1%**	2,863	**2.1%**	772	**4.9%**
2010	4,237	**2.7%**	9,592	**2.2%**	7,682	**2.2%**	4,991	**1.8%**	2,674	**1.9%**	787	**4.9%**

Appendix Table 3.2: Displacement number and rates by age category, 2006-2010 (Mass-Layoff)

Year	1: 16-25 years		2: 26-35 years		3: 36-45 years		4: 46-55 years		5: 56-64 years		6: 65 years +	
	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate
2005	519	**0.4%**	639	**0.3%**	341	**0.2%**	319	**0.2%**	-	-	-	-
2006	440	**0.1%**	662	**0.0%**	532	**0.0%**	-	-	-	-	-	-
2007	776	**0.1%**	1,185	**0.1%**	521	**0.0%**	320	**0.0%**	-	-	-	-
2008	2,067	**1.6%**	3,201	**1.1%**	1,453	**0.6%**	798	**0.4%**	-	-	-	-
2009	567	**0.1%**	1,684	**0.1%**	1,101	**0.1%**	792	**0.1%**	-	-	-	-
2010	320	**0.3%**	763	**0.3%**	590	**0.3%**	351	**0.2%**	-	-	-	-

Note: Some values have been suppressed for confidentiality reasons

As we can see from the tables above, the displacement rates are relatively high in the younger age categories 1 and 2 in both samples. While the numbers and rates increase in all age categories in 2008, we observe higher rates in the younger age categories. Those in category 4 and aged 46-55 years have a slightly lower displacement rate when compared to other age categories. Previous work by the OECD (2013) has found that the displacement rate is highest for the youngest and oldest workers. Our evidence here is broadly consistent with that, particularly for the youngest workers (category 1: 16-25 years) and oldest workers (category 6: 65 years +). As we saw earlier in chapter 2, the unemployment rate was particularly high for younger workers under the age of 25. This would clearly impact on the employment prospects of these younger displaced workers.

- **Displacement and nationality**

The final individual characteristic used to examine the displacement rate by is nationality. Here employees are categorised according to their nationality as below;

- Category 1: Irish
- Category 2: UK and Northern Ireland
- Category 3: Western Europe
- Category 4: Eastern Europe
- Category 5: Asia
- Category 6: Rest of the world

As can been seen from Appendix Tables 3.3 and 3.4, all country categories experienced an increasing number of displacements over the period. For all groups and both samples, we observe that 2008 sees a dramatic increase in displacement, relative to previous years. For Irish workers, the rate of displacement increases from under 1% in both samples in 2005 to 3% in 2008 for the closure sample and just over 0.6% in the mass-layoff sample. The highest rate of displacement occurs in the closure sample in 2008 with workers in the 'Rest of the world' group experiencing displacement rates of over almost 4%. In the mass layoff sample, we see that the group of non-Irish workers see a large increase in their rate of displacement, relative to the increase for Irish workers. Finally, it is worth noting that while the rate of displacement declined in 2009 and 2010, so did the number of employment records.

Appendix Table 3.3: Displacement numbers and rates by nationality, 2005-2010 (Closure)

Year	1: Irish		2: UK and NI		3: Western Europe		4: Eastern Europe		5: Asia		6: Rest of the world	
	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate
2005	10,975	**0.8%**	532	**1.0%**	182	**0.6%**	795	**1.3%**	256	**1.2%**	246	**0.9%**
2006	12,190	**1.0%**	558	**1.3%**	293	**1.2%**	1,577	**1.8%**	293	**1.3%**	302	**1.2%**
2007	15,758	**1.3%**	793	**1.8%**	379	**1.4%**	3,091	**2.6%**	414	**1.6%**	574	**2.0%**
2008	36,831	**3.0%**	1,724	**3.6%**	840	**2.7%**	4,434	**3.5%**	812	**2.7%**	1,304	**3.8%**
2009	25,158	**2.2%**	1,112	**2.4%**	646	**2.2%**	3,741	**3.2%**	755	**2.4%**	1,107	**3.3%**
2010	23,423	**2.1%**	1,054	**2.3%**	602	**2.2%**	3,174	**2.9%**	822	**2.8%**	1,006	**3.2%**

Appendix Table 3.4: Displacement numbers and rates by nationality, 2005-2010 (Mass-Layoff)

Year	1: Irish		2. Other nationality	
	Number	Rate	Number	Rate
2005	1,629	**0.2%**	350	**0.4%**
2006	1,864	**0.3%**	406	**0.4%**
2007	1,672	**0.2%**	1,333	**1.0%**
2008	4,982	**0.6%**	3,097	**1.9%**
2009	3,627	**0.5%**	1,032	**0.6%**
2010	1,637	**0.2%**	595	**0.5%**

Note: A detailed breakdown by nationality group was not possible for confidentially reasons

- **Displacement and firm size**

Moving from individual to firm characteristics, we examine the incidence of displacement by firm size and NACE Rev.2 sector. Staring with firm size, all firms are divided into 5 categories based on the number of employment records which are;

- Category 1: 1-9 employment records
- Category 2: 10-19 employment records
- Category 3: 20-49 employment records
- Category 4: 50-249 employment records
- Category 5: 250+ employment records

We can see from below that micro firms with <9 employment records account for a significant amount of the numbers displaced. In 2008, over 16,000 individuals were displaced due to firm closure. According to data from the CSO, these micro firms account for around 87% of all enterprises and 20% of employment in 2008[108]. The high displacement rates suggest much volatility for employees of small firms. In the mass layoff sample, we see a similar trend of increasing displacement up to 2008.

Appendix Table 3.5: Displacement number and displacement rate by firm-size category for 2005-2010 (Closure)

Year	1: 1-9 records		2: 10-19 records		3: 20-49 records		4: 50-249 records		5: 250+ records	
	Number	Rate	Number	Rate	Number	Rate	Number	Rate	Number	Rate
2005	4,675	**2.6%**	1,604	**1.5%**	1,637	**1.1%**	1,572	**0.7%**	733	**0.1%**
2006	5,945	**3.2%**	1,728	**1.6%**	2,117	**1.3%**	2,038	**0.8%**	2,247	**0.4%**
2007	9,316	**4.8%**	2,826	**2.4%**	2,865	**1.7%**	2,414	**0.9%**	2,095	**0.3%**
2008	15,603	**7.6%**	4,432	**3.7%**	5,372	**3.0%**	9,433	**3.4%**	10,418	**1.5%**
2009	12,637	**6.4%**	3,735	**3.2%**	4,006	**2.4%**	5,848	**2.3%**	6,226	**1.0%**
2010	13,609	**7.1%**	3,606	**3.3%**	3,621	**2.3%**	4,275	**1.7%**	4,852	**0.7%**

Appendix Table 3.6: Displacement number and displacement rate by firm-size category for 2005-2010 (Mass Layoff)

Year	4: 50-249 records		5: 250+ records	
	Number	Rate	Number	Rate
2005	469	**0.3%**	1,510	**0.2%**
2006	540	**0.3%**	1,730	**0.3%**
2007	831	**0.4%**	2,174	**0.3%**
2008	3,029	**1.5%**	5,050	**0.7%**
2009	1,395	**0.7%**	3,261	**0.5%**
2010	731	**0.4%**	1,501	**0.2%**

- **Displacement and industry**

Finally we examine the displacement number by NACE Rev.2 sector. The table below shows the numbers displaced by NACE sector over the period 2005-2010 due to firm closure (C) and mass-layoff (M). As we can see a similar trend to the previous tables is observed with 2008 seeing the largest number of displacements across the sectors for both samples. There is a particularly large increase in the

[108] Source:
http://www.cso.ie/px/pxeirestat/Statire/SelectVarVal/Define.asp?maintable=BRA08&PLanguage=0

construction sector (F) for both samples. The manufacturing sector (C) also experienced a large increase in displacements over the period from to over four thousand for both samples.

Work in the US in the early 90's by Podgursky (1992) and Farber et al. (1993) examined the incidence of displacement across industries. Both found possible evidence a shift in the incidence from goods-producing industries towards service industries. This trend is not detected here in the time-period covered and we generally observe an increase in displacements across all sectors, particularly up to 2008.

Appendix Table 3.7: The number displaced by NACE sector; 2005-2010 [Closure (C) & Mass-layoff (M)]

NACE Sector	YEAR 2005		2006		2007		2008		2009		2010	
	C	M	C	M	C	M	C	M	C	M	C	M
1. Agriculture, Forestry, Fishing (A)	182	-	195	-	-	-	**610**	**-**	805	-	654	-
2. Mining and Quarrying (B)	-	-	-	-	-	-	**113**	**727**	223	-	-	-
3. Manufacturing (C)	868	639	668	480	1,737	383	**4,527**	**916**	2,643	883	3,832	250
4. Electricity, Gas, Steam, Air conditioning, Water supply (D) & (E)	-	-	-	-	326	-	**-**	**-**	223	-	-	-
5.Construction (F)	2,745	-	3,146	159	7,029	422	**8,878**	**1,240**	4,913	809	4,405	256
6. Wholesale and Retail trade; repair of motor vehicles (G)	2,107	454	2,769	208	3,222	238	**7,329**	**892**	5,614	595	5,608	211
7. Transportation & Storage (H)	322	-	332	191	618	-	**870**	**252**	1,352	379	1,083	-
8. Accommodation & Food service activities (I)	1,300	100	1,699	142	1,766	549	**3,005**	**1,140**	5,305	133	3,411	501
9. Information & Communication (J)	383	-	476	-	1,288	137	**1,632**	**261**	1,025	258	834	212
10. Financial services, Insurance (K)	358	-	2,062	168	518	-	**1,381**	**149**	777	211	1,250	-
11. Real estate activities (L)	184	-	290	-	222	-	**602**	**108**	584	-	444	-
12. Professional, scientific & technical activities (M)	575	-	796	-	1,113	143	**2,951**	**338**	2,375	194	1,990	138
13. Administrative & support activities (N)	386	-	786	360	1,118	744	**2,296**	**1,086**	2,138	395	1,625	202
14. Public administration & Defence (O)	66	267	-	-	-	-	**3,624**	**-**	1,211	243	317	-
15. Education (P)	36	-	-	-	-	-	**1,974**	**-**	352	-	560	-
16. Human Health and Social work activities (Q)	124	-	247	378	329	-	**3,815**	**147**	1,506	440	1,629	-
17. Arts, entertainment & recreation (R)	176	128	191	-	230	107	**345**	**-**	471	-	882	-
18. Other services activities; activities of households; Extraterritorial bodies (S, T , U)	358	-	350	-	519	-	**1,212**	**-**	935	-	1,330	-

Note: Some figures in the mass-layoff sample have been suppressed for confidentiality reasons

Work in the US in the early 90's by Podgursky (1992) and Farber et al. (1993) examined the incidence of displacement across industries. Both found possible evidence a shift in the incidence from goods-producing industries towards service industries. This trend is not detected here in the time-period covered and we generally observe an increase in displacements across all sectors, particularly up to 2008.

Appendix 4 : Findings from the unrestricted mass-layoff sample

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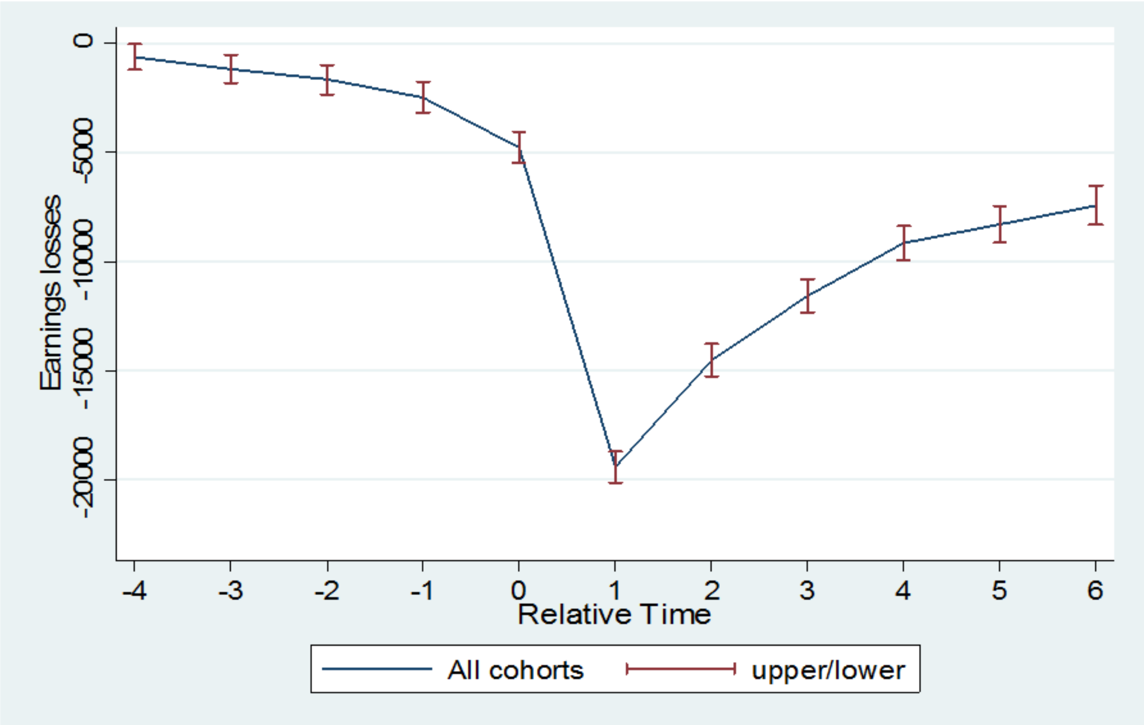
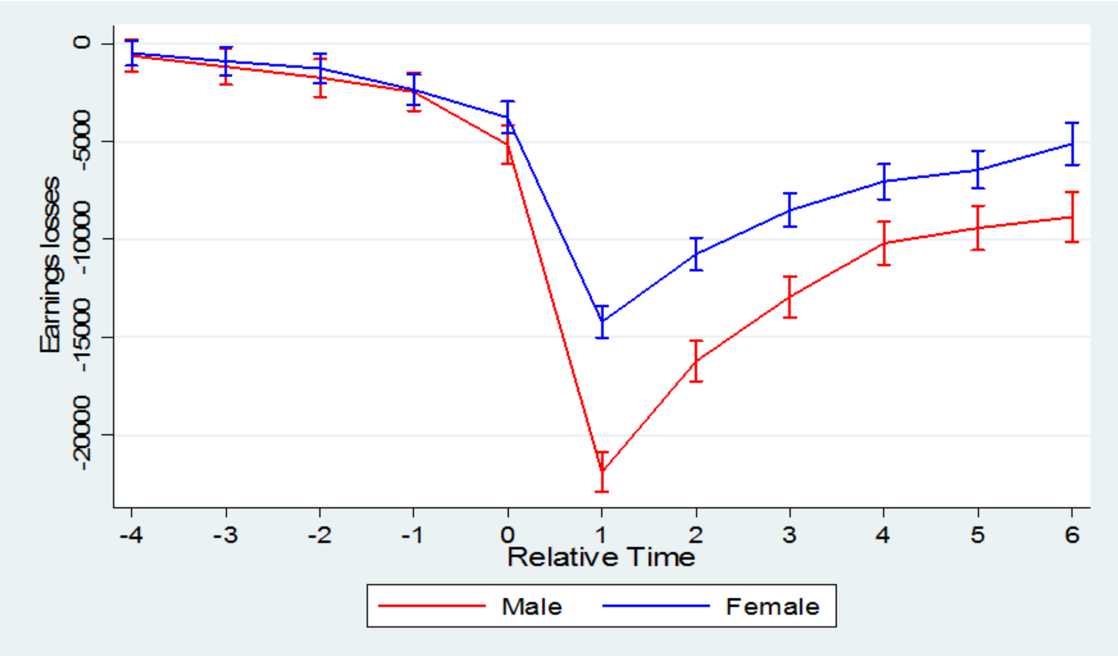
Here we briefly report findings from the unrestricted mass-layoff sample. As we can see from the above, the mass-layoff group experience losses of almost €20,000 (42%) in the period following displacement. Earnings do show signs of recovery but they do not return to their pre-displacement level within the period in question. When we compare these losses to those of the restricted mass-layoff sample, we see that these earnings losses here are smaller than those of the restricted sample. Thus we suggest the findings from the restricted sample is more representative of workers displaced due to mass-layoff. This unrestricted sample may be capturing voluntary as well as involuntary separations and so may not give a truly accurate picture of the earnings losses of displaced workers.

Appendix Figure 4.1: **Earnings losses of mass-layoff workers (unrestricted sample)**



Looking at gender differneces in the restricted sample we see that male workers experience greater losses when compared to female workers. Again this is the same as reported for the restricted mass-layoff sample, but we see that the group that reported losses are smaller in the unrestricted sample.

Appendix Figure 4.2: Earnings losses of mass-layoff workers by gender (unrestricted sample)



Appendix 5 : Nationality, Nace Rev.2 sectors and Firm size categories used in matching

Appendix Table 5.1: Overview of Nationality, NACE Rev.2 sector and Firm size categories used in matching

(A) Nationality groups

Nationality Group	**Countries**
Group 1	Ireland
Group 2	UK, Northern Ireland, Isle of Man
Group 3	Western Europe
Group 4	Eastern Europe
Group 5	Asia
Group 6	Rest of the world

(B) Age categories

Age Category	Years
1	16-25 years
2	26-35 years
3	36-45 years
4	46-55 years
5	56-64 years
6	65+ years

(C) NACE sector groups

NACE Group	**NACE Rev.2 Sectors**
Group 1	A, B, C, D, E, F
Group 2	G, H, I, J, L, R, S, T, U
Group 3	K, M, N
Group 4	O, P, Q

(D) Firm size groups

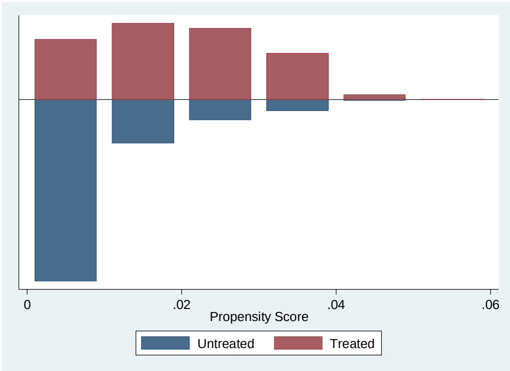
Firm size group	**Firm size (no. of employment records)**
Group 1	0-9
Group 2	10-19
Group 3	20-49
Group 4	50-249
Group 5	250+

Appendix 6 : Results of Common support & Balance tests

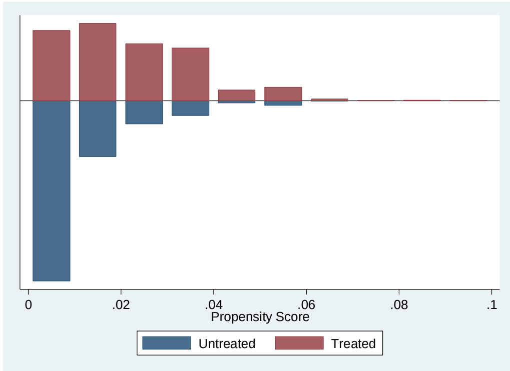
Appendix Figure 6.1: Graphs used to assess Common Support; Closure and Mass-Layoff samples

- **Closure**

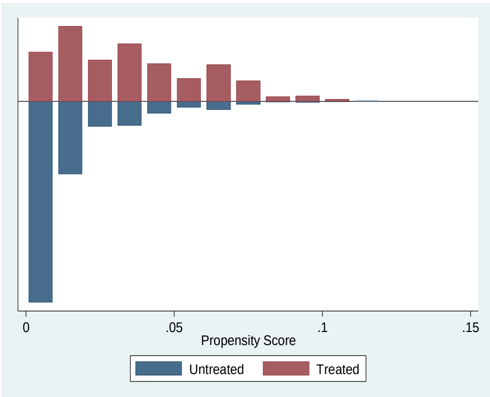
2005



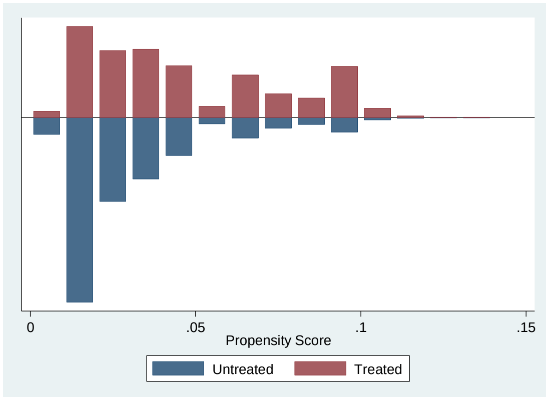
2006



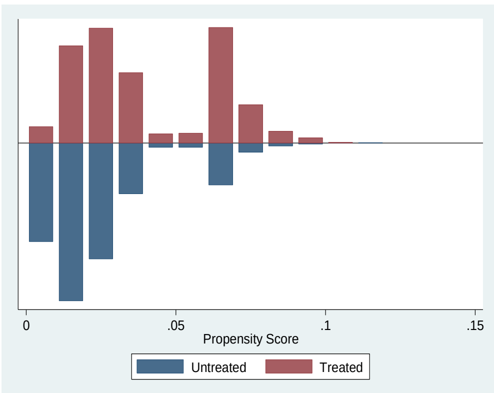
2007



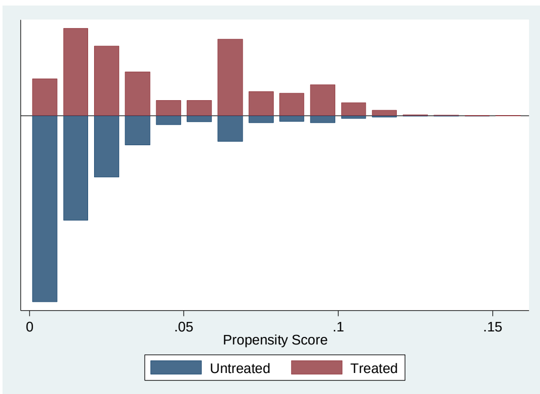
2008



2009

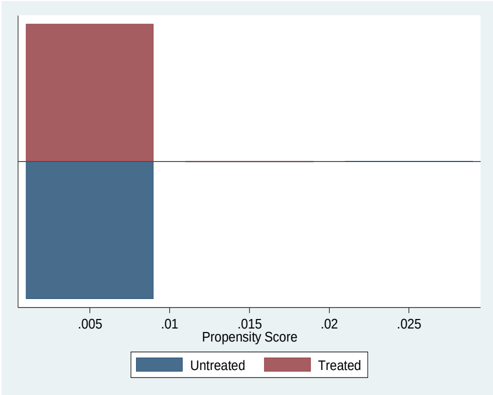


2010

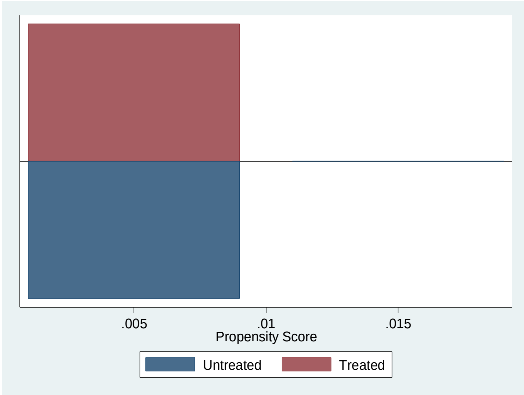


- **Mass layoff**

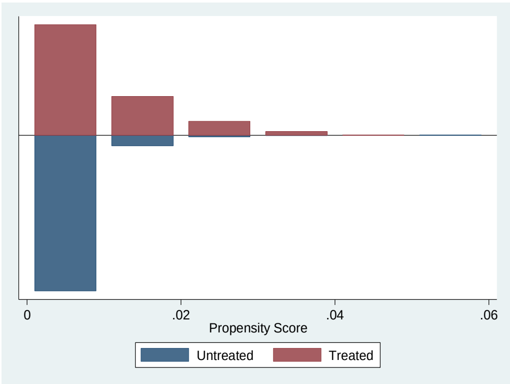
2005



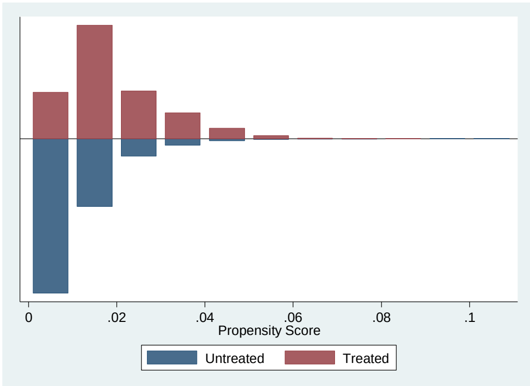
2006



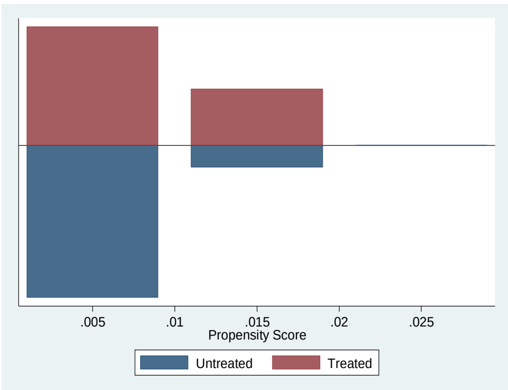
2007



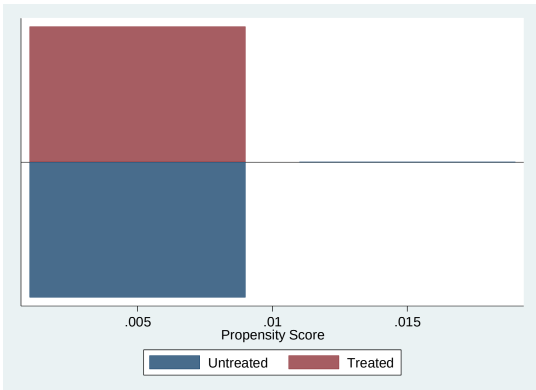
2008



2009



2010



Appendix Table 6.1: Balance Test results; Closure sample

(a) 2005

Variable		Mean Treated	Mean Control	%bias	%bias Reduction	T-test t	T-test p>|t|
sexd2	Unmatched	0.63869	0.53888	20.4		20.17	0
	Matched	0.63869	0.63908	-0.1	99.6	-0.06	0.954
age	Unmatched	37.009	38.179	-9.4		-9.69	0
	Matched	37.009	37.001	0.1	99.3	0.05	0.964
age2	Unmatched	1531.9	1605.4	-7.2		-7.4	0
	Matched	1531.9	1531	0.1	98.7	0.06	0.95
natd1	Unmatched	0.85217	0.88869	-10.9		-11.68	0
	Matched	0.85217	0.85236	-0.1	99.5	-0.04	0.969
natd2	Unmatched	0.03728	0.03009	4		4.23	0
	Matched	0.03728	0.03737	-0.1	98.6	-0.04	0.971
natd3	Unmatched	0.01243	0.01584	-2.9		-2.75	0.006
	Matched	0.01243	0.01243	0	100	0	1
natd4	Unmatched	0.0589	0.03555	11		12.67	0
	Matched	0.0589	0.05909	-0.1	99.2	-0.06	0.953
natd5	Unmatched	0.02152	0.01432	5.4		6.1	0
	Matched	0.02152	0.02152	0	100	0	1
firmscd1	Unmatched	0.45739	0.12883	77.4		98.29	0
	Matched	0.45739	0.45729	0	100	0.01	0.989
firmscd2	Unmatched	0.15693	0.07862	24.5		29.2	0
	Matched	0.15693	0.15625	0.2	99.1	0.13	0.893
firmscd3	Unmatched	0.16016	0.11836	12.1		13.01	0
	Matched	0.16016	0.16045	-0.1	99.3	-0.06	0.954
firmscd4	Unmatched	0.1538	0.18391	-8		-7.83	0
	Matched	0.1538	0.1539	0	99.7	-0.02	0.985
naced1	Unmatched	0.37628	0.24877	27.8		29.67	0
	Matched	0.37628	0.37677	-0.1	99.6	-0.07	0.942
naced2	Unmatched	0.47256	0.34602	25.9		26.77	0
	Matched	0.47256	0.47275	0	99.8	-0.03	0.978
naced3	Unmatched	0.12905	0.14026	-3.3		-3.25	0.001
	Matched	0.12905	0.12905	0	100	0	1

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.110
Matched	0.000

(b) 2006

Variable		Mean		% bias	% bias	T-test	
		Treated	Control		reduction	t	p>|t|
sexd2	Unmatched	0.60092	0.54943	10.4		12.23	0
	Matched	0.60092	0.60071	0	99.6	0.04	0.971
age	Unmatched	36.874	38.315	-11.7		-14.03	0
	Matched	36.874	36.861	0.1	99.1	0.09	0.931
age2	Unmatched	1515.8	1615.3	-9.8		-11.74	0
	Matched	1515.8	1514.7	0.1	99	0.08	0.932
natd1	Unmatched	0.79795	0.85876	-16.2		-20.6	0
	Matched	0.79795	0.79851	-0.2	99.1	-0.12	0.906
natd2	Unmatched	0.03676	0.03032	3.6		4.43	0
	Matched	0.03676	0.03676	0	100	0	1
natd3	Unmatched	0.01983	0.01742	1.8		2.17	0.03
	Matched	0.01983	0.01962	0.2	91.2	0.13	0.898
natd4	Unmatched	0.10567	0.06093	16.2		22.03	0
	Matched	0.10567	0.10567	0	100	0	1
natd5	Unmatched	0.01962	0.01561	3.1		3.82	0
	Matched	0.01962	0.01926	0.3	91.2	0.22	0.829
firmscd1	Unmatched	0.42103	0.13147	68.4		100.68	0
	Matched	0.42103	0.42103	0	100	0	1
firmscd2	Unmatched	0.12238	0.08143	13.6		17.66	0
	Matched	0.12238	0.12195	0.1	99	0.11	0.913
firmscd3	Unmatched	0.14993	0.12209	8.1		10.04	0
	Matched	0.14993	0.15028	-0.1	98.7	-0.08	0.934
firmscd4	Unmatched	0.14752	0.19319	-12.2		-13.69	0
	Matched	0.14752	0.14759	0	99.8	-0.02	0.987
naced1	Unmatched	0.28711	0.25802	6.5		7.86	0
	Matched	0.28711	0.28732	0	99.3	-0.04	0.969
naced2	Unmatched	0.43251	0.34774	17.4		21.03	0
	Matched	0.43251	0.43265	0	99.8	-0.02	0.981
naced3	Unmatched	0.25807	0.14129	29.5		39.51	0
	Matched	0.25807	0.25793	0	99	0.03	0.978

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.090
Matched	0.000

(c) 2007

Variable		Mean Treated	Mean Control	% bias	% bias reduction	T-test t	T-test p>|t|
sexd2	Unmatched	0.69229	0.54296	31.1		42.67	0
	Matched	0.69229	0.69283	-0.1	99.6	-0.12	0.906
age	Unmatched	36.437	38.407	-16.2		-23.13	0
	Matched	36.437	36.419	0.1	99.1	0.14	0.885
age2	Unmatched	1477.6	1621.8	-14.4		-20.43	0
	Matched	1477.6	1475.5	0.2	98.6	0.21	0.835
natd1	Unmatched	0.75122	0.83431	-20.6		-31.69	0
	Matched	0.75122	0.75146	-0.1	99.7	-0.06	0.954
natd2	Unmatched	0.03797	0.03085	3.9		5.84	0
	Matched	0.03797	0.03797	0	100	0	1
natd3	Unmatched	0.01833	0.0186	-0.2		-0.29	0.774
	Matched	0.01833	0.01803	0.2	-7.1	0.22	0.825
natd4	Unmatched	0.14598	0.07994	21		34.46	0
	Matched	0.14598	0.14623	-0.1	99.6	-0.07	0.944
natd5	Unmatched	0.0192	0.01672	1.9		2.75	0.006
	Matched	0.0192	0.01935	-0.1	94.1	-0.11	0.914
firmscd1	Unmatched	0.45408	0.12959	76.4		136.21	0
	Matched	0.45408	0.45394	0	100	0.03	0.976
firmscd2	Unmatched	0.13775	0.08004	18.6		30.11	0
	Matched	0.13775	0.13775	0	100	0	1
firmscd3	Unmatched	0.13965	0.12015	5.8		8.52	0
	Matched	0.13965	0.13955	0	99.5	0.03	0.977
firmscd4	Unmatched	0.16641	0.19142	-6.5		-9.05	0
	Matched	0.16641	0.1667	-0.1	98.8	-0.08	0.937
naced1	Unmatched	0.4595	0.24812	45.3		69.42	0
	Matched	0.4595	0.45964	0	99.9	-0.03	0.976
naced2	Unmatched	0.38336	0.34932	7.1		10.15	0
	Matched	0.38336	0.38375	-0.1	98.9	-0.08	0.935
naced3	Unmatched	0.13399	0.14651	-3.6		-5.04	0
	Matched	0.13399	0.1336	0.1	96.9	0.12	0.908

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.115
Matched	0.000

(d) 2008

Variable		Mean Treated	Control	%bias	% bias Reduction	T-Test t	p>|t|
sexd2	Unmatched	0.59673	0.53515	12.4		25.87	0
	Matched	0.59673	0.5966	0	99.8	0.04	0.968
Age	Unmatched	38.358	38.514	-1.3		-2.7	0.007
	Matched	38.358	38.343	0.1	90.9	0.17	0.862
age2	Unmatched	1620.4	1629	-0.9		-1.8	0.072
	Matched	1620.4	1618.9	0.1	83.3	0.21	0.833
natd1	Unmatched	0.80061	0.8201	-5		-10.61	0
	Matched	0.80061	0.80094	-0.1	98.3	-0.12	0.901
natd2	Unmatched	0.03761	0.03164	3.3		7.12	0
	Matched	0.03761	0.03767	0	98.9	-0.05	0.958
natd3	Unmatched	0.01847	0.0212	-2		-3.98	0
	Matched	0.01847	0.01818	0.2	89.5	0.32	0.747
natd4	Unmatched	0.09744	0.0855	4.1		8.92	0
	Matched	0.09744	0.09753	0	99.3	-0.04	0.964
natd5	Unmatched	0.01741	0.01896	-1.2		-2.38	0.017
	Matched	0.01741	0.01726	0.1	90	0.18	0.859
firmscd1	Unmatched	0.34476	0.12961	52.3		132.09	0
	Matched	0.34476	0.34482	0	100	-0.02	0.983
firmscd2	Unmatched	0.09793	0.08097	5.9		12.98	0
	Matched	0.09793	0.09786	0	99.6	0.03	0.973
firmscd3	Unmatched	0.1187	0.12175	-0.9		-1.96	0.05
	Matched	0.1187	0.11856	0	95.7	0.06	0.951
firmscd4	Unmatched	0.20843	0.18924	4.8		10.25	0
	Matched	0.20843	0.20856	0	99.3	-0.05	0.961
naced1	Unmatched	0.31424	0.22624	19.9		43.89	0
	Matched	0.31424	0.31435	0	99.9	-0.04	0.971
naced2	Unmatched	0.33132	0.36341	-6.7		-13.98	0
	Matched	0.33132	0.3315	0	99.4	-0.06	0.955
naced3	Unmatched	0.14645	0.15353	-2		-4.12	0
	Matched	0.14645	0.14629	0	97.8	0.07	0.948

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.049
Matched	0.000

(e) 2009

Variable		Mean		% Bias	% bias	T-Test	
		Control	Treated		reduction	t	p>|t|
sexd2	Unmatched	0.5865	0.51949	13.5		23.88	0
	Matched	0.5865	0.58659	0	99.9	-0.02	0.981
Age	Unmatched	38.27	38.853	-4.8		-8.64	0
	Matched	38.27	38.249	0.2	96.3	0.22	0.827
age2	Unmatched	1618.5	1653.4	-3.4		-6.17	0
	Matched	1618.5	1616.4	0.2	93.8	0.27	0.79
natd1	Unmatched	0.77388	0.81726	-10.8		-19.94	0
	Matched	0.77388	0.77428	-0.1	99.1	-0.12	0.903
natd2	Unmatched	0.03427	0.03335	0.5		0.91	0.362
	Matched	0.03427	0.03411	0.1	83.3	0.11	0.914
natd3	Unmatched	0.01991	0.0217	-1.3		-2.19	0.028
	Matched	0.01991	0.01969	0.2	88	0.2	0.844
natd4	Unmatched	0.115	0.08181	11.2		21.47	0
	Matched	0.115	0.11512	0	99.6	-0.05	0.961
natd5	Unmatched	0.02296	0.02212	0.6		1.01	0.312
	Matched	0.02296	0.0228	0.1	81.6	0.13	0.896
firmscd1	Unmatched	0.38941	0.13629	60		129.78	0
	Matched	0.38941	0.38941	0	100	0	1
firmscd2	Unmatched	0.11509	0.08323	10.7		20.45	0
	Matched	0.11509	0.11525	-0.1	99.5	-0.06	0.951
firmscd3	Unmatched	0.12344	0.12058	0.9		1.56	0.118
	Matched	0.12344	0.12335	0	96.8	0.04	0.971
firmscd4	Unmatched	0.1802	0.18822	-2.1		-3.65	0
	Matched	0.1802	0.18027	0	99.2	-0.02	0.984
naced1	Unmatched	0.27139	0.19918	17.1		32.09	0
	Matched	0.27139	0.27157	0	99.7	-0.05	0.958
naced2	Unmatched	0.47103	0.3768	19.2		34.59	0
	Matched	0.47103	0.47137	-0.1	99.6	-0.09	0.931
naced3	Unmatched	0.16301	0.15648	1.8		3.2	0.001
	Matched	0.16301	0.16242	0.2	91	0.2	0.84

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.063
Matched	0.000

(f) 2010

Variable		Mean Treated	Mean Control	% bias	% bias reduction	T-Test t	T-Test p>|t|
sexd2	Unmatched	0.5911	0.4989	18.6		31.58	0
	Matched	0.5911	0.5913	0	99.8	-0.05	0.96
age	Unmatched	38.664	39.53	-7.2		-12.5	0
	Matched	38.664	38.644	0.2	97.7	0.2	0.84
age2	Unmatched	1646.9	1702.9	-5.5		-9.57	0
	Matched	1646.9	1644.9	0.2	96.4	0.23	0.816
natd1	Unmatched	0.77906	0.82614	-11.8		-21.22	0
	Matched	0.77906	0.77956	-0.1	98.9	-0.15	0.883
natd2	Unmatched	0.03504	0.03261	1.3		2.34	0.019
	Matched	0.03504	0.03491	0.1	94.5	0.09	0.929
natd3	Unmatched	0.02006	0.02011	0		-0.06	0.952
	Matched	0.02006	0.01982	0.2	-370.3	0.2	0.838
natd4	Unmatched	0.1055	0.07776	9.6		17.67	0
	Matched	0.1055	0.10576	-0.1	99	-0.11	0.915
natd5	Unmatched	0.0269	0.02071	4.1		7.41	0
	Matched	0.0269	0.0266	0.2	95.1	0.23	0.82
firmscd1	Unmatched	0.45419	0.13391	75.1		159.03	0
	Matched	0.45419	0.45406	0	100	0.03	0.974
firmscd2	Unmatched	0.12035	0.07973	13.6		25.55	0
	Matched	0.12035	0.12035	0	100	0	1
firmscd3	Unmatched	0.12085	0.11538	1.7		2.93	0.003
	Matched	0.12085	0.12098	0	97.6	-0.05	0.96
firmscd4	Unmatched	0.14268	0.18161	-10.6		-17.32	0
	Matched	0.14268	0.14278	0	99.7	-0.04	0.972
naced1	Unmatched	0.30037	0.17306	30.3		57.32	0
	Matched	0.30037	0.3007	-0.1	99.7	-0.09	0.929
naced2	Unmatched	0.45363	0.3678	17.5		30.45	0
	Matched	0.45363	0.45359	0	100	0.01	0.993
naced3	Unmatched	0.16237	0.15321	2.5		4.35	0
	Matched	0.16237	0.1623	0	99.3	0.02	0.982

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.096
Matched	0.000

Appendix Table 6.2: Balance Test results; Mass Layoff sample

(a) 2005

Variable		Mean Treated	Mean Control	% bias	% bias reduction	T-Test t	T-Test p>|t|
sexd2	Unmatched	0.55382	0.49117	12.6		5.57	0
	Matched	0.55382	0.55382	0	100	0	1
age	Unmatched	35.293	38.307	-24.6		-11.28	0
	Matched	35.293	35.316	-0.2	99.2	-0.06	0.954
age2	Unmatched	1404	1608.3	-20.8		-9.33	0
	Matched	1404	1405.9	-0.2	99.1	-0.06	0.953
natd1	Unmatched	0.82314	0.8918	-19.7		-9.81	0
	Matched	0.82314	0.82314	0	100	0	1
natd2	Unmatched	0.02931	0.02839	0.5		0.24	0.807
	Matched	0.02931	0.0288	0.3	44.7	0.09	0.925
natd3	Unmatched	0.02779	0.01797	6.6		3.28	0.001
	Matched	0.02779	0.02779	0	100	0	1
natd4	Unmatched	0.07226	0.02995	19.3		11.01	0
	Matched	0.07226	0.07276	-0.2	98.8	-0.06	0.951
natd5	Unmatched	0.01819	0.01577	1.9		0.87	0.387
	Matched	0.01819	0.01819	0	100	0	1
firmscd1	Unmatched	0.23699	0.21085	6.3		2.85	0.004
	Matched	0.23699	0.23699	0	100	0	1
naced1	Unmatched	0.35068	0.20059	34.1		16.65	0
	Matched	0.35068	0.35068	0	100	0	1
naced2	Unmatched	0.40829	0.27552	28.3		13.2	0
	Matched	0.40829	0.40829	0	100	0	1
naced3	Unmatched	0.08691	0.13272	-14.7		-6	0
	Matched	0.08691	0.08691	0	100	0	1

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.032
Matched	0.000

(b) 2006

Variable		Mean Treated	Control	%bias	%bias reduction	T-Test t	p>|t|
sexd2	Unmatched	0.46432	0.5009	-7.3		-3.48	0
	Matched	0.46432	0.46432	0	100	0	1
age	Unmatched	37.633	38.401	-6.4		-3.09	0.002
	Matched	37.633	37.631	0	99.8	0	0.996
age2	Unmatched	1565.2	1614.8	-5.1		-2.43	0.015
	Matched	1565.2	1564.9	0	99.6	0.01	0.994
natd1	Unmatched	0.82115	0.86559	-12.2		-6.2	0
	Matched	0.82115	0.82115	0	100	0	1
natd2	Unmatched	0.037	0.02845	4.8		2.45	0.014
	Matched	0.037	0.037	0	100	0	1
natd3	Unmatched	0.02952	0.01996	6.2		3.25	0.001
	Matched	0.02952	0.02952	0	100	0	1
natd4	Unmatched	0.08018	0.05096	11.8		6.32	0
	Matched	0.08018	0.08018	0	100	0	1
natd5	Unmatched	0.01322	0.01709	-3.2		-1.42	0.155
	Matched	0.01322	0.01322	0	100	0	1
firmscd1	Unmatched	0.23789	0.2181	4.7		2.28	0.023
	Matched	0.23789	0.23789	0	100	0	1
naced1	Unmatched	0.29207	0.20426	20.4		10.36	0
	Matched	0.29207	0.29163	0.1	99.5	0.03	0.974
naced2	Unmatched	0.26652	0.28077	-3.2		-1.51	0.131
	Matched	0.26652	0.26652	0	100	0	1
naced3	Unmatched	0.24097	0.14083	25.7		13.69	0
	Matched	0.24097	0.24141	-0.1	99.6	-0.03	0.972

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.017
Matched	0.000

(c) 2007

Variable		Mean Treated	Control	%bias	%bias reduction	T-Test t	p>|t|
sexd2	Unmatched	0.65824	0.49083	34.4		18.33	0
	Matched	0.65824	0.6579	0.1	99.8	0.03	0.978
age	Unmatched	33.861	38.473	-39.4		-21.29	0
	Matched	33.861	33.826	0.3	99.2	0.12	0.907
age2	Unmatched	1280.2	1620.8	-35.7		-19.09	0
	Matched	1280.2	1276.5	0.4	98.9	0.15	0.878
natd1	Unmatched	0.55641	0.84318	-65.9		-43.09	0
	Matched	0.55641	0.55607	0.1	99.9	0.03	0.979
natd2	Unmatched	0.03827	0.02903	5.1		3.01	0.003
	Matched	0.03827	0.03794	0.2	96.4	0.07	0.946
natd3	Unmatched	0.10782	0.02088	36		33.07	0
	Matched	0.10782	0.10815	-0.1	99.6	-0.04	0.967
natd4	Unmatched	0.24759	0.06818	50.8		38.82	0
	Matched	0.24759	0.24792	-0.1	99.8	-0.03	0.976
natd5	Unmatched	0.01797	0.01861	-0.5		-0.26	0.794
	Matched	0.01797	0.01797	0	100	0	1
firmscd1	Unmatched	0.27654	0.2101	15.5		8.92	0
	Matched	0.27654	0.2772	-0.2	99	-0.06	0.954
naced1	Unmatched	0.27088	0.19545	17.9		10.4	0
	Matched	0.27088	0.27088	0	100	0	1
naced2	Unmatched	0.39434	0.28587	23		13.13	0
	Matched	0.39434	0.39368	0.1	99.4	0.05	0.958
naced3	Unmatched	0.30349	0.13791	40.7		26.25	0
	Matched	0.30349	0.30416	-0.2	99.6	-0.06	0.955

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.089
Matched	0.000

(d) 2008

Variable		Mean Treated	Mean Control	%bias	%bias reduction	T-Test t	T-Test p>|t|
sexd2	Unmatched	0.66543	0.48672	36.8		32.01	0
	Matched	0.66543	0.66543	0	100	0	1
age	Unmatched	33.886	38.487	-39.5		-34.82	0
	Matched	33.886	33.887	0	100	-0.01	0.994
age2	Unmatched	1279.8	1621.1	-36		-31.31	0
	Matched	1279.8	1279.8	0	100	0	0.997
natd1	Unmatched	0.61666	0.82568	-47.9		-49.16	0
	Matched	0.61666	0.61678	0	99.9	-0.02	0.987
natd2	Unmatched	0.03317	0.02981	1.9		1.77	0.077
	Matched	0.03317	0.0328	0.2	89	0.13	0.895
natd3	Unmatched	0.0562	0.02371	16.6		19	0
	Matched	0.0562	0.05607	0.1	99.6	0.03	0.973
natd4	Unmatched	0.22181	0.07698	41.5		48.32	0
	Matched	0.22181	0.22193	0	99.9	-0.02	0.985
natd5	Unmatched	0.02451	0.02086	2.5		2.29	0.022
	Matched	0.02451	0.02451	0	100	0	1
firmscd1	Unmatched	0.37492	0.21281	36.2		35.38	0
	Matched	0.37492	0.37517	-0.1	99.8	-0.03	0.974
naced1	Unmatched	0.36193	0.18308	41		41.29	0
	Matched	0.36193	0.36193	0	100	0	1
naced2	Unmatched	0.33457	0.29797	7.9		7.16	0
	Matched	0.33457	0.33445	0	99.7	0.02	0.987
naced3	Unmatched	0.28382	0.14374	34.7		35.63	0
	Matched	0.28382	0.28395	0	99.9	-0.02	0.986

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.099
Matched	0.000

(e) **2009**

Variable		Mean Treated	Mean Control	%bias	%bias reduction	T-Test t	T-Test p>|t|
sexd2	Unmatched	0.67461	0.47494	41.2		27.22	0
	Matched	0.67461	0.67461	0	100	0	1
age	Unmatched	38.404	38.949	-4.6		-3.17	0.002
	Matched	38.404	38.391	0.1	97.5	0.06	0.956
age2	Unmatched	1613.5	1653.8	-4.1		-2.82	0.005
	Matched	1613.5	1612.3	0.1	96.9	0.06	0.952
natd1	Unmatched	0.77899	0.8261	-11.9		-8.45	0
	Matched	0.77899	0.77921	-0.1	99.5	-0.02	0.98
natd2	Unmatched	0.0421	0.03113	5.8		4.29	0
	Matched	0.0421	0.04231	-0.1	98	-0.05	0.959
natd3	Unmatched	0.03759	0.02327	8.3		6.45	0
	Matched	0.03759	0.03716	0.3	97	0.11	0.913
natd4	Unmatched	0.093	0.07318	7.2		5.18	0
	Matched	0.093	0.09321	-0.1	98.9	-0.04	0.972
natd5	Unmatched	0.0204	0.02284	-1.7		-1.11	0.267
	Matched	0.0204	0.02062	-0.1	91.2	-0.07	0.942
firmscd1	Unmatched	0.29961	0.22811	16.3		11.59	0
	Matched	0.29961	0.29983	0	99.7	-0.02	0.982
naced1	Unmatched	0.37135	0.1674	47.2		37.12	0
	Matched	0.37135	0.37178	-0.1	99.8	-0.04	0.966
naced2	Unmatched	0.31014	0.28691	5.1		3.49	0
	Matched	0.31014	0.31014	0	100	0	1
naced3	Unmatched	0.17182	0.14178	8.3		5.86	0
	Matched	0.17182	0.17139	0.1	98.6	0.05	0.956

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.038
Matched	0.000

(f) 2010

Variable		Mean Treated	Control	%bias	%bias reduction	T-Test t	p>|t|
Variable	Matched	Treated	Control	%bias	|bias|	t	p>|t|
sexd2	Unmatched	0.62903	0.47085	32.2		14.95	0
	Matched	0.62903	0.62858	0.1	99.7	0.03	0.975
age	Unmatched	37.703	39.446	-15.2		-7.14	0
	Matched	37.703	37.682	0.2	98.8	0.06	0.952
age2	Unmatched	1553.4	1688.9	-14.1		-6.61	0
	Matched	1553.4	1551.3	0.2	98.5	0.07	0.943
natd1	Unmatched	0.73342	0.82782	-23		-11.79	0
	Matched	0.73342	0.73342	0	100	0	1
natd2	Unmatched	0.02778	0.03093	-1.9		-0.86	0.39
	Matched	0.02778	0.02733	0.3	85.8	0.09	0.927
natd3	Unmatched	0.04077	0.02298	10.1		5.6	0
	Matched	0.04077	0.04122	-0.3	97.5	-0.08	0.94
natd4	Unmatched	0.1241	0.07312	17.2		9.23	0
	Matched	0.1241	0.1241	0	100	0	1
natd5	Unmatched	0.03271	0.02206	6.5		3.42	0.001
	Matched	0.03271	0.03315	-0.3	95.8	-0.08	0.933
firmscd1	Unmatched	0.32751	0.23202	21.4		10.67	0
	Matched	0.32751	0.32796	-0.1	99.5	-0.03	0.975
naced1	Unmatched	0.26971	0.15497	28.3		14.95	0
	Matched	0.26971	0.27016	-0.1	99.6	-0.03	0.973
naced2	Unmatched	0.48522	0.28549	41.9		20.86	0
	Matched	0.48522	0.48477	0.1	99.8	0.03	0.976
naced3	Unmatched	0.194	0.14808	12.2		6.1	0
	Matched	0.194	0.194	0	100	0	1

Pseudo-R^2

Sample	Pseudo-R^2
Raw	0.095
Matched	0.000

Appendix 7 : Propensity score matching results

Appendix Table 7.1: Propensity score matching results; Closure sample

	2005	**2006**	**2007**	**2008**	**2009**	**2010**
VARIABLES	d_closure	d_closure	d_closure	d_closure	d_closure	d_closure
sexd2	0.001	-0.021***	0.047***	0.049***	0.022***	0.019***
	(0.009)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Age	-0.009***	-0.012***	-0.012***	-0.002*	-0.010***	-0.017***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
age2	0.0001***	0.0001***	0.0001***	0.0001	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
natd1	-0.109***	-0.098***	-0.192***	-0.133***	-0.197***	-0.219***
	(0.030)	(0.024)	(0.019)	(0.013)	(0.014)	(0.015)
natd2	-0.022	-0.018	-0.065***	-0.053***	-0.166***	-0.166***
	(0.036)	(0.030)	(0.024)	(0.017)	(0.019)	(0.020)
natd3	-0.100**	-0.009	-0.074***	-0.076***	-0.158***	-0.122***
	(0.045)	(0.034)	(0.028)	(0.020)	(0.022)	(0.023)
natd4	0.018	0.126***	0.000	-0.081***	-0.061***	-0.115***
	(0.034)	(0.026)	(0.020)	(0.015)	(0.016)	(0.017)
natd5	0.093**	0.058*	-0.019	-0.135***	-0.115***	-0.014
	(0.040)	(0.035)	(0.029)	(0.020)	(0.021)	(0.022)
firmscd1	1.005***	0.770***	0.956***	0.808***	0.742***	0.881***
	(0.013)	(0.010)	(0.009)	(0.006)	(0.007)	(0.007)
firmscd2	0.765***	0.446***	0.634***	0.444***	0.405***	0.507***
	(0.015)	(0.012)	(0.011)	(0.008)	(0.009)	(0.009)
firmscd3	0.627***	0.382***	0.484***	0.340***	0.285***	0.364***
	(0.015)	(0.012)	(0.011)	(0.007)	(0.008)	(0.009)
firmscd4	0.447***	0.192***	0.354***	0.383***	0.255***	0.230***
	(0.015)	(0.011)	(0.010)	(0.006)	(0.007)	(0.008)
naced1	0.662***	0.617***	0.755***	-0.074***	0.323***	0.516***
	(0.023)	(0.020)	(0.017)	(0.007)	(0.009)	(0.010)
naced2	0.580***	0.661***	0.553***	-0.241***	0.282***	0.316***
	(0.022)	(0.019)	(0.016)	(0.006)	(0.008)	(0.009)
naced3	0.516***	0.906***	0.541***	-0.161***	0.265***	0.336***
	(0.024)	(0.019)	(0.017)	(0.008)	(0.009)	(0.010)
_cons	-3.231***	-2.939***	-2.804***	-1.918***	-2.166***	-2.151***
	(0.051)	(0.044)	(0.038)	(0.026)	(0.029)	(0.031)
Observations	1,285,192	1,328,344	1,416,153	1,454,277	1,378,761	1,365,468
LR chi^2	13,137.46	14,143	24,758.34	19,882.29	19,460.79	27,641.12
Prob>chi^2	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.1102	0.0904	0.1154	0.0493	0.0633	0.0959

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 7.2: Propensity score matching results; Mass Layoff sample

VARIABLES	**2005** d_mass	**2006** d_mass	**2007** d_mass	**2008** d_mass	**2009** d_mass	**2010** d_mass
sexd2	0.003	-0.115***	0.147***	0.149***	0.171***	0.0888***
	(0.015)	(0.0144)	(0.0138)	(0.00943)	(0.0112)	(0.0149)
Age	-0.040***	-0.0145***	-0.0411***	-0.0518***	-0.0114***	-0.00789*
	(0.004)	(0.00368)	(0.00338)	(0.00234)	(0.00294)	(0.00405)
age2	0.000***	0.000196***	0.000479***	0.000572***	0.000151***	0.000110**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
natd1	-0.199***	-0.0129	-0.209***	-0.310***	-0.0476	-0.161***
	(0.046)	(0.0510)	(0.0375)	(0.0221)	(0.0320)	(0.0374)
natd2	-0.147**	0.0838	-0.000551	-0.178***	0.0639	-0.190***
	(0.062)	(0.0623)	(0.0492)	(0.0322)	(0.0408)	(0.0555)
natd3	-0.061	0.0891	0.391***	0.0285	0.100**	-0.0318
	(0.064)	(0.0652)	(0.0430)	(0.0291)	(0.0419)	(0.0514)
natd4	-0.001	0.0967*	0.218***	0.00722	-0.0511	-0.0907**
	(0.054)	(0.0564)	(0.0392)	(0.0237)	(0.0359)	(0.0418)
natd5	-0.157**	-0.0252	-0.113*	-0.138***	-0.00634	0.0533
	(0.072)	(0.0765)	(0.0593)	(0.0355)	(0.0473)	(0.0542)
firmscd1	-0.079***	-0.0161	-0.00563	0.171***	0.0203*	0.0121
	(0.018)	(0.0168)	(0.0146)	(0.00936)	(0.0119)	(0.0154)
naced1	0.457***	0.356***	0.719***	1.059***	0.555***	0.767***
	(0.023)	(0.0208)	(0.0317)	(0.0244)	(0.0161)	(0.0301)
naced2	0.373***	0.193***	0.708***	0.788***	0.314***	0.763***
	(0.022)	(0.0207)	(0.0307)	(0.0244)	(0.0162)	(0.0285)
naced3	0.117***	0.391***	0.880***	1.071***	0.369***	0.686***
	(0.030)	(0.0213)	(0.0314)	(0.0246)	(0.0179)	(0.0307)
Constant	-2.095***	-2.691***	-2.520***	-2.039***	-2.738***	-3.187***
	(0.086)	(0.0903)	(0.0800)	(0.0547)	(0.0682)	(0.0927)
Observations	809,695	826,122	879,004	920,533	915,577	887,179
LR chi^2	897.13	536.53	3,561.13	9,147.01	2,205.14	1,669.09
Prob>chi^2	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.0323	0.0171	0.0887	0.0988	0.0377	0.0535

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 8 : Regression results for closure and mass-layoff samples (all time periods)

Appendix Table 8.1: Regression output for Figure 4.1

VARIABLES	**Closure** Displaced emp	**Closure** Non-displaced emp	**Mass Layoff** Displaced emp	**Mass Layoff** Non-displaced emp
2.rel_time_group	0.727***	0.759***	0.658***	0.717***
	(0.00170)	(0.00142)	(0.00503)	(0.00445)
3.rel_time_group	0.782***	0.808***	0.622***	0.703***
	(0.00130)	(0.00108)	(0.00342)	(0.00302)
4.rel_time_group	0.829***	0.861***	0.703***	0.785***
	(0.00119)	(0.000994)	(0.00312)	(0.00275)
5.rel_time_group	0.891***	0.930***	0.878***	0.919***
	(0.00113)	(0.000943)	(0.00294)	(0.00259)
6.rel_time_group	1***	1***	1***	1***
	(0.00109)	(0.000911)	(0.00280)	(0.00248)
7.rel_time_group	0.542***	0.933***	0.272***	0.927***
	(0.00109)	(0.000911)	(0.00280)	(0.00248)
8.rel_time_group	0.572***	0.829***	0.285***	0.807***
	(0.00122)	(0.00102)	(0.00296)	(0.00261)
9.rel_time_group	0.565***	0.756***	0.298***	0.722***
	(0.00142)	(0.00119)	(0.00337)	(0.00298)
10.rel_time_group	0.508***	0.690***	0.341***	0.672***
	(0.00201)	(0.00168)	(0.00491)	(0.00433)
11.rel_time_group	0.522***	0.672***	0.382***	0.656***
	(0.00273)	(0.00228)	(0.00641)	(0.00566)
12.rel_time_group	0.511***	0.657***	0.409***	0.614***
	(0.00421)	(0.00352)	(0.00939)	(0.00830)
Observations	1,067,710	1,067,710	155,547	155,547
Fstat	-	-	-	-
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.752	0.853	0.695	0.835

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.2: Regression output for Figure 4.2

	Closure Displaced Males	**Closure** Displaced Females	**Mass-Layoff** Displaced Males	**Mass-Layoff** Displaced Females
VARIABLES	emp	emp	emp	emp
2.rel_time_group	0.738***	0.712***	0.678***	0.619***
	(0.00223)	(0.00262)	(0.00607)	(0.00888)
3.rel_time_group	0.783***	0.780***	0.645***	0.578***
	(0.00169)	(0.00200)	(0.00411)	(0.00605)
4.rel_time_group	0.826***	0.835***	0.714***	0.680***
	(0.00153)	(0.00187)	(0.00375)	(0.00552)
5.rel_time_group	0.888***	0.895***	0.902***	0.836***
	(0.00145)	(0.00177)	(0.00360)	(0.00504)
6.rel_time_group	1***	1***	1***	1***
	(0.00140)	(0.00172)	(0.00345)	(0.00476)
7.rel_time_group	0.509***	0.595***	0.262***	0.290***
	(0.00140)	(0.00172)	(0.00345)	(0.00476)
8.rel_time_group	0.534***	0.632***	0.275***	0.300***
	(0.00156)	(0.00193)	(0.00364)	(0.00502)
9.rel_time_group	0.517***	0.643***	0.270***	0.342***
	(0.00180)	(0.00228)	(0.00420)	(0.00563)
10.rel_time_group	0.464***	0.589***	0.303***	0.392***
	(0.00250)	(0.00335)	(0.00637)	(0.00769)
11.rel_time_group	0.477***	0.593***	0.347***	0.419***
	(0.00349)	(0.00434)	(0.00883)	(0.00939)
12.rel_time_group	0.484***	0.559***	0.381***	0.444***
	(0.00529)	(0.00690)	(0.0124)	(0.0145)
Observations	650,783	416,927	98,339	57,208
Fstat	-	-	-	-
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.744	0.768	0.710	0.672

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.3: Regression output for Figure 4.3

VARIABLES	**Closure** 26-35 years emp	**Closure** 56-64 years emp	**Mass layoff** 26-35 years emp	**Mass layoff** 56-64 years emp
2.rel_time_group	0.737***	0.807***	0.602***	0.861***
	(0.00299)	(0.00557)	(0.00843)	(0.0141)
3.rel_time_group	0.787***	0.851***	0.589***	0.841***
	(0.00227)	(0.00423)	(0.00555)	(0.0106)
4.rel_time_group	0.834***	0.876***	0.690***	0.871***
	(0.00208)	(0.00395)	(0.00504)	(0.00990)
5.rel_time_group	0.897***	0.904***	0.888***	0.903***
	(0.00197)	(0.00376)	(0.00482)	(0.00918)
6.rel_time_group	1***	1***	1***	1***
	(0.00191)	(0.00363)	(0.00462)	(0.00877)
7.rel_time_group	0.580***	0.452***	0.272***	0.181***
	(0.00191)	(0.00363)	(0.00462)	(0.00877)
8.rel_time_group	0.603***	0.465***	0.287***	0.153***
	(0.00213)	(0.00407)	(0.00486)	(0.00932)
9.rel_time_group	0.597***	0.436***	0.291***	0.189***
	(0.00248)	(0.00479)	(0.00553)	(0.0112)
10.rel_time_group	0.548***	0.334***	0.335***	0.220***
	(0.00352)	(0.00710)	(0.00835)	(0.0155)
11.rel_time_group	0.577***	0.299***	0.394***	0.197***
	(0.00484)	(0.00928)	(0.0116)	(0.0189)
12.rel_time_group	0.565***	0.273***	0.426***	0.170***
	(0.00757)	(0.0142)	(0.0165)	(0.0296)
Observations	341,327	89,761	56,931	11,221
Fstat	99,724.92	25,913.58	11,730.68	3,795.97
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.763	0.761	0.694	0.788

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.4: Regression output for Figure 4.4

VARIABLES	**Closure** pay2	VARIABLES	**Mass Layoff** pay2
1.d_ closure	81.1	1.d_mass	-109.0
			(1,034)
1.d_ closure #2.rel_time_group	-1,487***	1.d_mass#2.rel_time_group	-2,215***
	(180.5)		(809.1)
1.d_ closure #3.rel_time_group	-1,228***	1.d_mass#3.rel_time_group	-3,150***
	(206.9)		(900.1)
1.d_ closure #4.rel_time_group	1,816***	1.d_mass#4.rel_time_group	-3,720***
	(216.8)		(928.9)
1.d_ closure #5.rel_time_group	-2,939***	1.d_mass#5.rel_time_group	-4,734***
	(224.4)		(948.4)
1.d_ closure #6.rel_time_group	-3,914***	1.d_mass#6.rel_time_group	-6,123***
	(227.2)		(961.1)
1.d_ closure #7.rel_time_group	-13,689***	1.d_mass#7.rel_time_group	-27,124***
	(234.1)		(971.4)
1.d_ closure #8.rel_time_group	-9,339***	1.d_mass#8.rel_time_group	-22,964***
	(251.0)		(1,002)
1.d_ closure #9.rel_time_group	-6,894***	1.d_mass#9.rel_time_group	-18,375***
	(258.9)		(1,014)
1.d_ closure #10.rel_time_group	-6,828***	1.d_mass#10.rel_time_group	-15,544***
	(283.3)		(1,050)
1.d_ closure #11.rel_time_group	-5,873***	1.d_mass#11.rel_time_group	-14,221***
	(322.3)		(1,096)
1.d_ closure #12.rel_time_group	-6,084***	1.d_mass#12.rel_time_group	-10,382***
	(394.1)		(1,203)
Constant	29,683***	Constant	35,389***
	(171.6)		(729.7)
Observations	2,001,473	*Observations*	284,346
Fstat	4,039.67	*Fstat*	1,147.37
Prob > F	0.000	*Prob > F*	0.000
R-squared	0.0562	*R-squared*	0.165

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

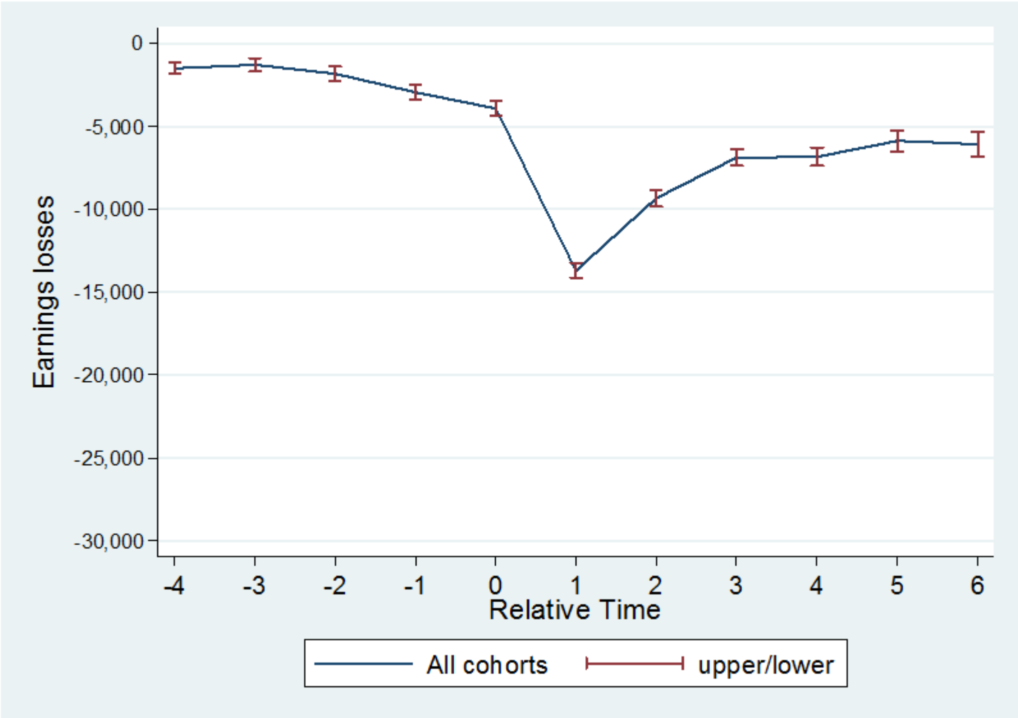
Appendix Table 8.5: Regression output for earnings losses with cohort dummies

	Closure		**Mass Layoff**
VARIABLES	pay2	VARIABLES	pay2
1.d_ closure	81.18	1.d_mass	-109.0
	(248.5)		(1,034)
1.d_ closure #2.rel_time_group	-1,488***	1.d_mass#2.rel_time_group	-2,197***
	(180.5)		(809.6)
1.d_ closure #3.rel_time_group	-1,283***	1.d_mass#3.rel_time_group	-3,241***
	(206.9)		(900.1)
1.d_ closure #4.rel_time_group	-1,834***	1.d_mass#4.rel_time_group	-3,762***
	(216.8)		(928.6)
1.d_ closure #5.rel_time_group	-2,937***	1.d_mass#5.rel_time_group	-4,677***
	(224.3)		(948.2)
1.d_ closure #6.rel_time_group	-3,914***	1.d_mass#6.rel_time_group	-6,123***
	(227.2)		(960.8)
1.d_ closure #7.rel_time_group	-13,690***	1.d_mass#7.rel_time_group	-27,124***
	(234.1)		(971.2)
1.d_ closure #8.rel_time_group	-9,339***	1.d_mass#8.rel_time_group	-22,964***
	(250.9)		(1,002)
1.d_ closure #9.rel_time_group	-6,894***	1.d_mass#9.rel_time_group	-18,375***
	(258.8)		(1,014)
1.d_ closure #10.rel_time_group	-6,829***	1.d_mass#10.rel_time_group	-15,544***
	(283.1)		(1,049)
1.d_ closure #11.rel_time_group	-5,873***	1.d_mass#11.rel_time_group	-14,221***
	(322.4)		(1,096)
1.d_ closure #12.rel_time_group	-6,085***	1.d_mass#12.rel_time_group	-10,382***
	(394.1)		(1,203)
Constant	32,103***	Constant	35,968***
	(236.9)		(739.5)
Observations	2,001,473	*Observations*	284,346
Fstat	3458.20	*Fstat*	1201.27
Prob > F	0.000	*Prob > F*	0.000
R-squared	0.059	*R-squared*	0.172

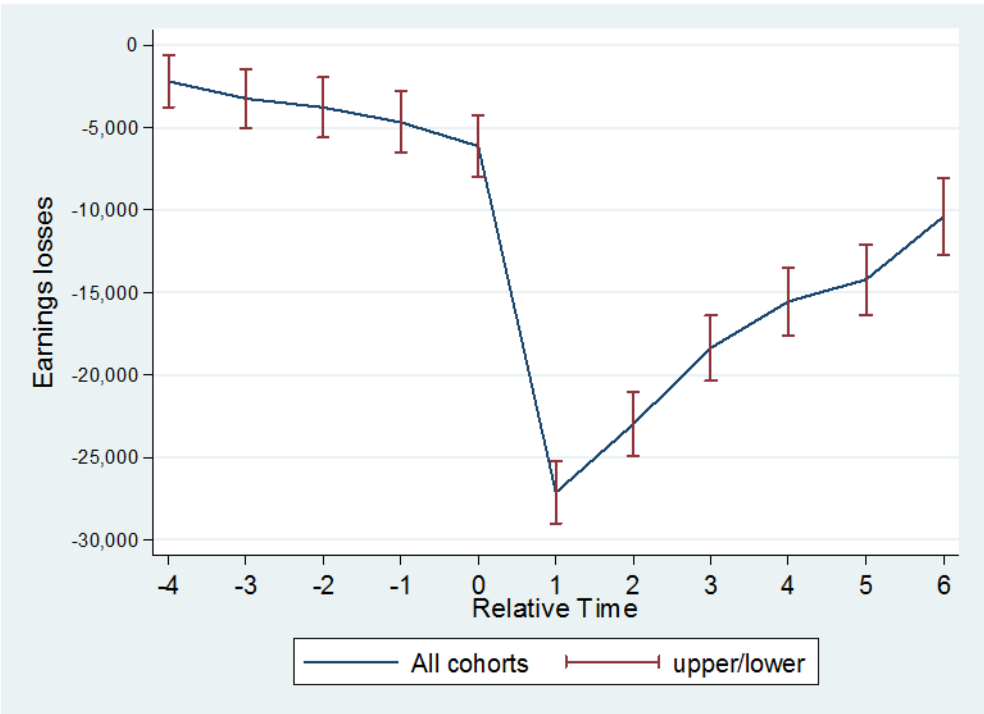
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Figure 8.1: Earnings losses for closure and mass-layoff samples (with cohort dummies included)

- **Closure**



- **Mass-layoff**



Appendix Table 8.6: Regression output for Figure 4.5

- **Closure sample – Males & Females**

VARIABLES	**Closure Males** pay2	**Closure Females** pay2
1.d_closure	-75.74	326.1
	(354.8)	(270.3)
1.d_closure#2.rel_time_group	-1,665***	-1,235***
	(259.9)	(201.1)
1.d_closure#3.rel_time_group	-1,451***	-1,041***
	(296.0)	(233.2)
1.d_closure#4.rel_time_group	-2,082***	-1,357***
	(310.6)	(242.6)
1.d_closure#5.rel_time_group	-3,363***	-2,284***
	(321.8)	(248.2)
1.d_closure#6.rel_time_group	-4,669***	-2,733***
	(325.7)	(250.5)
1.d_closure#7.rel_time_group	-16,230***	-9,723***
	(336.2)	(257.1)
1.d_closure#8.rel_time_group	-10,896***	-6,857***
	(358.9)	(282.5)
1.d_closure#9.rel_time_group	-8,015***	-5,019***
	(369.3)	(296.1)
1.d_closure#10.rel_time_group	-7,670***	-5,205***
	(399.4)	(336.4)
1.d_closure#11.rel_time_group	-6,489***	-4,874***
	(460.4)	(378.4)
1.d_closure#12.rel_time_group	-7,044***	-4,349***
	(554.6)	(472.9)
Constant	35,242***	21,174***
	(246.1)	(181.3)
Observations	1,222,873	778,600
Fstat	2,965.24	1,338.23
Prob > F	0.000	0.000
R-squared	0.073	0.037

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass Layoff sample – Males & Females**

VARIABLES	**Mass layoff Male** pay2	**Mass layoff Female** pay2
1.d_mass	-133.9	-674.3
	(1,359)	(1,259)
1.d_mass#2.rel_time_group	-2,303**	-1,952*
	(1,062)	(1,019)
1.d_mass#3.rel_time_group	-3,032**	-2,976***
	(1,185)	(1,110)
1.d_mass#4.rel_time_group	-3,595***	-3,434***
	(1,222)	(1,152)
1.d_mass#5.rel_time_group	-4,492***	-4,988***
	(1,244)	(1,183)
1.d_mass#6.rel_time_group	-6,499***	-4,870***
	(1,263)	(1,188)
1.d_mass#7.rel_time_group	-30,620***	-20,508***
	(1,275)	(1,210)
1.d_mass#8.rel_time_group	-25,796***	-17,480***
	(1,317)	(1,249)
1.d_mass#9.rel_time_group	-21,191***	-13,180***
	(1,333)	(1,265)
1.d_mass#10.rel_time_group	-18,401***	-11,177***
	(1,391)	(1,322)
1.d_mass#11.rel_time_group	-17,691***	-10,076***
	(1,483)	(1,375)
1.d_mass#12.rel_time_group	-13,438***	-5,993***
	(1,635)	(1,524)
Constant	40,958***	24,976***
	(972.8)	(859.5)
Observations	180,164	104,182
Fstat	1,007.86	535.20
Prob > F	0.000	0.000
R-squared	0.182	0.148

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.7: Regression output for Figure 4.6

VARIABLES	**16-25 years** pay2	**26-35 years** pay2	**36-45 years** pay2	**46-55 years** pay2	**56-65 years** pay2
1.d_closure	-3,943***	-3,115***	314.4	-1,038	1,194
	(260.5)	(299.0)	(537.0)	(728.2)	(954.2)
1.d_closure#2.rel_time_group	652.9***	-536.6**	-2,243***	-1,268**	-1,739**
	(209.9)	(218.8)	(381.7)	(519.8)	(708.3)
1.d_closure#3.rel_time_group	1,092***	446.5*	-1,607***	-775.3	-2,509***
	(234.4)	(248.5)	(438.1)	(593.0)	(818.9)
1.d_closure#4.rel_time_group	1,039***	105.5	-1,938***	-1,211*	-3,265***
	(245.4)	(264.2)	(459.6)	(623.0)	(838.3)
1.d_closure#5.rel_time_group	921.8***	-772.2***	-3,365***	-2,434***	-4,278***
	(252.1)	(273.0)	(475.3)	(649.0)	(870.2)
1.d_closure#6.rel_time_group	859.4***	-1,563***	-4,649***	-3,472***	-5,311***
	(252.6)	(276.2)	(481.4)	(653.3)	(892.5)
1.d_closure#7.rel_time_group	-5,386***	-11,050***	-16,194***	-14,648***	-15,201***
	(261.3)	(288.6)	(496.1)	(677.1)	(910.8)
1.d_closure#8.rel_time_group	-1,696***	-6,151***	-11,581***	-10,303***	-11,077***
	(271.8)	(317.7)	(540.8)	(727.8)	(970.8)
1.d_closure#9.rel_time_group	10.54	-3,617***	-8,541***	-7,761***	-8,560***
	(282.6)	(336.0)	(563.6)	(751.3)	(985.6)
1.d_closure#10.rel_time_group	481.0	-3,375***	-8,779***	-8,555***	-8,861***
	(308.5)	(397.5)	(636.4)	(832.1)	(1,060)
1.d_closure#11.rel_time_group	995.1***	-2,319***	-7,530***	-7,390***	-7,617***
	(367.1)	(490.5)	(748.0)	(935.9)	(1,110)
1.d_closure#12.rel_time_group	1,048**	-2,862***	-8,085***	-7,681***	-6,041***
	(492.7)	(661.9)	(933.0)	(1,138)	(1,178)
Constant	13,290***	28,163***	36,485***	36,723***	31,797***
	(180.9)	(215.9)	(380.5)	(546.7)	(681.1)
Observations	350,481	644,697	484,019	319,733	162,270
Fstat	1,200.58	1,583.18	941.13	605.08	435.01
Prob > F	0.000	0.000	0.000	0.000	0.000
R-squared	0.072	0.060	0.057	0.064	0.098

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.8: Regression output for Figure 4.7

VARIABLES	**16-25 years** pay2	**26-35 years** pay2	**36-45 years** pay2	**46-55 years** pay2	**56-65 years** pay2
1.d_mass	-7,855***	-6,758***	-2,894	367.3	-418.6
	(1,077)	(1,331)	(1,986)	(3,022)	(4,128)
1.d_mass#2.rel_time_group	1,926**	349.3	-1,907	-3,946	389.3
	(894.6)	(1,041)	(1,469)	(2,429)	(3,215)
1.d_mass#3.rel_time_group	2,817***	1,077	-2,140	-4,968*	-1,358
	(981.6)	(1,171)	(1,658)	(2,612)	(3,544)
1.d_mass#4.rel_time_group	3,533***	1,215	-3,000*	-6,148**	-1,971
	(1,017)	(1,198)	(1,749)	(2,648)	(3,642)
1.d_mass#5.rel_time_group	3,943***	833.5	-4,046**	-6,660**	-3,772
	(1,032)	(1,212)	(1,776)	(2,705)	(3,777)
1.d_mass#6.rel_time_group	2,424**	-2,003	-6,010***	-4,555	-1,015
	(1,033)	(1,220)	(1,788)	(2,777)	(3,946)
1.d_mass#7.rel_time_group	-8,619***	-20,895***	-33,564***	-33,818***	-28,692***
	(1,044)	(1,241)	(1,820)	(2,770)	(3,979)
1.d_mass#8.rel_time_group	-5,179***	-16,436***	-29,121***	-30,819***	-22,137***
	(1,062)	(1,275)	(1,912)	(2,918)	(4,088)
1.d_mass#9.rel_time_group	-2,660**	-12,040***	-24,832***	-24,760***	-15,253***
	(1,068)	(1,294)	(1,955)	(2,980)	(4,150)
1.d_mass#10.rel_time_group	-1,025	-9,116***	-21,449***	-20,482***	-8,388*
	(1,120)	(1,353)	(2,122)	(3,082)	(4,325)
1.d_mass#11.rel_time_group	752.3	-7,833***	-20,867***	-17,829***	-4,631
	(1,201)	(1,495)	(2,248)	(3,157)	(4,328)
1.d_mass#12.rel_time_group	2,518*	-5,980***	-14,386***	-11,477***	-2,706
	(1,316)	(1,744)	(2,703)	(3,446)	(4,491)
Constant	15,457***	33,357***	43,861***	45,632***	42,083***
	(821.7)	(996.2)	(1,429)	(2,340)	(3,500)
Observations	61,659	102,807	57,919	38,364	20,325
Fstat	494.74	730.28	305.45	192.96	163.64
Prob > F	0.000	0.000	0.000	0.000	0.000
R-squared	0.172	0.201	0.188	0.187	0.252

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.9: Regression output for Figure 4.8

- **Closure**

VARIABLES	**Irish 26-45 years** pay2	**Non-Irish 26-45 years** pay2
1.d_closure	-1,509***	-1,178**
	(334.1)	(549.3)
1.d_closure#2.rel_time_group	-1,285***	-1,302***
	(233.3)	(462.8)
1.d_closure#3.rel_time_group	-508.5*	-388.3
	(270.0)	(503.4)
1.d_closure#4.rel_time_group	-1,040***	-332.7
	(286.0)	(518.2)
1.d_closure#5.rel_time_group	-2,283***	-1,228**
	(297.2)	(524.6)
1.d_closure#6.rel_time_group	-3,341***	-2,187***
	(302.1)	(528.3)
1.d_closure#7.rel_time_group	-14,197***	-11,238***
	(314.5)	(538.3)
1.d_closure#8.rel_time_group	-9,395***	-6,545***
	(345.8)	(571.1)
1.d_closure#9.rel_time_group	-6,478***	-4,283***
	(363.0)	(588.5)
1.d_closure#10.rel_time_group	-6,568***	-3,979***
	(424.1)	(634.4)
1.d_closure#11.rel_time_group	-5,360***	-2,724***
	(500.4)	(763.3)
1.d_closure#12.rel_time_group	-5,961***	-2,494**
	(624.3)	(1,138)
Constant	33,677***	22,684***
	(233.4)	(386.9)
Observations	852,148	276,568
Fstat	1569.00	944.58
Prob > F	0.000	0.000
R-squared	0.052	0.081

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass Layoff**

VARIABLES	**Irish 26-45 years** pay2	**Non-Irish 26-45 years** pay2
1.d_mass	-5,420***	1,613
	(1,350)	(2,349)
1.d_mass#2.rel_time_group	-388.9	-5,191**
	(1,002)	(2,017)
1.d_mass#3.rel_time_group	-638.0	-4,535**
	(1,136)	(2,179)
1.d_mass#4.rel_time_group	-1,377	-4,477*
	(1,174)	(2,286)
1.d_mass#5.rel_time_group	-1,943	-5,529**
	(1,193)	(2,304)
1.d_mass#6.rel_time_group	-4,208***	-8,677***
	(1,206)	(2,297)
1.d_mass#7.rel_time_group	-29,303***	-25,240***
	(1,230)	(2,333)
1.d_mass#8.rel_time_group	-25,044***	-20,439***
	(1,289)	(2,365)
1.d_mass#9.rel_time_group	-20,722***	-16,645***
	(1,324)	(2,376)
1.d_mass#10.rel_time_group	-17,021***	-13,807***
	(1,436)	(2,449)
1.d_mass#11.rel_time_group	-14,912***	-12,886***
	(1,511)	(2,739)
1.d_mass#12.rel_time_group	-10,419***	-11,102***
	(1,761)	(3,094)
Constant	41,324***	23,647***
	(957.3)	(1,490)
Observations	105,755	54,971
Fstat	563.01	457.68
Prob > F	0.000	0.000
R-squared	0.198	0.190

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.10: Regression output for Figure 4.9

- **Closure**

VARIABLES	pay2
1.displ_**switch**#1b.rel_time_group	29,033***
	(424.8)
1.displ_**switch**#2.rel_time_group	-1,372***
	(295.1)
1.displ_**switch**#3.rel_time_group	-27.53
	(211.2)
1.displ_**switch**#4.rel_time_group	-712.5***
	(185.7)
1.displ_**switch**#5.rel_time_group	-1,712***
	(165.9)
1.displ_**switch**#6.rel_time_group	-2,691***
	(153.3)
1.displ_**switch**#7.rel_time_group	-10,590***
	(153.4)
1.displ_**switch**#8.rel_time_group	-4,591***
	(164.7)
1.displ_**switch**#9.rel_time_group	-2,016***
	(183.0)
1.displ_**switch**#10.rel_time_group	-2,256***
	(241.9)
1.displ_**switch**#11.rel_time_group	-1,373***
	(324.7)
1.displ_**switch**#12.rel_time_group	-339.6
	(465.5)
1.displ_**noswitch**#1b.rel_time_group	29,184***
	(279.0)
1.displ_**noswitch**#2.rel_time_group	701.5***
	(228.0)
1.displ_**noswitch**#3.rel_time_group	322.4*
	(169.5)
1.displ_**noswitch**#4.rel_time_group	101.0
	(153.1)
1.displ_**noswitch**#5.rel_time_group	-655.3***
	(139.1)
1.displ_**noswitch**#6.rel_time_group	-933.2***
	(130.9)
1.displ_**noswitch**#7.rel_time_group	-4,960***
	(126.4)
1.displ_**noswitch**#8.rel_time_group	-1,955***
	(136.9)
1.displ_**noswitch**#9.rel_time_group	-1,131***
	(154.7)
1.displ_**noswitch**#10.rel_time_group	-2,498***
	(222.0)
1.displ_**noswitch**#11.rel_time_group	-3,209***
	(296.2)
1.displ_**noswitch**#12.rel_time_group	-5,366***
	(398.8)
Observations	2,001,473
Fstat	5,793.06
Prob > F	0.000
R-squared	0.541

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass layoff**

VARIABLES	pay2
1.displ_**switch**#1b.rel_time_group	34,588***
	(1,643)
1.displ_**switch**#2.rel_time_group	-3,844***
	(919.1)
1.displ_**switch**#3.rel_time_group	-5,310***
	(664.6)
1.displ_**switch**#4.rel_time_group	-5,658***
	(571.7)
1.displ_**switch**#5.rel_time_group	-5,965***
	(488.1)
1.displ_**switch**#6.rel_time_group	-8,115***
	(425.6)
1.displ_**switch**#7.rel_time_group	-23,446***
	(373.3)
1.displ_**switch**#8.rel_time_group	-16,110***
	(399.5)
1.displ_**switch**#9.rel_time_group	-11,616***
	(444.9)
1.displ_**switch**#10.rel_time_group	-8,395***
	(626.4)
1.displ_**switch**#11.rel_time_group	-6,779***
	(772.4)
1.displ_**switch**#12.rel_time_group	-1,847*
	(967.2)
1.displ_**noswitch**#1b.rel_time_group	29,609***
	(1,514)
1.displ_**noswitch**#2.rel_time_group	-3,196***
	(964.4)
1.displ_**noswitch**#3.rel_time_group	-893.8
	(633.1)
1.displ_**noswitch**#4.rel_time_group	-1,580***
	(529.6)
1.displ_**noswitch**#5.rel_time_group	-2,291***
	(448.9)
1.displ_**noswitch**#6.rel_time_group	-2,821***
	(407.4)
1.displ_**noswitch**#7.rel_time_group	-11,524***
	(357.0)
1.displ_**noswitch**#8.rel_time_group	-8,920***
	(376.5)
1.displ_**noswitch**#9.rel_time_group	-5,942***
	(394.3)
1.displ_**noswitch**#10.rel_time_group	-6,494***
	(563.5)
1.displ_**noswitch**#11.rel_time_group	-9,278***
	(667.8)
1.displ_**noswitch**#12.rel_time_group	-13,055***
	(831.0)
Observations	284,346
Fstat	1,013.17
Prob > F	0.000
R-squared	0.582

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.11: Regression output for Figure 4.11

- **Closure**

VARIABLES	pay2
1.displ_switch#1b.rel_time_group	37,654***
	(1,162)
1.displ_switch#2.rel_time_group	1,586**
	(808.9)
1.displ_switch#3.rel_time_group	-603.1
	(567.0)
1.displ_switch#4.rel_time_group	-1,487***
	(432.2)
1.displ_switch#5.rel_time_group	-2,288***
	(361.9)
1.displ_switch#6.rel_time_group	-2,502***
	(308.0)
1.displ_switch#7.rel_time_group	-12,178***
	(299.5)
1.displ_switch#8.rel_time_group	-2,719***
	(317.7)
1.displ_switch#9.rel_time_group	791.5**
	(320.3)
1.displ_switch#10.rel_time_group	3,885***
	(419.2)
1.displ_switch#11.rel_time_group	6,680***
	(663.2)
1.displ_switch#12.rel_time_group	6,828***
	(888.7)
1.displ_noswitch#1b.rel_time_group	33,815***
	(1,182)
1.displ_noswitch#2.rel_time_group	3,046***
	(774.4)
1.displ_noswitch#3.rel_time_group	1,748***
	(516.6)
1.displ_noswitch#4.rel_time_group	925.5**
	(384.8)
1.displ_noswitch#5.rel_time_group	-741.7**
	(311.0)
1.displ_noswitch#6.rel_time_group	-1,257***
	(260.2)
1.displ_noswitch#7.rel_time_group	-8,317***
	(229.5)
1.displ_noswitch#8.rel_time_group	-3,146***
	(242.4)
1.displ_noswitch#9.rel_time_group	-2,597***
	(245.8)
1.displ_noswitch#10.rel_time_group	-3,276***
	(292.7)
1.displ_noswitch#11.rel_time_group	-3,962***
	(406.8)
1.displ_noswitch#12.rel_time_group	-4,536***
	(603.0)
Observations	372,337
Fstat	1,548.62
Prob > F	0.000
R-squared	0.569

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass Layoff**

VARIABLES	pay2
1.displ_switch#1b.rel_time_group	36,746***
	(5,255)
1.displ_switch#2.rel_time_group	-7,796*
	(4,093)
1.displ_switch#3.rel_time_group	-6,017**
	(2,578)
1.displ_switch#4.rel_time_group	-4,091*
	(2,220)
1.displ_switch#5.rel_time_group	-4,040**
	(2,001)
1.displ_switch#6.rel_time_group	-8,765***
	(1,638)
1.displ_switch#7.rel_time_group	-32,336***
	(1,549)
1.displ_switch#8.rel_time_group	-17,456***
	(1,569)
1.displ_switch#9.rel_time_group	-10,528***
	(1,678)
1.displ_switch#10.rel_time_group	-7,732***
	(2,584)
1.displ_switch#11.rel_time_group	3,416
	(3,979)
1.displ_switch#12.rel_time_group	-5,828
	(5,442)
1.displ_noswitch#1b.rel_time_group	42,946***
	(6,954)
1.displ_noswitch#2.rel_time_group	2,480
	(3,777)
1.displ_noswitch#3.rel_time_group	1,370
	(3,014)
1.displ_noswitch#4.rel_time_group	6,097***
	(2,332)
1.displ_noswitch#5.rel_time_group	-398.4
	(2,043)
1.displ_noswitch#6.rel_time_group	1,084
	(1,686)
1.displ_noswitch#7.rel_time_group	-12,060***
	(1,450)
1.displ_noswitch#8.rel_time_group	-5,356***
	(1,445)
1.displ_noswitch#9.rel_time_group	-4,096**
	(1,601)
1.displ_noswitch#10.rel_time_group	-7,456***
	(2,167)
1.displ_noswitch#11.rel_time_group	-2,925
	(3,045)
1.displ_noswitch#12.rel_time_group	-5,048
	(3,965)
Observations	25,395
Fstat	210.29
Prob > F	0.000
R-squared	0.656

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.12: Regression output for Figure 4.12

- **Closure**

VARIABLES	**Ire** pay2	**UK** pay2	**W. Euro** pay2	**E. Euro** pay2	**Asia** pay2	**ROW** pay2
1.d_closure	61.36	-1,820	-2,700	95.31	15.57	121.3
	(274.8)	(1,493)	(1,719)	(452.3)	(779.5)	(1,510)
1.d_closure#2.rel_time_group	-1,454***	-1,502	-2,852*	-697.9	-928.0	-2,474*
	(196.1)	(1,223)	(1,543)	(424.8)	(633.0)	(1,270)
1.d_closure#3.rel_time_group	-1,318***	-278.7	2,054	-561.1	-240.0	-3,156**
	(226.0)	(1,336)	(1,729)	(441.4)	(774.0)	(1,385)
1.d_closure#4.rel_time_group	-1,956***	-407.2	1,426	-757.2*	-422.7	-2,500*
	(237.3)	(1,389)	(1,771)	(451.9)	(778.1)	(1,395)
1.d_closure#5.rel_time_group	-3,122***	-2,029	483.1	-1,341***	-1,142	-3,840***
	(246.5)	(1,406)	(1,739)	(454.6)	(794.9)	(1,431)
1.d_closure#6.rel_time_group	-4,129***	-3,958***	-812.4	-1,893***	-1,829**	-4,372***
	(250.0)	(1,414)	(1,742)	(453.9)	(782.8)	(1,448)
1.d_closure#7.rel_time_group	-14,163***	-15,031***	-9,435***	-9,912***	-10,262***	-13,713***
	(258.3)	(1,437)	(1,777)	(463.1)	(803.2)	(1,473)
1.d_closure#8.rel_time_group	-9,861***	-9,312***	-5,685***	-5,655***	-5,567***	-9,088***
	(278.6)	(1,526)	(1,878)	(474.9)	(904.6)	(1,558)
1.d_closure#9.rel_time_group	-7,325***	-6,127***	-3,554*	-3,721***	-4,789***	-6,301***
	(288.1)	(1,568)	(1,938)	(483.8)	(970.9)	(1,603)
1.d_closure#10.rel_time_group	-7,377***	-5,655***	-4,418**	-3,421***	-3,566***	-5,560***
	(319.4)	(1,714)	(2,124)	(504.7)	(1,032)	(1,702)
1.d_closure#11.rel_time_group	-6,357***	-3,050	-2,337	-3,031***	-2,488**	-3,308
	(361.5)	(1,939)	(2,391)	(575.0)	(1,212)	(2,037)
1.d_closure#12.rel_time_group	-6,568***	-2,101	1,018	-3,196***	-2,564*	-3,319
	(433.1)	(2,437)	(4,282)	(790.3)	(1,546)	(2,662)
Constant	30,892***	32,517***	27,258***	16,114***	18,924***	25,345***
	(190.4)	(1,046)	(1,184)	(295.2)	(590.8)	(995.6)
Observations	1,606,914	70,755	34,169	197,664	40,443	51,528
Fstat	2,904.38	164.94	99.28	1,226.47	115.03	169.98
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.053	0.068	0.066	0.170	0.064	0.085

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass layoff**

VARIABLES	**Ire** pay2	**UK** pay2	**W. Euro** pay2	**E. Euro** pay2	**Asia** pay2	**ROW** pay2
1.d_mass	-425.1	2,012	4,729	-719.5	-4,041	5,465
	(1,136)	(8,160)	(4,709)	(2,235)	(2,785)	(5,264)
1.d_mass#2.rel_time_group	-2,199**	463.5	-7,809*	0.398	-2,384	-1,063
	(875.5)	(7,107)	(4,308)	(2,040)	(3,172)	(4,206)
1.d_mass#3.rel_time_group	-3,337***	-1,546	-9,749**	313.8	-1,984	-6,016
	(975.6)	(7,247)	(4,555)	(2,177)	(2,920)	(4,771)
1.d_mass#4.rel_time_group	-4,108***	-3,447	-9,041*	285.5	-1,414	-8,988*
	(1,001)	(7,785)	(4,681)	(2,201)	(2,979)	(5,007)
1.d_mass#5.rel_time_group	-5,122***	-7,338	-13,463***	474.6	-1,418	-8,786*
	(1,023)	(7,822)	(4,715)	(2,213)	(2,843)	(5,112)
1.d_mass#6.rel_time_group	-6,035***	-10,897	-15,506***	-2,551	15.76	-12,737**
	(1,043)	(7,786)	(4,748)	(2,219)	(2,827)	(5,141)
1.d_mass#7.rel_time_group	-29,421***	-36,534***	-28,611***	-16,573***	-17,389***	-28,018***
	(1,054)	(7,870)	(4,788)	(2,232)	(2,829)	(5,197)
1.d_mass#8.rel_time_group	-25,491***	-30,129***	-22,654***	-12,833***	-14,389***	-22,885***
	(1,096)	(8,074)	(4,836)	(2,243)	(3,004)	(5,342)
1.d_mass#9.rel_time_group	-20,737***	-27,227***	-17,513***	-10,392***	-7,356**	-20,179***
	(1,115)	(8,095)	(4,821)	(2,249)	(3,138)	(5,365)
1.d_mass#10.rel_time_group	-17,386***	-22,341***	-14,426***	-7,701***	-95.82	-18,497***
	(1,167)	(8,381)	(4,915)	(2,283)	(3,884)	(5,549)
1.d_mass#11.rel_time_group	-15,122***	-19,512**	-13,243**	-4,679*	-701.7	-15,483***
	(1,205)	(8,697)	(5,650)	(2,428)	(5,067)	(5,740)
1.d_mass#12.rel_time_group	-10,723***	-12,217	-8,831	-5,400**	-1,620	-17,769***
	(1,326)	(9,369)	(6,894)	(2,712)	(4,158)	(6,332)
Constant	37,423***	43,655***	20,234***	15,437***	26,077***	24,099***
	(801.4)	(6,379)	(3,054)	(1,460)	(2,229)	(3,059)
Observations	203,473	9,743	13,559	42,119	5,953	9,499
Fstat	943.58	63.71	113.10	583.64	42.57	70.12
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.167	0.186	0.183	0.281	0.166	0.182

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.13: Regression output for Figure 4.13

- **Closure**

VARIABLES	**Industry (B-E)** pay2	**Services (G-U)** pay2
1.d_closure	5,643***	-1,206
	(1,879)	(1,016)
1.d_closure#2.rel_time_group	-2,379*	-163.0
	(1,276)	(714.4)
1.d_closure#3.rel_time_group	-2,042	1,379*
	(1,613)	(828.7)
1.d_closure#4.rel_time_group	-2,702*	693.6
	(1,634)	(863.5)
1.d_closure#5.rel_time_group	-3,020*	107.3
	(1,654)	(896.7)
1.d_closure#6.rel_time_group	-4,529***	-1,205
	(1,630)	(905.6)
1.d_closure#7.rel_time_group	-16,499***	-9,737***
	(1,695)	(917.4)
1.d_closure#8.rel_time_group	-10,355***	-2,171**
	(1,868)	(962.4)
1.d_closure#9.rel_time_group	-5,289***	1,598
	(1,957)	(991.2)
1.d_closure#10.rel_time_group	-9,709***	1,619
	(2,102)	(1,028)
1.d_closure#11.rel_time_group	-12,415***	3,873***
	(2,399)	(1,086)
1.d_closure#12.rel_time_group	-13,355***	3,013**
	(3,009)	(1,202)
Observations	113,045	675,507
Fstat	334.88	1,433.31
Prob > F	0.000	0.000
R-squared	0.112	0.056

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass Layoff**

VARIABLES	**Industry B-E** pay2	**Services G-U** pay2
1.d_mass	-2,015**	8,419
	(864.7)	(5,792)
1o.d_mass#1b.rel_time_group	0	0
	(0)	(0)
1.d_mass#2.rel_time_group	-3,545	-8,706
	(10,917)	(6,059)
1.d_mass#3.rel_time_group	-43.08	-17,913**
	(5,230)	(7,245)
1.d_mass#4.rel_time_group	1,263	-13,874**
	(5,034)	(6,504)
1.d_mass#5.rel_time_group	-678.5	-14,509**
	(4,485)	(6,441)
1.d_mass#6.rel_time_group	-1,337	-14,687**
	(3,272)	(6,281)
1.d_mass#7.rel_time_group	-23,542***	-35,103***
	(3,679)	(6,518)
1.d_mass#8.rel_time_group	-5,575*	-22,341***
	(3,084)	(6,325)
1.d_mass#9.rel_time_group	915.2	-14,434**
	(2,908)	(6,503)
1.d_mass#10.rel_time_group	5,169**	-7,590
	(2,183)	(6,280)
1.d_mass#11.rel_time_group	2,151	-6,787
	(2,523)	(7,066)
1.d_mass#12.rel_time_group	4,089	2,786
	(3,768)	(6,390)
Constant	41,616***	28,739***
	(757.9)	(5,761)
Observations	29,921	87,004
Fstat	-	454.46
Prob > F	-	0.000
R-squared	0.293	0.219

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8.14: Regression output for Figure 4.14

VARIABLES	**Closure** Pay	**Mass Layoff** Pay
u_gap1	-4,000***	-2,584**
	(306.2)	(1,009)
u_gap2	-6,189***	-2,753***
	(267.1)	(661.4)
u_gap3	-4,704***	-9,932***
	(285.6)	(595.0)
u_gap4	-7,014***	-10,922***
	(362.1)	(783.3)
u_gap5	-9,529***	-8,728***
	(421.5)	(919.7)
u_gap6	-10,449***	-9,785***
	(441.8)	(1,220)
t_gap12	-1,603***	-1,233*
	(197.7)	(673.6)
t_gap13	-1,408***	-3,535***
	(233.5)	(775.2)
t_gap14	-2,718***	-3,893***
	(247.9)	(842.3)
t_gap15	-4,826***	-4,590***
	(264.4)	(874.6)
t_gap16	-5,258***	-5,555***
	(266.3)	(904.3)
t_gap17	-28,038***	-35,685***
	(279.7)	(946.9)
t_gap18	-13,926***	-22,826***
	(318.6)	(1,053)
t_gap19	-11,054***	-19,338***
	(347.8)	(1,135)
t_gap110	-14,489***	-19,120***
	(392.8)	(1,420)
t_gap111	-14,994***	-18,969***
	(486.9)	(1,533)
t_gap112	-15,292***	-22,044***
	(592.5)	(1,834)
t_gap23	-1,033***	-2,336***
	(174.7)	(379.9)
t_gap24	-1,250***	-2,076***
	(203.7)	(447.0)
t_gap25	-2,848***	-3,151***
	(210.2)	(489.0)
t_gap26	-3,951***	293.3
	(224.9)	(502.0)
t_gap27	-25,849***	-35,517***
	(236.3)	(562.3)

Appendix Table 8.14 continued

t_gap28	-25,849***	-35,517***
	(236.3)	(562.3)
t_gap29	-14,810***	-15,212***
	(352.2)	(883.2)
t_gap210	-12,399***	-7,748***
	(457.5)	(1,093)
t_gap211	-12,865***	-7,460***
	(784.1)	(1,208)
t_gap212	-14,986***	-15,520***
	(800.1)	(4,881)
t_gap34	-1,822***	-1,591***
	(200.8)	(313.6)
t_gap35	-2,512***	-1,732***
	(212.9)	(377.1)
t_gap36	-3,945***	-2,583***
	(222.8)	(406.6)
t_gap37	-27,333***	-28,338***
	(257.0)	(482.4)
t_gap38	-27,333***	-28,338***
	(257.0)	(482.4)
t_gap39	-27,333***	-28,338***
	(257.0)	(482.4)
t_gap310	-15,587***	-16,321***
	(621.4)	(1,012)
t_gap311	-14,012***	-10,979***
	(797.2)	(1,535)
t_gap312	-16,380***	-12,491***
	(1,044)	(3,657)
t_gap45	-2,489***	-2,242***
	(259.0)	(519.2)
t_gap46	-1,655***	830.9
	(282.3)	(592.3)
t_gap47	-25,023***	-27,347***
	(340.0)	(701.6)
t_gap48	-25,023***	-27,347***
	(340.0)	(701.6)
t_gap49	-25,023***	-27,347***
	(340.0)	(701.6)
t_gap410	-25,023***	-27,347***
	(340.0)	(701.6)
t_gap411	-14,028***	-10,256***
	(882.6)	(3,387)
t_gap412	-10,926***	-3,344
	(1,465)	(9,112)
t_gap56	-232.1	2,598***
	(342.9)	(810.7)
t_gap57	-22,508***	-29,542***
	(402.7)	(851.2)

Appendix Table 8.14 continued

t_gap58	-22,508***	-29,542***
	(402.7)	(851.2)
t_gap59	-22,508***	-29,542***
	(402.7)	(851.2)
t_gap510	-22,508***	-29,542***
	(402.7)	(851.2)
t_gap511	-22,508***	-29,542***
	(402.7)	(851.2)
t_gap512	-11,996***	-20,376***
	(1,360)	(2,374)
t_gap67	-21,589***	-28,485***
	(423.9)	(1,169)
t_gap68	-21,589***	-28,485***
	(423.9)	(1,169)
t_gap69	-21,589***	-28,485***
	(423.9)	(1,169)
t_gap610	-21,589***	-28,485***
	(423.9)	(1,169)
t_gap611	-21,589***	-28,485***
	(423.9)	(1,169)
t_gap612	-21,589***	-28,485***
	(423.9)	(1,169)
u_nogap	-914.9***	-3,630***
	(263.2)	(1,207)
t_nogap2	-665.5***	-2,301***
	(188.1)	(883.8)
t_nogap3	-194.0	-1,716*
	(211.2)	(1,029)
t_nogap4	-698.2***	-3,674***
	(217.7)	(1,076)
t_nogap5	-1,303***	-4,333***
	(219.7)	(1,096)
t_nogap6	-277.5	-3,245***
	(222.6)	(1,108)
t_nogap7	-5,368***	-12,505***
	(226.8)	(1,116)
t_nogap8	-4,977***	-12,342***
	(251.4)	(1,195)
t_nogap9	-6,632***	-15,199***
	(258.5)	(1,201)
t_nogap10	-11,032***	-16,286***
	(281.5)	(1,232)
t_nogap11	-11,280***	-17,445***
	(314.9)	(1,256)
t_nogap12	-12,705***	-17,311***
	(393.8)	(1,298)
u_wgap	-6,975***	-11,617***
	(494.6)	(1,719)

Appendix Table 8.14 continued

t_wgap2	-1,737***	3,256**
	(379.0)	(1,507)
t_wgap3	-1,455***	1,548
	(423.0)	(1,589)
t_wgap4	-2,014***	205.5
	(440.1)	(1,594)
t_wgap5	-1,362***	1,060
	(455.3)	(1,601)
t_wgap6	1,584***	5,214***
	(448.2)	(1,583)
t_wgap7	-7,578***	-5,835***
	(456.3)	(1,597)
t_wgap8	-14,133***	-14,817***
	(462.4)	(1,616)
t_wgap9	-17,570***	-19,110***
	(465.3)	(1,616)
t_wgap10	-19,592***	-20,656***
	(467.4)	(1,609)
t_wgap11	-20,153***	-21,077***
	(470.5)	(1,558)
t_wgap12	-19,872***	-21,062***
	(501.4)	(1,553)
Constant	32,038***	38,269***
	(124.6)	(348.3)
Observations	2,001,473	284,346
Fstat	-	-
Prob > F	-	-
R-squared	0.150	0.264

Appendix 9 : Likelihood ratio test results

Appendix Table 9.1: Results of Likelihood ratio test (Closure)

VARIABLES	**Full** pay2	**2005-2007** pay2	**2008-2010** pay2
1.d_closure	81.18	-2,167***	81.18
	(236.0)	(269.6)	(237.9)
1.d_closure#2.rel_time_group	-1,488***	-	-1,488***
	(283.9)	-	(286.2)
1.d_closure#3.rel_time_group	-1,289***	-	-1,283***
	(262.9)	-	(265.0)
1.d_closure#4.rel_time_group	-1,817***	-	-1,763***
	(257.3)	-	(262.6)
1.d_closure#5.rel_time_group	-2,940***	-1,259***	-2,780***
	(253.9)	(330.8)	(261.1)
1.d_closure#6.rel_time_group	-3,914***	-1,679***	-3,909***
	(251.9)	(312.7)	(260.3)
1.d_closure#7.rel_time_group	-13,690***	-12,210***	-13,370***
	(251.9)	(312.7)	(260.3)
1.d_closure#8.rel_time_group	-9,339***	-7,329***	-9,202***
	(255.6)	(312.7)	(268.4)
1.d_closure#9.rel_time_group	-6,894***	-5,729***	-5,821***
	(262.3)	(312.7)	(288.3)
1.d_closure#10.rel_time_group	-6,829***	-4,581***	-
	(286.4)	(312.7)	-
1.d_closure#11.rel_time_group	-5,873***	-3,625***	-
	(322.8)	(344.9)	-
1.d_closure#12.rel_time_group	-6,085***	-3,837***	-
	(413.9)	(427.7)	-
Constant	29,683***	32,155***	31,945***
	(164.9)	(205.7)	(175.8)
Observations	2,001,473	610,105	1,391,368
Fstat	5,178.41	2,202.83	3,480.54
Prob > F	0.000	0.000	0.000
R-squared	0.056	0.064	0.045

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Likelihood Ratio Test results**

Likelihood-ratio Test						
Model	**Obs**	**ll(null)**	**ll(model)**	**df**	**AIC**	**BIC**
Full	2001473	-2.31E+07	-2.31E+07	24	4.61E+07	4.61E+07
Pre 2008	610105	-7032513	-7012272	20	1.40E+07	1.40E+07
Post 2008	1391368	-1.61E+07	-1.60E+07	20	3.21E+07	3.21E+07
LR chi2(16) =	6834.74					
Prob > chi2 =	0					

Appendix Table 9.2: Results of Likelihood ratio test (Mass-Layoff)

VARIABLES	Full pay2	2005-2007 pay2	2008-2010 pay2
1.d_mass	-109.0	-4,229***	-109.0
	(930.7)	(766.2)	(943.4)
1.d_mass#2.rel_time_group	-2,215**	-	-2,196**
	(1,057)	-	(1,072)
1.d_mass#3.rel_time_group	-3,150***	-	-3,238***
	(992.6)	-	(1,006)
1.d_mass#4.rel_time_group	-3,720***	-	-3,708***
	(976.3)	-	(996.8)
1.d_mass#5.rel_time_group	-4,734***	-1,682*	-4,336***
	(965.0)	(912.1)	(989.2)
1.d_mass#6.rel_time_group	-6,123***	-935.1	-6,640***
	(959.5)	(860.5)	(986.5)
1.d_mass#7.rel_time_group	-27,124***	-19,700***	-28,725***
	(959.5)	(860.5)	(986.5)
1.d_mass#8.rel_time_group	-22,964***	-15,733***	-24,736***
	(962.6)	(860.5)	(993.8)
1.d_mass#9.rel_time_group	-18,375***	-13,188***	-19,333***
	(972.1)	(860.5)	(1,022)
1.d_mass#10.rel_time_group	-15,544***	-11,425***	-
	(1,016)	(860.5)	-
1.d_mass#11.rel_time_group	-14,221***	-10,101***	-
	(1,073)	(921.4)	-
1.d_mass#12.rel_time_group	-10,382***	-6,262***	-
	(1,216)	(1,072)	
Constant	35,389***	36,309***	31,564***
	(653.9)	(560.4)	(689.0)
Observations	284,346	97,916	186,430
Fstat	2434.07	922.05	2020.25
Prob > F	0.000	0.000	0.000
R-squared	0.165	0.152	0.171

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Likelihood Ratio Test results**

Likelihood-ratio Test						
Model	**Obs**	**ll(null)**	**ll(model)**	**df**	**AIC**	**BIC**
Full	284346	-3303882	-3278328	24	6556704	6556957
Pre 2008	97916	-1132864	-1124804	20	2249647	2249837
Post 2008	186430	-2169406	-2151953	20	4303945	4304148
LR chi2(16) =	3143.09					
Prob > chi2 =	0					

Appendix 10 : Regression results for closure and mass-layoff samples (pre/post 2008)

Appendix Table 10.1: Regression output Table 4.10

- **Closure**

VARIABLES	**Pre 2008** Emp	**Post 2008** Emp
2.rel_time_group	-	0.727***
	-	(0.00167)
3.rel_time_group	-	0.782***
	-	(0.00127)
4.rel_time_group	-	0.849***
	-	(0.00127)
5.rel_time_group	0.832***	0.910***
	(0.00259)	(0.00127)
6.rel_time_group	1***	1***
	(0.00227)	(0.00127)
7.rel_time_group	0.563***	0.534***
	(0.00227)	(0.00127)
8.rel_time_group	0.574***	0.570***
	(0.00227)	(0.00149)
9.rel_time_group	0.535***	0.594***
	(0.00227)	(0.00196)
10.rel_time_group	0.508***	-
	(0.00227)	-
11.rel_time_group	0.522***	-
	(0.00308)	-
12.rel_time_group	0.511***	-
	(0.00476)	-
Observations	313,999	753,711
Fstat	70,989.62	-
Prob > F	0.000	0.000
R-squared	0.644	0.773

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10.2: Regression output for Table 4.11

- **Mass Layoff**

VARIABLES	**Pre 2008** emp	**Post 2008** emp
2.rel_time_group	-	0.658***
	-	(0.00489)
3.rel_time_group	-	0.622***
	-	(0.00332)
4.rel_time_group	-	0.726***
	-	(0.00332)
5.rel_time_group	0.823***	0.898***
	(0.00630)	(0.00332)
6.rel_time_group	1***	1***
	(0.00538)	(0.00332)
7.rel_time_group	0.353***	0.233***
	(0.00538)	(0.00332)
8.rel_time_group	0.360***	0.242***
	(0.00538)	(0.00360)
9.rel_time_group	0.361***	0.241***
	(0.00538)	(0.00452)
10.rel_time_group	0.341***	-
	(0.00538)	-
11.rel_time_group	0.382***	-
	(0.00702)	-
12.rel_time_group	0.409***	-
	(0.0103)	-
Observations	50,778	104,769
Fstat	9,189.6	34,630.55
Prob > F	0.000	0.000
R-squared	0.592	0.726

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10.3: regression output for Figure 4.15

- **Closure**

VARIABLES	**Pre 2008** pay2	**Post 2008** pay2
1.d_closure	-2,167***	81.18
	(266.3)	(248.5)
1.d_closure#2.rel_time_group	-	-1,488***
	-	(180.5)
1.d_closure#3.rel_time_group	-	-1,283***
	-	(206.9)
1.d_closure#4.rel_time_group	-	-1,763***
	-	(217.5)
1.d_closure#5.rel_time_group	-1,259***	-2,780***
	(201.8)	(224.3)
1.d_closure#6.rel_time_group	-1,679***	-3,909***
	(220.5)	(226.8)
1.d_closure#7.rel_time_group	-12,210***	-13,370***
	(246.1)	(236.0)
1.d_closure#8.rel_time_group	-7,329***	-9,202***
	(254.4)	(260.5)
1.d_closure#9.rel_time_group	-5,729***	-5,821***
	(260.2)	(279.0)
1.d_closure#10.rel_time_group	-4,581***	-
	(266.9)	-
1.d_closure#11.rel_time_group	-3,625***	-
	(329.3)	-
1.d_closure#12.rel_time_group	-3,837***	-
	(399.6)	-
Constant	32,155***	31,945***
	(241.7)	(177.8)
Observations	610,105	1,391,368
Fstat	1598.07	3,778.34
Prob > F	0.000	0.000
R-squared	0.064	0.045

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass Layoff**

VARIABLES	**Pre 2008** pay2	**Post 2008** pay2
1.d_mass	-4,229***	-109.0
	(754.8)	(1,034)
1.d_mass#2.rel_time_group		-2,196***
		(809.6)
1.d_mass#3.rel_time_group		-3,238***
		(900.1)
1.d_mass#4.rel_time_group		-3,708***
		(931.8)
1.d_mass#5.rel_time_group	-1,682***	-4,336***
	(590.0)	(948.1)
1.d_mass#6.rel_time_group	-935.1	-6,640***
	(646.8)	(957.9)
1.d_mass#7.rel_time_group	-19,700***	-28,725***
	(684.8)	(972.3)
1.d_mass#8.rel_time_group	-15,733***	-24,736***
	(702.7)	(1,018)
1.d_mass#9.rel_time_group	-13,188***	-19,333***
	(730.9)	(1,041)
1.d_mass#10.rel_time_group	-11,425***	
	(743.5)	
1.d_mass#11.rel_time_group	-10,101***	
	(859.0)	
1.d_mass#12.rel_time_group	-6,262***	
Constant	36,309***	31,564***
	(611.0)	(653.8)
Observations	97,916	186,430
Fstat	500.82	1,446.25
Prob > F	0.000	0.000
R-squared	0.152	0.171

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10.4: Regression output for Figure 4.16

- **Closure**

VARIABLES	**Male 2005-2007** pay2	**Female 2005-2007** pay2	**Male 2008-2010** pay2	**Female 2008-2010** pay2
1.d_closure	-2,227***	-2,007***	-75.74	326.1
	(343.6)	(346.4)	(354.8)	(270.3)
1.d_closure#2.rel_time_group	-	-	-1,665***	-1,235***
	-	-	(259.9)	(201.1)
1.d_closure#3.rel_time_group	-	-	-1,447***	-1,040***
	-	-	(296.1)	(232.7)
1.d_closure#4.rel_time_group	-	-	-2,099***	-1,262***
	-	-	(311.8)	(243.8)
1.d_closure#5.rel_time_group	-1,506***	-916.3***	-3,277***	-2,059***
	(263.0)	(268.7)	(321.9)	(249.5)
1.d_closure#6.rel_time_group	-2,177***	-784.2***	-4,826***	-2,594***
	(286.3)	(293.4)	(325.7)	(250.7)
1.d_closure#7.rel_time_group	-14,499***	-7,973***	-16,037***	-9,513***
	(321.8)	(319.9)	(339.4)	(260.3)
1.d_closure#8.rel_time_group	-8,742***	-4,730***	-10,899***	-6,752***
	(332.8)	(330.8)	(373.0)	(295.7)
1.d_closure#9.rel_time_group	-6,791***	-3,789***	-7,013***	-4,071***
	(339.7)	(341.1)	(397.4)	(327.5)
1.d_closure#10.rel_time_group	-5,520***	-2,870***	-	-
	(348.6)	(350.2)	-	-
1.d_closure#11.rel_time_group	-4,337***	-2,539***	-	-
	(444.5)	(423.6)	-	-
1.d_closure#12.rel_time_group	-4,892***	-2,016***	-	-
	(542.3)	(509.5)	-	-
Constant	37,816***	21,378***	36,190***	25,344***
	(322.2)	(294.5)	(255.0)	(198.5)
Observations	396,957	213,148	825,916	565,452
Fstat	1,290.36	432.65	2,711.70	1,326.44
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.079	0.046	0.060	0.035

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass Layoff**

VARIABLES	**Male 2005-2007** pay2	**Female 2005-2007** pay2	**Male 2008-2010** pay2	**Female 2008-2010** pay2
1.d_mass	-4,776***	-2,493**	-133.9	-674.3
	(1,010)	(967.8)	(1,359)	(1,259)
1.d_mass#2.rel_time_group	-	-	-2,302**	-1,901*
	-	-	(1,062)	(1,019)
1.d_mass#3.rel_time_group	-	-	-3,149***	-3,014***
	-	-	(1,185)	(1,111)
1.d_mass#4.rel_time_group	-	-	-3,548***	-3,678***
	-	-	(1,226)	(1,151)
1.d_mass#5.rel_time_group	-1,365*	-3,644***	-4,046***	-4,566***
	(795.7)	(783.7)	(1,246)	(1,173)
1.d_mass#6.rel_time_group	-135.8	-3,007***	-7,215***	-4,898***
	(878.5)	(845.8)	(1,262)	(1,172)
1.d_mass#7.rel_time_group	-22,635***	-16,839***	-32,010***	-21,654***
	(922.1)	(910.3)	(1,279)	(1,202)
1.d_mass#8.rel_time_group	-17,793***	-14,027***	-27,425***	-18,691***
	(948.2)	(935.5)	(1,339)	(1,264)
1.d_mass#9.rel_time_group	-15,921***	-10,593***	-21,671***	-14,068***
	(989.5)	(963.7)	(1,370)	(1,294)
1.d_mass#10.rel_time_group	-13,757***	-9,358***	-	-
	(1,005)	(986.2)	-	-
1.d_mass#11.rel_time_group	-13,049***	-8,257***	-	-
	(1,203)	(1,127)	-	-
1.d_mass#12.rel_time_group	-8,796***	-4,174***	-	-
	(1,393)	(1,338)	-	-
Constant	42,133***	27,818***	36,000***	21,693***
	(847.3)	(743.8)	(865.5)	(794.9)
Observations	55,539	42,377	124,625	61,805
Fstat	318.83	247.89	1,067.50	490.94
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.177	0.133	0.185	0.176

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10.5: Regression output for Figure 4.17

- **Closure**

VARIABLES	**Irish 2005-2007** pay2	**Irish 2008-2010** pay2	**Non Irish 2005-2007** pay2	**Non Irish 2008-2010** pay2
1.d_closure	-2,450***	61.36	-1,153**	-429.2
	(303.2)	(274.8)	(500.5)	(491.5)
1.d_closure#2.rel_time_group	-	-1,454***	-	-1,329***
	-	(196.1)	-	(414.3)
1.d_closure#3.rel_time_group	-	-1,318***	-	-642.3
	-	(226.0)	-	(453.7)
1.d_closure#4.rel_time_group	-	-1,883***	-	-725.8
	-	(238.1)	-	(466.9)
1.d_closure#5.rel_time_group	-1,475***	-2,892***	-621.6	-1,756***
	(224.9)	(246.6)	(426.4)	(470.7)
1.d_closure#6.rel_time_group	-1,771***	-4,065***	-1,280***	-2,740***
	(247.6)	(249.6)	(451.9)	(473.7)
1.d_closure#7.rel_time_group	-12,395***	-13,852***	-11,462***	-11,009***
	(278.5)	(260.7)	(497.7)	(484.5)
1.d_closure#8.rel_time_group	-7,747***	-9,631***	-5,718***	-7,019***
	(288.6)	(289.8)	(512.5)	(520.6)
1.d_closure#9.rel_time_group	-6,095***	-6,073***	-4,321***	-4,241***
	(295.7)	(310.9)	(517.4)	(555.2)
1.d_closure#10.rel_time_group	-4,865***	-	-3,484***	-
	(304.3)	-	(521.6)	-
1.d_closure#11.rel_time_group	-3,845***	-	-2,372***	-
	(373.3)	-	(640.8)	-
1.d_closure#12.rel_time_group	-4,056***	-	-1,996**	-
	(442.7)	-	(899.8)	-
Constant	29,723***	30,892***	22,373***	22,243***
	(215.9)	(190.4)	(344.9)	(338.2)
Observations	485,412	1,121,502	124,693	269,866
Fstat	1,186.97	2,906.07	692.23	1,229.34
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.057	0.040	0.098	0.065

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass Layoff**

VARIABLES	**Irish pre 2008** pay2	**Irish post 2008** pay2	**Non-Irish Pre 2008** pay2	**Non-Irish Post 2008** pay2
1.d_mass	-5,990***	-425.1	-1,039	1,602
	(953.2)	(1,136)	(1,107)	(2,182)
1.d_mass#2.rel_time_group	-	-2,199**	-	-2,527
	-	(875.5)	-	(1,884)
1.d_mass#3.rel_time_group	-	-3,337***	-	-3,411*
	-	(975.6)	-	(2,019)
1.d_mass#4.rel_time_group	-	-3,918***	-	-4,003*
	-	(1,007)	-	(2,104)
1.d_mass#5.rel_time_group	-939.5	-4,745***	-2,535***	-4,457**
	(713.3)	(1,024)	(975.1)	(2,122)
1.d_mass#6.rel_time_group	703.4	-6,626***	-3,826***	-7,690***
	(800.2)	(1,041)	(1,009)	(2,117)
1.d_mass#7.rel_time_group	-19,910***	-31,410***	-18,021***	-23,922***
	(846.1)	(1,056)	(1,101)	(2,148)
1.d_mass#8.rel_time_group	-16,257***	-27,692***	-13,279***	-19,609***
	(869.8)	(1,120)	(1,135)	(2,193)
1.d_mass#9.rel_time_group	-13,664***	-22,298***	-10,864***	-15,770***
	(910.8)	(1,162)	(1,153)	(2,194)
1.d_mass#10.rel_time_group	-11,821***	-	-9,304***	-
	(932.1)	-	(1,147)	-
1.d_mass#11.rel_time_group	-9,557***	-	-7,697***	-
	(1,037)	-	(1,509)	-
1.d_mass#12.rel_time_group	-5,157***	-	-6,408***	-
	(1,193)	-	(1,840)	-
Constant	35,163***	37,423***	22,733***	23,718***
	(728.1)	(801.4)	(761.5)	(1,505)
Observations	70,856	132,617	27,060	53,813
Fstat	338.62	1073.21	273.76	670.14
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.151	0.162	0.171	0.183

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10.6: Regression output for Figure 4.18

- **Closure**

VARIABLES	**2005-2007** pay2	**2008-2010** pay2
1.d_closure	-1,381**	4,508***
	(675.3)	(546.1)
1.d_closure#2.rel_time_group	-	-2,292***
	-	(357.5)
1.d_closure#3.rel_time_group	-	-2,460***
	-	(434.8)
1.d_closure#4.rel_time_group	-	-2,802***
	-	(457.3)
1.d_closure#5.rel_time_group	47.61	-2,854***
	(477.8)	(461.8)
1.d_closure#6.rel_time_group	-1,463***	-3,137***
	(554.9)	(470.5)
1.d_closure#7.rel_time_group	-15,243***	-12,225***
	(673.2)	(500.8)
1.d_closure#8.rel_time_group	-9,788***	-10,678***
	(667.6)	(636.5)
1.d_closure#9.rel_time_group	-8,246***	-5,430***
	(687.1)	(717.3)
1.d_closure#10.rel_time_group	-7,958***	-
	(702.1)	-
1.d_closure#11.rel_time_group	-7,261***	-
	(897.0)	-
1.d_closure#12.rel_time_group	-9,506***	-
	(1,087)	-
Constant	33,281***	30,021***
	(541.7)	(395.4)
Observations	68,630	172,582
Fstat	214.20	332.52
Prob > F	0.000	0.000
R-squared	0.088	0.039

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Mass-Layoff**

VARIABLES	**2005-2007** pay2	**2008-2010** pay2
1.d_mass	-908.5	-11,261***
	(1,490)	(1,518)
1.d_mass#2.rel_time_group	-	6,591***
	-	(1,341)
1.d_mass#3.rel_time_group	-	5,078***
	-	(1,383)
1.d_mass#4.rel_time_group	-	5,179***
	-	(1,420)
1.d_mass#5.rel_time_group	-4,095***	5,287***
	(1,256)	(1,435)
1.d_mass#6.rel_time_group	-4,036***	3,332**
	(1,325)	(1,468)
1.d_mass#7.rel_time_group	-20,426***	-24,361***
	(1,414)	(1,399)
1.d_mass#8.rel_time_group	-17,829***	-19,194***
	(1,430)	(1,513)
1.d_mass#9.rel_time_group	-20,027***	-16,548***
	(1,532)	(1,591)
1.d_mass#10.rel_time_group	-18,617***	-
	(1,569)	-
1.d_mass#11.rel_time_group	-20,382***	-
	(1,680)	-
1.d_mass#12.rel_time_group	-17,928***	-
	(1,876)	-
1.d_mass#2.rel_time_group	-	6,591***
	-	(1,341)
1.d_mass#3.rel_time_group	-	5,078***
	-	(1,383)
1.d_mass#4.rel_time_group	-	5,179***
	-	(1,420)
Constant	35,962***	37,773***
	(1,118)	(1,057)
Observations	21,904	39,012
Fstat	181.91	378.83
Prob > F	0.000	0.000
R-squared	0.208	0.167

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 11 : Detailed results for Chapter 5

Appendix Table 11.1: Weibull & logit model for Table 5.11

- **Weibull: Separations to employment and non-employment**

	To employment	**To non-employment**
VARIABLES	_t	_t
lnwage	-0.377***	-0.715***
	(0.00268)	(0.00127)
age1	-0.0322***	-0.0144***
	(0.000210)	(8.96e-05)
male	0.0475***	0.257***
	(0.00329)	(0.00156)
natd1	-0.390***	-0.380***
	(0.00748)	(0.00294)
natd2	-0.224***	-0.129***
	(0.0110)	(0.00454)
natd3	0.0827***	0.0995***
	(0.0102)	(0.00393)
natd4	-0.245***	-0.171***
	(0.00826)	(0.00318)
natd5	-0.0861***	-0.403***
	(0.0107)	(0.00467)
naced1	-0.450***	0.0365***
	(0.0220)	(0.00717)
naced2	-0.245***	-0.0917***
	(0.00958)	(0.00391)
naced3	0.507***	0.623***
	(0.0110)	(0.00378)
naced4	0.118***	-0.00238
	(0.00805)	(0.00317)
naced5	-0.228***	-0.235***
	(0.00861)	(0.00351)
Constant	-1.865***	1.281***
	(0.0194)	(0.00805)
Wald statistic	-99.6	-648.57
	(0.000)	(0.000)
p	0.907	0.738
	(0.0009)	(0.0003)
Wald chi2(13)	83492.75	527996.76
Prob > chi2	0.000	0.000
Observations	1,211,936	3,611,390

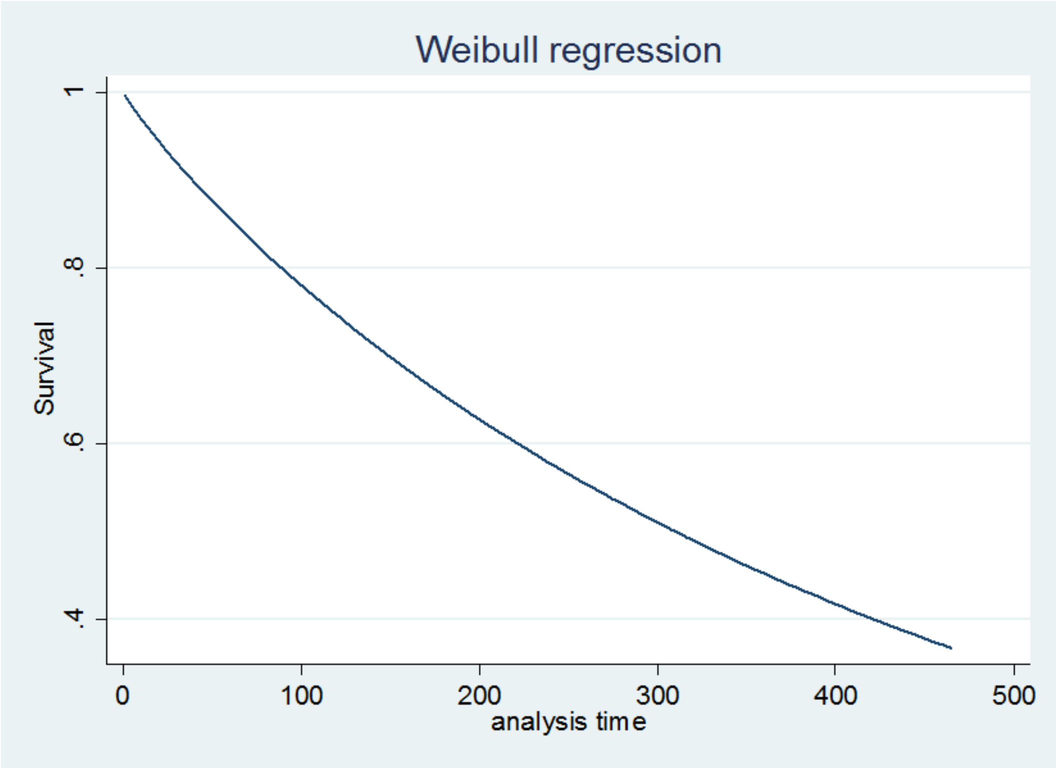
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

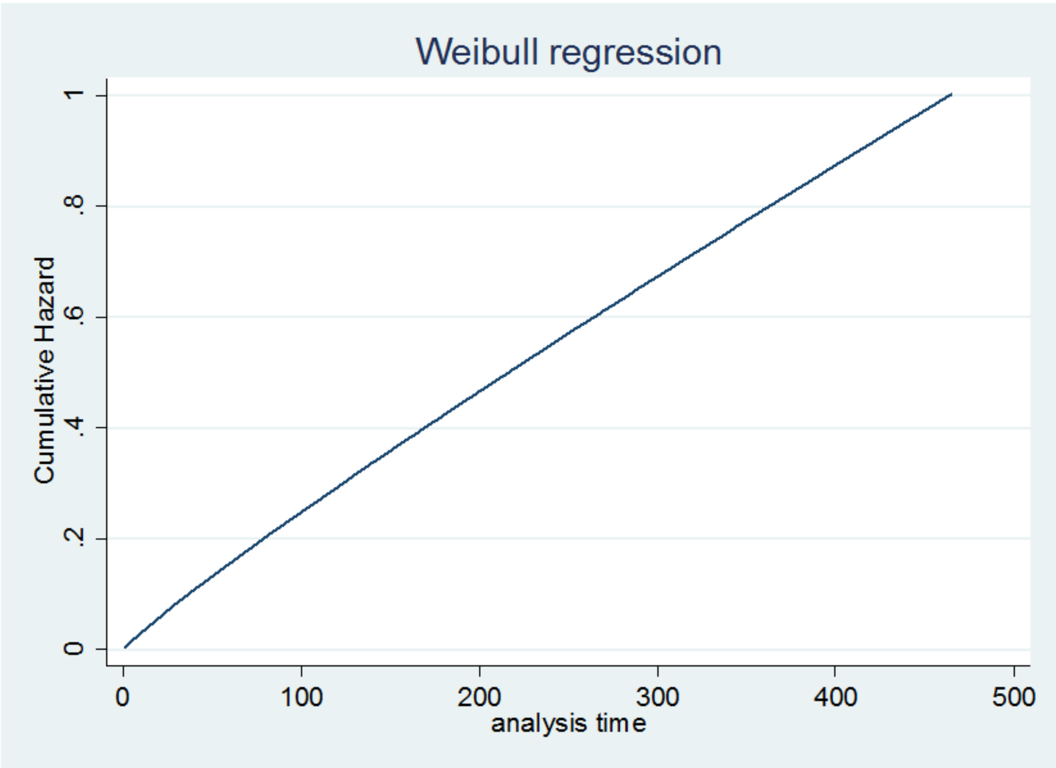
- **Logit: Hiring from employment**

VARIABLES	**Hiring from employment**
lnwage	0.995***
	(0.00236)
male	-0.321***
	(0.00310)
age1	0.00729***
	(0.000171)
natd1	0.550***
	(0.00735)
natd2	0.0330***
	(0.0105)
natd3	-0.0179*
	(0.0102)
natd4	0.178***
	(0.00820)
natd5	0.499***
	(0.0108)
naced1	-0.741***
	(0.0204)
naced2	-0.105***
	(0.00817)
naced3	-0.989***
	(0.00937)
naced4	-0.0105
	(0.00699)
naced5	0.0387***
	(0.00742)
Constant	-8.017***
	(0.0171)
LR chi2(13)	295950
Prob>chi2	0.000
Pseudo R2	0.0865
Observations	3,611,390

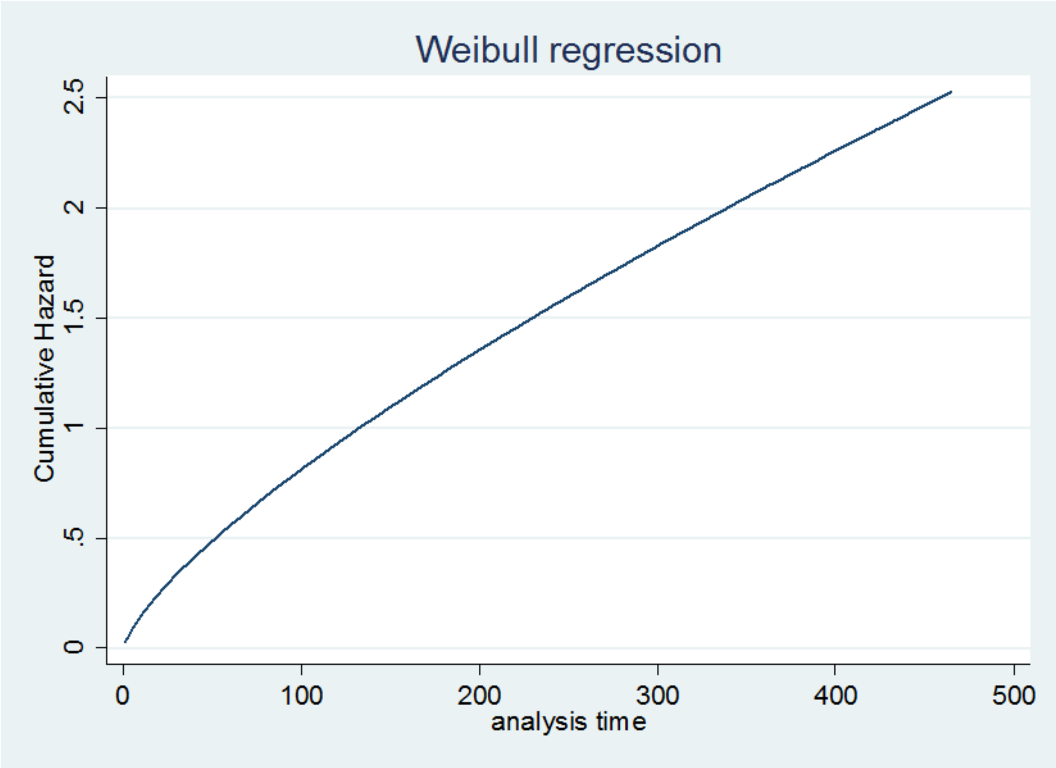
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Figure 11.1: Parametric survival and hazard curves; Transitions to employment





Appendix Figure 11.2: Parametric survival and cumulative hazard curves; Transitions to non-employment



Appendix Table 11.2: Weibull & Logit model for Table 5.13

- **Weibull: Separations to employment and non-employment**

VARIABLES	**Irish** To employment	**Non-Irish** To employment	**Irish** To non-employment	**Non-Irish** To unemployment
lnwage	-0.358***	-0.427***	-0.711***	-0.709***
	(0.00308)	(0.00536)	(0.00152)	(0.00226)
age1	-0.0338***	-0.0271***	-0.0161***	-0.00925***
	(0.000241)	(0.000417)	(0.000107)	(0.000159)
male	0.0185***	0.124***	0.275***	0.212***
	(0.00398)	(0.00586)	(0.00199)	(0.00248)
naced1	-0.583***	-0.300***	-0.139***	0.200***
	(0.0294)	(0.0339)	(0.0104)	(0.0102)
naced2	-0.148***	-0.472***	-0.0912***	-0.0816***
	(0.0112)	(0.0183)	(0.00488)	(0.00661)
naced3	0.446***	0.662***	0.593***	0.669***
	(0.0128)	(0.0213)	(0.00461)	(0.00653)
naced4	0.112***	0.151***	-0.0246***	0.0591***
	(0.00943)	(0.0155)	(0.00382)	(0.00566)
naced5	-0.285***	0.0343**	-0.250***	-0.194***
	(0.00997)	(0.0173)	(0.00411)	(0.00677)
Constant	-2.346***	-1.830***	1.037***	0.802***
	(0.0214)	(0.0366)	(0.00920)	(0.0141)
Wald statistic	-71.50	-74.02	-547.34	-370.33
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.9178	0.8855	0.7169	0.7671
	(0.0011)	(0.0018)	(0.0004)	(0.0005)
Wald chi2(13)	53043.07	17213.74	323864.4	133348.9
Prob > chi2	0.000	0.000	0.000	0.000
Observations	889,118	322,818	2,336,718	1,274,672

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment**

VARIABLES	**Irish** From employment	**Non-Irish** From employment
lnwage	1.046***	0.827***
	(0.00274)	(0.00461)
male	-0.349***	-0.227***
	(0.00368)	(0.00578)
age1	0.00580***	0.0112***
	(0.000194)	(0.000361)
naced1	-0.556***	-1.058***
	(0.0253)	(0.0350)
naced2	-0.0556***	-0.257***
	(0.00954)	(0.0159)
naced3	-0.923***	-1.205***
	(0.0108)	(0.0188)
naced4	-0.00911	-0.0562***
	(0.00813)	(0.0137)
naced5	0.0633***	0.00560
	(0.00848)	(0.0155)
Constant	-7.739***	-6.959***
	(0.0181)	(0.0307)
LR chi2(8)	208894.45	49740.76
Prob>chi2	0.000	0.000
Pseudo R2	0.0870	0.0505
Observations	2,336,718	1,274,672

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 11.3: Weibull & Logit model for Table 5.14

- **Weibull: Separations to employment**

	Irish	**UK**	**Western Europe**	**Eastern Europe**	**Asia**	**Rest of the World**
lnwage	-0.358***	-0.280***	-0.724***	-0.616***	-0.319***	-0.302***
	(0.00308)	(0.0129)	(0.0174)	(0.00945)	(0.0156)	(0.0123)
age1	-0.0338***	-0.0277***	-0.0361***	-0.0286***	-0.0303***	-0.0231***
	(0.000241)	(0.00112)	(0.00130)	(0.000665)	(0.00135)	(0.00105)
male	0.0185***	0.131***	0.0954***	0.108***	0.256***	0.217***
	(0.00398)	(0.0182)	(0.0156)	(0.00859)	(0.0181)	(0.0154)
naced1	-0.583***	-0.574***	-0.911***	-0.199***	-0.108	-0.450***
	(0.0294)	(0.144)	(0.200)	(0.0397)	(0.179)	(0.130)
naced2	-0.148***	-0.273***	0.276***	-0.548***	-0.618***	-0.322***
	(0.0112)	(0.0494)	(0.0627)	(0.0255)	(0.0709)	(0.0499)
naced3	0.446***	0.523***	0.618***	0.824***	0.412***	0.421***
	(0.0128)	(0.0555)	(0.0949)	(0.0286)	(0.104)	(0.0592)
naced4	0.112***	0.0873**	0.173***	0.145***	-0.0214	0.257***
	(0.00943)	(0.0397)	(0.0583)	(0.0224)	(0.0463)	(0.0373)
naced5	-0.285***	-0.330***	-0.103	-0.155***	-0.0628	0.459***
	(0.00997)	(0.0429)	(0.0642)	(0.0297)	(0.0484)	(0.0401)
Constant	-2.346***	-2.794***	-0.0974	-0.598***	-2.377***	-2.919***
	(0.0214)	(0.0967)	(0.119)	(0.0625)	(0.109)	(0.0843)
Wald statistic	-71.50	-21.77	0.70	-62.34	-22.78	-21.92
	(0.000)	(0.000)	(0.482)	(0.000)	(0.000)	(0.000)
p	0.9178	0.897	1.003	0.8632	0.8948	0.9092
	(0.001)	(0.004)	(0.005)	(0.002)	(0.004)	(0.0039)
Wald chi2(8)	53043.07	1928.86	2777.47	10999.63	1852.00	1706.49
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Observations	889,118	43,599	43,276	151,833	37,160	46,950

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Weibull: Separations to unemployment**

VARIABLES	Irish	UK	Western Europe	Eastern Europe	Asia	Rest of the World
lnwage	-0.711***	-0.585***	-0.858***	-0.812***	-0.702***	-0.619***
	(0.00152)	(0.00540)	(0.00684)	(0.00418)	(0.00707)	(0.00452)
age1	-0.0161***	-0.0113***	-0.0231***	-0.00668***	-0.0026***	-0.0150***
	(0.000107)	(0.000423)	(0.000538)	(0.000226)	(0.000628)	(0.000407)
male	0.275***	0.283***	0.158***	0.312***	0.0793***	0.113***
	(0.00199)	(0.00776)	(0.00652)	(0.00367)	(0.00837)	(0.00599)
naced1	-0.139***	-0.0309	0.0483	0.212***	-0.0319	0.283***
	(0.0104)	(0.0443)	(0.0524)	(0.0122)	(0.0701)	(0.0306)
naced2	-0.0912***	-0.140***	-0.0440*	-0.0992***	0.0107	0.0269
	(0.00488)	(0.0195)	(0.0238)	(0.00885)	(0.0310)	(0.0177)
naced3	0.593***	0.578***	0.605***	0.644***	0.790***	0.800***
	(0.00461)	(0.0181)	(0.0277)	(0.00883)	(0.0371)	(0.0163)
naced4	-0.0246***	0.0205	-0.0329	0.0287***	0.0639***	0.187***
	(0.00382)	(0.0148)	(0.0209)	(0.00792)	(0.0215)	(0.0133)
naced5	-0.250***	-0.306***	-0.207***	-0.272***	-0.202***	-0.00805
	(0.00411)	(0.0163)	(0.0233)	(0.0122)	(0.0233)	(0.0151)
Constant	1.037***	0.245***	2.030***	1.273***	0.157***	0.575***
	(0.00920)	(0.0364)	(0.0426)	(0.0248)	(0.0467)	(0.0290)
Wald statistic	-547.34	-131.41	-68.24	-268.99	-77.76	-159.25
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p	0.7169	0.7417	0.08613	0.7634	0.8123	0.7559
	(0.0004)	(0.0017)	(0.0019)	0.0007	(0.0021)	(0.0013)
Wald chi2(8)	323864.44	16094.43	19620.13	57123.77	15094.83	24947.17
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2,336,718	139,843	175,657	645,823	109,246	204,103

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment**

VARIABLES	Irish	UK	W.Europe	E.Europe	Asia	ROW
lnwage	1.046***	0.751***	0.934***	1.091***	0.628***	0.731***
	(0.00274)	(0.0108)	(0.0124)	(0.00948)	(0.0123)	(0.0101)
male	-0.349***	-0.307***	-0.306***	-0.417***	0.113***	-0.0111
	(0.00368)	(0.0168)	(0.0150)	(0.00863)	(0.0172)	(0.0151)
age1	0.00580***	0.0143***	0.0309***	0.00577***	0.00723***	0.0242***
	(0.000194)	(0.000916)	(0.00107)	(0.000553)	(0.00119)	(0.000965)
naced1	-0.556***	-0.328***	-0.879***	-1.280***	0.0443	-0.928***
	(0.0253)	(0.116)	(0.191)	(0.0416)	(0.150)	(0.125)
naced2	-0.0556***	0.0468	0.123**	-0.444***	-0.356***	-0.0869*
	(0.00954)	(0.0431)	(0.0577)	(0.0210)	(0.0647)	(0.0463)
naced3	-0.923***	-0.676***	-1.016***	-1.397***	-0.957***	-1.248***
	(0.0108)	(0.0474)	(0.0773)	(0.0247)	(0.0927)	(0.0544)
naced4	-0.00911	-0.00228	0.295***	-0.204***	0.0569	0.0959***
	(0.00813)	(0.0354)	(0.0513)	(0.0186)	(0.0462)	(0.0369)
naced5	0.0633***	0.0919**	0.0343	-0.0617**	0.00764	0.342***
	(0.00848)	(0.0380)	(0.0567)	(0.0261)	(0.0483)	(0.0394)
Constant	-7.739***	-6.726***	-8.645***	-8.092***	-5.528***	-7.234***
	(0.0181)	(0.0779)	(0.0911)	(0.0592)	(0.0870)	(0.0724)
LR chi2(8)	208894.45	6268.55	8936.53	21700.14	4120.05	10198.11
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.0870	0.0523	0.0647	0.0464	0.0384	0.0691
Observations	2,336,718	139,843	175,657	645,823	109,246	204,103

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 11.4: Weibull & Logit model for Table 5.15

- **Weibull: Separations to employment**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	-0.668***	-0.329***	-0.221***	-0.304***
	(0.00593)	(0.00430)	(0.00555)	(0.00815)
natd1	-0.136***	-0.403***	-0.619***	-0.557***
	(0.0165)	(0.0105)	(0.0151)	(0.0336)
natd2	-0.0218	-0.236***	-0.421***	-0.325***
	(0.0287)	(0.0162)	(0.0201)	(0.0406)
natd3	0.384***	0.0649***	-0.109***	-0.119**
	(0.0222)	(0.0137)	(0.0237)	(0.0537)
natd4	-0.0481***	-0.242***	-0.304***	-0.173***
	(0.0176)	(0.0114)	(0.0191)	(0.0393)
natd5	0.172***	-0.176***	-0.117***	0.0527
	(0.0221)	(0.0149)	(0.0243)	(0.0533)
male	-0.0989***	0.0511***	0.204***	0.166***
	(0.00600)	(0.00494)	(0.00803)	(0.0127)
naced1	-0.324***	-0.501***	-0.471***	-0.554***
	(0.0421)	(0.0350)	(0.0462)	(0.0697)
naced2	-0.165***	-0.275***	-0.250***	-0.189***
	(0.0179)	(0.0147)	(0.0222)	(0.0347)
naced3	0.659***	0.455***	0.512***	0.571***
	(0.0204)	(0.0169)	(0.0249)	(0.0381)
naced4	0.179***	0.113***	0.0785***	0.0906***
	(0.0140)	(0.0127)	(0.0194)	(0.0288)
naced5	-0.0888***	-0.235***	-0.252***	-0.332***
	(0.0156)	(0.0136)	(0.0202)	(0.0300)
Constant	-1.299***	-3.060***	-3.996***	-3.674***
	(0.0374)	(0.0292)	(0.0399)	(0.0633)
Wald statistic	-27.88	-75.86	-48.44	-17.44
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.9511	0.8963	0.8931	0.9320
	(0.0017)	(0.0013)	(0.0021)	(0.0038)
Wald chi2(12)	21792.79	20840.89	10220.82	5541.14
Prob > chi2	0.000	0.000	0.000	0.000
Observations	282,958	517,138	287,147	287,147

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Weibull: Separations to non-employment**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.836***	-0.757***	-0.578***	-0.495***
	(0.00257)	(0.00220)	(0.00256)	(0.00345)
natd1	-0.347***	-0.394***	-0.447***	-0.451***
	(0.00581)	(0.00442)	(0.00627)	(0.0124)
natd2	-0.0756***	-0.135***	-0.180***	-0.168***
	(0.0102)	(0.00729)	(0.00845)	(0.0150)
natd3	0.217***	0.0620***	0.0681***	-0.0163
	(0.00734)	(0.00569)	(0.00962)	(0.0191)
natd4	-0.168***	-0.207***	-0.0914***	-0.0616***
	(0.00620)	(0.00465)	(0.00720)	(0.0136)
natd5	-0.542***	-0.359***	-0.284***	-0.301***
	(0.00884)	(0.00663)	(0.0114)	(0.0239)
male	0.171***	0.247***	0.355***	0.349***
	(0.00269)	(0.00251)	(0.00379)	(0.00523)
naced1	0.144***	0.00791	-0.0532***	-0.0290
	(0.0132)	(0.0122)	(0.0151)	(0.0205)
naced2	0.0615***	-0.156***	-0.180***	-0.0489***
	(0.00700)	(0.00634)	(0.00887)	(0.0124)
naced3	0.599***	0.647***	0.627***	0.603***
	(0.00674)	(0.00622)	(0.00851)	(0.0117)
naced4	0.0328***	-0.0204***	-0.0234***	0.0137
	(0.00550)	(0.00527)	(0.00740)	(0.0100)
naced5	-0.0432***	-0.272***	-0.334***	-0.279***
	(0.00643)	(0.00583)	(0.00786)	(0.0104)
Constant	1.567***	1.032***	-0.0410**	-0.457***
	(0.0147)	(0.0129)	(0.0162)	(0.0239)
Wald statistic	-322.95	-379.45	-309.74	-204.93
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.7622	0.7499	0.7131	0.7219
	(0.0006)	(0.0006)	(0.0007)	(0.0011)
Wald chi2(12)	134585.20	205505.58	108073.35	46189.22
Prob > chi2	0.000	0.000	0.000	0.000
Observations	1,105,203	1,455,292	715,549	335,346

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	0.951***	1.096***	0.872***	0.822***
	(0.00588)	(0.00386)	(0.00440)	(0.00612)
male	-0.423***	-0.311***	-0.178***	-0.408***
	(0.00637)	(0.00458)	(0.00684)	(0.0103)
natd1	0.750***	0.680***	0.343***	0.486***
	(0.0187)	(0.0105)	(0.0138)	(0.0297)
natd2	-0.100***	0.0873***	-0.0593***	0.0790**
	(0.0324)	(0.0161)	(0.0183)	(0.0353)
natd3	-0.277***	0.122***	-0.0617***	-0.0147
	(0.0258)	(0.0138)	(0.0215)	(0.0471)
natd4	0.250***	0.385***	-0.194***	-0.169***
	(0.0198)	(0.0115)	(0.0177)	(0.0354)
natd5	0.924***	0.491***	0.228***	0.331***
	(0.0251)	(0.0150)	(0.0227)	(0.0487)
naced1	-0.935***	-0.716***	-0.631***	-0.435***
	(0.0444)	(0.0325)	(0.0406)	(0.0560)
naced2	-0.402***	-0.0317**	0.0145	-0.0102
	(0.0164)	(0.0127)	(0.0178)	(0.0264)
naced3	-0.996***	-0.977***	-0.964***	-0.913***
	(0.0185)	(0.0145)	(0.0203)	(0.0300)
naced4	-0.121***	0.0855***	-0.0356**	-0.0851***
	(0.0126)	(0.0110)	(0.0158)	(0.0227)
naced5	-0.401***	0.0933***	0.174***	0.327***
	(0.0143)	(0.0118)	(0.0164)	(0.0229)
Constant	-7.733***	-8.477***	-6.892***	-6.661***
	(0.0399)	(0.0271)	(0.0325)	(0.0513)
LR chi2(12)	47265.64	137749.22	62658.77	30342.99
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0573	0.0920	0.0861	0.0913
Observations	1,105,203	1,455,292	715,549	335,346

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 11.5: Weibull & Logit model for Table 5.16

- **Weibull: Separations to employment – Irish**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.639***	-0.272***	-0.246***	-0.334***
	(0.00663)	(0.00518)	(0.00627)	(0.00881)
male	-0.147***	0.0250***	0.176***	0.145***
	(0.00716)	(0.00619)	(0.00950)	(0.0142)
naced1	-0.408***	-0.608***	-0.639***	-0.836***
	(0.0539)	(0.0482)	(0.0625)	(0.0942)
naced2	-0.0400*	-0.185***	-0.167***	-0.130***
	(0.0206)	(0.0179)	(0.0257)	(0.0380)
naced3	0.613***	0.399***	0.450***	0.473***
	(0.0231)	(0.0204)	(0.0291)	(0.0428)
naced4	0.177***	0.106***	0.0680***	0.0628**
	(0.0158)	(0.0157)	(0.0227)	(0.0316)
naced5	-0.111***	-0.302***	-0.347***	-0.402***
	(0.0172)	(0.0164)	(0.0236)	(0.0328)
Constant	-1.703***	-3.818***	-4.442***	-4.001***
	(0.0392)	(0.0352)	(0.0443)	(0.0603)
Wald statistic	-12.20	-56.97	-37.96	-15.30
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.9737	0.9002	0.8980	0.09317
	(0.0022)	(0.0017)	(0.0025)	(0.0043)
Wald chi2(7)	14388.05	8365.47	5085.18	3877.70
Prob > chi2	0.000	0.000	0.000	0.000
Observations	208,400	353,384	221,515	105,819

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Weibull: Separations to employment – UK**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.568***	-0.286***	-0.251***	-0.258***
	(0.0445)	(0.0217)	(0.0208)	(0.0328)
male	-0.116**	0.0311	0.297***	0.284***
	(0.0490)	(0.0279)	(0.0330)	(0.0537)
naced1	0.147	-0.482**	-0.794***	-1.668**
	(0.335)	(0.224)	(0.259)	(0.731)
naced2	-0.332**	-0.383***	-0.153*	-0.200
	(0.149)	(0.0777)	(0.0840)	(0.141)
naced3	0.733***	0.379***	0.587***	0.759***
	(0.170)	(0.0886)	(0.0927)	(0.152)
naced4	0.0940	0.0568	0.110	0.224*
	(0.109)	(0.0604)	(0.0717)	(0.116)
naced5	-0.256**	-0.305***	-0.365***	-0.200
	(0.124)	(0.0658)	(0.0765)	(0.122)
Constant	-1.785***	-3.503***	-4.236***	-4.538***
	(0.272)	(0.146)	(0.143)	(0.234)
Wald statistic	-4.21	-14.38	-13.96	-3.48
	(0.000)	(0.000)	(0.000)	(0.001)
p	0.9423	0.8967	0.8843	0.9462
	(0.0132)	(0.0068)	(0.0078)	(0.0151)
Wald chi2(7)	255.23	391.76	539.77	225.56
Prob > chi2	0.000	0.000	0.000	0.000
Observations	4,240	15,886	16,930	6,543

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Weibull: Separations to employment – Western Europe**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-1.018***	-0.761***	-0.508***	-0.460***
	(0.0465)	(0.0237)	(0.0320)	(0.0626)
male	0.0233	0.0908***	0.186***	0.135
	(0.0328)	(0.0202)	(0.0425)	(0.0964)
naced1	-0.906**	-1.131***	-0.526	-0.614
	(0.396)	(0.311)	(0.396)	(0.737)
naced2	0.328**	0.270***	0.233	0.00610
	(0.132)	(0.0847)	(0.148)	(0.324)
naced3	0.142	0.523***	0.903***	1.181***
	(0.355)	(0.125)	(0.182)	(0.373)
naced4	-0.00174	0.177**	0.291**	0.513*
	(0.123)	(0.0789)	(0.137)	(0.280)
naced5	-0.199	-0.0461	-0.190	0.0214
	(0.147)	(0.0865)	(0.147)	(0.293)
Constant	0.809***	-0.946***	-2.799***	-3.513***
	(0.287)	(0.155)	(0.234)	(0.449)
Wald statistic	-4.82	-0.39	-3.85	-0.21
	(0.000)	(0.699)	(0.000)	(0.830)
p	1.050	1.002	0.9556	0.9941
	(0.0106)	(0.0059)	(0.0123)	(0.0273)
Wald chi2(7)	560.66	1064.38	341.34	90.02
Prob > chi2	0.000	0.000	0.000	0.000
Observations	8,360	25,064	8,118	1,734

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Weibull: Separations to employment – Eastern Europe**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.853***	-0.563***	-0.348***	-0.236***
	(0.0204)	(0.0127)	(0.0265)	(0.0448)
male	0.0730***	0.111***	0.248***	0.150***
	(0.0143)	(0.0122)	(0.0282)	(0.0488)
naced1	-0.189**	-0.307***	-0.174*	0.0521
	(0.0771)	(0.0590)	(0.0964)	(0.152)
naced2	-0.530***	-0.567***	-0.619***	-0.443***
	(0.0461)	(0.0350)	(0.0750)	(0.134)
naced3	0.868***	0.715***	0.877***	1.080***
	(0.0527)	(0.0396)	(0.0793)	(0.138)
naced4	0.135***	0.131***	0.168**	0.215*
	(0.0404)	(0.0307)	(0.0667)	(0.118)
naced5	-0.254***	-0.172***	-0.000599	-0.118
	(0.0583)	(0.0403)	(0.0807)	(0.146)
Constant	0.174	-1.763***	-3.523***	-4.272***
	(0.120)	(0.0782)	(0.163)	(0.277)
Wald statistic	-36.68	-43.67	-17.45	-6.53
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.8647	0.8639	0.8735	0.9155
	(0.0034)	(0.0029)	(0.0067)	(0.0124)
Wald chi2(7)	3483.42	4548.13	998.38	319.28
Prob > chi2	0.000	0.000	0.000	0.000
Observations	46,259	79,786	19,572	6,216

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To employment - Asia**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.791***	-0.376***	0.371***	0.308***
	(0.0353)	(0.0218)	(0.0363)	(0.0729)
male	0.0625*	0.201***	0.419***	0.523***
	(0.0356)	(0.0248)	(0.0437)	(0.0946)
naced1	-0.393	-0.649*	0.313	-0.138
	(0.671)	(0.391)	(0.218)	(0.698)
naced2	0.0160	-0.580***	-1.065***	-0.952***
	(0.162)	(0.0970)	(0.153)	(0.325)
naced3	0.600**	0.332**	0.413**	0.333
	(0.250)	(0.156)	(0.180)	(0.468)
naced4	0.146	-0.0419	-0.157	-0.0600
	(0.0977)	(0.0651)	(0.0986)	(0.215)
naced5	0.268**	-0.191***	-0.183*	0.167
	(0.109)	(0.0682)	(0.0970)	(0.216)
Constant	-0.635***	-2.946***	-7.897***	-7.932***
	(0.210)	(0.143)	(0.269)	(0.531)
Wald statistic	-3.25	-15.95	-10.68	-1.99
	(0.000)	(0.000)	(0.000)	(0.047)
p	0.9683	0.8964	0.8811	0.9486
	(0.0096)	(0.0061)	(0.0104)	(0.0252)
Wald chi2(7)	648.68	736.08	273.55	95.44
Prob > chi2	0.000	0.000	0.000	0.000
Observations	7,647	20,027	7,795	1,691

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To employment - Rest of the World**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	-0.746***	-0.336***	-0.135***	-0.164***
	(0.0327)	(0.0173)	(0.0222)	(0.0494)
male	-0.0289	0.189***	0.415***	0.440***
	(0.0336)	(0.0216)	(0.0326)	(0.0744)
naced1	-0.392	-0.530***	-0.313	-0.419
	(0.316)	(0.195)	(0.233)	(0.511)
naced2	-0.00128	-0.397***	-0.426***	0.0164
	(0.117)	(0.0699)	(0.101)	(0.229)
naced3	0.663***	0.369***	0.348***	0.690***
	(0.142)	(0.0826)	(0.123)	(0.253)
naced4	0.406***	0.197***	0.213***	0.410**
	(0.0794)	(0.0523)	(0.0796)	(0.186)
naced5	0.388***	0.445***	0.441***	0.297
	(0.0969)	(0.0563)	(0.0823)	(0.195)
Constant	-1.175***	-3.292***	-4.953***	-5.338***
	(0.196)	(0.114)	(0.153)	(0.347)
Wald statistic	-3.50	-17.21	-12.45	-0.71
	(0.000)	(0.000)	(0.000)	(0.476)
p	0.9640	0.9014	0.9003	0.9843
	0.0100	(0.0054)	(0.0076)	(0.0219)
Wald chi2(7)	623.85	645.73	282.82	70.54
Prob > chi2	0.000	0.000	0.000	0.000
Observations	8,052	22,991	13,217	2,690

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment - Ireland**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	-0.820***	-0.756***	-0.583***	-0.513***
	(0.00298)	(0.00285)	(0.00304)	(0.00386)
male	0.187***	0.278***	0.339***	0.322***
	(0.00339)	(0.00344)	(0.00465)	(0.00600)
naced1	0.0298	-0.192***	-0.237***	-0.219***
	(0.0190)	(0.0184)	(0.0218)	(0.0288)
naced2	0.137***	-0.190***	-0.215***	-0.0634***
	(0.00853)	(0.00843)	(0.0108)	(0.0143)
naced3	0.587***	0.633***	0.619***	0.621***
	(0.00779)	(0.00808)	(0.0104)	(0.0137)
naced4	0.0142**	-0.0436***	-0.0541***	-0.00557
	(0.00637)	(0.00681)	(0.00878)	(0.0111)
naced5	-0.0344***	-0.306***	-0.378***	-0.314***
	(0.00721)	(0.00726)	(0.00915)	(0.0115)
Constant	1.195***	0.791***	-0.325***	-0.707***
	(0.0161)	(0.0164)	(0.0184)	(0.0232)
Wald statistic	-272.17	-316.05	-261.91	-181.28
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.7473	0.7180	0.6941	0.0784
Wald chi2(7)	86512.91	101559.81	57002.75	27556.39
Prob > chi2	0.000	0.000	0.000	0.000
Observations	730,815	857,045	491,468	257,390

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment - UK**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.773***	-0.654***	-0.534***	-0.418***
	(0.0159)	(0.00946)	(0.00904)	(0.0124)
male	0.104***	0.213***	0.413***	0.340***
	(0.0185)	(0.0130)	(0.0143)	(0.0201)
naced1	0.153*	0.00481	-0.141*	-0.0171
	(0.0930)	(0.0803)	(0.0753)	(0.126)
naced2	0.00612	-0.189***	-0.189***	-0.0240
	(0.0496)	(0.0336)	(0.0337)	(0.0490)
naced3	0.536***	0.555***	0.613***	0.644***
	(0.0471)	(0.0312)	(0.0309)	(0.0461)
naced4	-0.00799	0.0120	0.0121	0.129***
	(0.0365)	(0.0252)	(0.0266)	(0.0386)
naced5	-0.195***	-0.282***	-0.333***	-0.214***
	(0.0441)	(0.0279)	(0.0285)	(0.0408)
Constant	1.005***	0.255***	-0.559***	-1.221***
	(0.0925)	(0.0579)	(0.0559)	(0.0787)
Wald statistic	-36.61	-71.75	-84.56	-52.08
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.8096	0.7570	0.7174	0.7346
Wald chi2(7)	2579.78	5933.64	5567.44	1835.85
Prob > chi2	0.000	0.000	0.000	0.000
Observations	20,744	50,096	48,193	20,810

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment – Western Europe**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	-0.988***	-0.906***	-0.620***	-0.430***
	(0.0126)	(0.00991)	(0.0137)	(0.0237)
male	0.104***	0.146***	0.266***	0.279***
	(0.0116)	(0.00915)	(0.0184)	(0.0372)
naced1	0.0941	0.0154	0.0305	-0.173
	(0.0780)	(0.0841)	(0.122)	(0.231)
naced2	0.0439	-0.0841**	-0.130**	-0.106
	(0.0436)	(0.0355)	(0.0525)	(0.0989)
naced3	0.189**	0.521***	0.701***	0.615***
	(0.0813)	(0.0394)	(0.0511)	(0.0887)
naced4	-0.0510	-0.0542*	-0.00310	0.0325
	(0.0384)	(0.0315)	(0.0439)	(0.0826)
naced5	-0.220***	-0.194***	-0.240***	-0.282***
	(0.0455)	(0.0347)	(0.0486)	(0.0904)
Constant	2.126***	1.533***	0.0303	-1.093***
	(0.0747)	(0.0632)	(0.0856)	(0.151)
Wald statistic	-19.39	-45.38	-48.14	-24.21
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.9244	0.8698	0.7738	0.7815
Wald chi2(7)	6889.98	8905.06	2658.85	596.03
Prob > chi2	0.000	0.000	0.000	0.000
Observations	52,433	90,032	26,578	6,614

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment – Eastern Europe**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.967***	-0.813***	-0.620***	-0.498***
	(0.00829)	(0.00585)	(0.0104)	(0.0156)
male	0.246***	0.315***	0.520***	0.562***
	(0.00599)	(0.00540)	(0.0115)	(0.0174)
naced1	0.250***	0.169***	0.169***	0.234***
	(0.0223)	(0.0192)	(0.0308)	(0.0447)
naced2	-0.0740***	-0.147***	-0.133***	-0.0356
	(0.0157)	(0.0124)	(0.0255)	(0.0392)
naced3	0.578***	0.624***	0.609***	0.553***
	(0.0162)	(0.0124)	(0.0248)	(0.0377)
naced4	0.0375***	-0.0134	0.0230	0.0716**
	(0.0139)	(0.0110)	(0.0236)	(0.0360)
naced5	-0.261***	-0.274***	-0.236***	-0.148***
	(0.0234)	(0.0167)	(0.0327)	(0.0497)
Constant	2.142***	0.978***	-0.262***	-0.940***
	(0.0462)	(0.0335)	(0.0605)	(0.0904)
Wald statistic	-153.27	-168.27	-100.94	-61.82
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.7606	0.7769	0.7604	0.7787
Wald chi2(7)	17041.70	29147.22	8701.53	3233.56
Prob > chi2	0.000	0.000	0.000	0.000
Observations	222,810	302,858	84,471	35,684

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

.

- **To unemployment – Asia**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	-0.841***	-0.750***	-0.496***	-0.293***
	(0.0154)	(0.00966)	(0.0165)	(0.0347)
male	-0.0313**	0.0637***	0.257***	0.362***
	(0.0155)	(0.0117)	(0.0222)	(0.0458)
naced1	0.0691	0.0806	-0.151	0.199
	(0.250)	(0.110)	(0.111)	(0.214)
naced2	0.426***	-0.0476	-0.230***	0.0609
	(0.0626)	(0.0444)	(0.0676)	(0.139)
naced3	0.647***	0.698***	0.770***	0.808***
	(0.0971)	(0.0576)	(0.0661)	(0.138)
naced4	0.0440	0.0704**	0.0276	0.251**
	(0.0426)	(0.0308)	(0.0508)	(0.106)
naced5	-0.0179	-0.266***	-0.282***	0.147
	(0.0490)	(0.0327)	(0.0533)	(0.111)
Constant	0.745***	0.303***	-0.947***	-2.184***
	(0.0892)	(0.0627)	(0.107)	(0.224)
Wald statistic	-31.38	-50.11	-43.98	-25.32
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.8529	0.8297	0.7436	0.7075
Wald chi2(7)	3493.76	9457.65	2026.57	264.43
Prob > chi2	0.000	0.000	0.000	0.000
Observations	28,706	57,290	18,878	4,372

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment – Rest of the World**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.726***	-0.643***	-0.556***	-0.381***
	(0.00960)	(0.00656)	(0.00915)	(0.0177)
male	-0.00933	0.0695***	0.302***	0.429***
	(0.0116)	(0.00864)	(0.0138)	(0.0281)
naced1	0.338***	0.217***	0.329***	0.375***
	(0.0559)	(0.0496)	(0.0622)	(0.110)
naced2	0.138***	-0.0400	-0.000209	0.155**
	(0.0385)	(0.0257)	(0.0352)	(0.0691)
naced3	0.793***	0.807***	0.817***	0.640***
	(0.0360)	(0.0235)	(0.0328)	(0.0640)
naced4	0.265***	0.157***	0.166***	0.0945*
	(0.0272)	(0.0194)	(0.0278)	(0.0567)
naced5	0.0404	-0.0151	-0.0559*	0.106*
	(0.0344)	(0.0218)	(0.0302)	(0.0609)
Constant	0.776***	0.235***	-0.419***	-1.345***
	(0.0561)	(0.0398)	(0.0560)	(0.111)
Wald statistic	-71.60	-105.01	-81.63	-40.83
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.7797	0.7653	0.7323	0.7233
Wald chi2(7)	6076.54	11470.83	5413.73	850.11
Prob > chi2	0.000	0.000	0.000	0.000
Observations	49,695	97,971	45,961	10,476

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment – Ireland**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	0.970***	1.195***	0.908***	0.872***
	(0.00657)	(0.00474)	(0.00508)	(0.00676)
male	-0.487***	-0.339***	-0.154***	-0.387***
	(0.00745)	(0.00567)	(0.00786)	(0.0113)
naced1	-0.732***	-0.454***	-0.592***	-0.383***
	(0.0533)	(0.0414)	(0.0507)	(0.0677)
naced2	-0.421***	0.0471***	0.0574***	0.0133
	(0.0188)	(0.0155)	(0.0204)	(0.0290)
naced3	-0.959***	-0.889***	-0.916***	-0.872***
	(0.0205)	(0.0174)	(0.0234)	(0.0333)
naced4	-0.105***	0.102***	-0.0608***	-0.106***
	(0.0140)	(0.0136)	(0.0182)	(0.0249)
naced5	-0.394***	0.171***	0.173***	0.357***
	(0.0156)	(0.0142)	(0.0186)	(0.0249)
Constant	-7.083***	-8.460***	-6.783***	-6.508***
	(0.0402)	(0.0314)	(0.0348)	(0.0460)
LR chi2(7)	32182.66	92527.40	43167.91	23506.11
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0539	0.0957	0.0810	0.0869
Observations	730,815	857,045	491,468	257,390

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment – UK**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	0.786***	0.827***	0.696***	0.620***
	(0.0479)	(0.0192)	(0.0168)	(0.0242)
male	-0.339***	-0.302***	-0.226***	-0.488***
	(0.0565)	(0.0262)	(0.0284)	(0.0445)
naced1	-0.244	-0.170	-0.354*	-0.631*
	(0.329)	(0.193)	(0.188)	(0.330)
naced2	-0.166	0.161**	0.0549	-0.151
	(0.157)	(0.0706)	(0.0713)	(0.105)
naced3	-0.503***	-0.607***	-0.697***	-0.880***
	(0.166)	(0.0778)	(0.0778)	(0.117)
naced4	0.0621	0.0990*	0.00122	-0.336***
	(0.110)	(0.0567)	(0.0610)	(0.0874)
naced5	-0.112	0.109*	0.0967	-0.0617
	(0.131)	(0.0618)	(0.0643)	(0.0909)
Constant	-7.059***	-6.707***	-5.809***	-4.999***
	(0.304)	(0.129)	(0.115)	(0.164)
LR chi2(7)	331.86	2326.44	2219.34	832.04
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0300	0.0512	0.0482	0.0461
Observations	20,744	50,096	48,193	20,810

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment – Western Europe**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	1.335***	1.029***	0.651***	0.424***
	(0.0410)	(0.0173)	(0.0225)	(0.0423)
male	-0.317***	-0.294***	-0.272***	-0.458***
	(0.0375)	(0.0190)	(0.0358)	(0.0801)
naced1	-0.826**	-1.158***	-0.675*	0.216
	(0.406)	(0.316)	(0.362)	(0.578)
naced2	-0.291*	0.147*	0.259**	0.633**
	(0.156)	(0.0759)	(0.119)	(0.265)
naced3	-0.413*	-0.884***	-1.073***	-0.905***
	(0.214)	(0.106)	(0.149)	(0.311)
naced4	0.132	0.339***	0.242**	0.608**
	(0.134)	(0.0676)	(0.106)	(0.239)
naced5	-0.212	0.00581	0.0796	0.561**
	(0.158)	(0.0749)	(0.116)	(0.252)
Constant	-10.62***	-8.150***	-5.672***	-4.661***
	(0.279)	(0.125)	(0.171)	(0.340)
LR chi2(7)	1266.76	4349.69	1141.65	208.59
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0516	0.0550	0.0466	0.0390
Observations	52,433	90,032	26,578	6,614

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment – Eastern Europe**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	1.122***	1.131***	0.828***	0.643***
	(0.0209)	(0.0125)	(0.0239)	(0.0383)
male	-0.400***	-0.424***	-0.504***	-0.778***
	(0.0162)	(0.0114)	(0.0265)	(0.0456)
naced1	-1.410***	-1.321***	-1.127***	-0.787***
	(0.0912)	(0.0624)	(0.0932)	(0.136)
naced2	-0.457***	-0.393***	-0.469***	-0.326***
	(0.0405)	(0.0279)	(0.0602)	(0.107)
naced3	-1.194***	-1.368***	-1.374***	-1.168***
	(0.0504)	(0.0331)	(0.0665)	(0.114)
naced4	-0.299***	-0.141***	-0.155***	-0.0925
	(0.0352)	(0.0248)	(0.0547)	(0.0964)
naced5	-0.0219	-0.123***	0.0347	0.0807
	(0.0555)	(0.0345)	(0.0692)	(0.122)
Constant	-8.361***	-7.987***	-6.380***	-5.407***
	(0.126)	(0.0767)	(0.146)	(0.234)
LR chi2(7)	4443.60	13171.23	2656.60	908.77
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0334	0.0522	0.0469	0.0447
Observations	222,810	302,858	84,471	35,684

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment - Asia**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	0.499***	0.611***	0.747***	0.592***
	(0.0300)	(0.0168)	(0.0262)	(0.0509)
male	0.127***	0.112***	-0.0327	-0.0816
	(0.0371)	(0.0230)	(0.0404)	(0.0863)
naced1	-1.313*	-0.0477	0.537**	1.002**
	(0.734)	(0.244)	(0.237)	(0.476)
naced2	-0.708***	-0.305***	-0.0630	0.0579
	(0.153)	(0.0872)	(0.146)	(0.286)
naced3	-0.700***	-0.851***	-0.701***	-0.884**
	(0.251)	(0.137)	(0.172)	(0.398)
naced4	-0.139	0.0153	0.326***	0.208
	(0.0922)	(0.0623)	(0.115)	(0.227)
naced5	-1.219***	-0.103	0.671***	0.663***
	(0.116)	(0.0653)	(0.115)	(0.228)
Constant	-4.430***	-5.107***	-6.339***	-5.337***
	(0.191)	(0.116)	(0.195)	(0.370)
LR chi2(7)	485.48	1671.29	1726.13	353.01
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0203	0.0289	0.0849	0.0766
Observations	28,706	57,290	18,878	4,372

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment - Rest of the World**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	0.672***	0.743***	0.791***	0.483***
	(0.0321)	(0.0148)	(0.0177)	(0.0327)
male	0.0269	0.0322	-0.0589**	-0.261***
	(0.0373)	(0.0211)	(0.0297)	(0.0623)
naced1	-1.513***	-0.927***	-0.593***	-1.050**
	(0.367)	(0.197)	(0.202)	(0.442)
naced2	-0.218*	-0.0625	-0.0424	-0.0336
	(0.122)	(0.0667)	(0.0850)	(0.178)
naced3	-1.378***	-1.281***	-1.221***	-0.844***
	(0.146)	(0.0779)	(0.101)	(0.199)
naced4	-0.0299	0.134**	0.0725	0.185
	(0.0874)	(0.0526)	(0.0708)	(0.150)
naced5	0.0180	0.277***	0.486***	0.367**
	(0.108)	(0.0566)	(0.0735)	(0.155)
Constant	-6.411***	-6.535***	-6.588***	-4.730***
	(0.204)	(0.101)	(0.124)	(0.241)
LR chi2(7)	612.75	3948.07	3462.91	380.00
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0254	0.0546	0.0861	0.0439
Observations	49,695	97,971	45,961	10,476

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 11.6: Weibull & logit model for Table 5.17

- **To employment – Gender**

VARIABLES	**MALE**	**FEMALE**
lnwage	-0.362***	-0.415***
	(0.00405)	(0.00364)
age1	-0.0220***	-0.0419***
	(0.000299)	(0.000300)
natd1	-0.434***	-0.333***
	(0.00995)	(0.0114)
natd2	-0.230***	-0.213***
	(0.0147)	(0.0166)
natd3	0.0447***	0.135***
	(0.0136)	(0.0153)
natd4	-0.254***	-0.222***
	(0.0109)	(0.0126)
natd5	-0.0744***	-0.0903***
	(0.0138)	(0.0171)
naced1	-0.529***	-0.288***
	(0.0280)	(0.0371)
naced2	-0.322***	-0.117***
	(0.0142)	(0.0137)
naced3	0.515***	0.391***
	(0.0150)	(0.0216)
naced4	0.0925***	0.141***
	(0.0128)	(0.0104)
naced5	-0.216***	-0.197***
	(0.0142)	(0.0110)
Constant	-2.168***	-1.429***
	(0.0288)	(0.0273)
Wald statistic	-70.73	-67.64
	(0.000)	(0.000)
p	0.9078	0.9109
Wald chi2(12)	34607.9	50986.22
Prob > chi2	0.000	0.000
Observations	594,085	617,851

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment – Gender**

VARIABLES	Male	Female
lnwage	-0.735***	-0.721***
	(0.00193)	(0.00174)
age1	-0.00648***	-0.0236***
	(0.000121)	(0.000136)
natd1	-0.315***	-0.452***
	(0.00391)	(0.00445)
natd2	-0.0576***	-0.211***
	(0.00600)	(0.00689)
natd3	0.102***	0.0963***
	(0.00527)	(0.00589)
natd4	-0.0986***	-0.278***
	(0.00415)	(0.00494)
natd5	-0.394***	-0.376***
	(0.00602)	(0.00735)
naced1	-0.00619	0.121***
	(0.00919)	(0.0125)
naced2	-0.113***	-0.0451***
	(0.00572)	(0.00587)
naced3	0.656***	0.164***
	(0.00540)	(0.00936)
naced4	-0.0122**	0.00874**
	(0.00509)	(0.00409)
naced5	-0.270***	-0.205***
	(0.00598)	(0.00442)
Constant	1.361***	1.626***
	(0.0119)	(0.0116)
Wald statistic	-482.60	-419.60
	(0.000)	(0.000)
p	0.7376	0.7446
Wald chi2(12)	258328.76	262368.37
Prob > chi2	0.000	0.000
Observations	1,911,077	1,700,313

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment - Gender**

VARIABLES	**Male**	**Female**
lnwage	0.985***	1.019***
	(0.00340)	(0.00332)
natd1	0.452***	0.671***
	(0.00971)	(0.0113)
natd2	-0.0751***	0.170***
	(0.0141)	(0.0159)
natd3	-0.0897***	0.0763***
	(0.0137)	(0.0152)
natd4	0.0294***	0.378***
	(0.0109)	(0.0126)
natd5	0.574***	0.347***
	(0.0138)	(0.0173)
age1	0.00499***	0.00951***
	(0.000249)	(0.000239)
naced1	-0.624***	-0.875***
	(0.0253)	(0.0368)
naced2	-0.0186	-0.151***
	(0.0124)	(0.0117)
naced3	-0.989***	-0.202***
	(0.0131)	(0.0195)
naced4	0.0810***	-0.0738***
	(0.0114)	(0.00889)
naced5	0.166***	-0.0296***
	(0.0126)	(0.00924)
Constant	-8.189***	-8.298***
	(0.0249)	(0.0247)
LR chi2(12)	152251.18	141674.31
Prob>chi2	0.000	0.000
Pseudo R2	0.0883	0.0837
Observations	1,911,077	1,700,313

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 11.7: Weibull & logit model for Table 5.18

- **To employment – Males & Age**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.714***	-0.355***	-0.137***	-0.198***
	(0.00978)	(0.00643)	(0.00810)	(0.0119)
natd1	-0.149***	-0.409***	-0.682***	-0.678***
	(0.0231)	(0.0140)	(0.0194)	(0.0425)
natd2	-0.00678	-0.243***	-0.427***	-0.375***
	(0.0422)	(0.0218)	(0.0261)	(0.0519)
natd3	0.425***	0.0521***	-0.191***	-0.247***
	(0.0314)	(0.0183)	(0.0299)	(0.0682)
natd4	0.0135	-0.251***	-0.330***	-0.228***
	(0.0246)	(0.0151)	(0.0245)	(0.0511)
natd5	0.171***	-0.165***	-0.112***	0.0555
	(0.0292)	(0.0194)	(0.0303)	(0.0662)
naced1	-0.446***	-0.549***	-0.520***	-0.635***
	(0.0536)	(0.0436)	(0.0608)	(0.0922)
naced2	-0.294***	-0.338***	-0.287***	-0.280***
	(0.0276)	(0.0215)	(0.0321)	(0.0490)
naced3	0.638***	0.471***	0.555***	0.558***
	(0.0282)	(0.0229)	(0.0340)	(0.0511)
naced4	0.140***	0.0990***	0.0576*	0.0123
	(0.0235)	(0.0197)	(0.0298)	(0.0441)
naced5	-0.290***	-0.141***	-0.215***	-0.344***
	(0.0287)	(0.0217)	(0.0318)	(0.0470)
Constant	-1.028***	-2.890***	-4.260***	-3.931***
	(0.0610)	(0.0445)	(0.0606)	(0.0927)
Wald statistic	-21.29	-48.67	-37.96	-16.27
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.9434	09074	0.8889	0.9139
Wald chi2(11)	10206.24	10403.50	4846.43	2157.77
Prob > chi2	0.000	0.000	0.000	0.000
Observations	127,205	262,854	146,056	57,970

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To employment – Females & Age**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	-0.644***	-0.308***	-0.302***	-0.396***
	(0.00744)	(0.00585)	(0.00776)	(0.0114)
natd1	-0.118***	-0.391***	-0.544***	-0.397***
	(0.0237)	(0.0159)	(0.0240)	(0.0551)
natd2	-0.0222	-0.220***	-0.427***	-0.248***
	(0.0392)	(0.0243)	(0.0319)	(0.0653)
natd3	0.358***	0.0798***	0.0234	0.0803
	(0.0312)	(0.0206)	(0.0390)	(0.0875)
natd4	-0.0916***	-0.226***	-0.252***	-0.0652
	(0.0251)	(0.0175)	(0.0303)	(0.0625)
natd5	0.140***	-0.201***	-0.110***	0.0616
	(0.0345)	(0.0234)	(0.0403)	(0.0889)
naced1	-0.154**	-0.415***	-0.316***	-0.403***
	(0.0714)	(0.0620)	(0.0729)	(0.110)
naced2	-0.0194	-0.156***	-0.163***	-0.102*
	(0.0245)	(0.0208)	(0.0331)	(0.0535)
naced3	0.583***	0.346***	0.282***	0.376***
	(0.0414)	(0.0341)	(0.0470)	(0.0724)
naced4	0.195***	0.124***	0.102***	0.138***
	(0.0174)	(0.0167)	(0.0257)	(0.0383)
naced5	-0.0353*	-0.272***	-0.246***	-0.289***
	(0.0188)	(0.0175)	(0.0264)	(0.0394)
Constant	-1.505***	-3.147***	-3.614***	-3.420***
	(0.0482)	(0.0402)	(0.0566)	(0.0936)
Wald statistic	-17.93	-58.24	-30.39	-8.67
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.9581	0.8855	0.8982	0.9503
Wald chi2(11)	11449.09	10578.05	4829.63	3402.88
Prob > chi2	0.000	0.000	0.000	0.000
Observations	155,753	254,284	141,091	66,723

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment – Males & Age**

VARIABLES	**21-25 years**	**26-35 years**	**36-45 years**	**46-55 years**
lnwage	-0.826***	-0.803***	-0.598***	-0.459***
	(0.00391)	(0.00340)	(0.00370)	(0.00485)
natd1	-0.269***	-0.296***	-0.429***	-0.486***
	(0.00805)	(0.00594)	(0.00798)	(0.0152)
natd2	-0.0295**	-0.0489***	-0.119***	-0.180***
	(0.0143)	(0.00977)	(0.0108)	(0.0186)
natd3	0.242***	0.0826***	0.0534***	-0.0593***
	(0.0103)	(0.00762)	(0.0119)	(0.0229)
natd4	-0.0864***	-0.120***	-0.0514***	-0.0494***
	(0.00859)	(0.00608)	(0.00880)	(0.0163)
natd5	-0.537***	-0.349***	-0.284***	-0.313***
	(0.0116)	(0.00863)	(0.0141)	(0.0292)
naced1	0.0686***	-0.0115	-0.0544***	-0.0337
	(0.0169)	(0.0153)	(0.0200)	(0.0272)
naced2	0.00896	-0.164***	-0.175***	-0.0526***
	(0.0103)	(0.00939)	(0.0129)	(0.0178)
naced3	0.570***	0.692***	0.711***	0.660***
	(0.00958)	(0.00895)	(0.0123)	(0.0167)
naced4	-0.0200**	-0.0228***	0.00957	0.0477***
	(0.00895)	(0.00846)	(0.0117)	(0.0158)
naced5	-0.0911***	-0.291***	-0.354***	-0.298***
	(0.0114)	(0.00998)	(0.0131)	(0.0172)
Constant	1.667***	1.512***	0.355***	-0.368***
	(0.0228)	(0.0205)	(0.0244)	(0.0343)
Wald statistic	-231.76	-294.33	-232.78	-151.32
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.7602	0.7424	0.7192	0.7291
Wald chi2(11)	58251.13	104699.74	64203.08	25075.83
Prob > chi2	0.000	0.000	0.000	0.000
Observations	548,581	791,994	394,342	176,160

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **To unemployment – Females & Age**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	-0.848***	-0.721***	-0.566***	-0.548***
	(0.00335)	(0.00292)	(0.00358)	(0.00494)
natd1	-0.433***	-0.512***	-0.474***	-0.394***
	(0.00833)	(0.00665)	(0.0102)	(0.0220)
natd2	-0.131***	-0.227***	-0.260***	-0.142***
	(0.0146)	(0.0109)	(0.0136)	(0.0257)
natd3	0.182***	0.0374***	0.106***	0.0574*
	(0.0104)	(0.00858)	(0.0163)	(0.0345)
natd4	-0.261***	-0.329***	-0.213***	-0.131***
	(0.00892)	(0.00726)	(0.0129)	(0.0249)
natd5	-0.500***	-0.354***	-0.270***	-0.263***
	(0.0136)	(0.0103)	(0.0194)	(0.0416)
naced1	0.243***	0.0144	0.0124	0.0813**
	(0.0226)	(0.0225)	(0.0245)	(0.0341)
naced2	0.0954***	-0.128***	-0.114***	0.00721
	(0.0103)	(0.00930)	(0.0136)	(0.0194)
naced3	0.254***	0.167***	0.0784***	0.0892***
	(0.0190)	(0.0148)	(0.0191)	(0.0278)
naced4	0.0694***	-0.0187***	-0.0429***	-0.0159
	(0.00699)	(0.00676)	(0.00956)	(0.0130)
naced5	-0.0108	-0.279***	-0.341***	-0.270***
	(0.00790)	(0.00728)	(0.00987)	(0.0132)
Constant	1.668***	0.869***	-0.0244	-0.150***
	(0.0194)	(0.0173)	(0.0232)	(0.0362)
Wald statistic	-224.74	-232.26	-201.94	-137.34
	(0.000)	(0.000)	(0.000)	(0.000)
p	0.7652	0.7633	0.7071	0.7145
Wald chi2(11)	79067.37	94577.94	37983.19	17850.07
Prob > chi2	0.000	0.000	0.000	0.000
Observations	556,622	663,298	321,207	159,186

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment - Male & Age**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	0.959***	1.111***	0.859***	0.706***
	(0.00929)	(0.00559)	(0.00604)	(0.00839)
natd1	0.525***	0.574***	0.359***	0.490***
	(0.0262)	(0.0141)	(0.0175)	(0.0372)
natd2	-0.254***	-0.0365*	-0.0994***	0.0201
	(0.0482)	(0.0220)	(0.0235)	(0.0454)
natd3	-0.388***	0.0222	-0.115***	-0.0898
	(0.0376)	(0.0188)	(0.0271)	(0.0598)
natd4	0.0874***	0.232***	-0.341***	-0.424***
	(0.0279)	(0.0154)	(0.0223)	(0.0454)
natd5	0.989***	0.592***	0.241***	0.408***
	(0.0330)	(0.0195)	(0.0284)	(0.0604)
naced1	-0.903***	-0.656***	-0.465***	-0.216***
	(0.0555)	(0.0399)	(0.0505)	(0.0717)
naced2	-0.445***	0.000555	0.179***	0.239***
	(0.0255)	(0.0191)	(0.0263)	(0.0401)
naced3	-1.066***	-1.020***	-0.899***	-0.783***
	(0.0258)	(0.0200)	(0.0279)	(0.0423)
naced4	-0.0813***	0.149***	0.0989***	0.0896**
	(0.0218)	(0.0176)	(0.0247)	(0.0374)
naced5	-0.338***	0.151***	0.339***	0.512***
	(0.0268)	(0.0197)	(0.0265)	(0.0390)
Constant	-8.032***	-8.833***	-7.113***	-6.469***
	(0.0629)	(0.0407)	(0.0474)	(0.0734)
LR chi2(11)	17928.27	70157.93	38018.03	13884.36
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0494	0.0909	0.0952	0.0848
Observations	548,581	791,994	394,342	176,160

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Logit: Hiring from employment - Female & Age**

VARIABLES	21-25 years	26-35 years	36-45 years	46-55 years
lnwage	0.954***	1.092***	0.889***	0.954***
	(0.00763)	(0.00536)	(0.00643)	(0.00912)
natd1	0.942***	0.802***	0.331***	0.496***
	(0.0266)	(0.0159)	(0.0227)	(0.0488)
natd2	0.0388	0.224***	0.00392	0.174***
	(0.0439)	(0.0237)	(0.0295)	(0.0565)
natd3	-0.171***	0.240***	0.0339	0.125*
	(0.0356)	(0.0205)	(0.0353)	(0.0760)
natd4	0.394***	0.592***	0.110***	0.222***
	(0.0281)	(0.0175)	(0.0293)	(0.0571)
natd5	0.666***	0.318***	0.193***	0.199**
	(0.0396)	(0.0234)	(0.0378)	(0.0816)
naced1	-0.941***	-0.759***	-0.912***	-0.825***
	(0.0782)	(0.0600)	(0.0736)	(0.0972)
naced2	-0.303***	-0.0189	-0.162***	-0.292***
	(0.0226)	(0.0178)	(0.0263)	(0.0399)
naced3	-0.0950**	-0.122***	-0.332***	-0.343***
	(0.0388)	(0.0297)	(0.0421)	(0.0618)
naced4	-0.145***	0.0335**	-0.135***	-0.186***
	(0.0155)	(0.0142)	(0.0207)	(0.0289)
naced5	-0.424***	0.0718***	0.0772***	0.200***
	(0.0171)	(0.0148)	(0.0208)	(0.0285)
Constant	-7.912***	-8.549***	-6.916***	-7.381***
	(0.0527)	(0.0375)	(0.0473)	(0.0776)
LR chi2(11)	26414.84	65467.85	25455.07	16234.44
Prob>chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.0578	0.0907	0.0775	0.0968
Observations	556,622	663,298	321,207	159,186

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 12 : Data access & the Central Statistics Office (CSO), Ireland

The data used in this thesis was accessed via the Central Statistics Office (CSO) in Ireland. In doing so, strict protocols and principals are adhered to. These include;

- **Safe data:** Access is only to protected data - no access is given to identifiable data.
- **Safe setting**: Access to data is only granted in a tightly controlled environment at the CSO.
- **Safe project:** Research project and access is signed off by Senior Management at the CSO.
- **Safe outputs**: All material/output taken away from CSO is first checked by CSO Statisticians.
- **Safe researchers**: Researchers undergo a vetting process before being granted access to data.