Monetary Policy Rules, Total Factor Productivity Growth and Uncertainty:An empirical Assessment

Zainab Jehan

A thesis submitted to the University of Sheffield for the degree of Doctor of Philosophy in the Department of Economics

Tuesday 6th August, 2013

To my daughter
The light of my life
Who always rekindled my energies in this hazardous task
And has cooperated with me like a little angel

Abstract

This dissertation explores how uncertainty affects different facets of an economy through three empirical essays. First, we presents an analytical framework to examine the policy reaction function of a central bank in an open economy context while allowing for asymmetric preferences. This implies that the policy makers can weigh negative and positive deviations of target variables (inflation and output gap) from their corresponding targets differently. We use an open economy New-Keynesian forward looking model where aggregate demand and supply depend on real exchange rate. Using quarterly data ranging from 1979q1-2007q4 for Canada, Japan, the UK and the US, the empirical evaluation is drawn through generalized methods of moments. The results strongly favor the presence of asymmetries in the response of monetary policy towards both inflation rate and output gap for all sample countries. The estimates show that central banks follow an active monetary policy. Also, there is evidence that changes in foreign interest rate and exchange rate significantly affects the domestic monetary policy formation.

Second, we examine the role of various sources of uncertainty on total factor productivity growth. Specifically, this essay estimates the role of of uncertainty emanating from global, country, and industry level on TFP growth in manufacturing industries of sixteen emerging economies. For this purpose, we use annual data covering the period from 1971-2008. Our findings suggest a significant impact of each source of uncertainty on TFP growth. Particularly, we observe that industry and country specific uncertainty have a positive impact on TFP growth of manufacturing industries. However, global uncertainty has statistically significant and negative impact on TFP growth. We also provide evidence that the impact of industry specific uncertainty strengthens as the size of industry increases whereas the reverse holds for both country specific and global uncertainty. In addition, we observe that the positive impact of both industry and country specific uncertainty gets stronger at higher levels of factor intensity.

Third, we examine the role of of uncertainty of technology diffusion in TFP convergence of manufacturing industries of frontier and non-frontier countries. For this purpose, we use annual data covering the time period from 1981-2008, eighteen manufacturing industries of five emerging economies. We employ superlative index number approach to compute the TFP level and growth in manufacturing industries of these countries. Our findings suggest a significant evidence of TFP convergence in manufacturing industries of non-frontier and frontier countries. Moreover, technology diffusion not only pertains a positive impact on TFP growth of manufacturing industries of non-frontier countries but also facilitates the process of TFP convergence. More importantly, we report a significant negative impact of uncertainty of technology diffusion on the TFP growth.

Acknowledgements

This dissertation is not the output of my individual efforts rather I am in indebted to many people who motivated, encouraged and supported me to complete it. I am gratified to Allah Almighty for endowing me with the strength and determination to retain my abilities in this endeavor.

My experience with my supervisors had been remarkable. Professor Mustafa Caglayan's exhaustive knowledge, critical thinking, deep understanding, and involvement in the work enabled me to produce this dissertation. His exceptional evaluation strategies not only improved the quality of my work but inculcated the sense of creativity in me.

I am highly indebted to the invaluable contribution of Dr. Kostas Mouratidis, my second supervisor, whose exceptional expertise in Econometrics encouraged me to learn and apply new technique in the conduction of my research. He brought great enthusiasm in me to experiment new things, which raised the challenge for me and consequently raised the quality of the work.

I thank the help and support of the staff members in the department of Economics at the University of Sheffield. Chiefly, I would like to thank Rachel Watson, Jane Mundy, and Louise Harte for their support and guidance. I also acknowledge the contribution of the administrative and technical staff of the department by providing a constructive and research oriented environment. I am filled with gratitude for my PhD colleagues especially Fatema Majeed, Hanan Naser, Ozge Kandemir, Syed Manzoor Quader, Javiera Cartagena Farias, Daniel J Gray, Meruyert Beisenbayeva, and Uzma Ahmed. I owe my special thanks to Dr. Abdul Rashid for his support and encouragement during my PhD.

I am thankful to Fatima Jinnah Women University, Rawalpindi, Pakistan for providing the opportunity for PhD studies. My special appreciation goes to Ms. Sadia Hina and Ms. Iram Khurram for facilitating the process of funding and making it smooth and timely.

I extend my heartfelt thanks to Dr. Naheed Zia Khan whose confidence in me encouraged me to step forward for PhD studies. She remained a constant support to me throughout my PhD studies. My deepest gratitude goes to Dr. Faiza Khan who always rekindled my enthusiasm and motivation. It would not have been easy to complete this long journey without her selfless support, particularly in the long night-stays for studying. Though we were living on two poles of the UK, she stayed always with me to support. My heartiest thank goes to Sanober Faiz and Sumaira Khan who had never disappointed me whenever I was in difficult times. They had proven herself to be a friend indeed whenever I was in need.

It is an immense pleasure to acknowledge my family; my parents and my siblings for their unwavering support, care and prayers. Their noteworthy support and encouragement made this period more enjoyable and fruitful. My gratitude will remain incomplete without my acknowledgment to my mother-in-law for her love and endless prayers. My husband's cooperation in my tough schedule during these years are worthy more than just words. It would not have been possible to accomplish this task without his fortitude and resilience. Finally, the innocent love and care, unlimited patience, heart touching smiles, long waits of my daughter deserve a special acknowledgment.

Zainab Jehan

Contents

List of Tables

List of Figures

Chapter 1

Introduction

There is a wide range of literature that explores the types, origins, and channels through which uncertainty influences different facets of an economy. A considerable attention in this regard is devoted to investigate the role of policy formation and macroeconomic performance. The prime aim of this dissertation is to empirically examine the direct and the indirect role of uncertainty in three important aspects of an economy: monetary policy responsiveness, total factor productivity (TFP) growth, and TFP convergence. This is achieved through following three empirical papers.

In explaining the role of uncertainty for macroeconomic policies, particulary monetary policy, Greenspan (2004) claim that uncertainty is not only a persistent feature but a defining characteristic of monetary policy landscape. Therefore, it is crucial that monetary policy formulation is carried out by taking the danger of uncertainty into consideration particularly in an open economy. There is lack of evidence on the response of monetary policy towards uncertainty of target variable in an open economy framework. Therefore, the first study of the dissertation, presented in the second chapter, aims to evaluate the responsiveness of monetary policy towards target variables such as inflation rate and output gap. We introduce a new element compared to the existing literature. First, we investigate the influence of real exchange rate on optimal policy reaction function. The dynamics of an open economy are analyzed by an open economy form of a New-Keynesian model where aggregate demand and supply depends on the real exchange rate. Second, we allow central banks to have an asymmetric linex loss function for both of its target variables in an open economy. This allows us to account both for asymmetric preferences of policy-makers and for the uncertainty of target variables. By doing so, policy-makers can weigh positive and negative deviations of inflation and output gap from their corresponding targets differently. More concretely, central banks might prefer to react more strongly to positive deviations of inflation from its target rather than to negative deviations. The reverse might be true for output gap deviations from its target.

The empirical investigation in this regard is largely motivated by the seminal work of Friedman (1948) who proposes rule-based monetary policy instead of discretionary monetary policy. Taylor (1975) tests for the impact of monetary policy on real economic activity. In doing so Taylor has provided a theoretical framework, which explains that monetary policy can influence real output growth if expectations about inflation are transitional. A major contribution to the literature can be found in the work of Kydland and Prescott

(1977), Barro and Gordon (1983), and Blanchard and Fischer (1989) where policy rule is preferred over discretion. Moreover, Kydland and Prescott (1977) stressed that inflationary expectations about optimal policy rule raise the problem of time inconsistency. In the same vein, Taylor (1993) has presented the famous Taylor rule in comparison to the money supply rule of Friedman and Schwartz (1963) by asserting that a policy rule with some weights to output stabilization is preferable to a pure price rule. The distribution of weights is still a matter to investigate, though. Further he argued that policy-makers cannot follow the policy rules mechanically but it would be interesting to incorporate the rule-like behavior in the actual policy-making process by central banks.[1]

Recently some researchers argue that central banks penalize differently the positive and negative deviations of target variables from their respective targets. This approach introduces a policy rule incorporating asymmetric preferences of central banks towards positive and negative deviations of target variables. The studies of (Nobay and Peel, 2000, 2003), Bec et al. (2002), Ruge-Murcia (2003b), (Dolado et al., 2004, 2005), and (Surico, 2003, 2007b, 2008) among others follow this strategy to evaluate the performance of policy rule across different phases of the business cycle.

Despite the theoretical and empirical progress, relatively less attention is paid to explore the behavior of central banks in an open economy framework. In recent years, central banks are influenced not only by changes in domestic factors but also by changes in exchange rate and foreign monetary policy. Ball (1999b) is the first to introduce an open economy Taylor rule. On similar ground, Svensson (2000), Leitemo et al. (2002), Leitemo and Söderström (2005), Dolado et al. (2005), and Adolfson et al. (2008) among others analyze the response of monetary policy towards changes in the international factors. However, these studies incorporate exchange rate and foreign monetary policy on an ad-hoc basis. It is therefore important to understand the link through which exchange rate and foreign monetary policy enters into the policy rule. Also, these researchers have largely evaluated the response of monetary policy towards target variables by assuming symmetric response of central banks in an open economy framework.

Differing from the existing literature, this chapter has various distinctive features. First, we derive the optimal policy rule for an open economy, which allows asymmetries in central bank preferences towards target variables. Thus we estimate an optimal policy reaction function accounting for the impact of real exchange rate, foreign monetary policy, and measures of volatility concerning both the state variables included in the objective

[1]This interest rate rule with both inflation and output gap as target variables has widely been used in the literature including (Ball (1999a), Rudebusch and Svensson (1999), Ireland (1999), Leitemo et al. (2002), and (Taylor, 1999a, 2001a) among others).[2] Indeed, a noteworthy contribution in the examination of monetary policy rules is made by (Clarida et al., 1998, 2000) who introduce the forward-looking expectations in the Taylor rule.

function of policy-makers. Second, on theoretical grounds, we extend the New-Keynesian model described by Clarida et al. (1999) by accounting for the behavior of real exchange rate. In this set-up, the optimal reaction function will include not only expected inflation and growth but also expected changes of real exchange rate and foreign monetary policy rule.

Although there are numerous specifications estimated for an open economy monetary policy rule such as Ball (1999b), Clarida et al. (1999), Clarida et al. (2001) and Svensson (2000) but our study differs from the existing literature. These studies incorporate exchange rate in the policy rule at an ad-hoc basis whereas we derive the policy rule which contains the exchange rate movement. Moreover, our specification differs from the open economy models of Ball (1999b) and Leitemo et al. (2002). The former gives completely backward-looking expression of output and inflation and presents the general form of exchange rate to explicate the scenario of an open economy. However, the latter incorporates exchange rate as the only forward-looking variable in the model. Whereas, we introduce a forward-looking policy rule for an open economy with asymmetric preferences of central banks. Thus we not only contribute to the literature by deriving a policy rule, which exploits more information but also provides a new insight into the literature on functioning of monetary policy asymmetries in an open economy framework.

To estimate the monetary policy rule, we utilize quarterly data from International Financial Statistics published by International Monetary Fund database. In particular, our dataset spans the period over 1979q1-2007q4, while for each country the starting point of the empirical analysis depends on the specific factors that affected the behavior of each central bank to implement independent monetary policy. We use data on seasonally adjusted series of Gross Domestic Product (GDP) of all selected economies. We implement the HP (Hodrick and Prescott (1997)) filter to generate the output gap from the log of GDP for all countries. Growth rate of Consumer Price Index of each country is used to measure Inflation rate of respective economies. We use the corresponding short-term interest rate such as the overnight interbank rate for the UK, the overnight money market rate for Canada, the call-money rate for Japan, and the Federal Funds rate for the US as policy instruments. In addition, the 3-month forward exchange rate is used as a proxy for the expected exchange rate.[3] Our empirical investigation is based on GMM where we test both for over and under-identification.

The empirical results show that all the central banks conduct an active monetary policy as it is indicated by the coefficient of expected inflation rate. Similarly, the response

[3] Data on forward exchange rate for the UK are accessed from the bank of England database whereas for the USA, Canada and Japan the forward exchange rate data are obtained from the WorldScope database via DataStream.

of interest rate towards output gap is positive and statistically significant. We provide a significant evidence that central banks have asymmetric preferences in the sense that they set interest rate accounting for uncertainty of inflation and output gap. Specifically, except for the bank of Japan, the response of all central banks towards output gap volatility is negative and statistically significant. This finding identifies that central banks are more conscious in times of recession as compare to expansionary times. We interpret the positive reaction of bank of Japan towards output gap volatility as the central bank is mainly concerned about inflation and considers a positive output gap as an indicator of future inflation. Next, We observe a positive and statistically significant response of central bank towards inflation volatility. This implies that the central banks are more aggressive when there is inflationary pressures in the economy relative to deflationary pressures. The impact of expected changes in exchange rate is statistically significant with mixed signs. Finally, we observe that domestic monetary policy has significant and positive response towards changes in foreign monetary policy. These findings suggest that the central bank follows an active monetary policy where the nominal interest rate must increase more in proportion to the expected inflation which changes as a consequence of movements in the foreign policy variables.

The third chapter of this dissertation examines the impact of different types of uncertainty on the TFP growth of manufacturing industries of emerging economies. The main objective of this chapter is to investigate how uncertainty stemming from different sources such as industry, country, and world level determines the TFP growth of manufacturing industries. This analysis will not only helps us to understand the underlying mechanism generating uncertainty but also in formulating policy to overcome its adverse impact.

Theoretically, the growth impact of uncertainty is documented by Friedman (1977) suggesting that inflation uncertainty dampens growth through allocative inefficiency. Empirically, Kydland and Prescott (1982) and Long Jr and Plosser (1983) present the idea of the unification of business cycle and growth theory to investigate the factors behind economic fluctuations. Both of these studies conclude that technological shocks are the main driving force of output fluctuations.[4] Lucas(987), in contrast, explains that there is no link between growth and macroeconomic volatility.[5]

[4]In a similar vein, King et al. (1988) document that temporary shocks may leave permanent impact on economic activity. Rebelo (1991) explains that the permanent changes in policy also affect the economic activity. King et al. (1988) merge the endogenous growth and real business cycle models and report that the short-run fluctuations in production may impact the path of output for a long time period.

[5]There are a large number of studies that focus on examining the link between macroeconomic uncertainty and growth. These include, among others, Nelson and Plosser (1982), Bernanke (1983), Pindyck (1982) , Pindyck (1991), Aizenman (1993), Ramey and Ramey (1991), Kormendi and Meguire (1985), Mirman (1971) , Zarnowitz and Moore (1986), Zarnowitz and Lambros (1987), Grier and Tullock (1989),

A large number of empirical studies argue that endogenous growth models potentially maintain both a positive and negative relationship depending on the nature of shocks and model parametrization (See, e.g., Stockman (1988), Aghion et al. (1998), Jones et al. (1999), Turnovsky and Chattopadhyay (2003), and Blackburn and Pelloni (2004) among others). In particular, Stockman (1988) argues that it is crucial to identify the origin of a shock to examine its impact on growth. He decomposes shocks into aggregate and industry level and provides evidence that industry-specific technology shocks play a stronger role in the business cycle as compared to country-specific shocks. Later, researchers such as Norrbin and Schlagenhauf (1990), Costello (1993), Kose et al. (2003), Imbs (2007), and Koren and Tenreyro (2007) among others, decompose different types of uncertainty and examine their impact on GDP growth.

Some researchers also focus on examining the link between uncertainty and productivity growth. On theoretical grounds, Comin (2000) and Oikawa (2010) formalize the relationship between productivity and volatility. The former explains that uncertainty leads to adoption and diffusion of new technologies and accelerates TFP growth by shifting the investment from inflexible capital to flexible capital. While the latter bases his argument on the firms' optimization behavior and concludes that uncertainty forces firms to invest more in R&D activities, which results in knowledge accumulation. On the empirical side, Dixit and Rob (1994), Leahy and Whited (1996), Miller and Upadhyay (2000), and Berument et al. (2011) explore the link between uncertainty and productivity.

The third chapter of the dissertation contributes to the existing literature on several grounds. First, to the best of our knowledge, there is no existing empirical work that analyzes how and to what extent uncertainty impacts the TFP growth in manufacturing industries.[6] In particular, we categorize uncertainty originating from industry, country, and world level and estimate the individual impact of each source of uncertainty on TFP growth. By doing so, we differ from Imbs (2007) in two manners: (a) we estimate the impact of each type of uncertainty individually whereas he uses the residual sum of four types of uncertainty as a proxy for uncertainty, (b) We conduct our analysis for the TFP growth of manufacturing industries whereas Imbs (2007) executes his analysis for output growth of manufacturing industries. Also, we cater a different set of countries. Second, in addition to scrutinizing the direct impact, we examine the conditional impact of uncertainty on TFP growth. We do so by identifying the impact of uncertainty on TFP growth through other factors such as industry size, factor intensity, and the level series of each type of uncertainty. Third, we present the total impact of each type of uncertainty on TFP

Aizenman and Marion (1999), Mascaro and Meltzer (1983), Abel (1983), Levine and Renelt (1992), Gregory and Head (1999), and Ventura and Zeidan (2000).

[6]However, there is some evidence showing the impact of different forms of uncertainty for growth both at aggregate and disaggregate levels.

growth by combining the direct and the conditional effect. Also, we plot the total impact of each type of uncertainty through all the conditioning factors. This exercise provides a detailed evidence on the relationship between TFP and uncertainty, which has been overlooked by the existing literature. Fourth, we are the first to present evidence concerning the link between uncertainty and TFP growth for the sample of emerging economies.[7]

To empirically examine how uncertainty affects TFP growth of manufacturing industries of emerging economies, we use data from various data sources. We access annual data of manufacturing industries of emerging economies from the United Nation's Industrial Development Organization (UNIDO) database. We also use country-specific investment, real GDP and inflation rate, which are obtained from the IFS database. The world-specific variables such as world inflation rate are accessed from the world development indicators. We employed a dynamic panel data estimator: two-step system GMM estimator developed by Blundell and Bond (1998) to carry out the empirical investigation in this chapter. Our findings not only report the direct impact of each type of uncertainty but also conditional effect through various other factors affecting TFP growth. This analysis is not only new but also interesting as these findings will identify the threshold level of conditioning factors where the impact of uncertainty turns to change.

Our results from this estimation suggests a statistically significant impact of each source of uncertainty on TFP growth. Furthermore, we have found that the impact of industry specific uncertainty is higher than the impact of country and world specific uncertainty. The impact of industry and country specific uncertainty is positive whereas the world uncertainty has a negative impact on the TFP growth of manufacturing industries. Next, in addition to the direct impact of uncertainty, we estimate the indirect impact of each source of uncertainty. To do this, we use three interaction terms (i)interaction of each source of uncertainty with industry size. This interaction measures how the impact of uncertainty changes when industry size increases. (ii) interaction of each source of uncertainty with factor intensity (capital-labor ratio). This interaction term captures if there is change in factor intensity, how the impact of uncertainty varies. (iii) interaction of each source of uncertainty with their own level series which identifies how the impact of uncertainty changes at different levels of their own series. The empirical estimation reveals that as the industry size increases, the positive impact of industry and country specific uncertainty increases. However, the negative impact of world uncertainty increases for larger industries. Similarly, as factor intensity of industries increases, the positive impact of industry specific uncertainty increases. Whereas, the positive impact of country specific uncertainty weakens at higher levels of factor intensity. In contrast, the negative impact

[7] The existing studies, however, mainly examined TFP convergence for a set of OECD or developed economies.

of world uncertainty monotonically decreases as factor intensity increases. Finally, the interaction of industry output (ratio to manufacturing sector output) with its uncertainty has positive sign which indicates that there is monotonic increase in the positive impact of industry specific uncertainty as the we move on higher level of industry output ratio to manufacturing sector output. The interaction of country specific uncertainty with country investment(ratio to country GDP) has negative sign. This indicates that as the level of country investment increases the positive impact of country specific uncertainty decreases. Finally, the interaction of world uncertainty with world inflation rate has shown a positive sign which identifies that the negative impact of world uncertainty is weaker at higher level of inflation whereas it is stronger at lower level of world inflation rate. We also plot the total impact of each type of uncertainty through all the conditioning factors. The figures further support our empirical findings.

In the current economic situation, not only the technological diffusion but also uncertainty attached to technology diffusion influences the convergence process. Therefore, the fourth chapter of this dissertation aims to examine how uncertainty attached to diffusion of technology affects TFP growth and TFP convergence. For doing so, we select emerging economies as non-frontier countries while taking the USA as the technological frontier country.

The debate on convergence has evolved in theoretical and empirical literature since the seminal work of Solow (1956). The empirical research following neo-classical growth theories advocates the dominant role of human capital for explaining cross-country income differences (Mankiw et al. (1992), Bernard and Jones (1996c)). However, neo-classical trade theory assumes that cross-country income differences accrue to the difference in factor endowment by assuming similar technology across countries (Islam (2001)). A wide range of empirical literature explores the cross-country income and productivity differences. The earlier studies such as Domar et al. (1964), Denison (1967) Barger (1969), Kuznets (1971), Bergson (1975), and Jorgenson and Nishimizu (1978) introduce the relative time series approach for TFP growth across countries. Later this approach is followed by Dowrick and Nguyen (1989), Dougherty and Jorgenson (1996), Dougherty and Jorgenson (1997), Wolff (1991), and Dollar and Wolff (1994). In contrast, the cross section and panel form of TFP comparison is implemented by (Hall and Jones, 1996, 1997), and Islam (1995). However, none of the above-mentioned studies incorporate the role of technological developments in measuring the productivity differences. On the theoretical forefront, endogenous growth models given by Romer (1986), Lucas (1988) and Romer (1990) advocate growth through endogenous technological change.[8]

Later studies such as Ben-David (1993) and Barro and Mankiw (1995) among others provide a new surge to the convergence literature. These studies introduce an open economy framework of the neoclassical growth model. Coe and Helpman (1995) have introduced the role of technology transfer through the channel of trade, which plays an important role in the TFP convergence. Following studies such as Griffith et al. (2004), Cameron et al. (2005), and Madsen (2008) also confirm the hypothesis presented in Coe and Helpman (1995). They conclude that in an open global economy framework, the economy's productivity levels are not only determined by its own innovation activities but also by the innovation activities of its trading partners.[9] Thenceforth, the empirical studies stressed upon the role of international trade in technology spill over and productivity convergence.[10]

The contribution of the fourth chapter can be summarized as: First, we select five large trading partners of the USA among emerging economies as non-frontier countries. We select emerging economies instead of a widely used sample of OECD countries. This is so because Bernard and Jones (1996a) and Keller (2000) report that the convergence analysis for developing economies can bring more interesting findings related to the TFP convergence.

Second, to the best of our knowledge, there is no empirical research that has analyzed the impact of uncertainty of technology diffusion on TFP growth and TFP convergence. We compute uncertainty in the import of technological products and estimate its impact on TFP growth of manufacturing industries of non-frontier countries. Third, we not only estimate the own impact of uncertainty of technology diffusion and TFP gap but also their conditional impact. In doing so, we introduce three interaction terms: (i) an interaction between uncertainty of technology diffusion and uncertainty of technology diffusion, which will capture how the uncertainty impact changes when the level of technology diffusion

[8]In this regard, further development is carried out by Aghion and Howitt (1992), Howitt (2000) Grossman and Helpman (1991), Klenow and Rodriguez-Clare (2005), Córdoba and Ripoll (2008), Romer (1993), Parente and Prescott (1994), and Bernard and Jones (1996c). Bernard and Jones (1996c) state that the role of technology in explaining the relative income levels is crucial for the convergence process but it has been ignored and misguided in the empirical literature.

[9] Griliches (1980), Mansfield (1980), Griliches and Lichtenberg (1984b), Hall and Mairesse (1995). Microeconomic foundation are supplied by the theoretical literature on endogenous innovation and growth see, e.g., Aghion et al. (1998) Aghion and Howitt (1992), and Romer (1990). At industry level, the productivity convergence is examined by Bernard and Jones (1996a), Bernard and Jones (1996b), Dollar and Wolff (1988), Dollar and Wolff (1994), Jorgenson and Kuroda (1991), Dowrick (1989), and Hansson and Henrekson (1994).

[10]See, e.g., Ben-David and Loewy (1998), Edwards (1998), Frankel and Romer (1999), and Lawrence and Weinstein (1999). Following studies such as Coe et al. (1997), Frantzen (2000), Guellec and Van Pottelsberghe de la Potterie (2001), Lumenga-Neso et al. (2001), del Barrio-Castro et al. (2002), Crespo et al. (2004), and Guellec and Van Pottelsberghe de la Potterie (2004) have concluded a significant contribution of technological spillover in the convergence process. In contrast, Keller (1998) and Kao et al. (1999) among others did not support the hypothesis that the technology spillover is important for convergence of TFP growth.

changes, and (ii) an interaction between TFP gap and technology diffusion. In this case, we aim to investigate how technology diffusion affects the process of TFP convergence among the frontier and non-frontier countries. (iii) we interact TFP gap with uncertainty of technology diffusion. In this manner, we scrutinize, how the convergence process takes place at different levels of uncertainty of technology diffusion. Fourth, having established the direct and conditional impact of uncertainty of technology diffusion in the convergence process, we compute the total impact of technology diffusion and its uncertainty on TFP convergence.

We obtain data from two datasets. The data on industry level output, value added, employment, wages and salaries, and gross fixed capital formation are taken from the United Nation's Industrial Development Organization (UNIDO) database published in 2011. We use two-digit ISIC Revision 3 classification for manufacturing industries over the period 1981-2008. To measure the impact of technology diffusion, we use data on industry-specific import of technological products from the frontier country. For this purpose we use the following standard international trade classification (SITC) for high technology products: chemicals and related products (SITC section 5), machinery and transport equipment (SITC section 7), professional and scientific instruments (SITC section 8.7). Data on industry-specific imports are accessed from the United Nation's commodity trade database published in 2011.

Based on a two-step system GMM estimator, our findings from this chapter enable us to understand the convergence process in emerging economies. We report a statistically significant impact of technology diffusion and its uncertainty on TFP convergence in non-frontier and frontier countries. Also, our empirical estimates identify the level of technology diffusion where the negative impact of uncertainty turns into positive for the TFP growth. Specifically, we first, estimate the impact of TFP growth of frontier country and the lagged TFP growth of the non-frontier countries. The results has shown statistically significant and positive impact of the lagged TFP growth of non-frontier countries as well as the current and lagged TFP growth of frontier country. Next, we augment our model with the measure of technology diffusion. The estimates have provided a positive impact of technology diffusion on the TFP growth of non-frontier countries. However, the uncertainty of technological trade, which we have computed through the RA(1) process of technological trade, have shown a negative impact on the TFP growth. In addition to the direct impact of uncertainty of technology diffusion, we have also computed the conditional impact through interaction of technology diffusion and its uncertainty. This exercise enables us to understand how uncertainty affects TFP growth at different levels of technology diffusion. The interaction of uncertainty has a positive impact on TFP growth. By combining both unconditional and conditional impact of uncertainty, we have found that although uncertainty has a negative impact on TFP growth but as the level of technology diffusion increases this negative impact weakens monotonically. Our empirical estimates have shown statistically negative impact of the relative TFP gap on the TFP growth of non-frontier countries. This finding has confirmed that further the countries lie behind the technological frontier, higher will be the growth and thus the speed of convergence. While estimating the impact of TFP gap through technology diffusion, our results have confirmed earlier empirical findings that at higher levels of technology diffusion rate of convergence is higher. Finally, the estimates on the interaction of TFP gap and uncertainty of technology diffusion show that uncertainty leads to weakens the TFP divergence among manufacturing industries of non-frontier and frontier countries. In addition, we have also plotted the total effect of uncertainty and TFP gap conditional on technology trade. The diagrammatical analysis have also supported the empirical findings.

The thesis is structured into five chapters. Chapter 2 empirically examines the asymmetric preferences of four central banks concerning the deviation of inflation and output gap from their respective targets in an open economy framework. Chapter 3 assesses the role of uncertainty originating from different sources on TFP growth of manufacturing industries of emerging economies. Specifically, this chapter identifies the direct and the indirect impact of industry-specific, country-specific and world-specific uncertainty. Chapter 4 explores the TFP convergence of manufacturing industries in non-frontier and frontier countries. This chapter empirically investigates how the technological distance from the frontier country affects TFP growth and TFP convergence of these economies. Chapter 5 presents the conclusion of this dissertation. Particularly, this chapter presents the background and summary of the thesis. Further, the chapter summarizes main empirical findings of all chapters and some policy implications. Also, it presents the limitations of this dissertation. Finally, the chapter exposes some interesting areas to which new research can be directed.

Chapter 2

Asymmetric Monetary Policy Rules for Open Economies: Evidence from Four Countries

2.1 Introduction

It is well accepted that monetary policy plays an essential role in providing a stable macroeconomic background which facilitates the efficient allocation of resources. To demonstrate that such an economic environment can be achieved by adopting an optimal monetary policy framework, researchers have proposed several alternative models leading to the development of a vast literature. For instance, a large number of studies advocate the adoption of inflation targeting and its implementation through variants of Taylor rule.[1] Yet many (recent) studies including McCallum and Nelson (2000), Clarida et al. (2001), Taylor (2001b), Clarida et al. (2002), Batini et al. (2003), Dennis (2003), Leitemo and Söderström (2005), and D'Adamo (2011) argue that the impact of foreign factors on the domestic policy is small, and therefore their effects can be excluded.[2]

However, in an open economy context, it is somewhat surprising to discount the role of exchange rate movements on the monetary transmission mechanism: exchange rates which respond to foreign disturbances do affect domestic prices. To that end, Ball (1999b) shows that although Taylor rules are optimal in a closed economy context these policies perform poorly in an open economy framework unless they are modified to account for the movements in the exchange rates. Svensson (2000) argues that the optimal reaction function in an open economy accounts for more information in comparison to a closed economy Taylor rule. He discusses the presence of various direct and indirect channels through which the exchange rate can affect monetary policy and shows that CPI-inflation responds to foreign variables including foreign inflation, foreign interest rate, exchange rate and shocks from the rest of the world. More recently Gali and Monacelli (2005), Lubik and Schorfheide (2007), and Adolfson et al. (2008) implement open economy DSGE models to investigate whether central banks respond to exchange rate movements. In this framework, Chen and MacDonald (2012) move a step further by incorporating parameter instability into a small scale open economy DSGE model.

[1] Researchers have examined different variants of the Taylor rule by introducing backward or forward looking components while allowing the policy makers to have linear or nonlinear objective functions. Among others see for instance Taylor (1993), Svensson (1997), Ball (1999a), Rudebusch and Svensson (1999), Ireland (1999), Clarida et al. (2000), Ruge-Murcia (2003b), Dolado et al. (2004), and Surico (2007a).

[2] For instance Taylor (2001b) argue that the exchange rate changes are implicitly incorporated through prices therefore the closed economy models are well representative of an open economy scenario. Similarly, Clarida et al. (2001) document that the open economy models are isomorphic to the closed economy models.

It is also important to note that the recent literature in monetary economics has challenged the assumption that policy makers minimize a quadratic loss function subject to a linear IS equation and a Philips curve —the assumption that the vast majority of research on optimal policy rules has used. Cukierman and Gerlach (2003) suggest that a central bank responds strongly to inflation when the economy is in expansion and to output gap when the economy is in contraction. Dolado et al. (2005) relax the assumption of a linear Phillips curve while allowing both inflation and the loss function to be convex functions of the output gap. In particular, Nobay and Peel (1998), Ruge-Murcia (2004), Ruge-Murcia (2003a), Dolado et al. (2004), Surico (2007a), and Surico (2003) assume that central banks have a linear exponential (i.e. linex) loss function. The use of this function allows the monetary policy authorities to have an asymmetric response towards inflation and/or output gap as actual inflation or output level exceeds or falls short of the target. In this approach since the quadratic loss function corresponds to a special case where the asymmetry parameter of the linex loss function is equal to zero, one can test the null hypothesis of quadratic preferences against the alternative of asymmetric preferences.

In this paper, different from the existing literature, we model the optimal monetary policy rule of a central bank in an open economy framework while we allow for asymmetric preferences such that the policy makers can weigh positive and negative deviations of inflation and output gap from their corresponding targets differently. To achieve our purpose, we use an open economy New-Keynesian model where aggregate demand and supply depend on the real exchange rate while we assume that policy makers have a linex loss function. The latter assumption implies that the certainty equivalence does not hold and uncertainty will induce a prudent behavior on the part of the central bank. Thus, in this set up, minimization of the loss function subject to the IS equation and the Philips curve lead to an optimal reaction function which respond not only to the deviation of inflation and output gap from their respective targets but also to changes in the exchange rate and to the volatility of inflation and output gap. Therefore, within this framework while we discuss the effect of changes in exchange rate and foreign monetary policy on the domestic interest rate, we can also examine whether policy makers have asymmetric response towards inflation and/or output gap across different phases of the business cycles.

We estimate the resulting optimal policy rule from our model using quarterly data for four major industrialized countries including Canada, Japan, the United Kingdom (UK) and the United States (US). Our dataset spans the period over 1979q1-2007q4, while for each country the starting point of the empirical analysis depends on the specific factors that affected the behavior of each central bank to implement independent monetary policy. Our empirical findings, based on the generalized method of moments approach, provide evidence that central banks follow an active monetary policy and control for the impact of real exchange rate on output and inflation. We show that policy makers in all four countries have asymmetric preferences with respect to both inflation and output gap such that they weigh positive and negative deviations of inflation and output gap differently. We also find that the domestic interest rate reacts positively with respect to changes in foreign interest rate.

The rest of the paper is organized as follows: Section 3 presents the model. Section 4 discusses the empirical issues and the data. Section 5 lays out the empirical results while Section 6 concludes.

2.2 The Model

In this section we present a New-Keynesian model for an open economy whose variants are implemented in, among others, Ball (1999b), Svensson (2000), Clarida et al. (2001), and Leitemo et al. (2002). The economic structure we present below differs from that of Ball (1999b) as our model contains forward looking elements. The structure we present here is also different from that of Leitemo et al. (2002) as the forward looking element in their model is embedded only in the behavior of the exchange rate which is determined by the uncovered interest parity (UIP) condition. Furthermore, different from both studies we allow the policy makers to have asymmetric response towards inflation and output gap as their actual levels exceeds or falls short of the corresponding targets. We obtain the policy rule for our proposed framework by solving an intertemporal optimization problem.

2.2.1 Economic Structure

The dynamics of the open economy are given by the following three equations which describe the behavior of the output gap, inflation and the exchange rate, respectively.

$$y_t = \alpha_1 E_t y_{t+1} - \alpha_2 (i_t - E_t \pi_{t+1}) + \alpha_3 q_t + \varepsilon_t^y \tag{2.1}$$

$$\pi_t = \beta_1 E_t \pi_{t+1} + \beta_2 y_t + \beta_3 (E_t q_{t+1} - q_t) + \varepsilon_t^\pi \tag{2.2}$$

$$q_t = E_t q_{t+1} - (i_t - E\pi_{t+1}) + (i_t^f - E\pi_{t+1}^f) \tag{2.3}$$

Equation (2.1) is an open economy forward looking aggregate demand curve (IS-curve). At any point in time t, the output gap is denoted by y_t, the domestic nominal interest rate is i_t and inflation is π_t. Expected value of variable x_{t+1} given the information set at time t is denoted by $E_t x_{t+1}$. This equation implies that the expected course of real interest rate has a negative impact on the output gap. Equation (2.1) also assumes that the real exchange rate, q_t, which is defined as the domestic currency price of foreign currency, has a positive effect on the output gap. ϵ_t^y depicts demand shocks.

Equation (2.2) describes an open-economy Phillips curve. This equation allows the price setters to adjust the current prices accounting for future marginal costs. In that sense this equation captures the Calvo-type world in which the price adjustment takes place with a constant probability by each firm in a given period of time. Here, inflation is a positive function of the output gap. We also assume that the real exchange rate affects inflation positively as suggested by Svensson (2000) who argues that the current exchange rate has a direct impact on the CPI inflation rate.[3,4] In this equation ϵ_t^π captures cost disturbances.

Equation (2.3) suggests that the real exchange rate is determined according to the UIP conditions. The foreign interest rate and the foreign expected inflation rate are denoted by i_t^f and π_{t+1}^f, respectively. Hence, the first and the second parenthesized terms capture the domestic and the foreign real interest rates at time t. Equation (2.3) shows that an increase in the domestic real interest rate leads to an appreciation of the exchange rate as the domestic assets become more attractive. This equation also shows that an increase in the foreign real interest rate will result in depreciation of the exchange rate (due to capital flight from the home country).

2.2.2 Objective Function

Following the earlier research, we assume that policy makers choose interest rate at the beginning of time t based upon the information available at the end of the previous period before the economic shocks are realized. The policy authorities therefore minimize the following intertemporal loss function:

$$\text{Min } E_{t-1} \sum_{\tau=0}^{\infty} \delta^\tau L_{t+\tau} \tag{2.4}$$

subject to the dynamics described in Equations (2.1-2.3). In Equation (2.4), δ is the discount factor and L_t stands for the period t loss function of the central bank. The objective of the central bank is to choose a path for its instrument, the short term interest rate, to minimize the expected loss.

Here, we use a linear exponential (linex) loss function that allows policy makers to weigh positive and negative deviation of output gap and inflation from their respective targets differently. The linex loss function was proposed by Varian (1974). Subsequently, Zellner (1986), Granger et al. (1996), and Christoffersen and Diebold (1998) used this function in the context of optimal forecasting. Nobay and Peel (2003) use the linex loss function to study optimal policy reaction function under both discretion and commitment.[5]

[3] Several other researchers, including Ball (1999b) and Leitemo et al. (2002), relate inflation to changes in real exchange rate. Ball (1999b) argues that changes in the real exchange rate affects the inflation rate by the import price pass through mechanism which constitute an indirect impact of exchange rate on domestic inflation.

[4] Introducing difference of the expected exchange rates in Equation (2.2) rather than the level of exchange rate does not change our results.

[5] Following Nobay and Peel (2003) several researchers have used linex form including Ruge-Murcia (2004), Ruge-Murcia (2003a), and Surico (2003) among others.

The loss function that we implement for our purposes takes the following form:

$$L(\pi_t, y_t) = \frac{e^{\mu(\pi_t - \pi^*)} - \mu(\pi_t - \pi^*) - 1}{\mu^2} + \lambda \frac{e^{\gamma y_t} - \gamma y_t - 1}{\gamma^2}$$

where the parameters μ and γ capture any asymmetry in the objective function with respect to inflation and output gap respectively. The policy preference towards inflation stabilization is normalized to one and λ represents the relative aversion of the policy maker towards output fluctuations around its long run equilibrium level. The inflation target set by the central banker is denoted by π^*. The output gap target is set to zero.

The significance of μ and γ identifies whether the policy makers have asymmetric response towards inflation and output gap, respectively, in different economic situations. For instance, a positive value for μ implies that the central bank is more worried about inflation exceeding the set target level π^* because the cost of high inflation exceeds that of low inflation. This is so because if $\mu > 0$ then the exponential term ($e^{\mu(\pi_t - \pi^*)}$) will rule over the linear component. Thus, positive deviations from the inflation target will have dominant effects on policy makers' loss function than negative deviations. The reverse is true if $\mu < 0$. In a similar vein, we can argue that should the central bank place more weight to output contractions ($y < 0$), then γ must take a negative value such that the exponential in the second term ($e^{\gamma y_t}$) plays the dominant role. However if the policy maker is more worried that the economy overshooting its long run growth ($y > 0$), then we should observe a positive value for γ. Hence, this framework can provide us information whether the business cycle fluctuations have welfare effects beyond the first order or not.

Besides the idea that the policymakers can have asymmetric weights depending on the stance of inflation and output gap with respect to their targets, the linex function also allows discretion on the part of the central bank so that higher moments of inflation and output gap might play an important role in designing optimal policy rules (see Kim et al. (2005)). Furthermore, the evidence of asymmetry implies that certainty equivalence does not hold. Thus, uncertainty about inflation and output gap will induce a prudent behavior on the part of the central bank. This is so because uncertainty raises the expected marginal cost of inflation and output gap from their respective targets. Finally, the model nests the quadratic preferences as a special case. The loss function reduces to symmetric parametrization when both μ and γ are equal to zero, which can be empirically tested.

2.2.3 Solution of the model

To solve the model, we first substitute Equation (2.3) into (2.1) and (2.2). After rearranging the terms, we obtain:

$$y_t = \alpha_1 E_t y_{t+1} - (\alpha_2+\alpha_3)(i_t - E_t\pi_{t+1}) + \alpha_3 E_t q_{t+1} + \alpha_3(i_t^f - E_t\pi_{t+1}^f) + \varepsilon_t^y \quad (2.5)$$

$$\pi_t = \beta_1 E_t\pi_{t+1} + \alpha_1\beta_2 E_t y_{t+1} - [\beta_2(\alpha_2+\alpha_3) - \beta_3](i_t - E_t\pi_{t+1}) \quad (2.6)$$
$$+(\beta_2\alpha_3 - \beta_3)(i_t^f - E_t\pi_{t+1}^f) + \beta_2\alpha_3 E_t q_{t+1} + \beta_2\varepsilon_t^y + \varepsilon_t^\pi$$

Next, we minimize Equation (2.4) subject to (2.5) and (2.6) with respect to the current interest rate i_t and obtain the following first order condition:

$$E_{t-1}\frac{\partial L(\pi_t, y_t)}{\partial i_t} = \frac{-(\beta_2\alpha_2+\beta_2\alpha_3-\beta_3)}{\mu}E_{t-1}[e^{\mu(\pi_t-\pi^*)}-1] - \frac{\lambda(\alpha_2+\alpha_3)}{\gamma}E_{t-1}[e^{\gamma y_t}-1] = 0 \quad (2.7)$$

We assume that the demand and supply shocks (ε_t^y and ε_t^π) are normally distributed. Hence, the exponential terms in Equation (2.7) are log normally distributed with conditional means $e^{[\mu(\pi_{t|t-1}-\pi^*+\frac{\mu}{2}\sigma_{\pi,t}^2)]}$ and $e^{(\frac{\gamma^2}{2}\sigma_{y,t}^2)}$, respectively.[6] Here, $\sigma_{\pi,t}^2$ and $\sigma_{y,t}^2$ denotes the conditional variance of inflation and output gap, respectively. Thus, we can rewrite Equation (2.7) in the following form:

$$E_{t-1}\frac{\partial L(\pi_t, y_t)}{\partial i_t} = \frac{-(\beta_2\alpha_2+\beta_2\alpha_3-\beta_3)}{\mu}[e^{(\mu(\pi_{t|t-1}-\pi^*)+(\frac{\mu^2}{2})\sigma_{\pi,t}^2)}-1] - \frac{\lambda}{\gamma}(\alpha_2+\alpha_3)[e^{(\frac{\gamma^2}{2}\sigma_{y,t}^2)}-1] = 0 \quad (2.8)$$

Linearizing the expression in Equation (2.8) by taking a first-order Taylor approximation and solving for expected inflation we arrive at:

$$E_{t-1}\pi_t = \pi^* - \frac{\mu}{2}\sigma_{\pi,t}^2 - \frac{\lambda(\alpha_2+\alpha_3)}{(\beta_2\alpha_2+\beta_2\alpha_3-\beta_3)}[(\frac{\gamma}{2})\sigma_{y,t}^2] \quad (2.9)$$

Taking the conditional expectation of Equation (2.6) with respect to information set available at time $t-1$ and substituting $E_{t-1}\pi_t$ into (2.9), we can show that the policy variable takes the following form:

$$i_t = \varphi_0 + \varphi_1 E_{t-1}y_{t+1} + \varphi_2 E_{t-1}\pi_{t+1} + \varphi_3 E_{t-1}q_{t+1} + \varphi_4 E_{t-1}(i_t^f - \pi_{t+1}^f) + \varphi_5\sigma_{\pi,t}^2 + \varphi_6\sigma_{y,t}^2 + (error) \quad (2.10)$$

Equation (2.10) depicts the forward looking policy rule of the central bank with asymmetric preferences in an open economy framework. The associated coefficients of the equation are the reduced form parameters (φ_i) which measures the response of monetary policy

[6] Recall that output gap is a zero mean normally distributed variable so that we have $E_{t-1}\exp(\gamma y_t)$ is equal to $e^{\frac{\gamma^2}{2}\sigma_{y,t}^2}$.

with respect to those variables in the policy rule. In particular, given the parameters in Equations (2.1- 2.4), each coefficient (φ_i) in Equation (2.10), can be written as follows:

$$
\begin{aligned}
\varphi_0 &= \frac{-\pi^*}{(\alpha_2\beta_2+\alpha_3\beta_2-\beta_3)},\ \varphi_1 = \frac{\alpha_1\beta_2}{(\alpha_2\beta_2+\alpha_3\beta_2-\beta_3)},\ \varphi_2 = \frac{\beta_1+\alpha_2\beta_2+\alpha_3\beta_2+\beta_3}{(\alpha_2\beta_2+\alpha_3\beta_2-\beta_3)} \\
\varphi_3 &= \frac{\alpha_3\beta_2}{(\alpha_2\beta_2+\alpha_3\beta_2-\beta_3)},\ \varphi_4 = \frac{\alpha_3\beta_2+\beta_3}{\alpha_2\beta_2+\alpha_3\beta_2-\beta_3},\ \varphi_5 = \frac{-\mu/2}{\alpha_2\beta_2+\alpha_3\beta_2-\beta_3} \\
\varphi_6 &= \frac{-\lambda(\alpha_2+\alpha_3)(\gamma/2)}{(\alpha_2\beta_2+\alpha_3\beta_2-\beta_3)^2}.
\end{aligned}
$$

The policy rule given in Equation (2.10) by construction differs from the standard Taylor rule on three facets. First, it incorporates the forward looking expressions of output gap and inflation rate. Second, it introduces exogenous variables such as the exchange rate and foreign interest rate. Third, it captures asymmetric preferences by accounting for the volatility of output gap and inflation rate.

2.3 Empirical Issues

The policy rule in Equation (2.10) contains expected future output gap, inflation, the exchange rate and the foreign real interest rate. We proxy for the expected exchange rate by using twelve-month ahead forward exchange rates. To compute the expected output gap and inflation rate we first construct an autoregressive model based upon the Akaike information criterion (AIC) and Bayesian Information criterion (BIC). The selected model is then used recursively to compute the h-step ahead out-of-sample forecasts for both series.[7] The foreign real interest rate is calculated as the deviation of nominal interest rate from the expected inflation rate of the corresponding country.

We estimate Equation (2.10) by implementing the generalized method of moments (GMM) technique as we replace the unobserved expectations with their forecasts and the volatility terms with proxies derived from GARCH models as described below. In doing so we face two major issues concerning the instruments employed in the GMM estimation. First, the reliability of our econometric methodology depends crucially on the validity of the instruments which we evaluate by computing the Sargan–Hansen J test of overidentifying restrictions, asymptotically distributed as χ^2 in the number of restrictions. A rejection of the null hypothesis that instruments are orthogonal to errors would indicate that the estimates are not consistent. We also test for the presence of the first and the second order serial correlation so as to determine the correct lag structure of the instrument set. In each of the models presented below, the Hansen J statistic for

[7]We compute the h-step ahead forecast for y_t implementing $\widehat{y}_{t+h|t} = \widehat{\phi_0} + \sum_{i=1}^{p} \widehat{\phi}_i \widehat{y}_{t+h-i|t}$ where $\widehat{\phi}_i$ are the estimated coefficients based on in-sample information. Then $\widehat{\phi}_i$ are used to forecast out-of-sample y_{t+h}.

overidentifying restrictions and the autocorrelation tests show that our instruments are appropriate and our models do not suffer from serial correlation problem, respectively.

Another important issue in implementing the GMM methodology is the possibility that the instruments could be weak; that the instruments could be weakly correlated with the endogenous variables. Weak instruments will distort the distribution of the estimators and the test statistics will lead to misleading statistical inference.[8] Therefore, for the reliability of the instrumental variable approach, the instruments should be relevant and strongly correlated with the endogenous variables. Indeed, a measure of the strength of the instruments can be determined by the concentration parameter (see Anderson (1977)).[9] We can test for weak instruments either by testing for rank deficiency of the concentration statistic or using the reduced rank regression technique developed by Anderson and Rubin (1950) which is later extended for the presence of autocorrelated errors by Cragg and Donald (1997), Robin and Smith (2000), and Kleibergen and Paap (2006). Here, we follow the latter approach and report the p-values of the reduced rank test suggested in Kleibergen and Paap (2006).

In view of the fact that our model employs expected variables which are generated by the use of autoregressive models, one may be concerned about the use of lags of these series as instruments in estimation. We address these concerns by investigating the forecast performance of the models that we employed. If the models perform well, lags of the series can be used as proper instruments in our investigation. We test for forecast rationality by checking whether the forecast minimizes the loss function of the decision maker. It should be noted that forecast rationality must be evaluated in consideration of the decision maker's loss function. If a forecaster has a quadratic loss function (QLF) then forecast rationality requires forecast to be unbiased implying that the forecast errors are not on average significantly different from zero. We test for forecast being unbiased by regressing the forecast error on a constant.[10]

To further investigate forecast rationality, we next relax the assumption that the forecasters have a QLF and employ another forecast evaluation test which is optimal for any loss function. We do so by using the density forecast criterion introduced by Diebold et al. (1998). The density forecast criterion allows us to test whether the forecasting model used by the researcher is not significantly different from the model that generated the actual data. If this is the case then obviously the forecasting model will be optimal for any

[8]For a review of weak instruments see Stock et al. (2002). For the impact of weak instruments on statistical inference see Mavroeidis (2004) and Hansen et al. (1996).

[9]Intuitively, it is possible to interpret the concentration statistic as a portmanteau F-test on the significance of instruments which are regressed on an endogenous variable.

[10]An h-step ahead forecast is autocorrelated of order h-1. We account for autocorrelation by using the heteroscedasticity and autocorrelation consistent variance covariance matrix suggested by Newey and West (1987). In our investigation, we adopt uniform weights.

loss function. Diebold et al. (1998) show that if a sequence of density forecasts are correctly conditionally calibrated then the sequence of the probability integral transform of standardized forecast errors are iid and U(0,1). Berkowitz (2001) suggests an alternative goodness-of-fit test where under the null, the sequence of standardized forecast errors is iid $N(0,1)$.[11] However, he also argues that to test for normality more powerful tools can be employed than testing uniformity.[12] Under the null the likelihood ratio test suggested in Berkowitz (2001) follows a χ^2_3. We use both tests but for the sake of brevity we present results only from the Berkowitz's test.

Figure 2.1 here

Figure 2.2 here

Figure 2.1 Presents the forecast performance of both output gap and inflation rate. Panel A of Figure 2.1 show the out of sample forecast of inflation rate of all the countries whereas panel B displays the forecast series of output gap of all the countries. **We provide the evidence that in both panels, for all cases, forecasts are unbiased in most of the time periods. The p-value tests the null hypothesis that the forecast is unbiased. In our context, the forecast is unbiased when the forecast error is not significantly different from zero. As, in most of the time periods, the p-value is greater than 0.05, therefore, we conclude that the inflation rate and output gap series are unbiased.** Thus, the naive autoregressive models that we use for the out-of-sample forecasting exercise do not systematically under-predict or over-predict the target variables. In Figure 2.2, we present recursive estimates of density forecasts which implement the naive autoregressive model for all the countries. Panel A represents the recursive estimates for density forecast of inflation whereas Panel B presents the density forecast of output gap for all the countries. However, Figure 2.2 shows that the naive autoregressive models does not represent the true data generating process (DGP) for the UK and Japan as the density forecast criterion fails either the distributional or independence assumption. Although such evidence may raise doubts concerning the use of lags of inflation as an instrument, Kleibergen and Paap (2006) show that lags of these variables are not subject to the problem of weak identification.

The last issue that needs to be addressed is the volatility terms that appear in Equa-

[11] The density forecast is constructed as follows. We assume that disturbances are i.i.d. Gaussian and compute the standardized forecast errors as $\{z^*_{t+1}\} = \{(\frac{y_{t+1}-\widehat{y}_{t+1}}{\widehat{\sigma}_{t+1}})\}$ where $\widehat{y}_{t+1}$ is the one-step-ahead forecast of y_{t+1} made at time t and $\widehat{\sigma}_{t+1}$ is the standard deviation of $\widehat{y}_{t+1}$. Then the probability integral transform values are given by $\{z_{t+1}\} = \{\Phi(z^*_{t+1})\}$ where Φ is the Normal *CDF*. Here, instead of testing for uniformity and independence of $\{z_{t+1}\}$ we follow Clements and Smith (2000) and test for normality and independence of $\{z^*_{t+1}\}$. We do so by employing the Doornik and Hansen (1994) normality test and the Ljung-Box for autocorrelation test.

[12] The Berkowitz test is computed as $z^*_t = c + \rho z^*_{t-1} + \varepsilon_t$, $LR_B = -2[L(0,1,0) - L(\widehat{c}, \widehat{\sigma}^2, \widehat{\rho})]$ where $L(\widehat{c}, \widehat{\sigma}^2, \widehat{\rho})$ is the value of the exact maximum likelihood function of an AR(1) model.

tion (2.10). To generate these two series (inflation volatility and output gap volatility), we implement a GARCH(1,1) model. As Pagan (1984) and Pagan and Ullah (1988) point out, the use of generated regressors may lead to some problems in estimation and statistical inference. According to Pagan (1984) although one may overcome these problems by using instrumental variables approach, the use of lagged series as instruments may not be possible when the variable under consideration is a function of the entire history of the available data. In such cases, Pagan and Ullah (1988) suggest testing the validity of the underlying assumptions of the model that generates the proxy. For instance, Ruge-Murcia (2003) follows these suggestions and uses lagged conditional volatility of unemployment obtained from a GARCH(1,1) model as an own instrument after checking for any remaining heteroscedasticity in the standardized squared residual. Here, we, too, follow a similar route. We generate output gap and inflation volatility measures implementing GARCH(p,q) and ARCH(p) models after we carefully check whether these models are well specified and whether there is any neglected heteroscedasticity. We then use the lags of these proxies as instruments to estimate our model.

2.3.1 Data Sources and Definition of Variables

In our empirical investigation we use quarterly data which cover the period between 1979q1-2007q4. We estimate the policy rule given in Equation (2.10) for Canada, Japan, the UK and the US where the starting point of the empirical analysis slightly differs for each country depending on the specific factors that have affected the behavior of each central bank. To that end, we start the analysis for the UK on 1979q1 as the bank of England increased its emphasis on controlling inflation. In the case of Japan we begin the analysis as of 1979q1, too, as she went through a period of financial market deregulation in 1979 where all capital controls were removed and the Bank of Japan began to use the interbank lending rate to conduct monetary policy.[13] In the case of Canada our starting date is 1980q1 as the bank of Canada began to float the bank rate. Last, for the US, our investigation begins as of 1983q4. In fact a large body of literature is devoted to empirically evaluating the monetary policy of the FED by classifying FED's policy preferences for pre and post 1979 to capture the role of Volcker period. However, Surico (2007a) and Ilbas (2010) argue that the period between 1979–1983 is a period of frequent shifts in the monetary policy and high uncertainty, and suggest to use the post 1983 period for analysis. Bernanke and Mihov (1998) also document that during the period 1979q4 -1982q3 the operating procedure of Fed switched from federal funds rate to non-borrowed reserves targeting. Similarly, Dolado et al. (2004) conclude that post-1983 period portrays the US policy preferences well. Therefore, we use the data between 1983q4 and 2007q4 to examine

[13] See Batten (1990).

the behavior of the FED's monetary policy.

The end date of our empirical analysis of each country is twelve months prior to the latest available data due to the fact that our investigation uses four quarter ahead out of sample forecast of inflation rate and output gap. In our empirical modeling, for each country we use the growth rate of consumer price index to measure inflation rate. As suggested in Svensson (2000) all inflation targeting countries in our data-set use CPI inflation targets. More importantly, direct exchange rate channel is more prominent in the CPI inflation.[14] Leitemo and Söderström (2005) also argue that imported inflation is considered as one of the components of inflation while setting the target for inflation. We use log of gross domestic product(GDP) of each country to obtain output gap. There are two widely used methods to compute output gap namely linear de-trending and Hodrick and Prescott (1997) filter[15].We employ HP filter to generate output gap from log of GDP for all the countries. The HP filter trend is the potential output level, hence output gap is the difference between actual and potential GDP.

Following the existing literature, we use the respective short term interest rate of each country as the policy instrument. As argued by Clarida et al. (1998) that the short term interest rate is considered as the main operating instrument for monetary policy. More specifically, they explained, an interbank lending rate for overnight loans made between banks is used as an policy instruments by most of the central banks. Thus, we use the overnight interbank rate for the UK and the overnight money market rate for Canada. We use the call-money rate for Japan as the policy variable as among others Miyao (2002), Miyao (2000), Kasa and Popper (1997), and Morgan (1993) use call money rate as an instrument of monetary policy for the bank of Japan. Miyao (2002) prefers call money rate over monetary aggregates as an appropriate measure of monetary policy because interest rate is predetermined for monetary aggregates. De Andrade and Divino (2005) also argue in favor of call rate as a policy instrument. For the US, we use the Federal-Funds rate as the appropriate policy instruments as argued by researchers including Bernanke and Mihov (1998), Clarida et al. (1998) and McCallum and Nelson (2000). Since our model embodies the foreign monetary policy instrument, the US is taken as the foreign country when we estimate the policy rule for the UK, Canada and Japan. The UK, on the other hand, is considered as the foreign country when we evaluate the policy rule for the US. The exchange rate appears in our model within a forward looking framework as suggested in Svensson (2000).

[14] The domestic inflation is more relevant when estimating the policy rule for closed economy.

[15] Taylor (1993)used linear de-trending to compute the output gap series whereas Taylor (1999b)employed HP filter for computation of output gap series

The data are collected from the international financial statistics (IFS) database published by the International Monetary Fund(IMF). The 12-month forward exchange rate for the UK is accessed from the bank of England data sources whereas for the US, Canada and Japan data are obtained form the datastream database.

2.4 Discussion of Results

In what follows, we present for each country several different variants of Equation (2.10) in Tables2.1–2.4 where we use four quarter ahead forecast horizon to proxy the forward looking variables. We must note that while our main results are based on the sample covering the time period 1979q1-2007q4, for robustness check, we also estimate all models by extending the time period up to 2010q4. Results from this set are reported in Appendix A of the chapter 2. This exercise allows us to observe the changes in responsiveness of monetary policy after the time period of 2007.

Table 2.1 presents results for Canada, Table 2.2 for Japan, Table 2.3 for the UK and Table 2.4 for the US. Each table provides estimates for six different models by following a specific to general approach. The first column presents results for a simple forward looking Taylor rule without the assumption of both asymmetry and open economy where policy makers are assumed to have quadratic loss function. In columns 2, we allow central banks to follow asymmetric preferences with respect to both inflation rate and output gap but we assume closed economy. Next, column 3 introduces open economy framework and relaxes the assumption of asymmetry for both inflation rate and output gap. In column 4 and 5, we still allow for the open economy framework, while the model in column 4 relaxes the assumption of asymmetry for inflation only, that in column 5 relaxes the assumption of asymmetry only for output gap. The last column depicts results for the full open economy model (Equation (2.10)) which assumes that the policy makers use an asymmetric loss function with respect to both inflation and output gap.

2.4.1 General Observations

We have three sets of key results. First, we observe that the monetary policy aims to stabilize the economic environment by reacting to inflationary pressures driven by both domestic and foreign factors. That is the central bank not only reacts to movements in expected inflation but also to movements in real exchange rate and foreign interest rate. Second, we provide empirical evidence that central banks have asymmetric preferences concerning the positive or negative deviation of inflation and output gap, respectively. We show that the central bank reacts more strongly to positive deviations of inflation from its target level than to negative deviations from the target. Furthermore, although our findings generally confirm that that the policy makers dislike negative output gap, there are some instances that the policy makers respond to positive output gap. We interpret this observation as that the central bank is mainly concerned about inflation and considers a positive output gap as an indicator of future inflation. Third, our findings provide evidence towards the importance of the use of an open economy framework in discussing monetary policy rules. Our claim is not only due to the significance of foreign policy variables in Equation (2.10) but it is also because of sign changes on the asymmetry parameters beyond our expectations as the open economy assumption is relaxed.

2.4.2 Bank of Canada

Table 2.1 provides our results for Canada. In all columns of this table, as expected, we observe that the impact of expected output gap and expected inflation (captured by φ_1 and φ_2, respectively) on the monetary policy rule is positive and significant. In fact, the impact of expected inflation is greater than unity indicating that an increase in expected inflation leads to a more than one-for-one increase in the nominal interest rate. This finding implies that the model is stable and has a unique equilibrium.

When we turn to inspect the coefficients that capture the presence of asymmetric preferences of the policy makers regarding inflation and output gap, we arrive at the following observations. In column 2 when we assume a closed economy framework, the coefficient of inflation volatility is negative and significant. However, the sign of inflation volatility is not according to expectations. The change in sign may be due to the absence of the open economy elements from the models, suggesting that the closed economy framework is not desirable. In column 5, this parameter is significant and positive when we relax the assumption of asymmetry with respect to the output gap and introduce the open economy framework. Column 5 and column 6 of Table 1 shows that the coefficient of inflation volatility (φ_5) is positive and significant. This observation provides further support to the view that the bank of Canada (BOC) is inflation averse. This is so because the significance of inflation volatility implies that the marginal cost of inflation will increase as inflation deviates from its target level. Thus, inflation uncertainty will induce a prudent behavior on the part of BOC which sets the interest rate accounting both for the expected inflation and its uncertainty. In doing so BOC increases nominal interest rate more than is required by the expected inflation.

As we explore the output gap asymmetry coefficient, results for the closed economy model presented in column 2, show that the coefficient takes a negative and significant sign at the 1% level. This is consistent with the view that central banks under-predict growth to reduce inflationary pressure. However, the evidence of negative φ_5 points to the direction of misspecification error which might be driven by the strong assumption of Canada being a close economy. When we turn to column 4, which relaxes the assumption of inflation asymmetry, the coefficient of output gap volatility becomes positive and significant at the 10% level. Although positive output gap asymmetry is not consistent with our expectations and the significance level is rather weak, this observation provides support for the view that the main focus of BOC is to keep inflation below target. In this context, one can argue that BOC considers output gap as a predictor of inflation. In our final specification, in column 6, we observe that the coefficient of output gap volatility is positive but insignificant.

We next focus on the impact of real exchange rate and that of real foreign interest rate on domestic monetary policy. The table shows that the coefficient associated with real exchange rate is negative ($\varphi_3 < 0$) and that with the real foreign interest rate is positive ($\varphi_4 > 0$) in all the specifications presented in columns 3-6. These two coefficients play a key role in identifying the type of policy rule pursued by the central bank (i.e. active or passive). To have the above sign structure, inspecting the components of φ_3 and φ_4, we should have $(\alpha_2\beta_2 + \alpha_3\beta_2 - \beta_3) > 0$, $(\alpha_3\beta_2) < 0$ and $(\alpha_3\beta_2 + \beta_3) > 0$. These requirements suggest that the central bank follows an active monetary policy where the nominal interest rate must increase more in proportion to the expected inflation which changes as a consequence of movements in the foreign policy variables. In particular, note that the first term of $(\alpha_2\beta_2 + \alpha_3\beta_2 - \beta_3)$ captures the reaction of domestic interest rate to expected inflation and to output changes. The remaining two terms reflect the impact of real exchange rate changes on output gap and inflation. The positive sign associated with the third component above ($(\alpha_3\beta_2 + \beta_3) > 0$), which appears as the numerator of (φ_4), implies that the total impact (current and expected) of real exchange rate on inflation is positive. However, to obtain $(\alpha_2\beta_2 + \alpha_3\beta_2 - \beta_3) > 0$ we must have $(\alpha_2\beta_2) > (\alpha_3\beta_2 - \beta_3)$. Thus, an expected depreciation will increase current and expected inflation but it will also increase nominal interest rate above expected inflation. This is consistent with the coefficient of expected inflation being above one in all columns ($\varphi_2 > 1$)

In conclusion, we provide results for both the closed economy framework (where the model lacks the asymmetry effects as well as the open economy elements) and the open economy model where central bank pertains asymmetric references with respect to both of its target variables. In that sense the results of former case presents the standard model where policy makers use quadratic loss function. Although the coefficient estimates appear to be reasonable, the standard model is misspecified in the light of the Wald tests which verifies joint significance of inflation and output gap volatilities as well as open economy variables.

2.4.3 Bank of Japan (BOJ)

We, next, focus on the estimates for the bank of Japan which are presented in Table 2.2. In line with those findings reported in the literature, the coefficients of both expected inflation and expected output gap are positive and significant in all the specifications presented in Table Table 2.2.[16] Similar to BOC, the monetary policy adopted by BOJ satisfy the Taylor principle as the estimated coefficient of expected inflation is greater than 1 ($\varphi_2 > 1$). This finding implies that the model is stable and has a unique equilibrium.

When we turn to the influence of output gap volatility and inflation volatility on the policy measure (presented in columns 2-5), we find that both measures exert a significant impact. Interestingly, we should note that BOJ reacts more when output overshoots its long run target than when it falls short of it, as captured by the positive sign of the output gap volatility coefficient. Hence, the interest rate is tightened more in periods of expansion as compared to easing of the interest rate when output contracts by the same magnitude. We argue that this observation is an outcome of the fact that Japan experienced a stagnant economy in most of the period under investigation. Particularly, results in column 2 for the closed economy case show that BOJ under-predict both expected inflation and output growth but at the same time BOJ follows an active monetary policy by fighting rather than accommodating inflation. This is consistent with the inflation averse policy followed by the BOJ prior to the financial crisis in the early 90s and after the long-lasting stagnation following the burst of the real estate bubble.[17]

Different from the case of Canada, in column 2, we observe that inflation volatility exerts a negative and significant effect on the policy rule . These findings suggest that an increase in inflation volatility leads to a reduction whereas an increase in output volatility causes an increase in the interest rate. However, it should be noted that the total impact of inflation and output gap uncertainty on nominal interest rate is positive ($\varphi_5 + \varphi_6 > 0$). Considering the implication of the estimates on the parameters of the model given in Equations (2.1-2.10), we argue that policy makers at BOJ are more concerned about inflation undershooting its target than overshooting it. In column 4 when we relax he assumption of inflation uncertainty and introduce an open economy framework, we see that the asymmetry parameter of output gap is still positive. These findings can be explained taking into account the long deflationary period that Japan went through in the 90s which still

[16] See for instance (Miyao, 2000, 2002) and Clarida et al. (2000).

[17] BOJ followed an expansionary monetary policy in the late 80s to mitigate the effects of Yen's appreciation. The expansionary monetary policy accompanied with current account surplus led to excess liquidity in the financial system fueling asset prices. To counteract inflationary pressure the BOJ doubled the bank rate. The increase in the bank rate led to the burst of assets prices and increase the number of loan defaults. The by-product of loan defaults was a long-lasting stagnation.

affects her economy.[18] In particular, Miyao (2000) argue that the Japanese economy experienced a stagnation after the bubble economy burst.[19] This led to a substantial decline in the short term interest rates such as the discount rate and call money rate to push the economy back to its long run track. In column 5, once we exclude the impact of output gap volatility the asymmetry parameter of inflation turns positive ($\varphi_5 > 0$).

Moving on to explore the impact of the real exchange rate and the real foreign interest rate on domestic monetary policy, presented in columns 3-6, we see that the coefficients associated with these two variables (φ_3 and φ_4, respectively) take the expected signs as they are both positive and significant at the 1% level in all models. This finding suggests that currency depreciation will lead the central bank to increase the interest rate as a loss in the value of the currency induces inflationary pressures on the economy. Likewise, the domestic interest rate follows the movement in the foreign interest rate.

It is also worth noting that we conduct the Wald test and verify that inflation and output gap volatility coefficients are significantly different from zero. This observation suggests that the Bank of Japan has asymmetric preferences towards movements in inflation and output. Also, we perform a Wald test to test the significance of open economy variables. The Wald test verifies the significant role of exchange rate and foreign interest rate. Thence, we can conclude that BOJ conduct monetary policy by taking into consideration the international factors.

2.4.4 Bank of England (BOE)

Table 2.3 presents our results for the UK. In columns 1-6, we see that the impact of expected output gap and expected inflation is positive. In particular, the impact of expected inflation on interest rate is positive ($\varphi_2 > 1$) and stronger than that of the expected output gap suggesting that the model is stable and has a unique equilibrium.

We next observe that the impact of inflation and output gap volatility on domestic interest rate is positive and negative, respectively. The estimates appear as statistically significant in all the models presented in column 2-column 6. Accounting for the effects of uncertainty concerning the state variables, it appears that the BOE tend to adopt a precautionary policy regarding the behavior of inflation as the signs associated with φ_2 and φ_5 are both positive and greater than one. While at the same time BOE, as depicted by the coefficients φ_1 and φ_6 under-predict output gap and respond less than one-for-one to output gap changes. In this context, our findings suggest that the BOE will increase the interest rate above the conditional mean of inflation but the under-prediction of output-

[18] Bec et al. (2002) found similar results for France where the deflationary pressures were weighted more than the inflationary pressures.

[19] Japan experienced a bubble economy following the strong economic boom in the late 80s as the asset prices increased substantially.

growth will lead to low interest rate which is preferred in periods of recession. In doing so, we argue that the BOE aims to strengthen its anti-inflationary credibility. Thus, although the BOE is inflation averse, it responds to real economic activity independently of its concerns about inflation. In all the models, the sign of output gap asymmetry is positive at the 10% significance level. Although this observation might be due to the restrictions imposed on the model, it is possible that the positive sign is reflecting that the BOE use output gap as an indicator to forecast inflation.

As we inspect the effects of the exchange rate and the foreign interest rate, column 3-column 6, we see that the results are similar to that of Japan. The expected real exchange rate has a positive and sizable impact on the UK interest rate ($\varphi_3 > 0$) reflecting the response of monetary policy to changes in real exchange rate. In addition, the real foreign interest rate has a positive ($\varphi_4 > 0$) and significant impact on domestic interest rate.[20] Yet, the size of this coefficient is smaller than that associated with the real exchange rate. In that context, the results presented in column 6 provide further support to the view that the BOE accounts for changes in the monetary policy of the US.

The Wald test statistics show that inflation and output gap volatility coefficients are significantly different from zero providing further evidence that the Bank of England has asymmetric preferences. Also, the Wald test confirms the significance of exchange rate and foreign interest rate. Therefore, we have significant evidence in favor of open economy framework for the UK monetary policy formation.

2.4.5 The Federal Reserve (FED)

Last, we focus on results for the US which we report in Table 2.4. Overall, signs of the associated variables estimated for the US are similar to that of Canada. In column 1- column 6, we find that expected output gap (φ_1) and expected inflation (φ_2) have a positive impact on the domestic interest rate. However, in several models, the coefficient associated with the expected inflation is low, in the vicinity of unity or smaller, except for the model where we assume closed economy with quadratic loss function. Although the coefficient estimates of the expected inflation that we report in columns 1-6 could raise questions about the stability of the model, arguments carried out in Lubik and Schorfheide (2004) as well as in Bullard and Mitra (2002), and Lubik and Marzo (2007a) point out that equilibrium is a system property which depends on the linkages between the parameters of the Taylor rule and of the structural parameters.[21] Thus, a low inflation coefficient should

[20] Similar findings are documented by Clarida et al. (1998) regarding the effect of German interest rate on the UK monetary policy when Germany was used as the foreign country. Clarida et al. (1998) show that one percent increase of German interest rate induce 60 basis points rise in the British interest rate.

[21] Clarida et al. (2000) show that if the policy rule includes only current level of inflation (i.e. $i_t = \varphi_0 + \varphi_2 E_t \pi_t$) then determinancy requires $\varphi_2 > 1$. Alternatively, Bullard and Mitra (2002) and Lubik and Marzo (2007a) show that if the policy rules includes forward looking values of inflation and output gap (i.e.

be interpreted with caution and should not be taken as evidence for indeterminacy. More concretely, in column 1, the coefficient of expected inflation is marginally above one but the total response of interest rate to inflationary pressure is well above one ($\varphi_2 + \varphi_5 > 1$); there is no evidence of indeterminacy in the full model. However, in columns 3-5 where we gradually remove the assumption of asymmetry, the coefficient associated with inflation variability is estimated to be insignificant while the coefficient of expected inflation is below one. In this case, one can suggest that there is evidence of indeterminacy which might be an outcome of specification error.

Next, we inspect the coefficients that capture the presence of asymmetric preferences of the policy makers regarding inflation and output gap. The estimates are presented in column 2 and column4-column6 of Table 2.4. In column 2 when we have a closed economy model, we observe that the signs for both asymmetries are opposite to our expectation. In column 4, where we incorporate international factors into our specifications and exclude the role of inflation asymmetry, we observe a negative coefficient of output gap volatility. This finding suggests that FED is more cautious about the negative output gap. however, when we relax the assumption of output gap volatility and maintains the open economy scenario, we still observe that the unexpected response of central bank towards inflation variation around its target level. These findings may indicate the specifications error.

In column6 of this Table, we find that both measures exert a significant impact on the policy rule pursued by the FED with expected signs. We observe that inflation volatility has a positive impact on the domestic interest rate suggesting that the FED increases the interest rate to achieve a stable economic environment. Moreover, as in the earlier cases, the positive and statistically significant association between the volatility of inflation rate and the domestic interest rate suggests that the response of the FED is asymmetric with respect to changes in the inflation rate. In other words, the FED puts more weight to the upward swings of inflation from the target than the downward swings. This finding is consistent with earlier research such as Dolado et al. (2004) and Bec et al. (2002) among others who provide an evidence in favor of asymmetric preference of central bank with respect to inflation rate for the post 1979 period. These authors argue that a nonlinear policy rule for the post 1983 period reasonably portrays the US policy preferences.[22]

We also find that the volatility of output gap is negative and statistically significant at the 1% level. This indicates that the FED is more responsive to output contractions rather than to expansions similar to the case of UK and Canada. In other words, output

$i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1}$) then determinacy is achieved if $0 \leq \varphi_1 < \frac{1}{\alpha_2}$, and $\max\{1 - \frac{1-\beta}{\beta_2}\varphi_1, 0\} < \varphi_2 < 1 + 2\frac{1+\beta}{\beta_2\alpha_2} - \frac{1+\beta}{\beta_2}$ holds.

[22]However, we must also note that Surico (2007a) and Surico (2003) document a statistically insignificant response of federal funds rate towards squared inflation and conclude that the preferences of central bank towards inflation are not asymmetric.

contractions induce relatively more loosening of the interest rate than an increase in interest rate induced by output expansions of the same size. This finding is in line with Surico (2007a) who argues that an output contraction is more important than an expansion in implementation of asymmetric monetary policy rules for the US.

When we inspect the coefficients associated with the exchange rate and the foreign real interest rate (φ_3 and φ_4, respectively), we see that these coefficients follow the pattern that we observed for Canada (column 3-6).[23] The coefficient associated with the real exchange rate is negative ($\varphi_3 < 0$) and that with the real foreign interest rate is positive ($\varphi_4 > 0$). Similar to the case of Canada, these findings suggest that the FED follows an active monetary policy where the nominal interest rate increases more than in proportion to an increase in the expected inflation which changes as a consequence of movements in the foreign policy variables. Thus, an expected depreciation will increase current and expected inflation but it will also increase nominal interest rate above expected inflation.

Overall, although the closed economy model results are reasonable in terms of the sign and size of the coefficient estimates (the coefficient of expected inflation is positive and greater than 1), the model is too naive as the Wald tests reject the null that the coefficients of asymmetric preferences and of foreign variables are not significantly different from zero.

2.5 Conclusions

In this paper we construct an analytical model to investigate the optimal policy rule of a central bank with an asymmetric loss function subject to an open economy forward looking New Keynesian macroeconomic framework. We then estimate the policy rule that we obtain from the above framework along with a number models which we formulate imposing restrictions on the original model. The empirical investigation is carried out on quarterly data for four industrialized countries—Canada, Japan, the UK and the US. The data cover the period between 1979q1-2007q4.

Our empirical results can be summarized in three main categories. First, we provide evidence that the central banks in our study follow an active monetary policy as they account for the impact of foreign policy variable. More concretely, central banks carefully consider the impact that real exchange rate have on output and inflation while setting the interest rate. Our investigation also provides evidence that central banks increase the nominal interest rate more than one-for-one to a change in expected inflation. Overall, estimated coefficients provide support that the models we estimate are stable except for some cases when we discuss the behavior of the FED where the estimated expected inflation coefficient is less than one. Although this could be a result of the omitted variables in that specific case, some researchers (including Lubik and Schorfheide (2004), Bullard and Mitra

[23] Recall that we take the UK as the foreign country for the case of US.

(2002), and Lubik and Marzo (2007a)) point out that equilibrium is a system property which depends on the interrelations between the parameters of the Taylor rule and those of the structural model.

Second, we find evidence suggesting that all central banks whose policy choices we investigate in this paper have asymmetric preferences for their target variables. In particular, we find that the inflation volatility coefficient is positive suggesting that central banks change the nominal interest rate more when inflation exceeds the target level rather than when it falls below. When we look at the presence of asymmetry associated with the output gap we are confronted with differing reactions. Although we expect to see that a central bank should be more concerned when output gap falls below the target, for some cases we find that the central bank can be more reactionary during periods of positive output gap. We address this observation arguing that the central banks may be inflation averse and may take a positive output gap as an indicator of future inflation. Third, in line with the first finding, foreign variables have a significant impact on domestic monetary policy. This view is based not only on the significant effect of the real exchange rate and foreign real interest rate on domestic monetary policy but also on the closed economy models. We find that once we relax the open economy assumption, the sign of asymmetry parameters change providing evidence of specification error which might be driven by an omitted variable problem.

Overall, the findings we present here help us better understand the behavior of policy makers who have an asymmetric response towards inflation and/or output gap under an open economy framework. Yet, for future research, we believe that it would be fruitful to model and empirically investigate the interest rate smoothing hypothesis by implementing a framework as in this paper. We also think that expanding the set of countries under investigation can broaden our understanding. Finally, in line with the recommendation of Lubik and Schorfheide (2007) one can pursue a multivariate approach by estimating the entire structural model using system GMM. Although, Lubik and Schorfheide (2007) argue that full-information maximum likelihood exploit cross-equation restrictions, Ruge-Murcia (2007a) show that limited information procedures are more robust to model mispecification. Ruge-Murcia (2007a) show that GMM and simulated method of moment deliver more precise estimates than maximum likelihood. Thus, it would be useful to extend the current study employing system GMM approach to account for the recommendations of both Lubik and Schorfheide (2007) and Ruge-Murcia (2007a).

Table 2.1: GMM Estimates for Canada

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Estimation Results						
φ_0	2.889***	3.684***	7.394***	7.189***	7.568***	6.867***
	(0.368)	(0.395)	(0.682)	(0.664)	(0.607)	(0.651)
φ_1	0.480***	0.186	0.391***	0.404***	0.427***	0.423***
	(0.135)	(0.136)	(0.091)	(0.092)	(0.079)	(0.087)
φ_2	4.781***	5.414***	1.458***	1.156***	1.341***	1.302***
	(0.309)	(0.239)	(0.198)	(0.246)	(0.187)	(0.238)
φ_3			-4.032***	-4.340***	-4.262***	-4.284***
			(0.382)	(0.315)	(0.367)	(0.361)
φ_4			0383***	0.404***	0.383***	0.408***
			(0.068)	(0.070)	(0.065)	(0.072)
φ_5		-1.855**			0.681***	0.696*
		(0.911)			(0.397)	(0.423)
φ_6		-1.621***		1.199***		1.089
		(0.354)		(0.422)		(0.431)
Panel B: Diagnostic Tests						
Observations	114	120	107	107	107	107
Underidentification(p-value)†	0.000	0.000	0.001	0.002	0.019	0.007
Weakidentification(F-test)‡	55.422	28.463	21.454	21.262	22.481	22.549
J stat (p-value)	0.154	0.207	0.347	0.122	0.131	0.132
AR(1)	0.317	0.318	0.318	0.318	0.318	0.318
AR(2)	0.317	0.318	0.318	0.318	0.318	0.318
Panel C: The Wald Test(Joint Significance)						
$H_0 : \varphi_3; \varphi_4 = 0$			873.31***	639.80***	896.72***	656.42***
$H_0 : \varphi_5; \varphi_6 = 0$		32.590***				7.34**
$H_0 : \varphi_3; \varphi_4; \varphi_5 = 0$					960.66***	
$H_0 : \varphi_3; \varphi_4; \varphi_6 = 0$				859.25***		
$H_0 : \varphi_3; ...; \varphi_6 = 0$						1045.75***

Notes: $i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1} + \varphi_3 E_t q_{t+1} + \varphi_4 (i_t^f - E_t \pi_{t+1}^f) + \varphi_5 \sigma_{\pi,t}^2 + \varphi_6 \sigma_{y,t}^2$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients.
The time period for estimation is 1980q1-2007q4.
† represents the the Kleibergen-Paap rk LM-statistic testing the null hypothesis that the equation is under identified.
‡ represents the Kleibergen-Paap rk Wald F-statistic testing the null hypothesis that the equation is weakly identified.

Table 2.2: GMM Estimates for Japan

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Estimation Results						
φ_0	1.088***	-1.440*	-23.578***	-32.689***	-25.866***	-30.426***
	(0.236)	(0.860)	(2.111)	(1.874)	(2.422)	(1.928)
φ_1	0.064	-0.345	-0.001	0.034	0.031	0.023
	(0.242)	(0.239)	(0.108)	(0.077)	(0.111)	(0.076)
φ_2	4.122***	7.135***	1.539***	0.893***	1.519***	1.064***
	(0.309)	(0.579)	(0.194)	(0.186)	(0.191)	(0.206)
φ_3			5.034***	3.369***	5.445	5.917***
			(0.465)	(0.413)	(0.514)	(0.346)
φ_4			0.168***	092**	0.136	0.123***
			(0.051)	(0.043)	(0.053)	(0.040)
φ_5		-1.794*			1.457**	-1.220***
		(1.028)			(0.664)	(0.346)
φ_6		1.954		4.228***		4.426***
		(0.975)		(0.255)		(0.255)
Panel B: Diagnostic Tests						
Observations	112	112	109	109	109	109
Underidentification(p-value)†	0.000	0.000	0.025	0.025	0.045	0.008
Weakidentification(F-test)‡	30.334	21.229	52.908	22.903	41.265	41.899
J stat (p-value)	0.756	0.658	0.140	0.135	0.137	0.153
AR(1)	0.356	0.320	0.318	0.318	0.318	0.318
AR(2)	0.317	0.318	0.317	0.317	0.317	0.318
Panel C: The Wald Test(Joint Significance)						
$H_0 : \varphi_3; \varphi_4 = 0$			389.87***	1016.300***	390.56***	743.61***
$H_0 : \varphi_5; \varphi_6 = 0$		6.190**				323.58***
$H_0 : \varphi_3; \varphi_4; \varphi_5 = 0$					413.69***	
$H_0 : \varphi_3; \varphi_4; \varphi_6 = 0$				1237.15***		
$H_0 : \varphi_3; ...; \varphi_6 = 0$						891.390***

Notes: $i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1} + \varphi_3 E_t q_{t+1} + \varphi_4 (i_t^f - E_t \pi_{t+1}^f) + \varphi_5 \sigma^2_{\pi,t} + \varphi_6 \sigma^2_{y,t}$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients.
The time period for estimation is 1980q1-2007q4.
† represents the the Kleibergen-Paap rk LM-statistic testing the null hypothesis that the equation is under identified.
‡ represents the Kleibergen-Paap rk Wald F-statistic testing the null hypothesis that the equation is weakly identified.

Table 2.3: GMM Estimates for UK

Panel A: Estimation Results						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
φ_0	2.758***	0.4389	8.548***	8.101***	8.373***	7.868***
	(0.819)	(0.632)	(1.362)	(1.352)	(1.355)	(1.369)
φ_1	0.942*	0.810*	1.452***	1.347***	1.360***	1.274***
	(0.487)	(0.425)	(0.341)	(0.349)	(0.368)	(0.373)
φ_2	3.961***	2.375***	1.689***	1.535***	1.292***	1.139***
	(0.614)	(0.507)	(0.341)	(0.322)	(0.322)	(0.312)
φ_3			11.698***	10.996***	11.118***	10.454***
			(2.271)	(2.281)	(2.215)	(2.228)
φ_4			0.414***	0.418***	0.364***	0.369***
			(0.085)	(0.084)	(0.084)	(0.081)
φ_5		3.985***			0.824**	0.843***
		(0.587)			(0.323)	(0.319)
φ_6		1.949**		0.506*		0.626*
		(0.695)		(0.277)		(0.358)
Panel B: Diagnostic Tests						
Observations	109	108	114	114	114	114
Underidentification(p-value)†	0.000	0.002	0.001	0.001	0.001	0.001
Weakidentification(F-test)‡	28.649	19.806	25.495	25.745	22.745	24.716
J stat (p-value)	0.159	0.294	0.264	0.302	0.223	0.321
AR(1)	0.321	0.319	0.318	0.318	0.318	0.318
AR(2)	0.320	0.319	0.318	0.318	0.318	0.318
Panel C: The Wald Test(Joint Significance)						
$H_0 : \varphi_3; \varphi_4 = 0$			143.15***	127.97***	115.88***	108.41***
$H_0 : \varphi_5; \varphi_6 = 0$		66.79***				11.22***
$H_0 : \varphi_3; \varphi_4; \varphi_5 = 0$					175.43***	
$H_0 : \varphi_3; \varphi_4; \varphi_6 = 0$				137.83***		
$H_0 : \varphi_3; ...; \varphi_6 = 0$						177.04***

Notes: $i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1} + \varphi_3 E_t q_{t+1} + \varphi_4 (i_t^f - E_t \pi_{t+1}^f) + \varphi_5 \sigma_{\pi,t}^2 + \varphi_6 \sigma_{y,t}^2$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients.
The time period for estimation is 979q1-2007q4.

† represents the the Kleibergen-Paap rk LM-statistic testing the null hypothesis that the equation is under identified.

‡ represents the Kleibergen-Paap rk Wald F-statistic testing the null hypothesis that the equation is weakly identified.

Table 2.4: GMM Estimates for the USA

Panel A: Estimation Results						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
φ_0	2.781***	0.353	5.214***	8.127***	4.768***	8.660***
	(0.456)	(0.712)	(0.579)	(0.891)	(0.571)	(1.104)
φ_1	1.193***	1.463***	1.326***	1.373***	1.395***	1.300***
	(0.254)	(0.370)	(0.115)	(0.126)	(0.121)	(0.371)
φ_2	3.112***	1.710**	1.109*	1.389**	1.027***	1.584***
	(0.539)	(0.600)	0.332)	(0.369)	(0.340)	(0.382)
φ_3			-6.271***	-8.021***	-5.183***	-9.095***
			(0.940)	(1.233)	(1.120)	(1.675)
φ_4			0.279***	0.211***	0.302***	0.186***
			(0.043)	(0.055)	(0.045)	(0.062)
φ_5		-4.677***			-0.586	1.447*
		(1.068)			(0.634)	(0.873)
φ_6		12.636***		-5.639***		-6.688***
		(1.634)		(1.048)		(1.387)
Panel B: Diagnostic Tests						
Observations	97	97	95	93	94	93
Underidentification(p-value)†	0.000	0.000	0.014	0.001	0.007	0.006
Weakidentification(F-test)‡	95.384	35.950	25.223	19.834	27.365	11.171
J Stat (p-value)	0.186	0.785	0.226	0.552	0.785	0.496
AR(1)	0.318	0.318	0.319	0.319	0.317	0.318
AR(2)	0.318	0.318	0.318	0.320	0.318	0.318
Panel C: The Wald Test(Joint Significance)						
$H_0 : \varphi_3; \varphi_4 = 0$			158.80***	147.59***	144.61***	121.43***
$H_0 : \varphi_5; \varphi_6 = 0$		64.78***				26.66
$H_0 : \varphi_3; \varphi_4; \varphi_5 = 0$					174.54***	-
$H_0 : \varphi_3; \varphi_4; \varphi_6 = 0$				160.43***		-
$H_0 : \varphi_3; ...; \varphi_6 = 0$						154.65***

Notes: $i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1} + \varphi_3 E_t q_{t+1} + \varphi_4 (i_t^f - E_t \pi_{t+1}^f) + \varphi_5 \sigma^2_{\pi,t} + \varphi_6 \sigma^2_{y,t}$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients. The time period for estimation is 1983q4-2007q4.

† represents the the Kleibergen-Paap rk LM-statistic testing the null hypothesis that the equation is under identified.

‡ represents the Kleibergen-Paap rk Wald F-statistic testing the null hypothesis that the equation is weakly identified.

Figure 2.1: Testing the Forecast Bias

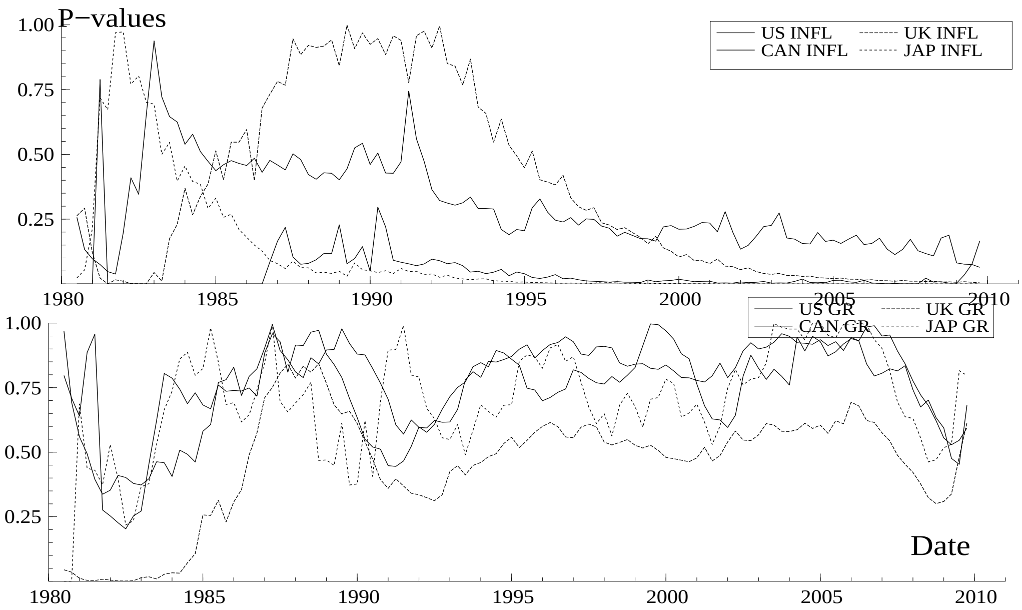
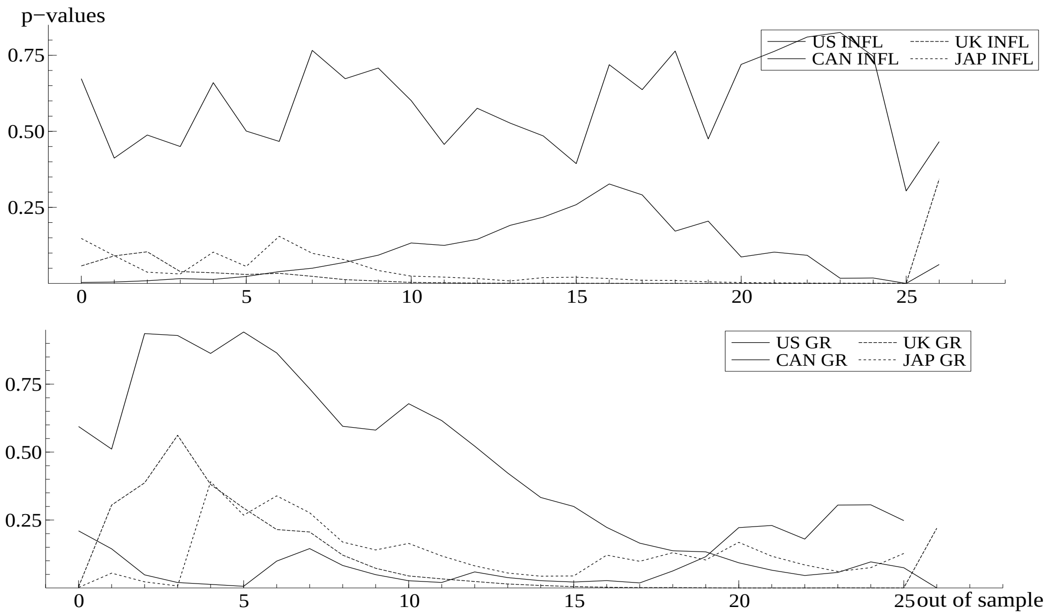


Figure 2.2: Recursive Forecasts



Appendix A: Monetary Policy Rules Estimates for the time period 1979-2010

A.1 Monetary Policy Rules Estimates for the time period 1979-2010:Canada

Table 1-A.1: GMM Estimates for Canada

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Estimation Results						
φ_0	2.177***	4.058***	6.787***	6.758***	6.496***	6.609***
	(0.365)	(0.385)	(0.743)	(0.619)	(0.746)	(0.541)
φ_1	0.300**	0.167	0.265***	0.291***	0.295***	0.279***
	(0.152)	(0.117)	(0.069)	(0.064)	(0.071)	(0.057)
φ_2	5.257***	5.220***	1.431***	1.204***	1.244***	1.030***
	(0.322)	(0.268)	(0.228)	(0.207)	(0.229)	(0.179)
φ_3			-3.788***	-3.908**	-3.881***	-3.775***
			(0.401)	(0.347)	(0.388)	(0.313)
φ_4			0.477***	0.495***	0.530***	0.529***
			(0.074)	(0.058)	(0.077)	(0.055)
φ_5		-1.921**			0.904***	0.691**
		(0.949)			(0.299)	(0.307)
φ_6		-1.995***		0.290**		-0.085
		(0.409)		(0.132)		(0.173)
Panel B: Diagnostic Tests						
$Observations$	122	122	117	116	117	116
$Under_{ID}test$	32.017	26.247	40.328	57.71	45.713	63.715
$p-value$	0.000	0.035	0.001	0.003	0.000	0.009
$Jstat$	6.9850	18.029	19.362	27.670	15.361	34.027
$p-value$	0.696	0.205	0.250	0.638	0.637	0.430
$AR(1)$	0.317	0.317	0.318	0.318	0.318	0.317
$AR(2)$	0.318	0.318	0.319	0.318	0.319	0.318
Panel C: The Wald Test(Joint Significance)						
$H_0:\varphi_3;\varphi_4=0$			791.28***	866.06***	774.74***	931.00***
$H_0:\varphi_5;\varphi_6=0$		44.14***				7.56**
$H_0:\varphi_3;\varphi_4;\varphi_5=0$					889.18***	
$H_0:\varphi_3;\varphi_4;\varphi_6=0$				993.41***		
$H_0:\varphi_3;...;\varphi_6=0$						1131.04***

Notes: $i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1} + \varphi_3 E_t q_{t+1} + \varphi_4 (i_t^f - E_t \pi_{t+1}^f) + \varphi_5 \sigma_{\pi,t}^2 + \varphi_6 \sigma_{y,t}^2$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients. The time period for estimation is 1980q1-2010q1.

A.2 Monetary Policy Rules Estimates for the time period 1979-2010:Japan

Table 1-A.2: GMM Estimates for Japan

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Estimation Results						
φ_0	0.981***	0.723	-21.23***	-29.890***	-23.107***	-27.506***
	(0.206)	(0.639)	(1.964)	(1.827)	(2.092)	(1.969)
φ_1	-0.135	-0.092	-0.077	0.160**	-0.042	0.128*
	(0.178)	(0.161)	(0.075)	(0.067)	(0.078)	(0.074)
φ_2	4.159***	3.920***	1.557***	1.013***	1.434***	1.333***
	(0.296)	(0.269)	(0.173)	(0.157)	(0.188)	(0.179)
φ_3			4.567***	5.876***	4.865***	5.371***
			(0.438)	(0.395)	(0.450)	(0.420)
φ_4			0.173***	0.146***	0.198***	0.192***
			(0.049)	(0.045)	(0.046)	(0.045)
φ_5		-3.528**			0.870**	-1.254**
		(1.618)			(0.377)	(0.507)
φ_6		1.871***		3.273***		3.458***
		(0.578)		(0.264)		(0.279)
Panel B: Diagnostic Tests						
$Observations$	121	121	117	117	117	118
$Under_{ID}test$	42.025	30.120	76.657	79.277	78.476	67.023
$p-value$	0.000	0.036	0.051	0.048	0.046	0.044
$Jstat$	10.436	10.195	68.170	70.812	67.432	56.716
$p-value$	0.403	0.895	0.150	0.140	0.186	0.182
$AR(1)$	0.345	0.339	0.318	0.318	0.318	0.318
$AR(2)$	0.317	0.317	0.317	0.317	0.317	0.317
Panel C: The Wald Test(Joint Significance)						
$H_0:\varphi_3;\varphi_4=0$			562.54***	1030.41***	490.47***	761.50***
$H_0:\varphi_5;\varphi_6=0$		11.32**				153.83***
$H_0:\varphi_3;\varphi_4;\varphi_5=0$					703.17***	
$H_0:\varphi_3;\varphi_4;\varphi_6=0$				1140.49***		
$H_0:\varphi_3,...,\varphi_6=0$						1024.65***

Notes: $i_t=\varphi_0+\varphi_1E_ty_{t+1}+\varphi_2E_t\pi_{t+1}+\varphi_3E_tq_{t+1}+\varphi_4(i_t^f-E_t\pi_{t+1}^f)+\varphi_5\sigma_{\pi,t}^2+\varphi_6\sigma_{y,t}^2$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients.
The time period for estimation is 1979q1-2010q1.

A.3 Monetary Policy Rules Estimates for the time period 1979-2010:UK

Table 1-A.3: GMM Estimates for UK

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Estimation Results						
φ_0	1.634	1.332**	4.410***	4.619***	5.501***	5.188***
	(1.855)	(0.663)	(0.808)	(0.793)	(0.939)	(0.893)
φ_1	2.403***	0.363	0.591***	0.780**	0.858***	0.794***
	(0.618)	(0.295)	(0.162)	(0.162)	(0.211)	(0.182)
φ_2	4.493***	2.824***	1.720***	1.664***	1.437***	1.286***
	(1.361)	(0.512)	(0.306)	(0.277)	(0.303)	(0.297)
φ_3			5.301***	6.169***	7.373***	6.904***
			(1.369)	(1.294)	(1.538)	(1.375)
φ_4			0.640***	0.629***	0.502***	0.522***
			(0.055)	(0.051)	(0.058)	(0.060)
φ_5		4.207***			1.020***	1.435***
		(0.608)			(0.317)	(0.509)
φ_6		-1.616***		0.349*		-0.438*
		(0.508)		(0.183)		(0.261)
Panel B: Diagnostic Tests						
$Observations$	122	117	119	117	119	116
$Under_{ID}test$	11.213	46.749	53.177	52.943	52.527	54.497
$p-value$	0.011	0.000	0.032	0.043	0.012	0.040
$Jstat$	3.899	24.417	42.263	45.233	32.308	44.093
$p-value$	0.142	0.181	0.186	0.140	0.402	0.197
$AR(1)$	0.327	0.318	0.317	0.317	0.318	0.317
$AR(2)$	0.325	0.319	0.318	0.318	0.317	0.318
Panel C: The Wald Test(Joint Significance)						
$H_0 : \varphi_3; \varphi_4 = 0$			210.24***	231.99***	218.48***	155.32***
$H_0 : \varphi_5; \varphi_6 = 0$		48.55***				8.66**
$H_0 : \varphi_3; \varphi_4; \varphi_5 = 0$					235.45***	
$H_0 : \varphi_3; \varphi_4; \varphi_6 = 0$				232.47***		
$H_0 : \varphi_3; ...; \varphi_6 = 0$						278.95***

Notes: $i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1} + \varphi_3 E_t q_{t+1} + \varphi_4 (i_t^f - E_t \pi_{t+1}^f) + \varphi_5 \sigma_{\pi,t}^2 + \varphi_6 \sigma_{y,t}^2$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients. The time period for estimation is 1979q1-2010q1.

A.4 Monetary Policy Rules Estimates for the time period 1979-2010:USA

Table 1-A.4: GMM Estimates for US

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Estimation Results						
φ_0	2.466***	1.617**	4.111***	5.587***	5.324***	8.468***
	(0.594)	(0.765)	(0.573)	(0.612)	(0.579)	(0.848)
φ_1	0.788**	1.060***	1.205***	1.034***	1.138***	0.842***
	(0.357)	(0.256)	(0.115)	(0.130)	(0.113)	(0.137)
φ_2	3.188***	1.351***	0.498*	0.440*	0.476*	1.024***
	(0.768)	(0.466)	(0.289)	(0.243)	(0.251)	(0.252)
φ_3			-4.071***	-5.395***	-5.566***	-7.596***
			(1.010)	(0.915)	(0.997)	(1.067)
φ_4			0.383***	0.344***	0.311***	0.328***
			(0.041)	(0.037)	(0.038)	(0.041)
φ_5		-3.819***			-0.217	2.524***
		(0.860)			(0.161)	(0.533)
φ_6		9.176***		-1.617**		-9.886*
		(2.591)		(0.693)		(1.774)
Panel B: Diagnostic Tests						
$Observations$	106	106	104	104	104	102
$Under_{ID}test$	20.939	17.394	39.951	52.063	44.853	53.643
$p-value$	0.021	0.002	0.003	0.007	0.004	0.009
$Jstat$	11.202	2.370	22.387	34.743	28.953	31.930
$p-value$	0.262	0.499	0.215	0.213	0.146	0.420
$AR(1)$	0.318	0.317	0.317	0.317	0.317	0.318
$AR(2)$	0.317	0.317	0.318	0.318	0.318	0.318
Panel C: The Wald Test(Joint Significance)						
$H_0 : \varphi_3; \varphi_4 = 0$			184.87***	220.59***	198.51***	189.74***
$H_0 : \varphi_5; \varphi_6 = 0$		21.34***				35.75***
$H_0 : \varphi_3; \varphi_4; \varphi_5 = 0$					229.95***	
$H_0 : \varphi_3; \varphi_4; \varphi_6 = 0$				221.91***		
$H_0 : \varphi_3; ...; \varphi_6 = 0$						228.88***

Notes: $i_t = \varphi_0 + \varphi_1 E_t y_{t+1} + \varphi_2 E_t \pi_{t+1} + \varphi_3 E_t q_{t+1} + \varphi_4 (i_t^f - E_t \pi_{t+1}^f) + \varphi_5 \sigma_{\pi,t}^2 + \varphi_6 \sigma_{y,t}^2$

In Panel A, values in parenthesis are standard errors. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Panel C reports the Wald test for testing the joint significance of the underlying coefficients.
The time period for estimation is 1983q4-2010q1

Chapter 3

Does the Source of Uncertainty Matter for the TFP Growth?: Evidence from Emerging Economies

3.1 Introduction

Uncertainty has become one of the central issues in both theoretical and empirical literature since Friedman (1977) documented that high inflation not only leads to high uncertainty but also dampens growth through allocative inefficiency. A significant contribution to the empirical literature in this field is by Kydland and Prescott (1982) and Long Jr and Plosser (1983). They present the idea of the unification of business cycle models and growth theory to investigate the factors behind economic fluctuations. Both of these studies conclude that technological shocks are the main driving force of output fluctuations. In a similar vein, King et al. (1988) merge the endogenous growth and real business cycle models and report that short-run fluctuations in production may impact the path of output for a long time period.

Thenceforth, a considerable attention has been paid to explore the link between macroeconomic uncertainty and the state of the economy measured by output growth (See, e.g., Abel (1983), Kormendi and Meguire (1985), Levine and Renelt (1992), Gregory and Head (1999), Ventura and Zeidan (2000), and Fountas and Karanasos (2007) among others). However, the existing empirical findings are conflicting. For instance, Ramey and Ramey (1995) explain that advanced commitment of firms to their technology leads to a negative relationship between growth and volatility. Their finding is based on the argument that in post volatility times, firms produce at lower level. Judson and Orphanides (1999) stress upon the significance of time dimension while examining the link between volatility and growth. Grier and Perry (2000) point out that the nature of shocks, such as real or nominal, plays an important role while examining their impact on growth. Furthermore, Imbs (2007) argues that the impact of uncertainty on growth depends on many factors. For instance, the irreversibility of investment results in a negative relationship between business cycle uncertainty and endogenous growth. In contrast, precautionary savings and high returns to investment may help in establishing a positive link between growth and its volatility. On the other hand, a large number of empirical studies report that endogenous growth models potentially maintain both positive and negative relationship depending on the nature of shocks and model parametrization (See, e.g., Aghion et al. (1998), Jones et al. (1999), Turnovsky and Chattopadhyay (2003), and Blackburn and Pelloni (2004) among others).

The studies focusing on the aggregate level relationship only present the tip of the iceberg and may not scrutinize the underlying mechanism between growth and volatility. As a consequence, the focus of the empirical research has been shifting from aggregate output growth to the components of growth such as total factor productivity (hereafter TFP) growth.[1] Thus, several recent studies such as Comin (2006), Aghion et al. (2009), and Oikawa (2010) among others have emphasized the determinants of labor productivity or TFP growth. Also, most recent studies have explored this relationship either at industry or at firm level (See, e.g., Imbs (2007) and Comin and Mulani (2009)).

On theoretical grounds, Comin (2000) is the first who have systematically formalized the relationship between productivity and volatility. He explains that uncertainty leads to adoption and diffusion of new technologies and accelerates TFP growth by shifting the investment from inflexible capital to flexible capital. Oikawa (2010) also establishes the theoretical basis for the relationship between productivity and volatility. In contrast to Comin (2000), Oikawa (2010) presents a different mechanism through which uncertainty affects the growth. He base his argument on firms' optimization behavior and concludes that uncertainty enforces firms to invest more in R&D activities which results in knowledge accumulation. Thus, the economy experiences a low level of productivity growth in the short-run but enjoys the benefit of high productivity growth in the long run.

On the empirical side, Dixit and Pindyck (1994) find that uncertainty associated with government expenditures affect productivity growth negatively through investment channel. Leahy and Whited (1996) argue that uncertainty affects the efficiency of capital. However, the extent of the impact depends on whether the capital is flexible or inflexible. More recent contributions include Miller and Upadhyay (2000) and Berument et al. (2011).

Another strand of empirical literature focuses on the decomposition of aggregate volatility of growth into different components such as sector and country level.[2] In this regard, the recent contribution is made by Koren and Tenreyro (2007). Specifically, they decompose aggregate volatility into sector and country level, and also incorporate the covariance between country and sector specific shocks. Other studies such as Kose et al. (2003) and Imbs (2007), however, examine how uncertainty emanating from different sources such as sectoral, country, regional, and global level is contributing to growth at aggregate and sector level.[3]

[1]There are two important components of growth explained by endogenous growth models namely, TFP growth and factor accumulation growth. As it is argued by Solow (1956) that a significantly large proportion of output growth is based on TFP while factor accumulation attributes only a minor share. Similarly, Hall and Jones (1999) explain that the cross national differences in human capital are not because of the per capita income but the main source of these differences is TFP growth. Moreover, Ramey and Ramey (1995), too, show that the volatility affects growth through the low technology adoption and not through accumulation of capital

[2]The earlier studies include Stockman (1988), Costello (1993), and Norrbin and Schlagenhauf (1990). These studies use factor augmented model to decompose the components of aggregate volatility

[3]Kose et al. (2003) analysis is based on aggregate growth whereas Imbs (2007) focuses on the manufacturing industries value-added growth

Decomposing uncertainty into different categories helps us to understand the underlying mechanism generating uncertainty and to formulate a policy to overcome its impact. Therefore we investigate how uncertainty stemming from different source determines the TFP growth of manufacturing industries of sixteen emerging economies covering the time period 1971-2008.[4] We use the ratio of industry output to total manufacturing sector output, ratio of country investment to its GDP, and world inflation rate to generate a proxy for industry specific, country specific, and global uncertainty, respectively. To generate a proxy for uncertainty, we estimate a first order autoregressive model for each type of uncertainty separately for all industries in the sample countries and over the selected time period. Next, we use translog production function to compute the TFP growth which is considered more efficient in contrast to the Cobb-Douglas production function. Finally, to examine the impact of each type of uncertainty on the TFP growth, we employ the dynamic panel data estimator: robust two-step system GMM approach.

Our study differs from the existing empirical work in various aspects. To the best of our knowledge, there is no existing empirical work to analyze how and to what extent uncertainty impacts TFP growth, particularly for manufacturing industries of developing countries.[5] We categorize uncertainty originating from industry, country, and world level and estimate the individual impact of each source of uncertainty on TFP growth. By doing so, we differ from Imbs (2007) in two aspects: (a) we estimate the impact of each type of uncertainty individually, (b) we conduct our analysis for the TFP growth instead of output growth of manufacturing industries. Therefore, we would be able to determine the unique impact of each source of uncertainty in contrast to their combined impact on the TFP growth.

In addition to scrutinize the direct impact, we also examine the conditional impact of uncertainty on the TFP growth. This is done by identifying the impact of uncertainty through other factors such as industry size, factor intensity level of industries, and the level series of each type of uncertainty. Therefore, we not only present the empirical evidence on the direct (own) impact but also on the indirect (conditional) impact of uncertainty emanating form different sources on the TFP growth. Finally, we present the total impact of each type of uncertainty on TFP growth by combining the direct and conditional impact. This exercise provides a detailed evidence on the TFP-uncertainty link which has been overlooked by the existing literature.

Our findings suggest that uncertainty plays a significant role in determining the TFP

[4]The countries which we use in our empirical investigation are: Chile, Chez Republic, Cyprus, Egypt, Hungary, India, Indonesia, Malaysia, Malta, Mexico, New Zealand, Philippines, Poland, Singapore, Sri Lanka, Turkey.

[5]However, there is some evidence showing the impact of different forms of volatility for growth both at aggregate and disaggregate levels.

growth. Moreover, the impact of each type of uncertainty on the TFP growth differs from each other. Specifically, we find that uncertainty associated with industry output and country investment affects the TFP growth positively. This indicates that higher industry and country specific uncertainty leads to an increase in the TFP growth. This finding is consistent with Imbs (2007) and Kose et al. (2003). In contrast, we provide an evidence of a negative impact of global uncertainty on the TFP growth which suggests that higher world inflation imposes a cost on the TFP growth.

We also present estimates on the conditional impact of each type of uncertainty on the TFP growth. We provide evidence that the industry specific uncertainty impact becomes stronger whereas the impact of country and global level uncertainty becomes weaker as the industry size increase. Turning to the conditional impact through factor intensity, the industry and country specific uncertainty has stronger impact for capital intensive industries whereas the negative impact of global uncertainty strengthens for relatively high capital intensive industries. Finally, the positive impact of industry specific uncertainty becomes weaker as industry output increases. Similarly, country specific uncertainty exhibits a weaker impact at higher level of country investment. Also, we find that there is a decrease in the negative impact of world uncertainty at higher levels of world inflation rate.

The rest of the paper is structured as follows: Section 3 discusses the existing empirical literature and how our study differs from the existing research on the impact of uncertainty on the TFP growth. Section 4 presents the empirical model. Section 5 explains the econometric framework to carry out empirical estimation, data and data sources, variable computation, and summary statistics. Section 6 is devoted to the discussion of the empirical results. Finally, Section 7 concludes.

3.2 Literature Review

As pointed out by Solow (1956), a significant contribution to output growth is attributed to the TFP growth. Later, Hall and Jones (1999) also argue that TFP growth is the main driving force of cross country income differences. However, there is little empirical work which explores the role of uncertainty in TFP growth is only trivial.

Several researchers have investigated the factors that affect the TFP growth. For instance, Harris et al. (1999) claims a positive effect of human capital, innovations and trade openness whereas a negative impact of inflation on the TFP growth. Miller and Upadhyay (2002) also report a negative impact of export volatility and inflation whereas a positive impact of trade openness on TFP growth. In addition, they show that the impact of R&D is conditional on the market structure and technology regime. In a same vein, Scarpetta and Tressel (2002) conclude that the impact of R&D expenditures on the TFP growth is conditional on the market structure and technology regimes. Aiyar and Feyrer (2002) provide an evidence of a positive relationship between human capital development and the TFP growth. Cororaton et al. (1999) and Ferrett (2004) show a positive relationship between foreign direct investment and the TFP growth. Relatively more recently, empirical studies conclude financial depth as an important determinant of the TFP growth (See, e.g., Tadesse (2005), Jeong and Townsend (2005), Beck et al. (2000), and Akinlo (2005)). Jajri and Ismail (2007) state that capital-labor ratio is an important factor for labor productivity growth as it measures the level of technology in an industry.

There are only few studies that investigate the impact of uncertainty on TFP growth. For example, Comin (2000) argues that a rise in uncertainty induces the replacement of old capital with flexible capital (such as information technology capital) which in turn results in higher productivity growth after the so called productivity slowdown. The finding is based on the assumption that productivity growth is higher with flexible capital relative to the old capital.

Aghion et al. (2009) test the impact of uncertainty, measured as exchange rate volatility, on the TFP growth through financial development. Their findings suggest that the impact of exchange rate uncertainty depends on the level of financial development in a country. Particularly, they show that the negative impact of exchange rate uncertainty weakens as the level of financial development increases. Similarly, Comin and Mulani (2009) analyze the productivity growth at the aggregate and firm level by presenting the evolution of the first and the second moments of productivity growth through the endogenous growth model. They report an ambiguous impact of R&D innovations on the TFP growth. However they observe a decline in the aggregate volatility in response to R&D innovations.

Oikawa (2010) studies the relationship between firm-level uncertainty and aggregate TFP growth for manufacturing sector of the USA in the absence of macroeconomic uncertainty. He argues that uncertainty stimulates R&D activities which lead to the accumulation of knowledge capital and delivers a positive impact on output growth in the long run. The short-run impact, however, remains negative. At the aggregate level, Berument et al. (2011) measure macroeconomic instability by estimating volatilities of inflation, trade openness, and financial market depth. They find a positive and statistically significant impact of inflation uncertainty on the TFP growth, whereas the impact of uncertainty in financial depth on the TFP growth is negative. Distinctively, Gregory and Head (1999) empirically evaluate the common and country specific components of TFP growth, investment, and current account by using dynamic factor model for G7 countries. The common and country specific fluctuations postulate a positive impact on TFP growth in all countries with few exceptions.

There is lack of evidence on the impact of uncertainty on TFP growth, particularly at industry and firm level. However, there is large number of studies which examine the impact of uncertainty on growth. (See, e.g., Ramey and Ramey (1995), Lee (2010), Blackburn and Pelloni (2004), Bredin and Fountas (2009), and Ventura and Zeidan (2000) among others). Other studies examine the multi-faceted relationship between growth and volatility by investigating the role of different types of uncertainty in determining output growth, both at aggregate and sector level. For instance, Kose et al. (2003) and Koren and Tenreyro (2007) investigate the impact of different factors such as sector, country, and regional uncertainties on the output growth volatility. On the other hand, Imbs (2007) examine the impact of uncertainty originating from different sources on manufacturing sector value added growth. He shows that there is a positive impact of sectoral uncertainty on sector value added growth and a negative impact of aggregate volatility on aggregate growth.

The review of the existing empirical work suggests that most of the research is still confined to empirically evaluating the determinants of TFP growth. There is little evidence on how uncertainty affects the TFP growth. We aim to investigate the link between different types of uncertainty and TFP growth of manufacturing industries of emerging economies. In this regard, we not only estimate the direct but also the conditional impact of each type of uncertainty on TFP growth. However, we know relatively less how uncertainty affects the TFP growth particularly at sector level. Therefore, our study aims at bridging this gap in the existing empirical literature by exploring the nature and origin of potential uncertainties affecting the TFP growth.

3.3 The Model

As mentioned earlier, our study has a broader perspective as we investigate the link between different measures of uncertainty and the TFP growth. Our work is distinct on the following grounds. First, we aim to empirically evaluate the role of different levels of uncertainty for the TFP growth.[6] Second, we incorporate each source of uncertainty individually to capture their unique impact on the TFP growth. Third, we also estimate the conditional impact of each source of uncertainty through different factors affecting the TFP growth. Fourth, we focus on a sample of emerging economies which is not considered by the researchers so far. The main reason for selecting this sample is that emerging economies in our sample are rapidly growing and liberalizing to achieve a compatible economic system.[7] Finally, differing from the existing literature, we employ robust two-

[6] There is enormous number of studies focused on the link between growth and volatility at macro and micro level see e.g., Ramey and Ramey (1995), Kose et al. (2003), Imbs (2007), and Koren and Tenreyro (2007) among others.

[7] In contrast, most of the studies focus on the OECD countries whereas the OECD countries have already reached to the steady state level of development where their growth rate is stable. Therefore there

step system GMM which allows us to account for endogeneity and the problem of generated regressors.

3.3.1 Baseline Specification

We use global, country, and industry specific uncertainty measures to carry out our investigation. The empirical model takes the following form:

$$TFP_{ij,t} = \phi_0 + \phi_1 TFP_{ij,t-1} + \beta_g(\sigma^2_\pi)_{t-1} + \beta_c(\sigma^2_I)_{i,t-1} + \beta_s(\sigma^2_y)_{ij,t-1} + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \tag{3.1}$$

where i , j and t denote countries, industries, and time indicators. $TFP_{ij,t}$ indicates the total factor productivity growth in industry j of country i and at time t. The lagged dependent variable ($TFP_{ij,t-1}$) accounts for the persistence of the TFP growth among industries. $(\sigma^2_\pi)_t$ captures global uncertainty which is constant across all the countries and industries, $(\sigma^2_I)_{i,t}$ refers to country specific uncertainty which remains constant across industries in country i, and $(\sigma^2_y)_{ij,t}$ denotes the industry specific uncertainty affecting industry j in country i at time t. $X_{ij,t}$ and $\mathcal{C}_{j,t}$ represents industry specific and country specific control variables, respectively. $\beta's$ measure the impact of global, country and industry specific uncertainty on TFP growth. The subscripts s, c, and g refers to industry specific, country specific, and global uncertainty. These denominations through out the analysis will remain same to indicate industry, country, and global uncertainty. ε_{ijt} is the disturbance term.

To proxy the uncertainty at industry level, existing studies have used manufacturing sector value added, output growth, and R&D investment (See, e.g., Imbs (2007), and Moomaw and Williams (1991) among others). Since UNIDO data do not provide any information on sales of industries whereas R&D data are not available for emerging economies, we use industry output to compute industry specific uncertainty.[8]

For country specific uncertainty, Kose et al. (2003) suggest various factors such as aggregate investment level, output growth, size of country relative to world (measured country's GDP relative to the US GDP), and the monetary policy of the respective country. However, Ramey and Ramey (1995) instrumented output volatility by fiscal policy shocks. Similarly, Fatás and Mihov (2003) argue that aggregate shocks mainly arise from exogenous fiscal policy shocks. Moreover, Koren and Tenreyro (2007) compute various sources of volatility in GDP by the breakdown of the value added per worker of country in to the sum of value added of different sectors. We use country's investment ratio to its

may not be enough margin for the uncertainty to impact their TFP growth.

[8] We also proxy industry specific uncertainty by using the ratio of industry value added to total manufacturing value added as a robustness check and results remain same. Both, industry output and value added, measure the impact of economies of scale on the TFP growth. See e.g. Moomaw and Williams (1991).

GDP to proxy country specific uncertainty.

Turning to the global uncertainty, Kose et al. (2003) suggested wold inflation, world oil prices and the output of major oil exporting countries as the potential source of uncertainty for output growth of a country. We, here, employ growth rate of world CPI to to generate a proxy for global uncertainty.

We also incorporate the underlying series of each type of uncertainty in Equation (3.1). Equation (3.1) takes the following form:

$$\begin{aligned} TFP_{ij,t} &= \phi_0 + \phi_1 TFP_{ij,t-1} + \beta_\pi(\pi)_{t-1} + \beta_g(\sigma^2_\pi)_{t-1} + \beta_I(I)_{t-1} + \beta_c(\sigma^2_I)_{i,t-1} \\ &+ \beta_y(y)_{ij,t-1} + \beta_s(\sigma^2_y)_{ij,t-1} + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \end{aligned} \tag{3.2}$$

where β_π, β_I, and β_y, measure the impact of world inflation rate, country investment ratio to GDP, and industry's output ratio to total manufacturing sector output on the TFP growth, respectively.

3.3.2 Sources of Uncertainty and Conditioning Factors

This section describes the uncertainty impact on the TFP growth through other factors affecting the TFP growth. By doing so, we are not only able to measure the direct impact of uncertainty but also the indirect impact of uncertainty on the TFP growth. This enables us to understand that how the impact of uncertainty varies through changes in other factors which may influence the TFP growth. For this purpose, we use industry size, factor intensity level of industries, and the underlying series of each type of uncertainty. These variables are used as conditioning factors for the above mentioned measures of uncertainty. Moreover, this exercise permits us to compute the total effect of uncertainty which is comprised of both the unconditional and conditional effect.

First, we estimate uncertainty impact through industry size. Industry size is measured as the total number of employees in industries.[9] In order to evaluate whether the uncertainty has varying impact due to size differentials across industries, we use the interaction between industry size and our selected sources of uncertainty. This interaction term identifies whether the impact of uncertainty on the TFP growth varies when industry size

[9] Imbs (2007) measured industry size as the share of employment in total employment and also the share of value addition in total value addition. Whereas Demir and Caglayan (2012) has incorporated the industry size as a control variable and measured it as the log of real total assets. Guariglia (2008) used the size interactions with cash flow to capital stock in order to identify the impact on investment across industry size. She computed three different quartiles of industry size to present the impact of cash flow across small, medium, and large industries.

changes.

$$\begin{aligned} TFP_{ij,t} = &\phi_0 + \phi_1 TFP_{ij,t-1} + \beta_\pi (\pi)_{t-1} + \beta_g(\sigma_\pi^2)_{t-1} + \alpha_{gs}(\sigma_\pi^2 \times size)_{t-1} \\ &+ \beta_I(I)_{i,t-1} + \beta_c(\sigma_I^2)_{i,t-1} + \alpha_{cs}(\sigma_I^2 \times size)_{i,t-1} + \beta_y(y)_{ij,t-1} \\ &+ \beta_s(\sigma_y^2)_{ij,t-1} + \alpha_{ss}(\sigma_y^2 \times size)_{ij,t-1} + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \end{aligned} \tag{3.3}$$

where α_{gs}, α_{cs}, and α_{ss} are the coefficients attached to the interaction of industry size with global, country, and industry specific uncertainty, respectively. These coefficients measure the conditional impact of each type of uncertainty on the TFP growth through industry size. Further it also illustrates how the uncertainty impact on the TFP growth varies as the industry size changes across industries and over time.

Second, we estimate the impact of uncertainty through factor intensity of industries. Imbs (2007) emphasized that sector specific factor intensity is an important determinant of sectoral growth rate. Moreover, Bernard and Jensen (2001) explain that the trade theories suggest using capital to output ratio as measure of factor intensity. Following these studies, we, too, measure factor intensity as capital-labor ratio in industry j of country i and at time t. When we augment Equation (3.2) with a variable measuring factor intensity and also its interaction with each measure of uncertainty, we obtain the following specification:

$$\begin{aligned} TFP_{ij,t} = &\phi_0 + \phi_1 TFP_{ij,t-1} + \phi_2 FI_{ij,t} + \beta_\pi(\pi)_t + \beta_g(\sigma_\pi^2)_t + \alpha_{gf}(\sigma_\pi^2 \times FI)_t + \beta_I(I)_{i,t} \\ &+ \beta_c(\sigma_I^2)_{i,t} + \alpha_{cF}(\sigma_I^2 \times FI)_{i,t} + \beta_y(y)_{ij,t} + \beta_s(\sigma_y^2)_{ij,t} + \alpha_{sf}(\sigma_y^2 \times FI)_{ij,t} \\ &+ \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \end{aligned} \tag{3.4}$$

where α_{gf}, α_{cf}, and α_{sf} are the coefficients attached to the interaction of factor intensity with global, country, and industry specific uncertainty, respectively. The estimates for these coefficients measure the indirect impact of uncertainty on the TFP growth i.e., how the uncertainty impact on the TFP growth varies as factor intensity level of industries changes. $FI_{ij,t}$ represents factor intensity level of industries, ϕ_2 measures the impact of impact of factor intensity (capital-labor ratio) on TFP growth of manufacturing industries.

Third, to empirically investigate whether the level of underlying source of uncertainty have any significant influence on the relationship between uncertainty and the TFP growth, we introduce an interaction between each type of uncertainty with its own underlying series namely, world inflation rate, ratio of country investment to its GDP, and industry output ratio to manufacturing sector output. This helps us identifying whether the impact of uncertainty is different on different levels of their respective series. This is captured in the following model:

$$
\begin{aligned}
TFP_{ij,t} &= \phi_0 + \phi_1 TFP_{ij,t-1} + \beta_\pi(\pi)_{t-1} + \beta_g(\sigma_\pi^2)_{t-1} + \alpha_{g\pi}(\sigma_\pi^2 \times \pi)_{t-1} \\
&\quad + \beta_I(I)_{i,t-1} + \beta_c(\sigma_I^2)_{i,t-1} + \alpha_{cI}(\sigma_I^2 \times I)_{i,t-1} + \beta_y(y)_{ij,t-1} \\
&\quad + \beta_s(\sigma_y^2)_{ij,t-1} + \alpha_{sy}(\sigma_y^2 \times y)_{ij,t-1} + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}
\end{aligned} \tag{3.5}
$$

where $\alpha_{g\pi}$, α_{cI}, and α_{sy} are the coefficients attached to the interaction of each uncertainty measure with its own level series. The estimates for these coefficients measure the indirect impact of uncertainty on the TFP growth i.e., how uncertainty impact on the TFP growth varies as their own level series changes across countries and over time.

3.4 Estimation Technique

The models presented in Equations (3.1–3.5) contains the lagged dependent variable which can be correlated with the error term. Moreover, all of our models contain uncertainty measures which are considered to be measured with error. As pointed out by Hendry et al. (1984) and Pagan and Ullah (1988) that the presence of generated regressors in estimation and statistical inference may lead to some problems. According to Hendry et al. (1984) although one may overcome these problems by using instrumental variables approach, the use of lagged observations as instruments may not be possible when an endogenous variable is function of the entire history of available data.

Given these problem, we employ robust two step dynamic panel data (DPD) estimator, system GMM approach to estimate our models. This approach is developed by Arellano and Bover (1995) and further extended by Blundell and Bond (1998). The key feature of this approach is that it uses a system of two equations one in the first differenced form whereas the other in levels. By adding the second equation, additional instruments can be obtained. Thus, the variables in levels in the second equation are instrumented with their own first differences which increases the efficiency gains significantly. Therefore in system GMM, the model is estimated in levels as well as in first differences. In addition, time invariant regressors can still be included in the system GMM which would disappear in difference GMM. Since all instruments for the level equations are assumed to be orthogonal to the fixed effects, particularly to all time invariant variables, therefore it will not effect the estimates for the other regressors.

To test the validity of the instruments, Hansen (1982) proposed a test for the join validity of the instruments in any standard GMM estimation. We use the Hansen (1982) J-statistics for over identification to confirm the robustness of instruments. The J-statistics is asymptotically distributed as χ^2 with degrees of freedom equal to the number of overidentifying restrictions. The Hansen test works under the null of "the instruments are jointly exogenous". Therefore a higher p-value will ensure the validity of instruments as a group.

Moreover, we test for the second order serial correlation by implementing the Arellano and Bond (1991) test for autocorrelation. The Arrelano-Bond test tests the null of "no autocorrelation" and asymptotically follows a standard normal distribution. The dynamic panel data model generally exhibits a first order serial correlation. However, for instruments to be strictly exogenous the residuals should not carry a second order serial correlation.

3.4.1 Total Factor Productivity Growth and its Components

There are two major approaches to measure efficiency: labor productivity and total factor productivity. We compute TFP growth to proxy the efficiency in manufacturing industries.[10] We estimate the total factor productivity growth by employing the stochastic frontier production function approach.

Aigner et al. (1977) and Meeusen and van den Broeck (1977) proposed stochastic frontier production function as follows.

$$y_{ij,t} = f(x_{ij,t}, \beta, t)e^{(v_{ij,t})}e^{(-u_{ij,t})} \tag{3.6}$$

where $y_{ij,t}$ is the output produced by the j^{th} manufacturing industry in i^{th} country at time t, $x_{ij,t}$ is the input vector, the vector of technology parameter is denoted by β, t is the time index, and exhibits the technical change, $v_{ij,t}$ is the random error which represents the measurement error, and all other unobservable factors outside the control of firm. This is assumed to be normally distributed with $N(0, \sigma^2)$. On the other hand, $u_{ij,t} > 0$ is the output oriented technical inefficiency. It is one sided error term and represents the non-zero truncation of normal distribution with a positive mean (μ) and variance $N(\sigma_u^2)$. It can be modeled as follows:

$$u_{ij,t} = \eta_t u_{ij} = e^{-\eta(t-T)u_{ij}}, i = 1, ...I; j = 1, ...J; t = 1, ..., T \tag{3.7}$$

Where, η is the unknown parameter which indicates the rate of change of technical inefficiency whereas u_i, the non negative random variable is the technical inefficiency effect

[10] Total factor productivity growth defined as the increase in output not explained by the input used in the production process. There is a large number of studies advocating the importance of TFP growth regarding the long-term growth process. Solow (1956) stated that long run growth in per capita income must be the outcome of TFP growth with in a country. He argued that cross-country per capita income differences may be driven by the cross country technological differences. Similarly, Griliches (1996) claims that the productivity growth is the main explanation for the output growth. Later, Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999) also document similar findings and state that a substantial differences between per capita income between rich and poor countries is attributed to the TFP growth differences in these countries. More recently, Comin et al. (2006) confirms that the cross-country technological differences are five times higher than cross country differences in per capital income. Moreover he explained that technology and income are positively associated.

of the j^{th} production unit of country i in the last year of the data set.[11] Furthermore, a positive value of η refers to the fact that industries will improve their technical efficiency whereas the reverse is true for the negative value of η. In addition, if $\eta = 0$ then technical efficiency is constant over time.

3.4.2 Estimation of TFP

We use translog production function to compute the TFP growth. There are two main reasons to prefer translog production function over the Solow residual approach for computing the TFP growth. First, it incorporates the idiosyncratic shocks which are useful while investigating the determinants of technical efficiency and therefore the TFP growth. Second, translog production function allows us to decompose the TFP growth into its components which enables us to compute TFP growth based on the extended information set. The functional form of the stochastic frontier production function in the translog form is as follows:

$$\begin{aligned} y_{ij,t} = {} & \phi_0 + \phi_l l_{ij,t} + \phi_k k_{ij,t} + \phi_t t + 0.5\vartheta_{ll}(l_{ij,t})^2 + 0.5\vartheta_{kk}(k_{ij,t})^2 \\ & + 0.5\vartheta_{tt}(t)^2 + \vartheta_{lk}(l_{ij,t})(k_{ij,t}) + \vartheta_{tl}(l_{ij,t})(t) + \vartheta_{tk}(k_{ij,t})(t) + (\nu_{ijt} + u_{ij,t}) \end{aligned} \tag{3.8}$$

where $y_{ij,t}$ refers to natural logarithm of industry output, $l_{ij,t}$ represents natural logarithm of industry labor input, $k_{ij,t}$ explains the capital input, and t represents time trend.

This specification allows us to estimate both the technological progress and technical efficiency. We should note that if all ϑ_{ts} are equal to zero then the technical progress will be zero. Also the translog production function will reduced to Cobb Douglas function if all the $\vartheta's$ are equal to zero. The distribution of technical inefficiency effect (u_{ijt}), is taken to be non negative truncation of the normal distribution $N(\mu, \sigma_u^2)$.

Sharma et al. (2007) explain TFP growth as the sum of three main components namely, technical efficiency, technical progress, and the scale effect. The translog production function enables us to compute these components as follows:

Technical efficiency is defined as the ratio of actual output to the potential output determined by the production frontier, therefore

$$TE_{ij,t} = e^{(-u_{ij,t})|\epsilon_{ij,t}} \tag{3.9}$$

Similarly, the rate of technical progress can be explained as

$$TP_{ij,t} = \frac{\partial(y_{ijt})}{\partial t} = \phi_t + \vartheta_{tt}(t) + \vartheta_{tl}(l_{ijt}) + \vartheta_{tk}(k_{ijt}) \tag{3.10}$$

[11] Mandal and Madheswaran (2012) explain u_i as the technical inefficiency effects in earlier periods are deterministic exponential function of the inefficiency effects for the corresponding forms in the final period $(u_{ij,t} - u_{ij})$ given the data for the j^{th} production unit are available in the final period.

The scale component will be calculated as follows:

$$SE = (rts - 1) \times [(\frac{\epsilon_l}{rts})(\Delta l) + (\frac{\epsilon_k}{rts})(\Delta k)] \tag{3.11}$$

whereas, rts = $\epsilon_k + \epsilon_l$.

The output elasticities with respect to both inputs i.e., labor and capital are:

$$\epsilon_l = \vartheta_l + \vartheta_{kl}(k_{ijt}) + \vartheta_{ll}(l_{ijt}) + \vartheta_{lt}(t) \tag{3.12}$$

$$\epsilon_k = \vartheta_k + \vartheta_{kl}(l_{ijt}) + \vartheta_{kk}(k_{ijt}) + \vartheta_{kt}(t) \tag{3.13}$$

Finally, by summing these components we obtain the TFP growth for manufacturing industries of selected sample countries.

$$TFP = TE + TP + SE \tag{3.14}$$

3.4.3 Generating Uncertainty

There are several methods proposed in the literature to compute uncertainty. The standard deviation of residuals of the underlying series as a proxy for uncertainty is relatively more common in existing studies. For instance, Aizenman and Marion (1999) and Turnovsky and Chattopadhyay (2003) have utilized the standard deviations of the residuals of the autoregressive processes of the logarithm of the GDP to compute uncertainty. Whereas, Comin and Mulani (2009) used centered standard deviation of 10 consecutive annual growth rate of the series. Another common approach to measure uncertainty is to compute moving average standard deviation of the underlying series. As this method gives equal weights to all the observations at each interval which may increase the probability of serial correlation. Therefore, it is not considered a preferred measure of uncertainty. Some existing studies have used the conditional variance computed from GARCH models to gauge the uncertainty. However, GARCH based specifications are more common in the literature where the series are of high frequency such as quarterly or monthly. In addition, the GARCH process generates uncertainty by taking all the industries/countries collectively. This process is unable to isolate the unobservable shocks related to one series while computing the volatility of another series in the sample.

We estimate a first order autoregressive model to generate the residuals for the underlying series across each industry for the time period 1971-2008.[12] One-period ahead residuals are saved for each industry. Later, using one period ahead residuals, we compute the cumulative-volatility of the underlying series. In particular, the cumulative volatility

[12] We prefer using AR(1) process to generate the residuals. We did not run a family of autoregressive series to select the appropriate model as for the annual data with a limited time series observations a higher order AR process may not generate consistent measure of uncertainty. Similar practice is adopted by Aizenman and Marion (1999)

for the year 1972 is computed by calculating the standard deviation of the residuals from the AR(1) model of the respective series that uses the data for the year 1972 and 1971. We repeat this process to construct the cumulative volatility for all the years in the sample(see, e.g., Aizenman and Marion (1999) and Turnovsky and Chattopadhyay (2003) for further detail). All the variables which we use to construct the uncertainty are normalized. This transformation of variables will make the unit free and allows us to conduct a cross industry and cross country analysis.

To compute the industry specific uncertainty we use industry output ratio to the total manufacturing sector output. Similarly, industry value-added is taken as the ratio of total manufacturing sector value-added. To generate a proxy for country-specific uncertainty, we use the ratio of investment to GDP. Finally, world inflation rate is used to generate a proxy for global uncertainty.

3.4.4 Data and Data Sources

We use an extensive annual data set which is accessed from various different sources. We use three-dimensional panel data covering the period 1971-2008, eighteen industries of the manufacturing sector, and sixteen emerging economies. The data on industry level output, value added, employment, wages and salaries, and gross fixed capital formation are taken from United Nation Industrial Development Organization (UNIDO) database. We use two-digit International standard industrial classification (ISIC) Revision 3 classification to select manufacturing industries.

We ensure that at least 10 industries for the selected countries and minimum 10 years of data on each industry is available. The selected number of industries remains constant over time and across counties. The panel combining the countries, industries and time observations is unbalanced with some industries containing more observations than others. Although, the original dataset provide information for 28 manufacturing industries, we focus on eighteen of them to avoid a large number of missing observations in the data.

Following the previous literature, we deflate the industry level variables by using the producer price index.[13] The data on aggregate investment as a percentage of GDP, GDP growth, income size of each country relative to the USA are accessed from the Penn World Tables version 7.0. In addition, world inflation measured as the annual percentage change in the log CPI is obtained from International Financial Statistics (IFS) database published by International Monetary Fund (IMF).

[13] Industry specific price deflators for the selected sample of countries are not available

3.4.5 Summary Statistics

Before empirical analysis, we present summary statistics of uncertainty measures and its correlations with the TFP growth. Table 3.1 portrays the correlation among sources of uncertainty and the TFP growth. The correlation estimates reflect a positive association of the TFP growth with industry and country specific uncertainty whereas negative correlation is observed with global uncertainty. Koren and Tenreyro (2007) also report a considerable variability in the correlation between country specific and sector specific risk fr a large sample of countries. Imbs (2007), too, verifies that manufacturing industries growth is positively correlated with sector specific volatilities. However, country specific volatility has negative impact on manufacturing industries growth. Stockman (1988) find a positive and significant relationship of sectoral and national disturbances for the performance of manufacturing industries of European countries. Also, they state that sectoral disturbances have relatively stronger impact. We also observe that the correlation is more stronger for the country and industry specific uncertainty with the TFP growth whereas the it is weaker for global uncertainty and the TFP growth. The other selected variables present a blurry picture of the nature of relationship with the TFP growth. The impact of uncertainty through its own level series is statistically significant only for industry and world level uncertainties.

The impact of uncertainty through industry size shows that only country specific uncertainty maintains a significant correlation with the TFP growth. Surprisingly, uncertainty through factor intensity has an insignificant correlation with the TFP growth across all measures of uncertainty. Finally, the correlation between TFP growth and the industry size itself is negative and statistically significant. This implies that industry size affects TFP growth negatively. In contrast, factor intensity and TFP growth maintains a statistically significant and positive correlation. This implies that capital intensive industries grow faster than the labor intensive industries.

The table also provides estimates on the mean, standard deviation and 10th, 50th, and 90th percentiles of variables used in the estimation. The mean value as well as the dispersion of the uncertainty is increasing as we move from industry specific uncertainty, to country specific uncertainty, and from country specific uncertainty to global uncertainty. In addition, the mean value of factor intensity is lower than the mean value of industry size but there is large dispersion in the former relative to the latter.

3.4.5.1 TFP Estimates

In order to carry out the empirical investigation, we compute the TFP growth, as shown in Equation (3.9). Table 3.2 displays the estimates of TFP growth and its components. The estimates show that the scale component of the TFP growth has the lowest mean value whereas the highest mean value is observed for technical efficiency component. Giving a more closer look, we can observe that the mean value of technical efficiency is higher than TFP growth. The reason for this finding is the negative average technical progress over the selected time period. Whereas the mean value of scale effect is lowest. The dispersion, in contrast, is highest in the TFP growth followed by technological progress and technical efficiency. These observations specify that over time and across industries, technical efficiency, the ratio of actual output to the potential output, has improved whereas the technological progress has deteriorated. Since improvement in the technical efficiency is significantly higher than deterioration in the technological progress therefore the TFP growth on average has shown a moderate positive mean value.

Output elasticity with respect to both inputs, namely labor and capital are reported in the last two rows of Table 3.2. We observe that output is more elastic with respect to capital . However, the output elasticity with respect to labor has shown more variation in contrast to the dispersion in capital elasticity of output. Notably, the mean value of returns to scale appears as less than one which means that on average the industries follow decreasing returns to scale over the selected time period.

In sum, we can conclude that, on average, there is a modest growth of TFP in manufacturing industries of the selected emerging economies. Moreover, the TFP growth is mainly derived by the technical efficiency as it is obvious from the findings reported in Table 3.2.

3.5 Empirical Results

We first present the direct impact of each type of uncertainty on the TFP growth. Having established the impact of each source of uncertainty individually, we, next, evaluate the productivity-uncertainty link conditional on different factors such as the industry size, factor intensity and the underlying source of uncertainty. The control variables included in the model are industry size, real GDP growth, and trend variable which throughout all specifications remain same.

We report the diagnostics tests in Panel B of each table to evaluate the model performance. The J statistics for all specifications indicates the acceptance of null hypothesis which verifies the orthogonality of our selected set of instruments. The Arellano and Bond (1991) test for autocorrelation rejects the presence of second order serial correlation in all models.

3.5.1 Uncertainty-Productivity Link

Table 3.3 reports the empirical estimates based on Equation (3.1) and Equation (3.2). Specifically, column 1 of Table 3.3 reports the empirical estimates of the effect of uncertainty emanating from different sources on the TFP growth. We find that the lagged TFP growth attains a negative coefficient. This negative coefficient indicates the low productive industries convergence towards high productive industries. This finding is consistent with the existing literature (see, e.g., Imbs (2007) and Aghion et al. (2009) among others). The speed of convergence is observed as 10 percent and statistically significant at the one percent significance level.

Notably, the estimates from this model suggest a significant impact of all the sources of uncertainty on the TFP growth. The impact of industry specific uncertainty is remarkably higher than country and world specific uncertainties. Moreover, the impact of industry specific uncertainty is positive implying that the lagged industry level output volatility leads to higher productivity growth in manufacturing industries. Comin and Mulani (2009) also observe a positive impact of firm specific uncertainty on the TFP growth. They proxy firm level uncertainty through the variance of growth rate of sales. Similarly, Imbs (2007) reports a positive impact of manufacturing industries uncertainty, measured as the standard deviation of the value-added, on manufacturing industries' value-added growth. Oikawa (2010) explains that high volatility is associated with more expenditures on research and development which consequently increases the TFP growth in following years.

We next turn to evaluate the impact of country specific uncertainty on the TFP growth. The marginal impact of country specific uncertainty is positive impact on TFP growth. Pindyck (1991) explains two important characteristics of investment expenditures. First, most of the investment expenditures are irreversible. The irreversibility in investment expenditures makes it sensitive towards various shocks e.g, future prices, future interest rate and most importantly the uncertainty in the cost and timing of investment itself. Second, the investment projects can be delayed. This enables industries to wait for the new information to arrive in the market. Therefore, uncertainty in the previous year may lead to delay of investment projects to the next year which resultantly raise the TFP growth for the current year. This finding is consistent with Kose et al. (2003).

Last, we observe that global uncertainty portrays a negative impact on the TFP growth of manufacturing industries. This result is consistent with the existing literature which argues that inflation dampens the TFP growth as there is a cost attached with higher inflation.[14]

[14]Some existing studies report the negative impact of domestic inflation on the TFP growth. See, e.g., Miller and Upadhyay (2000) observed a negative impact of inflation volatility on the TFP growth for

The results presented in Table 3.3 portrays the general impact of uncertainty on TFP growth in manufacturing industries of emerging economies. Based on our findings from the baseline model, we can state that the industry related uncertainty in relation to country and global uncertainties has a stronger impact on TFP growth.

3.5.2 Uncertainty-Productivity Link and the Underlying Source

Turning to column 2 in Table 3.3, which combines uncertainty measures and the level effect of uncertainty measures, we observe that uncertainty measures exert similar impact on TFP growth as in column 1. We also observe the negative and statistically significant coefficient of lagged dependent TFP growth. This implies that low productive industries catch up with high productive industries in emerging economies.

The impact of industry specific uncertainty is positive and significant at the 5% significance level. However, the magnitude of this impact has reduced in comparison to the findings in column 1 but still it remains the major source of uncertainty for TFP growth. In addition, the impact of the lagged industry output ratio to total manufacturing sector output is positive and significant at the 1% significance level. This explains that industries with higher economies of scale tend to achieve higher TFP growth.

Moving to the role of country specific uncertainty, we observe a positive and statistically significant impact on TFP growth. The magnitude of country specific uncertainty has marginally increased relative to results in column 1. Also, country investment ratio to country GDP pertains a positive impact on the TFP growth of manufacturing industries. Last, not only inflation uncertainty but also inflation itself has a negative and statistically significant impact on TFP growth.

It is important to note that the magnitude of the impact of each type of uncertainty differs from each other. Industry specific uncertainty has greater impact in comparison to country and world level uncertainties in both specification presented in Table 3.3. This finding, though, is in contrast with Kose et al. (2003) as their results assert that world factors are more important for advanced and developed economies whereas country factors are more dominant for developing countries. However, they perform a cross country analysis whereas our analysis is based on manufacturing industries. Moreover, our findings can be justified on the grounds that our data set contains fast growing emerging economies for which world factors can be equally important as country specific factors due to their extensive integration with the world economy.

In sum, we conclude that the impact of uncertainty on TFP growth remains similar not only in terms of their size but also the direction of impact remains unchanged when

middle income countries. Bruno and Easterly (1998) find that inflation exerts a negative impact on growth. However, Bredin and Fountas (2009) find an insignificant impact of inflation uncertainty on output growth.

we control for the level series of uncertainties emanating from different sources.

3.5.3 Uncertainty-Productivity Link Under Conditioning Factors

Having established the direct impact of each type of uncertainty on TFP growth, we examine the conditional impact of uncertainty on TFP growth. For this purpose, we investigate whether different types of uncertainty affect TFP growth through other factors that influence TFP growth. In addition to this, we explore the total impact of each type of uncertainty on TFP growth i.e., we combine the direct and the indirect impact of uncertainty.

Following the existing empirical work such as Imbs (2007) and Comin and Mulani (2009), we consider three factors: industry size, factor intensity, and the level series of the underlying source of uncertainty.

3.5.3.1 Uncertainty-Productivity Link and Industry Size

Our first conditioning variable is industry size. We investigate whether uncertainty impact on TFP growth changes as industry size alters. For this purpose, we introduce an interaction term between industry size and each measure of uncertainty. This interaction captures the conditional impact of uncertainty on the TFP growth through industry size. We measure industry size as the log of total number of employees.[15] Table 3.4 presents the findings based on this specification given in Equation (3.3). The lagged TFP growth maintains a statistically significant and negative coefficient indicating convergence in low and high productive manufacturing industries. The industry, country, and global uncertainty is statistically significant and maintains the expected signs. Similarly, the level effect of each source of uncertainty also carries the expected signs and significance level.

The industry specific uncertainty conditional on the industry size is positive and statistically significant. This implies that in times of industry specific uncertainty, an increase in industry size will lead manufacturing industries to attain higher TFP growth.

In contrast, the conditional impact of country specific uncertainty through industry size on TFP growth is negative and statistically significant. This suggests that large industries experience decrease in TFP growth in times of country specific uncertainty. This finding can be justified on the grounds that risk in country investment may dwindle the growth rate of the economy which leads to lower the demand of long-term investment. This further reduces the productivity growth across the economy as well as in industries particularly industries with large number of employees. Notably, the direct impact of

[15] There are various measures of size such as Comin and Mulani (2009) used total real sales, Imbs (2007) measured industry size as share of employment in total employment or through share of value addition in total value addition. Whereas Demir and Caglayan (2012) measured firm size as the real total assets in log form.

the country specific uncertainty is positive whereas the indirect impact is negative. This explains that the impact of investment uncertainty is positive but as the industry size increases the positive impact of investment uncertainty weakens. On the other hand, the magnitude of the direct impact is higher than the magnitude of the indirect impact. This concludes that the net effect of investment uncertainty is positive though decreasing.

The estimates of global uncertainty conditional on industry size appears as positive and maintains a statistically significant impact on TFP growth of manufacturing industries. This implies that large industries experience an increase in TFP growth given there is global uncertainty. The rationale for this effect is as follows: large industries are able to explore international markets to earn higher profits and therefore maintains higher TFP growth in relation to small industries.

3.5.3.2 Uncertainty-Productivity Link and Factor Intensity

In this subsection, we examine the impact of each type of uncertainty conditional on the factor intensity level of industries. We measure factor intensity as the ratio of capital to labor in each industry. We conduct this analysis in two steps. At the first step, we incorporate factor intensity measure in our baseline model (given in Equation (3.2)) and estimate its impact on TFP growth. Having established the impact of factor intensity on TFP growth, we next turn to examine how the impact of uncertainty on TFP growth varies as the level of factor intensity changes. For this purpose, we introduce an interaction between each measure of uncertainty and factor intensity. Table 3.5 reports these results.

The direct effect of each source of uncertainty is similar to the findings aforementioned. Moreover, results reported in Table 3.5 also provide evidence of productivity convergence among low and high productive manufacturing industries.

The first column of Table 3.5 clearly indicates a statistically significant and positive impact of factor intensity on TFP growth. This implies that industries with higher capital-labor ratio attains higher TFP growth. This finding is consistent with Imbs (2007), who studies the impact of factor intensity for value added growth of manufacturing industries and reported a positive link between capital-labor ratio and value-added growth.

In the next step, when we interact the factor intensity with each measure of uncertainty, we find that the interaction of industry specific uncertainty with factor intensity is positive and statistically significant at the 5% significance level. This implies that when there is industry uncertainty, industries experience higher TFP growth given an increase in the capital-labor ratio. The rationale of this finding is that as the capital labor ratio increases, industries become more efficient and thus attain higher TFP growth.

Similar to the findings of industry specific uncertainty, we observe a positive and significant impact of country specific uncertainty on TFP growth through factor intensity.

In other words, capital intensive industries experience an increase in TFP growth when there is country specific uncertainty.

In contrast, the conditional impact of global uncertainty through factor intensity is negative and statistically significant. This negative impact indicates that under uncertainty in global economy, industries experience a decrease in TFP growth as the level of factor intensity increases. This finding can be rationalized as: higher world inflation will increase the cost of production, through the import of technological products, which dampens TFP growth of industries with high capital-labor ratio.

3.5.3.3 Uncertainty-Productivity Link and the Underlying Source of Uncertainty

We investigate the impact of each type of uncertainty on TFP growth through its own level series. Thus, we interact each source of uncertainty with its own level series namely industry output ratio to manufacturing output, country investment ratio to GDP, and world inflation rate. The estimates are reported in Table 3.6.

The conditional impact of industry specific uncertainty through industry output is negative and statistically significant. This implies a decline in TFP growth in response to industry uncertainty as the share of industry output in total manufacturing sector output increases. Since output growth measures economies of scale therefore the negative conditional impact may refers to dis-economies of scale at a higher level of output.

Similar finding is observed for country specific uncertainty conditional on its own level series i.e., country investment ratio to GDP. The interaction term on country specific uncertainty and country investment ratio to GDP is negative and statistically significant. This finding shows that When there is macroeconomic uncertainty, industries experience low TFP growth as the level of aggregate investment to GDP ratio increases.

Last but not the least, the conditional impact of world uncertainty on TFP growth through world inflation rate attains a positive and statistically significant impact. The negative sign of this interaction shows inflation uncertainty is in line with the fact that under global uncertain environment, industries will experience an increase in TFP growth at higher level of world inflation. Although higher inflation fluctuations put a cost on industries but it also provide opportunities to gain higher profit through export earnings therefore industries which are rightly able to avail this chance they can manage to acquire a higher level of TFP growth.

3.5.4 Total Impact in Uncertainty-Productivity Linkage

Having explained the unconditional and conditional impact of each source of uncertainty on TFP growth separately, we next move to compute the total impact of uncertainty emanating from different sources on TFP growth. To calculate the total effect, we compute the total derivative of TFP growth Equations (3.1–3.5) with respect to all uncertainty measures separately. In order to gauge the uncertainty impact across different levels of conditioning factors i.e. industry size, factor intensity, and the level series of each uncertainty measure, we compute the total effect at the 25th, 50th, 75th, and 90th percentiles of the respective conditioning variable. By doing so, we report the $\frac{\partial TFP}{\partial \sigma^2}$ for industry size, factor intensity, and own series of uncertainty measures in Table 3.7, Table 3.8, and in Table 3.9, respectively. In addition to the calculation of total effect, we plot the total effect with respect to each source of uncertainty conditional on factors mentioned earlier. Figures 3.1–3.9 presents the plot of total effect of each type of uncertainty on TFP growth with respect to all the conditioning factors.

Table 3.7 lays the total effect of uncertainty with respect to industry size. Panel A, B, and C explain, respectively, the total impact of industry, country, and global uncertainty based on industry size. The total impact of industry uncertainty is positive and statistically significant across all percentiles of industry size. As we move to higher percentiles of industry size, the magnitude of the total impact increases. Therefore, we can conclude that as industry size increases, industries experience an increase in TFP growth in times of industry specific uncertainty.

Further, Figure 3.1 display the total effect of industry specific uncertainty with respect to industry size. The industry specific uncertainty has a positive impact on TFP growth and the impact is increasing moderately when we move towards higher percentiles of industry size. The figure augments our earlier findings of the positive impact of industry specific uncertainty on TFP growth conditional on the industry size.

Panel B of Table 3.7 reports the total effect of country specific uncertainty on TFP growth through industry size. The total impact of country specific uncertainty is statistically significant only at $25th$ and $50th$ percentiles of industry size. The total impact of country specific uncertainty on TFP growth decreases as industry size increases. Figure 3.2 supports our findings aforementioned in Table 3.7 that the country specific uncertainty leads to an increase in the TFP growth but as the industries get larger in size, the magnitude of the impact is weakens.

The total impact of global uncertainty on TFP growth through industry size is presented in panel C of Table 3.7.We observe a statistically significant and negative total impact on TFP growth across different percentiles of industry size. The estimates suggest that as the industry size increases, the global uncertainty leads to decrease in TFP growth. Figure 3.3 also confirms that as we move towards the upper tail of the percentiles of industry size, the negative impact of global uncertainty weakens.

Next, Table 3.8 reports the total effect of uncertainty originating from different sources across different levels of factor intensity. The total impact of industry specific uncertainty is positive and statistically significant across all percentiles of factor intensity. Moreover, the magnitude of the impact is higher as we move to the upper tail of percentiles of factor intensity. This implies that factor intensive industries experience a larger increase in TFP growth in the presence of industry specific uncertainty. Also, Figure 3.4 displays an increase in the TFP growth in presence of industry uncertainty across different percentiles of factor intensity. The impact becomes stronger as factor intensity increases. This implies that factor intensity reinforces the positive impact of industry specific uncertainty on TFP growth.

Similar observations are reported in panel B of Table 3.8 that displays the total impact of country specific uncertainty through factor intensity. The estimates are positive and statistically significant for all percentiles of factor intensity. This identifies that industries with higher capital-labor ratio experience an increase in TFP growth in the presence of country specific uncertainty. Figure 3.5 further supports this finding as the total impact of country specific uncertainty is positive for TFP growth and increasing with respect to factor intensity. This positive impact becomes stronger as we reach to the 70th percentile of factor intensity.

When we turn to discuss the total effect of global uncertainty, given in panel C of Table 3.8, we observe that the total effect is negative across all percentiles of factor intensity and also statistically significant. Moreover, there is a monotonic decline in the magnitude of the impact as we move from lower to higher percentiles of factor intensity. Hence, relatively high capital intensive industries experience larger decrease in TFP growth when there is global uncertainty. Figure 3.6 shows that the global uncertainty causes a decline in TFP growth across all percentiles of factor intensity. However, the negative impact of uncertainty strengthens as the level of factor intensity increases in manufacturing industries. There is a sharp increase in the negative impact of global uncertainty at the 70th percentile of factor intensity.

Finally, Table 3.9 presents the total impact of uncertainty through the underlying series of each type of uncertainty. The total impact of industry specific uncertainty, presented in Panel A of Table 3.9, is positive and statistically significant at all percentiles of industry output. However, the magnitude of the impact is decreasing as we move towards the upper tail of the percentile distribution. This explains that the positive impact of industry specific uncertainty weakens, as the industry output increases. This result supports our earlier findings that the industry uncertainty has a positive impact on TFP growth but at higher levels of industry output we observe dis-economies of scale. Figure 3.7 confirms our findings of the total impact of industry specific uncertainty on TFP growth. We can observe a positive but decreasing effect of industry specific uncertainty on TFP growth.

Panel B of Table 3.9 shows the total impact of country specific uncertainty on TFP growth through different percentiles of aggregate investment ratio to GDP. The estimates of total impact of investment uncertainty are statistically significant only at 75th and 90th percentiles. Figure 3.8 shows that country specific uncertainty impact on TFP growth is positive for the 10th and 20th percentiles but turns negative at and above the 25th percentile, though decreasing through out. A possible explanation for this finding could be that at higher levels of country investment, country specific uncertainty may induce industries to invest less and save more which leads to low TFP growth.

The total impact of global uncertainty through world inflation rate on TFP growth is shown in panel C of Table 3.9. The estimates are negative for the first three percentiles of world inflation rate and turns positive at and above the 80th percentile. Moreover, the total effect is statistically significant only for the first two percentiles of world inflation rate. This result can be justified as at or above a certain level of inflation the industries may exploit the increase in world prices for earning higher profits through export earnings.

Last but not the least, Figure 3.9 indicates that global uncertainty pertains both negative and positive impact on TFP growth. The impact is negative up to 80th percentile of world inflation rate. However, as the world inflation rate crosses the 80th percentile, the impact of global uncertainty on TFP growth turns in to positive.

3.5.5 Robustness Check

We also estimate the models presented in (3.1) and Equation (3.5). by using same indicator of uncertainty at all levels, i.e. output growth at industry, country and world level. In doing so, we compute uncertainty of industry output ratio to sectoral output to measure the impact of industry specific uncertainty on TFP growth. To estimate the impact of country specific uncertainty, we compute conditional variance of country GDP growth. Finally, we compute conditional variance of World GDP growth to estimate the impact of global uncertainty on TFP growth of manufacturing industries of emerging economies. The results are reported in table 3-A–3-A.3 of Appendix A of chapter 3.

We observe that industry and country specific uncertainty maintains a positive impact on the TFP growth. However, the impact of global uncertainty has turned to positive when we change the proxy of global uncertainty. Also, the major source of uncertainty varies between industry and country specific uncertainty.

Turning to the conditional impact of each type of uncertainty, we observe that the positive impact of industry specific uncertainty strengthens as the size of industry increases. Similarly, the positive impact of country specific uncertainty is more stronger for larger industries. Uncertainty in world GDP not only has a direct positive impact on the TFP growth of manufacturing industries of emerging economies but also the impact becomes more stronger as the size of industries increases.

when we augment the baseline model with factor intensity, we observe as in the main findings that capital intensive industries have higher TFP growth relative to labor intensive industries. The conditional impact of uncertainty through factor intensity show that the positive impact of industry specific uncertainty strengthens as the capital labor ratio increases. Similar to our main results, we find that country specific uncertainty has positive impact on TFP growth of manufacturing industries, however, the positive impact of uncertainty weakens as industries become more capital intensive. Global uncertainty affects the TFP positively, however, this positive impact weakens as the industries turn to be more capital intensive.

Finally, when we turn to investigate the conditional impact of each type of uncertainty through their own level series, we have the following observations. The direct impact of industry, country, and global uncertainty is positive and statistically significant. However, the conditional impact of each type of uncertainty through their own level series appears as negative and statistically significant.

The estimates presented in the robustness check reveal that not only the source of uncertainty matters but also the proxy of uncertainty for each source plays an important role while determining the TFP growth of manufacturing industries of emerging economies.

3.6 Conclusions

This paper explores the link between the TFP growth and uncertainty originating from different sources such as global, country, and industry level. To this end, we utilize industry level data for sixteen emerging economies covering the time period 1971-2008. Our empirical investigation employs the robust two-step system GMM estimation technique which effectively controls for endogeneity and measurement error in generated regressors. We investigate the impact of three different types of uncertainty which can potentially affect the manufacturing industries' TFP growth. We measure industry specific uncertainty by computing the cumulative variance of the ratio of industry output to manufacturing sector output. Country specific uncertainty is measured as the cumulative variance of ratio of aggregate investment to GDP. Finally, global uncertainty is proxied by the cumulative variance of world inflation rate. We, then, estimate the TFP growth by employing a translog production function approach. In our empirical specifications, we control for industry size, factor intensity, country's real GDP, and year dummies which are known to affect the TFP growth.

To carry out our empirical investigation, we use an extensive data set accessed from various data sources. We use three dimensional panel data covering the period 1971-2008, sixteen emerging economies and eighteen industries of their respective manufacturing sector. We use the UNIDO database published in 2011 to obtain the data on two-digit ISIC revision 3 classification for the manufacturing sector. Moreover, for global and country specific variables, we use the IFS database published by the IMF and the Penn World Tables version 7.0. To avoid a large number of missing values, we ensure that there should be at least 10 industries for the selected countries and minimum 10 years of data on each industry are available.

Based on the GMM estimation technique, our findings can be summarized as follows: The direct impact of uncertainty varies across different measures of uncertainty. We find that industry and country specific uncertainty have a positive impact on TFP growth. However, the magnitude of the impact of industry specific uncertainty is higher than that of country specific uncertainty. Global uncertainty, in contrast, leads to a decline in TFP growth.

The conditional impact of industry specific uncertainty through industry size is positive and statistically significant. This implies that is as the size of industry increases, the impact of industry specific uncertainty strengthens. In contrast, the converse is true for the impact of country level uncertainty on TFP growth when it is interacted with industry size. The conditional impact of global uncertainty through industry size is positive. By combining the unconditional and conditional impact, we observe that the negative impact of global uncertainty weakens as industry size increases.

Second, when we use interaction between each measure of uncertainty and the factor intensity level of industries, we observe that the impact of industry and country specific uncertainty is positive and get stronger as the factor intensity increases: as industries become more capital intensive, TFP growth will increase if there is country and industry specific uncertainty. In contrast, the conditional impact of global uncertainty on the TFP growth is negative and statistically significant. In other words, as the capital-labor ratio increases, TFP growth diminishes in presence of global uncertainty. Third, uncertainty impact through its own level series provides evidence that the impact of industry and country specific uncertainty is negative for TFP growth. We can conclude that TFP growth diminishes as industry output increases under industry uncertainty. Similarly, In times of country uncertainty, the TFP growth decreases as country investment increases.

Our results provide evidence that there is a significant role of each type of uncertainty in determining the TFP growth. This suggest that all potential sources of uncertainty must be considered by researchers and policy makers otherwise the results would be biased. In addition, uncertainty also indirectly effects TFP growth through other factors such as industry size, capital labor ratio, and their own level series. Therefore the policy makers and industries must consider the direct and the indirect channels through which uncertainty can affect TFP growth.

Table 3.1: Summary Statistics of Uncertainty Measures

Variables	**Mean**	**Std.Dev**	P_{10}	P_{50}	P_{90}	**TFPG**
TFP	0.1300	0.246	-0.035	0.089	0.350	
σ^2_{Output}	0.011	0.022	0.002	0.006	0.024	0.088***
$\sigma^2_{Investment}$	0.031	0.0254	0.010	0.026	5.4541	0.095***
$\sigma^2_{W.Inflation}$	0.014	4.696	1.026	1.248	2.216	-0.053***
$\sigma^2_{Output}\times$Output	0.001	0.006	0.00002	0.0002	0.003	0.0534***
$\sigma^2_{Investment}\times$Investment	0.008	0.942	1.763	5.330	15.427	-0.001
$\sigma^2_{W.Inflation}\times$Inflation	0.047	0.399	5.653	31.608	10.264	0.022*
$\sigma^2_{Output}\times$Size	0.009	0.028	0.00004	0.001	0.019	0.015
$\sigma^2_{Investment}\times$Size	0.040	2.735	0.044	0.473	3.439	-0.043***
$\sigma^2_{W.Inflation}\times$Size	0.010	2.297	0.164	2.969	26.056	-0.016
$\sigma^2_{Output}\times$FI	0.023	0.703	3.5e-06	0.00003	0.0005	0.011
$\sigma^2_{Investment}\times$FI	0.005	1.745	0.0017	0.0144	0.1868	0.006
$\sigma^2_{W.Inflation}\times$FI	0.026	0.820	0.0121	0.0660	1.0625	0.012
Industry Size	9.806	1.926	7.1228	9.9381	12.1335	-0.017***
Factor-Intensity	1.146	28.581	9.1803	54.9439	682.0886	0.027**

Table 3.2: Summary Statistics of TFP growth and its Components

Mean, Standard Deviations, and Percentile Distribution					
Variables	**Mean**	**Std.Dev**	P_{10}	P_{50}	P_{90}
TFP Growth	0.1300	0.246	-0.035	0.089	0.350
Technical Efficiency	0.140	0.157	0.043	0.089	0.024
Returns to Scale	0.894	0.294	0.536	0.870	1.296
Scale Effect	0.006	0.187	-0.116	0.001	0.138
Technical Progress	-0.015	0.030	-0.048	-0.168	0.023
ξ_K	0.523	0.196	0.309	0.495	0.771
ξ_L	0.372	0.313	-0.001	0.351	0.797

Note: This table presents the percentile distribution of TFP growth and its components. These summary statistics are computed for three dimensional panel based on 18 manufacturing industries of 16 emerging economies over the time period 1971-2008. ξ_K and ξ_L indicate capital and labor elasticities of output across industries.

Table 3.3: Unconditional Impact of Uncertainty on TFP Growth

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Model 1**		**Model 2**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP_{ij,t-1}$	-0.104	(0.038)***	-0.114	(0.037)***
$\sigma^2_{(Output)_{ij,t-1}}$	0.031	(0.273)**	0.012	(0.005)**
$\sigma^2_{(Investment)_{ij,t-1}}$	0.012	(0.005)**	0.019	(0.006)***
$\sigma^2_{(W.Inflation)_{t-1}}$	-0.012	(0.002)***	-0.024	(0.003)***
$Output_{ij,t-1}$			0.004	(0.001)***
$Investment_{i,t-1}$			0.003	(0.001)**
$W.inflation_{t-1}$			-0.111	(0.056)**
$RGDP_{i,t-1}$	0.001	(0.000)**	-0.003	(0.000)***
$Size_{ijt}$	0.075	(0.036)**	0.066	(0.000)***
$Trend$	-0.003	(0.000)***	-0.006	(0.001)***
Constant	0.294	(0.049)***	0.416	(0.144)***
Panel B: Diagnostic tests				
Observations		6,100		5,565
AR(2)		1.180		1.070
p-value		0.238		0.283
J-statistic		281.210		279.050
p-value		0.633		0.621

Note:

$$TFP_{ij,t} = \phi_0 + \phi_1 TFP_{ij,t-1} + \beta_s(\sigma^2_y)_{ij,t-1} + \beta_c(\sigma^2_I)_{i,t-1} + \beta_g(\sigma^2_\pi)_{t-1} + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different sources of uncertainty i.e. global, country and industry level uncertainty on TFP growth. The dependent variable is TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. Model 1 estimates the impact of uncertainty originating from different sources on TFP growth whereas Model 2 presents the estimates of uncertainty as well as their level series. One period lagged values of the first difference of independent variables are used as instruments for equations in level whereas for differenced equations, second - fourth lag of independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL (Real GDP at country level), Size(Industry size), and Year Dummies are the control variables. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively. Standard errors are displayed in parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

Table 3.4: Impact of Uncertainty on the TFP Growth: Conditional on Industry Size

Panel A: Estimation Results: Dependent Variable: TFP Growth		
Regressors.	**Model 1**	
	Coeff.	Std.Err.
TFP_{ijt-1}	-0.108	(0.035***)
$\sigma^2_{(Output)_{ij,t-1}}$	0.004	(0.001)***
$\sigma^{Investment}_{i,t-1}$	0.009	(0.004)**
$\sigma^{W.Inflation}_{t-1}$	-0.008	(0.003)***
$Output_{ij,t-1}$	0.008	(0.003)***
$Investment_{i,t-1}$	0.004	(0.001)**
$W.Inflation_{t-1}$	-0.211	0.054
$Size \times \sigma^2_{Output_{ij,t-1}}$	0.001	(0.000)***
$Size \times \sigma^2_{Investment i,t-1}$	-0.0004	(0.000)***
$Size \times \sigma^2_{W.Inflation_{t-1}}$	0.0003	(0.0000)*
$RGDP_{it}$	-0.007	(0.002)
$Size_{ijt}$	0.138	(0.053)***
$Trend$	0.003	(0.002)*
Constant	0.134	(0.069)***
Panel B: Diagnostic tests		
Observations		5,636
AR(2)		1.21
p-value		0.226
J-statistic		277.430
p-value		0.349

Note:

$$\begin{aligned} TFP_{ij,t} &= \phi_0 + \phi_1 TFP_{ij,t-1} + \beta_\pi(\pi)_{t-1} + \beta_g(\sigma^2_\pi)_{t-1} + \alpha_{gs}(\sigma^2_\pi \times size)_{t-1} \\ &+ \beta_I(I)_{i,t-1} + \beta_c(\sigma^2_I)_{i,t-1} + \alpha_{cs}(\sigma^2_I \times size)_{i,t-1} + \beta_y(y)_{ij,t-1} \\ &+ \beta_s(\sigma^2_y)_{ij,t-1} + \alpha_{ss}(\sigma^2_y \times size)_{ij,t-1} + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \end{aligned}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different levels of uncertainty i.e. global, country and industry level uncertainty on the TFP growth conditional on industry size. The dependent variable is the TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. The estimates shows the impact of uncertainty originating from different sources through industry size on TFP growth. One period lagged values of the first difference of independent variables are used as instruments for equations in level whereas for differenced equations, second - fourth lag of independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL (Real GDP at country level), Size(Industry size), and Year Dummies are the control variables. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively. Standard errors are displayed in parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels. within panels.

Table 3.5: Conditional Impact of Uncertainty on TFP Growth:Factor Intensity

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Model 4**		**Model 4a**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP_{ij,t-1}$	-0.107	(0.040)	0.139	(0.062)**
$FI_{ij,t-1}$	0.002	(0.001)**	0.001	(0.000)***
$\sigma^2_(Output)_{ij,t-1}$	0.006	(0.250)**	0.007	(0.002)***
$\sigma^2_(Investment)_{i,t-1}$	0.008	(0.004)**	0.007	(0.004)*
$\sigma^2_(W.Inflation)_{t-1}$	-0.013	(0.003)***	-0.009	(0.003)***
$Output_{ij,t-1}$	0.546	(0.221)**	0.005	(0.002)**
$Investment_{i,t-1}$	0.003	(0.001)**	0.003	(0.001)*
$W.Inflation_{t-1}$	-0.109	(0.051)***	-0.009	(0.003)***
$FI \times \sigma^{Output}_{ij,t-1}$			0.003	(0.000)***
$FI \times \sigma^{Investment}_{ij,t-1}$			0.003	(0.000)***
$FI \times \sigma^{W.Inflation}_{ij,t-1}$			-0.002	(0.000)***
$RGDP_{i,t}$	-0.003	(0.001)***	-0.002	(0.000)**
$Size_{ij,t}$	0.082	(0.034)**	0.081	(0.034**)
$Trend$	-0.002	(0.0001)*	-0.001	(0.001)
Constant	0.243	(0.084)***	0.181	(0.080)**
Panel B: Diagnostic tests				
Observations		6,100		6,100
AR(2)		1.130		0.600
p-value		0.257		0.551
J-statistic		279.220		260.080
p-value		0.353		0.156

Note:

$$
\begin{aligned}
TFP_{ij,t} = {} & \phi_0 + \phi_1 TFP_{ij,t-1} + \phi_2 FI_{ij,t} + \beta_\pi(\pi)_t + \beta_g(\sigma^2_\pi)_t + \alpha_{gf}(\sigma^2_\pi \times FI)_t + \beta_I(I)_{i,t} \\
& + \beta_c(\sigma^2_I)_{i,t} + \alpha_{cF}(\sigma^2_I \times FI)_{i,t} + \beta_y(y)_{ij,t} + \beta_s(\sigma^2_y)_{ij,t} + \alpha_{sf}(\sigma^2_y \times FI)_{ij,t} \\
& + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}
\end{aligned}
$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different levels of uncertainty i.e. global, country and industry level uncertainty on the TFP growth conditional on industry size. The dependent variable is the TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. Model 1 presents the estimates of baseline model while incorporating the impact of factor intensity on TFP growth whereas Model 2 presents the estimates of each source of uncertainty through factor intensity on TFP growth. One period lagged values of the first difference of independent variables are used as instruments for equations in level whereas for differenced equations, second - fourth lag of independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL (Real GDP at country level), Size(Industry size), and Year Dummies are the control variables. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively. Standard errors are displayed in parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

Table 3.6: Impact of Uncertainty on the TFP Growth: Conditional on the Respective Level Series

Panel A: Estimation Results: Dependent Variable: TFP Growth		
Regressors.	**Model 1**	
	Coeff.	Std.Err.
TFP_{ijt-1}	-0.103	(0.034)***
$\sigma^2_{(Output)_{ijt-1}}$	0.005	(0.001)***
$\sigma^2_{(Investment)_{i,t-1}}$	0.033	(0.017)**
$\sigma^2_{(W.Inflation)_{t-1}}$	-0.014	(0.005**)
$Output_{ij,t-1}$	0.005	(0.001)***
$Investment_{i,t-1}$	0.040	(0.022)*
$W.Inflation_{t-1}$	0.068	(0.062)
$Output_{ij,t-1} \times \sigma^{Output}_{ij,t-1}$	-0.002	(-0.001)**
$Investment_{i,t-1} \times \sigma^{Investment}_{i,t-1}$	-0.002	(0.001)***
$W.Inflation_{t-1} \times \sigma^{W.Inflation}_{t-1}$	0.002	(0.001)**
$RGDP_{i,t}$	-0.011	(0.006)*
$Size_{ij,t}$	-0.038	(0.022)*
$Trend$	-0.011	(0.004)***
Constant	0.416	(0.144)***
Panel B: Diagnostic tests		
Observations		6,047
AR(2)		1.270
p-value		0.203
J-statistic		266.110
p-value		0.231

Note:

$$\begin{aligned} TFP_{ij,t} &= \phi_0 + \phi_1 TFP_{ij,t-1} + \beta_\pi(\pi)_{t-1} + \beta_g(\sigma^2_\pi)_{t-1} + \alpha_{g\pi}(\sigma^2_\pi \times \pi)_{t-1} \\ &+ \beta_I(I)_{i,t-1} + \beta_c(\sigma^2_I)_{i,t-1} + \alpha_{cI}(\sigma^2_I \times I)_{i,t-1} + \beta_y(y)_{ij,t-1} \\ &+ \beta_s(\sigma^2_y)_{ij,t-1} + \alpha_{sy}(\sigma^2_y \times y)_{ij,t-1} + \psi X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \end{aligned}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different levels of uncertainty i.e. global, country and industry level uncertainty on the TFP growth conditional on industry size. The dependent variable is the TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. This table presents the estimates for the impact of each source of uncertainty through their own level series on TFP growth. One period lagged values of the first difference of independent variables are used as instruments for equations in level whereas for differenced equations, second - fourth lag of independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL (Real GDP at country level), Size(Industry size), and Year Dummies are the control variables. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively. Standard errors are displayed in parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

Table 3.7: Percentiles of Total Effect of Uncertainty Conditional on the Industry Size

Panel A: Industry-Specific Uncertainty				
	P_{25}	P_{50}	P_{75}	P_{90}
$P_{IndustrySize}$	8.684	9.938	11.144	12.133
FOD	0.015	0.017	0.018	0.019
S.E	(0.003)***	(0.004)***	(0.004)***	(0.005)***
Panel B: County-Specific Uncertainty				
$P_{IndustrySize}$	8.684	9.938	11.144	12.133
FOD	0.011	0.010	0.006	-0.002
S.E	(0.004)***	(0.004)**	(0.004)	(0.004)
Panel C: World-Specific Uncertainty				
$P_{IndustrySize}$	8.684	9.938	11.144	12.133
FOD	-0009	-0.008	-0.006	-0003
S.E	(0.003)***	(0.003)***	(0.003)**	(0.003)

Note: The time period for estimation is 1971-2008. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively. $P_{IndustrySize}$ represents the percentile distribution of Industry Size measured as log of total number of employees in manufacturing industries of selected countries. FOD indicates Total derivative of dependent variable with with respect to each source of uncertainty. S.E shows Standard errors given in parenthesis.

Table 3.8: Percentiles of Total Effect of Uncertainty Conditional on Factor Intensity

Panel A: Industry-Specific Uncertainty				
	P_{25}	P_{50}	P_{75}	P_{90}
$P_{FactorIntensity}$	21.195	51.944	141.714	682.088
FOD	0.007	0.008	0.011	0.012
S.E	(0.002)***	(0.002)***	(0.002)***	(0.003)***
Panel B: County-Specific Uncertainty				
$P_{FactorIntensity}$	21.195	51.944	141.714	682.088
FOD	0.008	0.008	0.012	0.031
S.E	(0.004)*	(0.004)**	(0.004)***	(0.006)***
Panel C: World-Specific Uncertainty				
$P_{FactorIntensity}$	21.195	51.944	141.714	682.088
FOD	-0.012	-0.016	-0.030	-0.113
S.E	(0.002)***	(0.002)***	(0.004)***	(0.018)***

Note: The time period for estimation is 1971-2008. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively. $P_{FactorIntensity}$ represents the percentile distribution of factor intensity measured as capital-labor ratio in the manufacturing industries of selected countries. FOD indicates Total derivative of dependent variable with with respect to each source of uncertainty. S.E shows Standard errors given in parenthesis.

Table 3.9: Percentiles of Total Effect of Uncertainty Conditional on the Underlying Source of Uncertainty

Panel A: Industry-Specific Uncertainty				
	P_{25}	P_{50}	P_{75}	P_{90}
$P_{IndustryOutput}$	1.693	2.826	6.815	14.023
FOD	0.005	0.004	0.003	0.002
S.E	(0.001)***	(0.001)***	(0.001)**	(0.114)**
Panel B: County-Specific Uncertainty				
$P_{CountryInvestment}$	17.715	2.572	24.434	36.541
FOD	-0.0002	-0.008	-0.019	-0.036
S.E	(0.007)	(0.007)	(0.008)**	(0.013)***
Panel C: World-Specific Uncertainty				
$P_{WorldInflation}$	5.264	25.313	82.991	90.541
FOD	-0.013	-0.009	-0.001	0.001
S.E	(0.005)**	(0.004)*	(0.004)	(0.004)

Note: The time period for estimation is 1971-2008. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively. $P_{IndustryOutput}$, $P_{CountryInvestment}$, $P_{WorldInflation}$ represents the percentile distribution of industry output, Country investment, and world inflation, respectively. FOD indicates Total derivative of dependent variable with with respect to each source of uncertainty. S.E shows Standard errors given in parenthesis.

Figure 3.1: **Industry Specific Uncertainty through Industry Size**

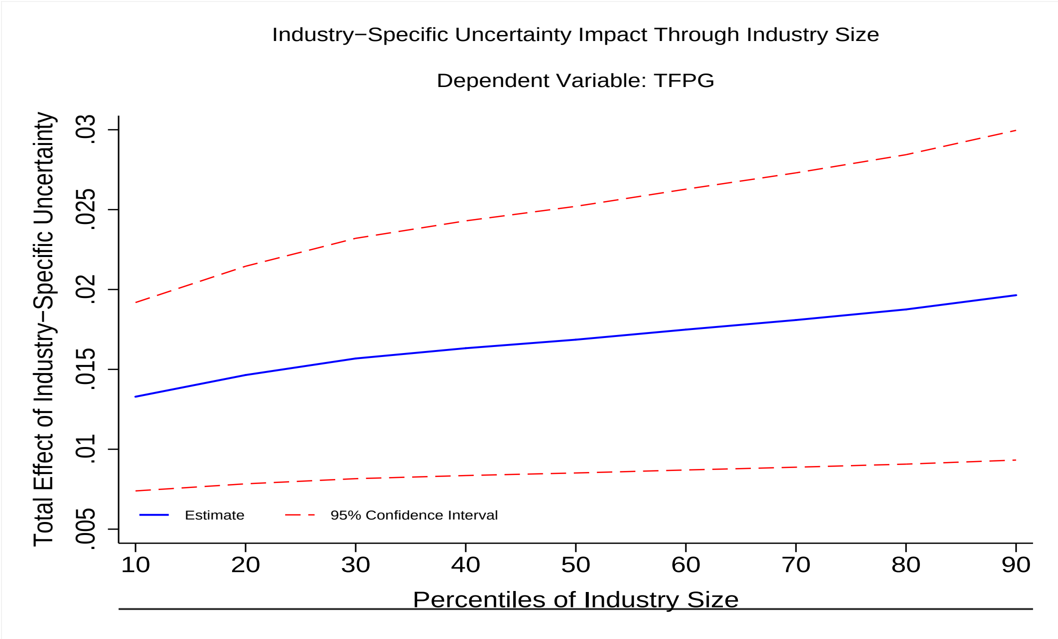


Figure 3.2: **Country Specific Uncertainty through Industry Size**

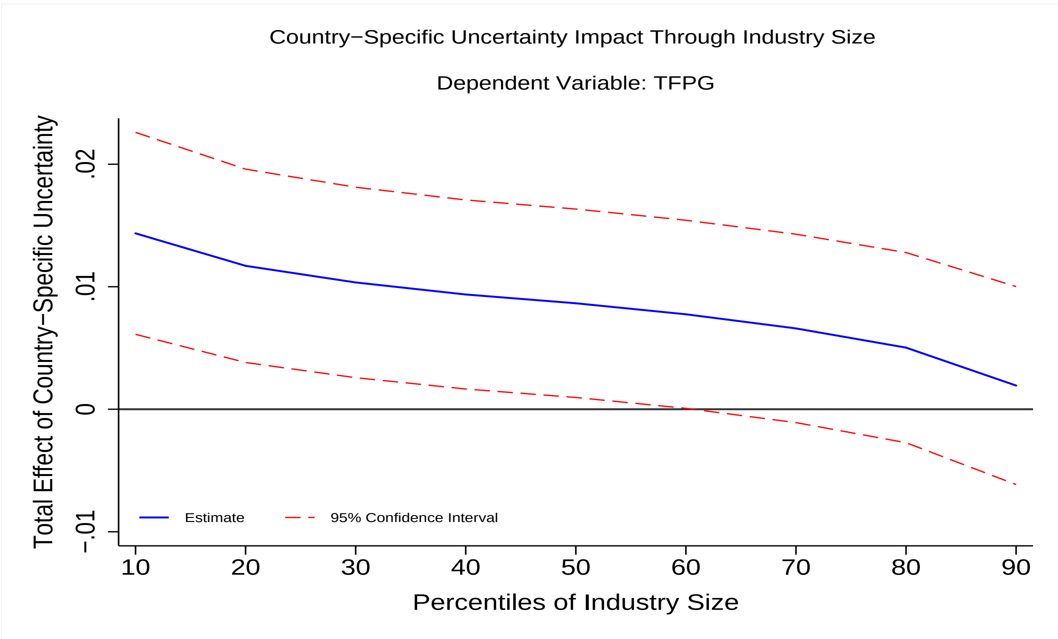


Figure 3.3: World-Specific Uncertainty through Industry Size

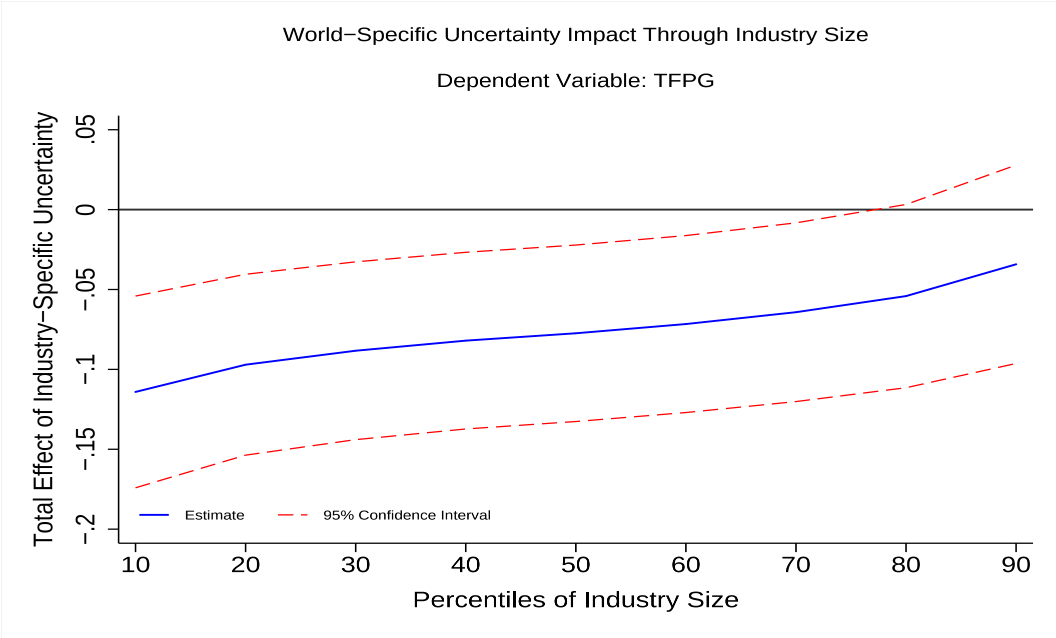


Figure 3.4: Industry-Specific Uncertainty through Factor Intensity

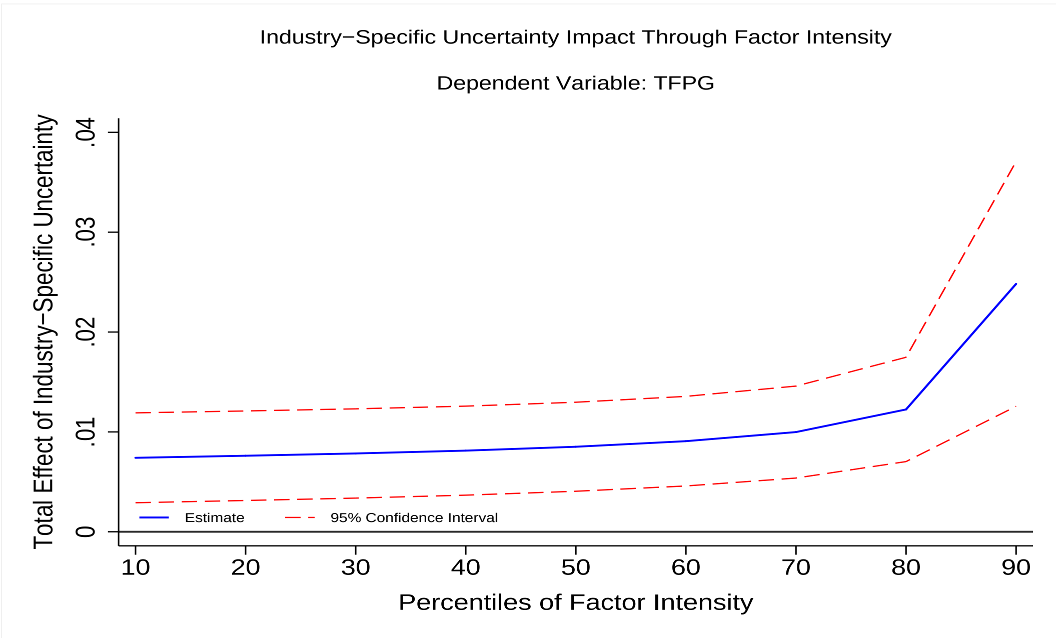


Figure 3.5: Country-Specific Uncertainty through Factor Intensity

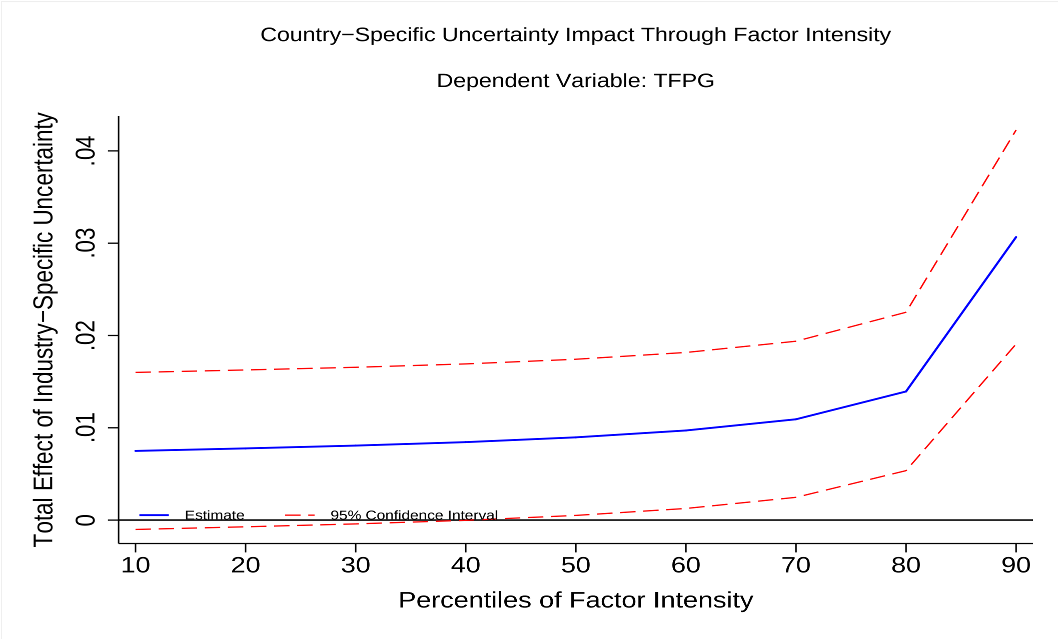


Figure 3.6: World-Specific Uncertainty through Factor Intensity

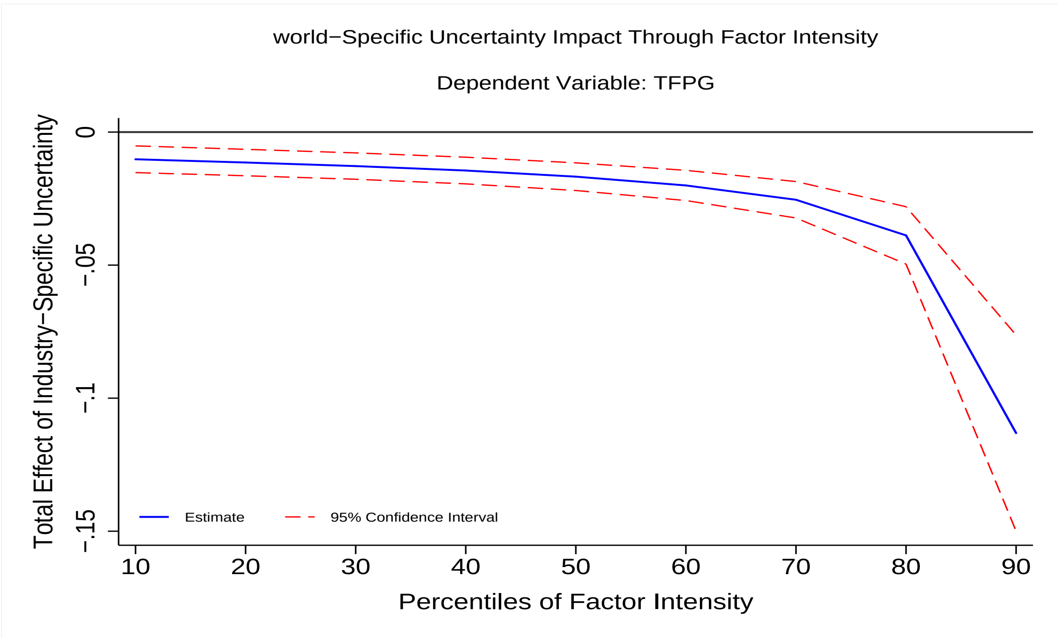


Figure 3.7: **Industry-Specific Uncertainty through Output**

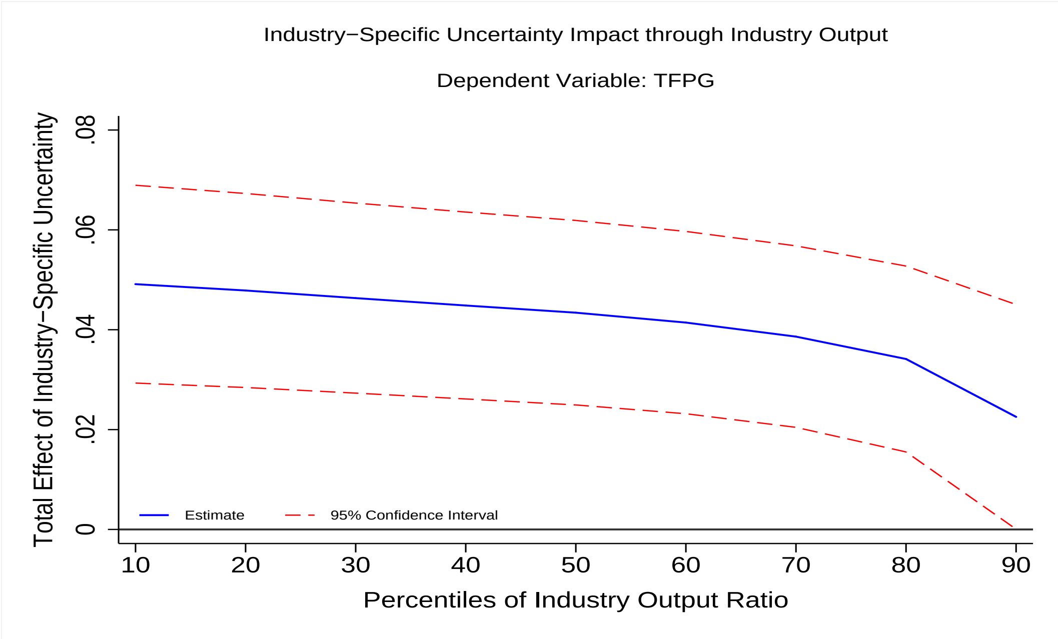


Figure 3.8: **Country-Specific Uncertainty through Investment**

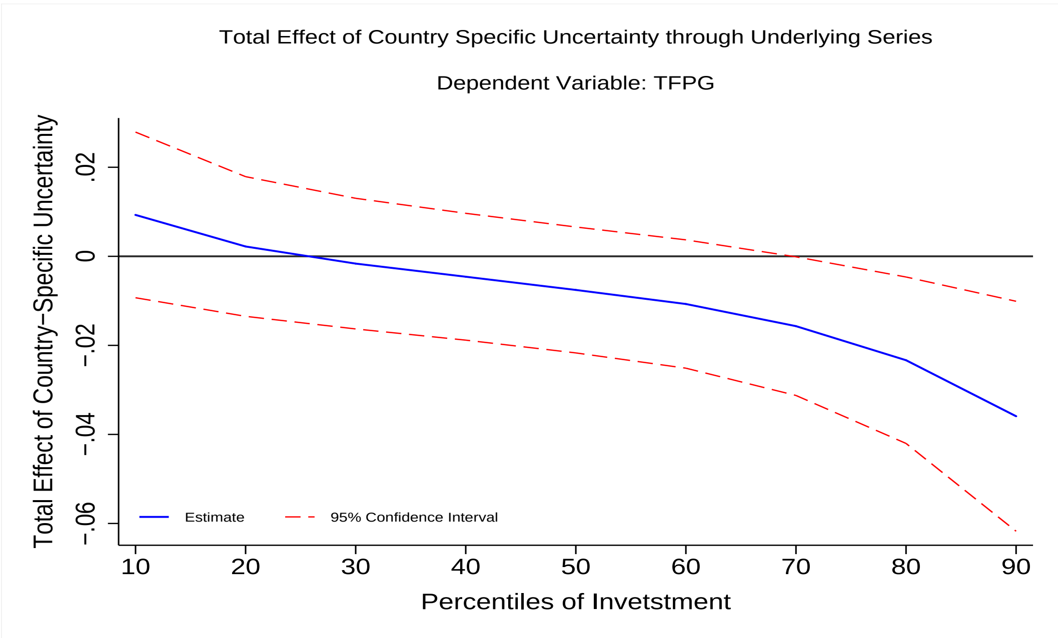
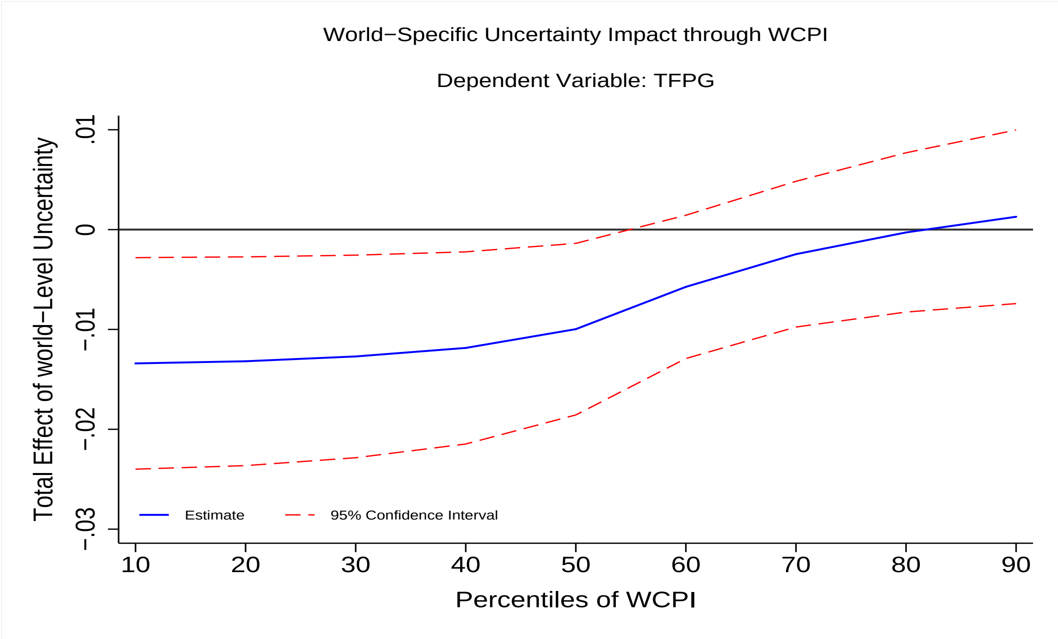


Figure 3.9: World-Specific Uncertainty through W.Inflation



Appendix A: Alternative Measures of Global, Country and Industry Level Uncertainty

Table 3-A: Unconditional Impact of Uncertainty on TFP Growth

Panel A: Estimation Results: Dependent Variable: TFP Growth

Regressors.	**Model 1**		**Model 2**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP_{ij,t-1}$	-0.110***	(0.037)	-0.120***	(0.037)
$\sigma^2_{(Output)_{ij,t}}$	0.036**	(0.018)	0.039***	(0.015)
$\sigma^2_{(GDP)_{ij,t}}$	0.012**	(0.007)	0.061	(0.428)
$\sigma^2_{(WGDP)_t}$	0.042**	(0.019)	0.012***	(0.004)
$Output_{ij,t-1}$			0.062***	(0.326)
$GDP_{i,t-1}$			0.011*	(0.006)
$WGDP_{t-1}$			0.045**	(0.020)
$Size_{ijt}$	0.053**	(0.019)	0.074	(0.051)
Constant	0.292	(0.034)	-0.003***	(0.036)
Panel B: Diagnostic tests				
Observations		6,298	6,298	
AR(2)		1.060	0.950	
p-value		0.290	0.341	
J-statistic		269.300	256.310	
p-value		0.501	0.141	

Note: Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different levels of uncertainty i.e. global, country and industry level uncertainty on the TFP growth. The dependent variable is the TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. Model 1 estimates the impact of uncertainty originating from different sources on the TFP growth whereas Model 2 presents the estimates of the uncertainty as well as their level series. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second -fourth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL(Real GDP at country level), Size(Industry size), and Trend are the control variables. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

A.1 Alternative Measures of Global, Country and Industry Level Uncertainty

Table 3-A.1: Indirect Impact of Uncertainty on the TFP Growth: Conditional on Industry Size

Panel A: Estimation Results: Dependent Variable: TFP Growth		
Regressors.	**Model 1**	
	Coeff.	Std.Err.
TFP_{ijt-1}	-0.132***	(0.037)
$\sigma^2_{(Output)_{ij,t-1}}$	0.021***	(0.009)
$\sigma^{GDP}_{i,t-1}$	0.003**	(0.001)
σ^{WGDP}_{t-1}	-0.007**	(0.003)
$Output_{ij,t-1}$	0.004*	(0.002)
$GDP_{i,t-1}$	-0.006	(0.004)
$WGDP_{t-1}$	0.020***	0.005
$Size \times \sigma^2_{Output_{ij,t-1}}$	0.009***	(0.004)
$Size \times \sigma^2_{GDPi,t-1}$	0.007***	(0.003)
$Size \times \sigma^2_{WGDPt-1}$	0.001***	(0.0000)
$Size_{ijt}$	0.086***	(0.053)
Constant	0.134*	(0.046)
Panel B: Diagnostic tests		
Observations		6,298
AR(2)		0.850
p-value		0.396
J-statistic		263.650
p-value		0.495

Note: Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different levels of uncertainty i.e. global, country and industry level uncertainty on the TFP growth conditional on industry size. The dependent variable is the TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. Model 1 estimates the impact of uncertainty originating from different sources on the TFP growth whereas Model 2 presents the estimates of the uncertainty as well as their level series. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second -fourth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL(Real GDP at country level), Size(Industry size), and Trend are the control variables. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

A.2 Alternative Measures of Global, Country and Industry Level Uncertainty

Table 3-A.2: Conditional Impact of Uncertainty on TFP Growth:Factor Intensity

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Model 4**		**Model 4a**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP_{ij,t-1}$	-0.107	(0.040)	0.130***	(0.038)
$FI_{ij,t-1}$	0.002**	(0.001)	0.008**	(0.003)
$\sigma^2_(Output)_{ij,t-1}$	0.628**	(0.250)	0.009**	(0.004)
$\sigma^2_(GDP)_{i,t-1}$	0.008**	(0.004)	0.013*	(0.007)
$\sigma^2_(WGDP)_{t-1}$	-0.013***	(0.003)	0.047*	(0.026)
$Output_{ij,t-1}$	0.546**	(0.221)	0.003***	(0.001)
$Investment_{i,t-1}$	0.003**	(0.001)	-0.005	(0.004)
$W.Inflation_{t-1}$	-0.109***	(0.051)	0.015***	(0.005)
$FI \times \sigma^{Output}_{ij,t-1}$			0.007*	(0.003)
$FI \times \sigma^{GDP}_{ij,t-1}$			-0.004**	(0.001)
$FI \times \sigma^{WGDP}_{ij,t-1}$			-0.002***	(0.001)
$Size_{ij,t}$	0.082**	(0.034)	0.103**	(0.042)
Constant	0.243***	(0.084)	0.014**	(0.052)
Panel B: Diagnostic tests				
Observations		6,100		6,298
AR(2)		1.130		0.940
p-value		0.257		0.349
J-statistic		279.220		263.170
p-value		0.353		0.468

Note: Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different levels of uncertainty i.e. global, country and industry level uncertainty on the TFP growth conditional on industry size. The dependent variable is the TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. Model 1 estimates the impact of uncertainty originating from different sources on the TFP growth whereas Model 2 presents the estimates of the uncertainty as well as their level series. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second -fourth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL(Real GDP at country level), Size(Industry size), and Trend are the control variables. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

A.3 Alternative Measures of Global, Country and Industry Level Uncertainty

Table 3-A.3: Indirect Impact of Uncertainty on the TFP Growth: Conditional on the Respective Level Series

Panel A: Estimation Results: Dependent Variable: TFP Growth		
Regressors.	**Model 1**	
	Coeff.	Std.Err.
TFP_{ijt-1}	-0.137***	(0.037)
$\sigma^2_{(Output)_{ijt-1}}$	0.003***	(0.001)
$\sigma^2_{(GDP)_{i,t-1}}$	0.012*	(0.001)
$\sigma^2_{(WGDP)_{t-1}}$	0.073**	(0.033)
$Output_{ij,t-1}$	0.004***	(0.002)
$Investment_{i,t-1}$	0.003**	(0.001)
$W.Inflation_{t-1}$	0.028	(0.021)
$Output_{ij,t-1} \times \sigma^{Output}_{ij,t-1}$	-0.016**	(-0.007)
$Investment_{i,t-1} \times \sigma^{GDP}_{i,t-1}$	-0.009**	(0.004)
$W.Inflation_{t-1} \times \sigma^{WGDP}_{t-1}$	-0.015	(0.012)
$Size_{ij,t}$	0.091**	(0.040)
Constant	-0.054	(0.062)
Panel B: Diagnostic tests		
Observations		6,298
AR(2)		0.800
p-value		0.422
J-statistic		267.550
p-value		0.479

Note: Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates for the impact of three different levels of uncertainty i.e. global, country and industry level uncertainty on the TFP growth conditional on industry size. The dependent variable is the TFP growth of the 18 manufacturing industries in 16 emerging economies and covering the time period over 1971-2008. Model 1 estimates the impact of uncertainty originating from different sources on the TFP growth whereas Model 2 presents the estimates of the uncertainty as well as their level series. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second -fourth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test the instruments validity whereas the autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. RGDPL(Real GDP at country level), Size(Industry size), and Trend are the control variables. ***,**, and * indicate level of significance at 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

Chapter 4

TFP Convergence: Explaining the Role of Volatility

4.1 Introduction

The theoretical and empirical debate on convergence has been a pertinent element of the growth literature. A wide range of empirical research based on Neo-classical growth models has centralized the role of capital accumulation in explaining the cross country income differences and convergence (Mankiw et al., 1992, Bernard and Jones, 1996c). However, later studies suggest that cross country growth and productivity differences are not completely due to the differences in human and physical capital (Keller (2000), Hall and Jones (1999), and Bernard and Jones (1996c)).

Endogenous growth models given by Romer (1986), Lucas (1988), and Romer (1990) advocate endogenous technological change as an important determinant of growth. In this regards, further empirical contribution is carried out by Aghion and Howitt (1992), Howitt (2000), Grossman and Helpman (1991), Klenow and Rodriguez-Clare (2005), and Córdoba and Ripoll (2008). Grossman and Helpman (1991) and Rivera-Batiz and Romer (1991), in particular, argue that technological change plays a dominant role in the long run growth. Similarly, Romer (1993), Parente and Prescott (1994), and Bernard and Jones (1996c) also stress upon the importance of technological development. Also, these studies explain that technology diffusion across countries leads towards faster growth and more importantly for convergence among countries. Specifically, Bernard and Jones (1996c) state that the role of technology in explaining the relative income levels is crucial for convergence process but it has been ignored and misguided in the empirical literature.

By linking international trade and neoclassical growth model, Ben-David (1993) and Barro and Mankiw (1995) among others introduce an open economy framework of the neoclassical growth model. These studies specifically emphasize on the significance of international trade, capital flows and technology transfer in convergence process. A noteworthy empirical contribution in this perspective is Coe and Helpman (1995) which introduced the role of technology transfer through the trade channel in TFP convergence. Following studies such as Griffith et al. (2004), Cameron et al. (2005), and Madsen (2008) also confirm the hypothesis presented in Coe and Helpman (1995). They conclude that in an open economy framework, the economy's productivity levels are not only determine by its own innovation activities but also by the innovation activities of its trading partners. Several researchers including Coe et al. (1997), Frantzen (2000), Guellec and Van Pottelsberghe de la Potterie (2001), Lumenga-Neso et al. (2001), del Barrio-Castro et al. (2002), Crespo et al. (2004), and Guellec and Van Pottelsberghe de la Potterie (2004) conclude a significant contribution of technological spillover in the convergence process. In contrast, Keller (1998) and Kao et al. (1999) among others do not support the hypothesis that technology spillover is important for the convergence of TFP growth.

Recent researchers not only explain the role of technological diffusion in determining the TFP growth but these studies also estimate the impact of technological development in TFP convergence. In this regard, empirical studies estimate the relationship between country TFP growth and its initial distance from the technological frontier. In other words, they estimate the relative TFP level of non-frontier country with respect to the frontier country (See, e.g., Bernard and Durlauf, 1991, 1996). Much of the earlier empirical focus is devoted towards aggregate TFP convergence. However, to understand the major source of TFP convergence at the aggregate level, recent studies divert their investigation towards TFP convergence at the sector level, particularly at manufacturing sector. Bernard and Jones (1996a) state that empirical research should focus on industry-specific particularly manufacturing industries' productivity convergence.

Therefore, we investigate how technological transmission from a frontier country affects the TFP growth of manufacturing industries of emerging economies over the time period 1981-2008. Our study has three distinctive features in relations to the existing empirical literature. First, we select large trading partners of the USA among emerging economies as non-frontier countries. We select emerging economies instead of widely used sample of OECD countries. Bernard and Jones (1996a) and Keller (2000) report that the convergence analysis for developing economies can bring more interesting findings related to the TFP convergence. Moreover, they also specify that the convergence hypothesis test for the developing countries would help in understanding new facets of the convergence process. We conduct our empirical analysis for the sample of five Asian emerging economies.

Second, to the best of our knowledge, there is no empirical research which has analyzed the impact of uncertainty of technology diffusion on TFP growth and its convergence. We compute uncertainty in the imports of technological products and estimate its impact on TFP growth of the manufacturing industries of selected non-frontier countries. In addition to investigate direct impact of uncertainty of technology diffusion, we also examine the conditional impact of uncertainty on TFP growth. For doing so, we use an interaction between technology diffusion and its uncertainty. The interaction, in this case, captures how uncertainty impact on TFP growth changes when the level of technology diffusion changes. In addition to this, we also estimate the conditional impact of relative TFP level (TFP gap) in the following two ways: (i) the conditional impact of TFP gap through technology diffusion which is estimated by an interaction between TFP gap and technology diffusion. In this case, we aim to investigate how technology diffusion affects the process of TFP convergence among the frontier and non-frontier countries. (ii) The conditional impact of TFP gap through uncertainty of technology diffusion. For this purpose, we interact TFP gap with uncertainty of technology diffusion. This exercise permits us to evaluate whether uncertainty of technology diffusion improves or deteriorates the convergence process. In other words, we scrutinize, how the convergence process takes place at different levels of uncertainty of technology diffusion. Third, having established the direct and conditional impact of the uncertainty of technology diffusion and TFP gap, we compute and plot the total effect of both of these variables for TFP convergence.

We take the USA as the frontier country whereas five trading partners of the USA among Asian emerging economies are considered as non-frontier countries. We measure technology diffusion by using industry specific technological products import of non-frontier countries from the frontier country. In addition, industry value added, capital stock generated through perpetual inventory method and total number of employees of manufacturing industries of non-frontier countries are used to compute TFP level as well as TFP growth. Similar to the existing literature, we augment our baseline model of TFP convergence with other factors affecting the TFP growth of non-frontier countries. The control variables include capital-labor ratio and real wage growth rate which remains same across all the estimation models.[1] We also use second measure of technology diffusion which is industry specific total imports of non-frontier countries from the frontier country.

Before carrying out the empirical investigation, we compute the TFP level by employing the superlative index number approach proposed by Caves et al. (1982b) and Caves et al. (1982a). To generate the proxy of uncertainty of technology diffusion, we use first order autoregressive model of technology import for all manufacturing industries over the selected time period. Finally, to empirically estimate the impact of technology diffusion and its uncertainty on the TFP growth and convergence process, we implement the dynamic panel data estimator, two step system GMM approach.

Our empirical findings suggest a significant evidence of convergence among manufacturing industries of the frontier and non-frontier countries for both samples of non-frontier countries. We observe a significant impact of technology diffusion on TFP growth of emerging economies. Also, we find that technology diffusion triggers TFP convergence process among frontier and non-frontier countries over the selected sample period. In contrast, the uncertainty of technological products' import lead not only to a decline in the TFP growth but also it results in divergence of TFP of manufacturing industries of the

[1] The yearly data on human capital and R&D expenditure for the selected emerging economies is not available, therefore our model lacks the information on these two factors affecting the TFP growth and convergence process.

frontier and non-frontier countries.

The rest of the paper is organized as follows: Section 3 discusses the existing empirical literature, its weaknesses and how our study differs from the existing research on the impact of technology diffusion on TFP growth. Section 4 presents the empirical model, explains the data, data sources, and variable construction. Section 5 is devoted to the discussion of the empirical results. Finally, section 6 concludes.

4.2 Literature Review

Since the seminal contribution of Romer (1986) and Romer (1990), most of the empirical research endogenize the technological development in growth models. The recent growth models, therefore, not only advocates the importance of innovative research activities but also report international trade as an important mechanism for productivity gains (Grossman and Helpman (1991) and Russell and Kumar (2002)). Researchers such as Dowrick and Nguyen (1989), Dougherty and Jorgenson (1996), Dougherty and Jorgenson (1997), Wolff (1991), and Dollar and Wolff (1994) have also interpreted the process of technological catch-up. Since TFP is the closest measure for technology, these researchers examine whether countries have been converging in terms of TFP levels or not.

Later, a large number of studies stress upon the role of international trade particularly imports in determining TFP growth. This research classifies international trade as the mechanism of technology diffusion towards technologically lagging countries. These studies include Coe and Helpman (1995), Coe et al. (1997),[2] Ben-David (1996), Keller (1996), Keller (1998) among others. Coe and Helpman (1995), in particular, explain that countries with higher trade openness experience larger productivity gains from the technological development of their trading partners. Particularly, the gains are stronger for small open economies. Similarly, Aghion and Howitt (1992), by following the schumpeterian type models, state that overall research activities in an economy determine the expected growth rate of the economy.

Wolff (1991) states that countries lagging behind in technological advancements should exhibit rapid growth in the technology to catch-up with the leader country. He empirically support the existence of convergence among G7 countries while taking the USA as the benchmark country. However, Bernard and Jones (1996a) find weak evidence of convergence of the TFP or labor productivity among the manufacturing sector of 14 OECD economies. In the similar vein, Bernard and Jones (1996c) state that the traditional approaches overstate the role of capital accumulation and under-emphasized the role of

[2] Coe and Helpman (1995), Coe et al. (1997), and Park (1995) used the country level data which as identified by Keller (2002) is incapable of capturing the diversity of sectoral trade for evaluating the impact of international trade on the TFP growth in importing countries particularly when we consider the case of developing countries.

technological diffusion in explaining the convergence hypothesis. In addition, they argue that the role of technology is even more important when we consider the convergence hypothesis at the sector level particularly for the manufacturing sector.

Gouyette and Perelman (1997) evaluate the productivity performance measured through two components of TFP growth, namely technological change and efficiency change. Their study based on the manufacturing industries of 13 OECD countries does not present evidence for catching up in manufacturing industries. Cameron et al. (1998) present the convergence among manufacturing industries of the UK and the leader country, USA. Also, their results portray that productivity gap from the benchmark country has significant impact on the TFP growth of the UK manufacturing industries. Moreover, their study confirms the significant impact of trade openness on the TFP convergence of manufacturing industries of both countries.

Researchers support the hypothesis that the technology diffusion favors the TFP growth and convergence of technologically lagging countries. However, the empirical literature has not examine how this impact is different for developing relative to developed countries. Keller (2000) document that technology diffusion form the leader country may have different implications for developed and developing countries depending on two important factors: domestic R&D expenditures and import composition. He considers these two factors crucial for determining whether technology diffusion from leading country contributes more relative to the domestic technology innovations in the TFP growth of lagging countries. Moreover, he verifies that the domestic innovation has larger impact on TFP growth of OCED countries relative to technology diffusion from the average foreign country whereas the reverse implies for developing countries. Similarly, Keller (2002) supports the findings that domestic, both inter and intra industry, innovations contributes more than any foreign source of technology diffusion i.e. R&D of foreign industries or technological products import for large OECD manufacturing industries.

Differing form other studies, Scarpetta and Tressel (2002) present a new dimension of technological convergence. They argue that the process of innovation and adoption of technology depends on the underlying market conditions and institutions affecting the labor and product market functioning. They identify a significant affect of technological gap on the TFP growth of manufacturing industries of selected OECD countries which suggests the presence of technological catch-up in most of these industries. Russell and Kumar (2002) estimate the world wide production frontier and relative efficiency levels for all economies by employing a non-parametric approach. They claim that technological catch-up reflects the movement towards the frontier country by adopting their technologies which reduces the technical and allocative gap.

At the aggregate level, Miller and Upadhyay (2002) support the argument built by

Bernard and Jones (1996c) that technology diffuses from developed to developing counties which facilitates the convergence process. Their findings provide a strong evidence of TFP convergence for low and middle income countries. In addition, the evidence of σ-convergence is only observed for high income countries whereas for low income countries the evidence is mixed.

Stehrer and Wörz (2003) argue that there is difference in the catching up of countries based on their regional classifications and also on types of industries. Their findings indicate productivity convergence in the medium-low-tech and medium-high-tech industries of East Asian countries whereas it is lowest for the low-tech industries of these countries. In the case of OECD, the convergence is more prominent in the low-tech industries. In addition to this, they state a significant link between trade and technological catch-up.

Another strand of literature focuses on estimating the role of domestic as well as foreign innovations measured through R&D expenditures. This literature explains that research innovations facilitate the productivity growth of technologically lagging countries via two channels: direct and indirect. Through direct channel, R&D activities in domestic industries provide opportunities for innovations. Through indirect channel, R&D activities accelerate the process of technology diffusion by improving the absorptive capacity of industries to adopt and imitate the existing technology of the leading countries. Both of these channels facilitate TFP convergence among leader and lager countries. In this regards, Griffith et al. (2004) provide the evidence of significant direct and indirect impact of R&D activities in convergence of OECD countries towards the technological leader. On the similar grounds, Cameron et al. (2005) highlight two important factors for the TFP growth in countries lagging in the technological development namely, domestic innovations and technology transfer from the frontier country. By empirically estimating long run equilibrium error correction model of productivity growth, they provide evidence of a statistically significant adjustment towards the long run steady state equilibrium. Moreover, they identify that international trade plays a significant role in the convergence of TFP growth among manufacturing industries of the UK and the USA. Deliktas and Balcilar (2005) assess the catch-up and convergence for the transition economies and conclude that the transition economies are well below the frontier.

Madsen (2007) reports a statistically significant and positive impact of domestic and foreign knowledge on the TFP growth of 16 OECD countries. He does not find any significant evidence that the relationship between foreign knowledge and the TFP growth is driven by the trade openness. In contrast, Madsen (2008) reports a mixed impact of the domestic knowledge on the TFP growth whereas the world knowledge pertains a statistically significant impact on the TFP growth through the channel of imports. Moreover, he does not find a significant impact of trade openness on the TFP growth of selected OECD economies. More recently, Lee (2009) investigate the role of international factors such as international trade and FDI in the long run convergence process of manufacturing industries of 25 OECD countries. He argues that both of these international factors attribute to the diffusion of knowledge. By applying the panel unit root methodology, his study provide evidence of a significant role of trade and FDI in the productivity convergence of sample countries. However, the speed of convergence is higher for the trade related productivity in contrast to the FDI related productivity convergence. By using the error correction model, Mc Morrow et al. (2010) support the catching-up process taking place between the EU-US manufacturing industries. Moreover, a significant contribution by the technological advancement in the leader country is also observed for the TFP growth of the follower countries.

Overall, the review of literature not only explains the importance of domestic factors such as capital accumulation and research innovations but also provides an evidence of the significant role of international factors, particularly, international trade of intermediate goods in TFP growth and convergence. Another important implication which can be drawn from the existing research is that the quality of domestic institutions is crucial in enhancing the innovative activities. However, the existing studies have not considered the impact of uncertainty, particularly uncertainty attached to international factors on the TFP growth and convergence process. It is important to incorporate the role of uncertainty not only in determining the TFP growth but also to assess how and to what extent it effects the convergence process among technologically lagging and leader countries.

In addition to this , much of the empirical investigation is undertaken for the TFP convergence of manufacturing industries of OCED economies towards a leader country. However, OECD is mainly comprised of developed economies where most of the economies pertains relatively higher TFP growth in manufacturing industries. Less developed or developing countries, as explained by Bernard and Jones (1996c), may provide more interesting findings regarding the TFP convergence at sectoral level. Therefore, we aim to fill this gap in the literature by incorporating the role of uncertainty of technology diffusion in determining the TFP growth and its convergence. Given that, we examine the convergence analysis for emerging economies which has not been considered earlier. Therefore, we can provide empirical findings which can compliment earlier research.

4.3 Theoretical Framework

Building on the existing empirical studies, we consider an autoregressive distributed lag (ADL) model to capture the adjustment towards the long run equilibrium point between TFP growth of the frontier and non-frontier countries. Nicoletti and Scarpetta (2003), Griffith et al. (2004), Cameron et al. (2005), and Mc Morrow et al. (2010) among others employ an ADL (1 1) specification by assuming no persistence of TFP growth of non-frontier countries with its own lagged values. Differing from this practice, we assume an ADL (2 2) specification which is relatively more flexible as it not only allows the contemporaneous but also the lagged effect of TFP growth of the frontier country on TFP growth of non-frontier countries.[3]

As Bernard and Jones (1996a), Bernard and Durlauf (1996), Griffith et al. (2004), and Cameron et al. (2005) document that TFP growth in countries which lacks technological development is not only determine by domestic innovation but also by technology transfer from the technologically advanced countries. Since the data on domestic innovation (measured as the R&D expenditures) is not available for the selected non-frontier countries, we proxy the impact of domestic innovation through the lagged TFP growth of manufacturing industries of these countries. The ADL (2 2) model takes the following form.

$$\begin{aligned} TFP_{ijt}^{nonfrontier} &= \alpha_0 + \alpha_1 TFP_{ijt-1}^{nonfrontier} + \alpha_2 TFP_{ijt-2}^{nonfrontier} + \beta_0 TFP_{jt}^{frontier} \\ &+ \beta_1 TFP_{jt-1}^{frontier} + \beta_2 TFP_{jt-2}^{frontier} + \lambda X_{ij,t} + \upsilon_{ij,t} \end{aligned} \tag{4.1}$$

We perform a linear transformation on the above model under the assumption of long run homogeneity of the equilibrium relationship.[4] (see e.g., Banerjee et al. (1990) and Banerjee et al. (1993) for further detail). This assumption dictates a proportional relationship of productivity growth in the frontier and non-frontier countries at the long run equilibrium point. Hence, we can write the above expression as follows:

$$\begin{aligned} \Delta TFP_{ijt}^{nonfrontier} &= \alpha_0 + \gamma_0 \Delta TFP_{ijt-1}^{nonfrontier} + \gamma_1 \Delta TFP_{jt}^{frontier} + \gamma_2 \Delta TFP_{jt-1}^{frontier} \\ &- \Omega_0 \left(\frac{TFP_{ijt-2}^{nonfrontier}}{TFP_{jt-2}^{frontier}} \right) + \lambda X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \end{aligned} \tag{4.2}$$

Subscript j denotes number of industries, i denotes number of countries, t refers to number of years. ΔTFP indicates the total factor productivity growth in industry j of country i and at time t. $\gamma_0 = (\alpha_1 - 1)$, $\gamma_1 = \beta_0$, $\gamma_2 = (\beta_0 + \beta_1)$ and $\Omega_0 = (\frac{\beta_0+\beta_1+\beta_2}{\alpha_2+\alpha_1-1})$ and $\upsilon_{ij,t} = f_{ij} + \zeta_t + \varepsilon_{ij,t}$ which represents the country-industry fixed effect, year fixed effects and serially uncorrelated error, respectively.

[3]An ADL (1 1) specification is based on the one period lagged values of both the dependent and independent variables whereas in ADL (2 2) specification, take two lags of dependent and independent variables.

[4] The linear transformation leads to derivation of various other models e.g., Sargan (1964), Hendry and Anderson (1977), and Davidson et al. (1978) have used the ADL (1 1) specification to derive the error correction term and describe it as a way to capture the adjustment towards a long run equilibrium point between a dependent and independent variable which is deviated from an equilibrium point from the dependent variable.

$\Delta TFP_{ijt}^{nonfrontier}$ denotes the total factor productivity growth in emerging economies which are classified here as non-frontier countries. $\Delta TFP_{ij,t-1}^{nonfrontier}$ is the lagged TFP growth which measures the persistence of TFP growth among manufacturing industries of non-frontier countries over the selected time span. Thus, γ_0 captures the link between $TFP_{ijt}^{nonfrontier}$ and technological developments in the previous year taken place in non-frontier countries.

The coefficient γ_1 and γ_2 measure the contemporaneous and the lagged effect of TFP growth in the frontier country ($\Delta TFP_{jt}^{frontier}$) on the TFP growth of non-frontier countries. Finally, ($\frac{TFP_{ijt-2}^{nonfrontier}}{TFP_{jt-2}^{frontier}}$) captures TFP level in manufacturing industries of non-frontier countries relative to the TFP level in manufacturing industries of the frontier country.[5] The coefficient of the relative TFP level (Ω) captures the impact of efficiency gap on the TFP growth of non-frontier countries. Since the lager country experiences lower TFP growth relative to the frontier country, the (Ω) is expected to be negative for a non-frontier country to remain at the steady state level (see, e.g., Griffith et al. (2004)). This dictates that farthest the country lies from the benchmark country, negative and smaller will be the coefficient, and greater will be the potential for efficiency gain (see, e.g., Cameron et al. (2005) and Griliches and Lichtenberg (1984a)).

Cameron et al. (2005) state that the TFP in sector j of non-frontier countries lies at an equilibrium distance behind the frontier country such that at the steady state equilibrium, the TFP growth in manufacturing industries of frontier and non-frontier countries will be equal to each other. They explains that the relative TFP at the steady-state equilibrium depends on the innovation in both countries as well on the speed of technology transfer from the frontier to non-frontier country. In addition, Coe and Helpman (1995) and Madsen (2007) explain that import of intermediate goods from the frontier country facilitates the process of faster TFP growth.[6] Hence, to estimate the impact of technology diffusion, we incorporate the import of technological products from the frontier country into Equation (4.2). The model then takes the following form:

$$\begin{aligned}\Delta TFP_{ijt}^{nonfrontier} &= \alpha_0 + \gamma_0 \Delta TFP_{ijt-1}^{nonfrontier} + \gamma_1 \Delta TFP_{jt}^{frontier} + \gamma_2 \Delta TFP_{jt-1}^{frontier} \\ &\quad - \Omega_0 \left(TFP_{ijt-2}^{Gap} \right) + \psi_0 Tech_{ijt-1} + \lambda X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t} \qquad (4.3)\end{aligned}$$

This specification is similar to Nicoletti and Scarpetta (2003), Griffith et al. (2004),

[5] Banerjee et al. (1990) explain this term as the adjustment towards the long run equilibrium point. Furthermore, this term represents the existence of long run co-integrating relationship between the TFP of each non-frontier country and TFP of the frontier country.

[6] A substantial number of studies emphasized the role of international trade in the diffusion of technology. These studies presents various mechanisms through which trade can impact the productivity growth in lager countries. Most notable mechanism are the diffusion of technology and competition. See, e.g., Ben-David and Loewy (1998), Edwards (1998), Frankel and Romer (1999), and Lawrence and Weinstein (1999).

Cameron et al. (2005), and Mc Morrow et al. (2010) among others. $Tech_{ijt-1}$ represents technology diffusion and measured as the ratio of technological products' import, of non-frontier countries from the frontier country, to the value added.

Differing from these studies, we augment equation (4.2) with a measure of uncertainty of technology diffusion and estimate its impact on the TFP growth and convergence of manufacturing industries of non-frontier and frontier countries. This helps us to understand how the effect of technology diffusion changes in presence of the uncertainty of technology diffusion.

Further, we also estimate a secondary channel through which uncertainty of technology diffusion and TFP gap affects TFP growth of non-frontier countries. For this purpose, we augment the model given in Equation (4.3) with following interaction terms: (i) interaction between uncertainty of technology diffusion with the level of technology diffusion. This approach allows us to evaluate how uncertainty affects TFP growth of non-frontier countries at different levels of technology diffusion. (ii) interaction between TFP gap and technology diffusion. This interaction identifies whether TFP convergence changes at different levels of technology diffusion from the frontier towards non-frontier countries. (iii) interaction between TFP gap and uncertainty of technology diffusion. This captures changes in TFP convergence through different levels of uncertainty. Hence, our model takes the following form.

$$\begin{aligned}\triangle TFP_{ijt}^{nonfrontier} &= \alpha_0 + \gamma_0 \triangle TFP_{ijt-1}^{nonfrontier} + \gamma_1 \triangle TFP_{jt}^{frontier} + \gamma_2 \triangle TFP_{jt-1}^{frontier} \\ &- \Omega_0 \left(TFP_{ijt-2}^{Gap} \right) + \psi_0 Tech_{ij,t-1} + \psi_1 \sigma_{ij,t-1}^{Tech} + \psi_2 Tech_{ij,t-1} \times \sigma_{ij,t-1}^{Tech} \\ &+ \psi_3 Tech_{ij,t-2} \times TFP_{ij,t-2}^{GAP} + \psi_4 \sigma_{ij,t-2}^{Tech} \times TFP_{ij,t-2}^{GAP} + \lambda X_{ij,t} \\ &+ f_{ij} + \zeta_t + \varepsilon_{ij,t}\end{aligned} \tag{4.4}$$

The term σ_{ijt-1}^{Trade} measures the own impact of technology diffusion uncertainty on the TFP growth of non-frontier countries. Whereas $Tech_{ijt-1} \times \sigma_{ijt-1}^{Tech}$ specify how the impact of technology diffusion's uncertainty changes conditional on the level of technology diffusion. $TFP_{ij,t-2}^{GAP} \times Tech_{ij,t-2}$ identifies the impact of TFP convergence through different levels of technology diffusion on TFP growth of non-frontier countries. We expect the coefficient of the interaction of technological trade and the relative TFP level as negative which indicates that trade of technological products between frontier and non-frontier countries support the convergence process. Finally, $TFP_{ij,t-2}^{GAP} \times \sigma_{ijt-2}^{Tech}$ indicates uncertainty augmented TFP convergence. Alternatively, this term captures the TFP convergence in manufacturing industries of non-frontier and frontier countries at different levels of uncertainty.

4.3.1 Computation of Relative TFP

By following the existing literature such as Nicoletti and Scarpetta (2003), Griffith et al. (2004), and Cameron et al. (2005), we compute TFP growth in industry j of i^{th} country using a superlative index number approach proposed by Caves et al. (1982b) and Caves et al. (1982a). This approach allows the flexibility in specification for computing the productivity growth. Cameron et al. (2005) explain that this methodology is consistent with the translog production function and TFP measure through index number approach. We prefer superlative index number approach to compute TFP growth in this chapter instead of using translog production function approach itself due to two reasons. (i) Translog production function approach only estimates the TFP growth whereas superlative index number approach allows us to compute the TFP level of each respective country in addition to compute the TFP growth. (ii) superlative index number approach enables us to compute the relative level of TFP of each country with respect to the frontier country. This is the distinctive characteristic of this approach which enables us to compute the relative TFP levels or TFP gap of each non-frontier country with respect to the frontier country. Jorgenson and Nishimizu (1978) initiate the computation of international TFP comparison by using multilateral translog production function. However, to compute the relative levels of TFP, they have used Caves et al. (1982a)'s superlative index number approach as we have followed to compute the relative TFP levels. Moreover, the translog production function approach introduced by Jorgenson and Nishimizu (1978) uses dummy variable of foreign country to introduce the technological differences. Therefore it is more appropriate for the time series analysis with bilateral trade. Our study is based on three-dimensional panel data where frontier country is repeating and introducing dummy will lead to the problem of repeated time observations and dummy variable trap. Also, it is more flexible than the simple Cobb-Douglas production function. We compute TFP growth in non-frontier countries as follows:

$$ln\left(\frac{A_{ij,t}}{A_{ij,t-1}}\right) = ln\left(\frac{Y_{ij,t}}{Y_{ij,t-1}}\right) - \bar{\alpha}_{ij,t} ln\left(\frac{L_{ij,t}}{L_{ij,t-1}}\right) - (1-\bar{\alpha}_{ij,t})\, ln\left(\frac{K_{ij,t}}{K_{ij,t-1}}\right) \tag{4.5}$$

where $Y_{ij,t}$ indicates the real value added of industry j in country i at time t in constant international dollars. $L_{ij,t}$ denotes labor input in industry j of country i at time t measured as the total number of employees. $K_{ij,t}$ denotes the physical capital in industry j of country i at time t measured in constant international dollars. $\bar{\alpha}_{ij,t}$ indicates $(\alpha_{ij,t} + \alpha_{ij,t-1})/2$, the average labor share in industry j of country i for the period t and $t-1$. As Cameron et al. (2005) argue that labor share at industry level are highly volatile which can lead to a measurement error in $\alpha_{ij,t}$. Following Harrigan (1999), $\alpha_{ij,t}$ can be computed as the function of capital-labor ratio and a country industry constant as follows:[7]

$$\alpha_{ij,t} = \vartheta_{ij} + \xi_j ln\left(\frac{K_{ij,t}}{L_{ij,t}}\right) \tag{4.6}$$

The fitted values from this equation are then used as the labor share in the computation of TFP. Next, we employ the superlative index number technique to compute the relative TFP of manufacturing industries in non-frontier and frontier countries. Thus TFP level in manufacturing industries of non-frontier countries relative to manufacturing industries of frontier country is expressed as below:

$$ln\left(\frac{A_{ij,t}}{A_{Fj,t}}\right) = ln\left(\frac{Y_{ij,t}}{Y_{Fj,t}}\right) - \tilde{\alpha}_{ij,t} ln\left(\frac{L_{ij,t}}{L_{Fj,t}}\right) - (1 - \tilde{\alpha}_{ij,t})\, ln\left(\frac{K_{ij,t}}{K_{Fj,t}}\right) \tag{4.7}$$

where $\tilde{\alpha}_{ij,t}$ represents $(\alpha_{ij,t}+\alpha_{Fj,t})/2$, average share of labor in value added of industry j of frontier and non-frontier countries. An intuition for this computation is given by Easterly et al. (2003) that this index explains the TFP level across industries and countries if the labor cost is same across all industries in the frontier and non-frontier countries.

4.3.2 Generating a proxy for Uncertainty

There are several methods proposed in the literature to compute a proxy for uncertainty. The standard deviation of residuals of the underlying series as a proxy for uncertainty is relatively common in the literature. For instance, Turnovsky and Chattopadhyay (2003) have utilized the standard deviation of the residuals of the autoregressive processes of the logarithm of GDP to compute uncertainty. Aizenman and Marion (1999), too, measure the uncertainty as the standard deviation of the residuals of the autoregressive processes of variables of interest. Whereas, Comin and Mulani (2009) used centered standard deviation of 10 consecutive annual growth rate of the series.

Another common approach to generate a proxy of uncertainty is to compute moving average standard deviation of the underlying series. However this method is criticized as it gives equal weights to all the observations at each interval which may lead to high serial correlation. Some existing studies have used the conditional variance computed from GARCH models to gauge the uncertainty. GARCH based specifications are more common in the literature where the series are of high frequency such as quarterly or monthly. In addition, the GARCH process generates uncertainty by taking all the industries/countries collectively. Thus, this process cannot isolate the unobservable shocks related to one series while computing the volatility of another series in the sample.

Following Aizenman and Marion (1999) and Turnovsky and Chattopadhyay (2003), we estimate a first order autoregressive model to generate the residuals for the industry specific imports of technological products and industry specific total imports across each

[7] This strategy is implemented by Nicoletti and Scarpetta (2003) and Griffith et al. (2004) among others.

industry for the time period 1981-2008.[8] One-period ahead residuals are saved for each industry. Later, using one period ahead residuals, we compute the cumulative-volatility of the underlying series. In particular, the cumulative volatility for the year 1982 is computed by calculating the standard deviation of the residuals from the AR(1) model of the respective series that uses the data for the year 1982 and 1981. We repeat this process to construct the cumulative volatility for all the years in the sample.

4.3.3 Generating the Capital Stock

To compute the capital stock by using gross fixed capital formation series, we employ perpetual inventory method. For this purpose, we first compute the initial capital stock which is calculated as a ratio of the gross fixed capital formation in 1980 to the sum of the annual geometric growth rate of output of each industry over the selected time period.[9] and the depreciation rate of capital. We assume a constant depreciation rate of 5% (See, Easterly et al. (2003)). Having obtained the initial capital stock for 1980, we compute capital stock series by following the perpetual inventory method, $K_t = K_{t-1} + GFCF_t(1-\delta)$. Where δ is the depreciation rate set to 5%.

4.3.4 Empirical Issues

Our models presented in Equation (4.3) – Equation (4.4) contain uncertainty of technology diffusion and TFP growth which are generated regressors. As pointed out by Hendry et al. (1984) and Pagan and Ullah (1988) that generated regressors in estimation and statistical inference may be problematic. To overcome this problem, we employ dynamic panel data (DPD) estimator, two step system GMM approach to estimate our models given in equations (4.3) to (4.4). This approach is developed by Arellano and Bover (1995) and further extended by Blundell and Bond (1998). The key feature of this approach is that it uses a system of two equations one in first differenced form whereas the other in levels. Therefore in system GMM, the model is estimated in levels as well as in first differences. In addition, time invariant regressors can still be included in the system GMM which would disappear in the difference GMM. Since all instruments for the level equations are assumed to be orthogonal to fixed effects, particularly to all time invariant variables, it will not effect the estimates for the other regressors.

We use time dummies in all of our estimated specification to tackle the problem of non-stationarity in the level equation. For doing so, we follow Bond et al. (2001) who argue that including time dummies is equivalent to transforming the variables into devia-

[8] We prefer using AR(1) process to generate the residuals. We did not run a family of autoregressive series to select the appropriate model as for the annual data with a limited time series observations, a higher order AR process may not generate consistent measure of uncertainty. Similar practice is adopted by Aizenman and Marion (1999)

[9] We have computed the geometric mean (g) as $[(\frac{GFCF_{startyear}}{GFCF_{endyear}})^{1/N} - 1]$

tions from time means.

To test the validity of the instruments, we use the Hansen (1982) J-statistics for over identification to confirm the robustness of instruments. The J-statistics is asymptotically distributed as χ^2 with degrees of freedom equal to the number of overidentifying restrictions. The Hansen test works under the null of "the instruments are jointly exogenous". Therefore a higher p-value will ensure the validity of instruments as a group.

Moreover, we test for the second order serial correlation by implementing the Arellano and Bond (1991) test for autocorrelation. This test works under the null of "no autocorrelation" and asymptotically follows a standard normal distribution. The dynamic panel data model generally exhibits a first order serial correlation. However, for instruments to be strictly exogenous the residuals should not carry a second order serial correlation.

4.3.5 Data and Data Sources

We use an extensive data set which is accessed from various data sources. We use 3-dimensional panel data covering the time period 1981-2008, eighteen industries of the manufacturing sector, and five emerging economies. The data on industry level output, value added, employment, wages and salaries, and gross fixed capital formation are taken from the United Nation's Industrial Development Organization (UNIDO) database. We use two-digit International Standard Industrial Classification (ISIC) Revision 3 classification for manufacturing sector with twenty-eight industries.

We ensure, by following the standard practice, that there should be at least 10 industries for the selected countries and minimum 10 years of data on each industry is available. The selected number of industries remains constant over time and across counties. The panel combining countries, industries and time observations is unbalanced with some industries containing more observations than others. To avoid a large number of missing observations we drop some industries. Therefore, the final number of industries for which we conduct our empirical analysis is eighteen.

To measure the impact of technology diffusion, we use data on industry specific imports of technological products from the frontier country. For this purpose we use the following Standard International Trade Classification (SITC) for high technology products: chemicals and related products (SITC section 5), machinery and transport equipment (SITC section 7), professional and scientific instruments (SITC section 8.7).[10] In addition to this, we also use industry specific total imports of the selected emerging economies from the frontier country as a second measure of technology diffusion.

We match the SITC classification with ISIC classification. For this purpose, we use SITC data on three digit industries to match the data with the 2-digit ISIC categories.

[10] see, e.g., Madsen (2008).

The major decomposition of the SITC data was in the "food and live animals" and "tobacco". We drop the item code which represents the trade of "live animals" in the SITC categories and include the item codes which represents the trade of "beverages" to make it compatible with the ISIC classification of "food and beverages". This is done as we separate the SITC classification of "beverages and tobacco" in to two separate parts to make tobacco an independent classification just as in the ISIC classification. By following the similar scheme, we match other classification codes of SITC and ISIC to be compatible with each other. Data on industry specific import are accessed from the United Nation's commodity trade database.

We deflate industry level variables by using the producer price index (see, e.g., Imbs (2007)).[11] The data on PPI is accessed from International Financial Statistics (IFS) database by International Monetary Fund (IMF) published in 2012. We normalize the industry specific import of technological products and total industry specific import by the value added of the respective industry.

4.3.6 Summary Statistics

Table 4.1 presents the summary statistics of variables which are used in the estimation process. The mean value of the TFP level of non-frontier countries is lower than that of the frontier country. These estimate reveal that TFP level of non-frontier countries lies below the TFP level of the frontier country. However, the rate of TFP growth is higher in case of non-frontier countries which indicates catch-up of manufacturing industries of frontier and non-frontier countries. Lederman et al. (2005) also report a decreasing TFP gap among of south American countries towards the USA. Derviş (2012) reports catchup of emerging economies towards advanced economies. Lee (2009) also report productivity convergence in manufacturing industries of twenty-five OECD countries. Miller and Upadhyay (2002) provide ranks of TFP levels for a large sample of developed and developing countries based on different approaches. They find USA as the leading country whereas the TFP levels of other countries varies across different approaches to measure TFP levels. The dispersion in the TFP growth is extremely high for the case of non-frontier countries. TFP gap (measured as relative TFP level of non-frontier to the TFP level of frontier country) is negative which shows that non-frontier countries experience low TFP levels in manufacturing industries relative to the frontier country. Similarly, we can observe a negative capital stock gap and value added gap which indicates that the level of capital stock and value added is also lower in non-frontier country.

Moreover, the average value of capital stock in manufacturing industries of non-frontier countries is higher than the average value of the number of employees. Whereas, we ob-

[11] The data on industry specific price deflators for the selected sample of countries is not available.

serve higher dispersion for number of employees across manufacturing industries and over the selected time period. In addition, Table 4.1 reports the percentiles of the selected variables. The TFP growth is negative at the lowest percentile whereas as it turns to positive as we move towards higher percentiles of TFP growth in manufacturing industries of frontier and non-frontier countries. It is important to note that through out the percentile distribution, TFP growth in non-frontier countries remain higher than the TFP growth of the frontier country.

Table 4.2 presents the growth and relative TFP levels of manufacturing industries of all the selected non-frontier countries. We can observe that highest TFP growth is obtained by manufacturing industries of Philippines followed by and Indonesia and Singapore, respectively. The lowest positive TFP growth is maintained by manufacturing industries of Malaysia. On the other hand, the highest dispersion is observed in the TFP growth of manufacturing industries of Indonesia followed by Philippines, respectively.

Moving towards the relative TFP levels (TFP gap), we can observe that the largest gap between the TFP growth of manufacturing industries is for India whereas the lowest TFP gap is observed for manufacturing industries of Singapore. In contrast the largest variation in TFP gap is observed for manufacturing industries of Phillipines and lowest is reported for manufacturing industries of India followed by Singapore and Malaysia, respectively.

4.4 Empirical Results

At the first step, we examine the relationship between TFP growth in manufacturing industries of frontier and non-frontier countries without incorporating the role of technological transmission and its uncertainty. Having established this relationship, we next evaluate the role of technology diffusion, its uncertainty and other factors affecting TFP growth in manufacturing industries of selected non-frontier countries. We use capital-labor ratio, and real wage growth rate as control variables in all empirical specifications. It is important to note that through out our empirical estimation, the USA remains as the frontier country.

The specifications presented in Equations (4.3–4.4) are estimate five emerging economies. Column 2 of Tables 4.3– 4.4 report the estimates based on first measures of technology diffusion, i.e., import of technological products ratio to value added. In addition, we also estimate each specification by taking an alternative measure of technology diffusion i.e. industry specific total import from the frontier country. Columns 3 of Tables 4.3– 4.4 display the estimates based on this alternative measure of technology diffusion.

We report diagnostic tests in Panel B of each table to evaluate the model performance. The J statistics for all specifications indicates the acceptance of null hypothesis which verifies the orthogonality of our selected set of instruments. The Arellano and Bond (1991) test for autocorrelation rejects the presence of second order serial correlation in all models.

4.4.1 Productivity Convergence

Table 4.3 presents the results of baseline specification described in Equation (4.3). Particularly, column 2 displays the empirical estimates based on the proxy of technology diffusion measured as technological products import ratio to industry value added. Column 3 shows the results for display the estimates based on alternative measure of technology diffusion. We observe that the coefficient of the lagged TFP growth of non-frontier countries attains a negative sign and it is statistically significant at the 1% significance level. This negative coefficient indicates that low productive industries catch-up with high productive industries of non-frontier countries. The speed of convergence in these manufacturing industries is observed as 0.144%. Notably, the speed of convergence is very for the manufacturing industries of these emerging economies with the manufacturing industries of the USA. One important reason could be that the sample of five emerging economies include only those countries which are geographically located in the same region.

To identify the impact of technological development in the frontier country on the TFP growth of non-frontier countries, we augment our model with both the contemporaneous and lagged values of TFP growth of manufacturing industries of the frontier country. The coefficient attached to the contemporaneous and the lagged values of TFP growth of frontier country is positive and statistically significant. This specify that TFP growth in the frontier county leaves a positive impact on the TFP growth of manufacturing industries of non-frontier countries (col 2). The magnitude of the contemporaneous effect is higher than the lagged effect of TFP growth in manufacturing industries of the frontier country. However, we observe an insignificant lagged effect of TFP growth of the frontier country.

To estimate the impact of imports as a measure of technology diffusion, we use industry specific import of technological products of non-frontier countries from the frontier country. The coefficient of the technology diffusion is positive and statistically significant at the 5% level of significance. This result supports the findings of earlier studies which also report the positive impact of technology transfer from the frontier country on the TFP growth of non-frontier countries.

Next, we turn to observe the impact of TFP gap (TFP^{Gap}_{ijt-2}) on TFP growth of manufacturing industries of non-frontier countries.[12]The coefficient attached to the relative TFP levels or TFP gap is negative and statistically significant at the 5% significance level. The

[12]We employ Fisher test for panel unit root to test the order of integration between the TFP level of frontier and non-frontier countries. The test statistics reveal that both the series are integrated of order one. This is inline with the earlier studies which proposed that the relative TFP level should be integrated of order one.

negative coefficient confirms the TFP convergence in manufacturing industries of frontier and non-frontier countries. We can conclude based on this finding that countries which lies further behind the frontier have more potential of efficiency gain and therefore they will converge at faster rate towards the frontier country. Notably, the speed of catchup is three-times higher for the sample of five non-frontier counties which are geographically located in the same region.

4.4.2 Direct Impact of Uncertainty of Technology Diffusion

Having established the impact of technology diffusion and the relative TFP level, we now examine how the impact of technology diffusion and TFP gap changes when the model is augmented with the uncertainty of the technology diffusion. Table 4.4 presents the empirical estimates based on the specification given in Equation (4.4).

Column 2 verifies the initial results as we find a statistically significant and negative coefficient of the lagged value of the TFP growth of non-frontier countries. Moreover, this specification also indicates that the TFP growth in manufacturing industries of the frontier country maintains a positive and statistically significant impact on the TFP growth of non-frontier countries. Similar to the above, we observe a statistically significant impact of relative TFP level on TFP growth of manufacturing industries of non-frontier countries. This verifies a statistically significant convergence of TFP among manufacturing industries of the frontier and non-frontier countries. We observe a moderate decline in the speed of convergence. This states that uncertainty of the technology diffusion has an indirect negative impact on the speed of convergence of these five non-frontier countries.[13]

The coefficient of the industry specific technology diffusion is positive but statistically insignificant. The coefficient of uncertainty of technology diffusion ($\sigma_{ij,t}^{Trade}$) is negative and statistically significant at the 5% significance level. This negative impact dictates that the uncertainty of technological products reduces TFP growth in manufacturing industries of non-frontier countries.

From the results reported in Table 4-A, we observe that uncertainty of industry specific imports not only itself has a negative impact on the TFP growth of non-frontier countries but also weakens the speed of TFP convergence in manufacturing industries of the frontier and non-frontier countries. Also, it eliminates the positive impact of the technology diffusion for non-frontier countries.

[13] Table 4-A in Appendix A presents the estimates where Equation (4.3) is estimated by considering only the impact of uncertainty of technology diffusion. The uncertainty of technology diffusion is negative and lowers TFP growth persistence in manufacturing industries of non-frontier countries

4.4.3 Conditional Impact of Uncertainty of Technology Diffusion

Table 4.4 also reports the empirical estimates where we interact technology diffusion with its uncertainty. This is termed as conditional impact of uncertainty through different levels of technology diffusion. We observe that the coefficient of the interaction term is positive and statistically significant for non-frontier countries. This finding refers that the conditional impact of uncertainty through channel of technology diffusion is positive. When we combine the direct and conditional impact of the uncertainty of technology diffusion, we find that uncertainty of technology diffusion has negative impact on the TFP growth. However, the negative impact decreases as the level of technological diffusion increases from the frontier country. In other words, the negative impact of the uncertainty weakens as the technology diffusion increases.[14]

4.4.4 TFP Convergence through Channel of Transmission and Uncertainty

Turning to the conditional impact of TFP gap through technology diffusion which is captured by the interaction between TFP gap and the measure of technology diffusion and termed in Equation (4.4) as $(TFP^{GAP}_{ij,t-2} \times Tech_{ij,t-2})$, we observe that the coefficient of this interaction term is negative and statistically significant. This negative coefficient shows that non-frontier countries' import from the frontier country helps in the adjustment process towards the long run equilibrium point. Alternatively, we observe that the technology diffusion strengthens the process of TFP convergence.

By combining the direct and conditional impact of TFP gap, we observe TFP convergence in manufacturing industries of the frontier and non-frontier countries and the rate of convergence increase as the technology diffusion increases. Alternatively, we can conclude that the technology diffusion triggers the rate of TFP convergence. [15]

Next, we move towards the conditional impact of TFP gap through uncertainty of technology diffusion which is captured through the interaction between TFP gap and uncertainty of technology diffusion $(\sigma^{2,Tech}_{ij,t-2} \times TFP^{GAP}_{ij,t-2})$. The coefficient is statistically significant and positive. This reveal that uncertainty leads to divergence of TFP in manufacturing industries of frontier and non-frontier countries. By combining the direct and conditional impact of TFP gap through uncertainty, we find that the TFP convergence decreases as the level of uncertainty increases.

[14] Table 4-A.1 in Appendix A1 report the empirical results when we augment Equation (4.3) with with uncertainty of technology diffusion and an interaction term of technology diffusion and is uncertainty. This table indicates that if we only keep the direct and conditional impact of uncertainty of technology diffusion, the direction of impact does not change. Therefore, our findings are consistent across different specifications

[15] In Appendix A2, Table 4-A.2 presents the empirical results excluding the conditional impact of TFP gap through uncertainty of technology diffusion. We observe that technology diffusion strengthens the convergence process which is depicted through a negative coefficient of the interaction term of technology diffusion and TFP gap.

4.4.5 Robustness Check: Alternative Channel of Transmission

We also estimate specifications given in Equations (4.3–4.4) by using industry specific total imports from the frontier country as an alternative measure of technology diffusion. column 3 of Tables 4.3– 4.4 present these results. In all the results based on industry specific total imports, we find a statistically significant and negative coefficient of the lagged TFP growth of non-frontier countries. This finding states that there is convergence among the low and high productive industries of non-frontier countries. Moreover, in all of our specifications, we find a significant and negative coefficient of the relative TFP levels. This finding suggests that in both of our samples, there is significant adjustment towards the long run equilibrium point.

The direct impact of total industry specific import from the frontier country on the TFP growth of non-frontier countries is statistically significant and positive. However, the magnitude of the impact of total industry specific imports is higher than the impact of the technological products import.

Finally, the impact of uncertainty of total import is larger than the impact of uncertainty of technological products' imports from the frontier country, though remain negative. In addition, we estimate the secondary channel of the effect through which uncertainty affects the TFP growth. The conditional impact of uncertainty is positive and statistically significant. This implies that the negative impact of uncertainty weaken at higher levels of technology diffusion.[16]

This robustness check implies that the technological products' imports play more important role in the technology diffusion from the frontier towards non-frontier countries. Also, TFP convergence is higher in the case of industry specific technological products import as compared to industry specific total imports.[17]

4.4.6 Total Impact of Changes in Uncertainty and TFP Gap

In addition to evaluating the marginal impact, both unconditional and conditional, we also compute the total effect of both uncertainty and TFP gap on the TFP growth of non-frontier countries. To compute the total impact, we calculate the total derivative of the TFP growth Equation (4.4) with respect to uncertainty of technology diffusion and TFP gap. We compute total effect at the $25th$, $50th$, $75th$, and $90th$ percentiles of conditioning variables. We report first order derivative with respect to uncertainty of technology diffusion and TFP gap. Also, we plot the total effect of both uncertainty and TFP gap which is displayed in Figure 4.3.

[16] Table 4-A, 4-A.1, and 4-A.2 report some additional estimates to support that our findings are robust across various specifications

[17] For the sake of brevity, we do not report the estimates of total effect of uncertainty of industry specific total imports. However, they are available from author upon request.

Table 4.5 reports the total effect conditional on technology diffusion. Panel A reports the total impact of uncertainty of technology diffusion on TFP growth of non-frontier countries conditional on the industry specific technology diffusion. The total impact of uncertainty remains positive and statistically significant across all the percentiles of technology diffusion. Also the positive impact strengthens as we move towards higher percentiles of technology diffusion. This finding is confirmed from the empirical estimates given in table 4 where we can observe that the direct negative impact of uncertainty of technology imports (-0.012) is lower than the indirect positive impact of uncertainty (0.039). This suggests that the positive impact outweigh the negative impact of uncertainty of technological products' import. Figure 4.1 display the total impact of uncertainty of technology diffusion which also confirms that uncertainty impact on TFP growth throughout remains positive and it becomes stronger at higher levels of technology diffusion.

Next, We turn to evaluate the total effect of TFP gap on the TFP growth of non-frontier countries conditional on technology diffusion. The computed total effect is presented in panel B of Table 4.5. We can observe from that the total impact of TFP gap is negative and statistically significant across all percentiles of technology diffusion. Moreover, the magnitude of this impact is increasing as we move towards the upper tail of percentile distribution of technology diffusion. This finding is further strengthened by Figure 4.2 which depicts a monotonically decreasing impact of TFP gap on TFP growth of non-frontier countries. Thus it suggests an improvement in the convergence process at higher levels of technology diffusion.

Finally, we examine the total impact of TFP gap through various levels of technology diffusion uncertainty. Table 4.6 reports these estimates. We observe that the total impact of TFP gap through uncertainty of technology diffusion is positive and statistically significant across all percentiles of uncertainty of technology diffusion. This implies that uncertainty of technology diffusion leads to TFP divergence in manufacturing industries of non-frontier and frontier countries. Figure 4.3 also portrays that as the uncertainty of technology diffusion increases, the rate of TFP divergence increases.

In conclusion, our findings suggest a significant evidence of TFP convergence among manufacturing industries of the frontier and non-frontier countries. Moreover, we also report the evidence that the rate of convergence is higher for the countries which are geographically located in the same region. Also, uncertainty not only has a significant direct impact but it also effects the TFP growth through the second channel.

4.5 Conclusions

A growing body of empirical literature has focused on the importance of international linkages particularly international trade in the convergence process among countries with different levels of productivity. The recent empirical literature argues that international trade helps in diffusion of knowledge and technology from technologically advanced counties towards technologically lagging countries. This diffusion process helps in improving the TFP growth and thus convergence among these countries.

In this study, we investigate the long run convergence of TFP growth of manufacturing industries of five emerging economies. To do so, we use data for manufacturing industries of these large emerging economies over the time period 1981-2008. We use the USA as the frontier country and empirically test whether the technology transfer from the USA towards emerging economies improves the TFP growth and the convergence process. Furthermore, we empirically test the impact of uncertainty of industry specific technological products' imports on the TFP growth of non-frontier countries.

We employ an extensive data set to carry out our empirical investigation. We use a three dimensional panel dataset covering the period 1981-2008, five emerging economies and eighteen manufacturing industries. We use UNIDO database to obtain the data on the two digit ISIC revision 3 classification for the manufacturing sector. In addition to this, we use UN commodity trade database to obtain the data on the industry specific technological products' import. Further, we match ISIC codes with SITC codes to make the data compatible with ISIC classification of two-digit industries.

We compute relative TFP level of non-frontier countries with respect to frontier country by using superlative index number approach. To estimate the long run dynamics of TFP growth of non-frontier countries, we use the dynamic panel data estimator, two step system GMM.

Our empirical results provide a significant evidence that there is convergence among manufacturing industries of the frontier and non-frontier countries. Also, we report a statistically significant and positive impact of international transmission of technology on the TFP growth of the non-frontier countries. However, there is negative impact of uncertainty of imports on the TFP growth. We report that the negative impact of uncertainty decreases as the level of technology diffusion increases. Particulary at the $50th$ percentile of technology imports the negative impact of uncertainty turns in to positive. In the similar vein, we conclude that the technology diffusion facilitates the convergence process of TFP growth of manufacturing industries of the frontier and non-frontier countries.

Collectively, we can conclude that there is significant direct and conditional role of technological diffusion in the convergence process. Moreover, the uncertainty impact weakens at the higher level of technology diffusion. Our findings contribute in to the existing literature by providing the evidence on how uncertainty affects the TFP growth and its convergence through direct and indirect channel. Moreover, we also provide evidence of the direct and indirect impact of technology diffusion in the convergence process. A future research could be based on implementing this analysis on the firm level data for an extended number of countries. Moreover, the role of factor intensity gap can also be explored in the TFP convergence among the non-frontier and frontier countries.

Table 4.1: **Summary Statistics of Selected Variables**

Variables	**Mean**	**Std.Dev**	P_{10}	P_{50}	P_{90}
$TFP_{nonfrontier}$	1.526	0.925	0.458	1.545	2.460
$TFP_{frontier}$	2.215	0.903	1.126	2.291	3.319
TFP_{gap}	-0.692	1.348	-2.192	-0.878	0.883
$\Delta TFP_{nonfrontier}$	0.055	0.184	-0.061	0.028	0.138
$\Delta TFP_{frontier}$	0.011	0.096	-0.034	0.016	0.061
$Tech.Import$	20.431	4.696	1.214	4.689	15.376
$K.Stock_{nonfrontier}$	17.630	0.028	16.292	17.630	18.975
$Employmee_{nonfrontier}$	10.692	2.735	9.764	10.712	11.721
$VA_{nonfrontier}$	16.485	22.966	15.317	16.327	17.348
$K.Stock_{gap}$	3.102	1.805	2.047	3.103	4.315
$Employee_{gap}$	2.763	174.50	1.947	2.896	3.847
VA_{gap}	4.035	0.703	3.224	4.248	5.149

Note: This table presents the summary statistics of variables used in empirical estimation. The statistics are based on the sample of five large trading partners of the USA among the emerging economies in Asia. These countries include India, Indonesia, Malaysia, Philippines, and Singapore. The time period under consideration ranges from 1981-2008. The variables with the subscript of 'non-frontier' refers to the statistics of selected emerging economies whereas variables with the subscript of 'gap' indicates gap between the non-frontier and frontier country for indicated variables. Tech.Import is used for the technological good's import. K.Stock, Employee, VA denote capital stock, number of employees and value added in manufacturing industries of emerging economies(non-frontier countries)

Table 4.2: TFP Growth and TFP Gap of Emerging Economies

Countries	TFP Growth		TFP Gap	
	Mean	Std.Dev.	Mean	Std.Dev.
India	0.037	(0.154)	-1.293	(1.076)
Indonesia	0.101	(0.235)	-0.898	(1.202)
Malaysia	0.024	(0.158)	-0.442	(1.159)
Philippines	0.110	(0.224)	-0.845	(1.376)
Singapore	0.036	(0.154)	-0.082	(1.124)

Note: This table presents the Mean and Standard Deviation of the TFP growth and TFP gap(relative TFP) between frontier and all the selected non-frontier countries. These countries include India, Indonesia, Malaysia, Philippines, and Singapore. The time period under consideration ranges from 1981-2008.

Table 4.3: GMM Estimates of the TFP Growth Convergence and Technological Diffusion

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Tech. Import**		**Total Import**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP^{gap}_{ij,t-1}$	-0.144	(0.055**	-0.063	(0.031)**
$TFP^{nonfrontier}_{ij,t-1}$	-0.213	(0.069)***	-0.130	(0.064)**
$TFP^{frontier}_{ij,t}$	0.590	(0.211)***	0.335	(0.190)*
$TFP^{frontier}_{ij,t-1}$	0.242	(0.233)	0.242	(0.113)**
$Tech.Diffusion_{ij,t-1}$	0.019	(0.009)**	0.089	(0.039)**
$Wages^{nonfrontier}_{ij,t-1}$	0.248	(0.123)**	0.311	(0.113)***
$FI_{ij,t-1}$	0.118	(0.071)*	0.052	(0.022)***
Constant	-0.952	(0.516)*	-0.353	(0.161)**
Year Fixed Effects		Yes		Yes

Panel B: Diagnostic tests		
$Observations$	789	789
$J-Stat$	67.070	59.880
$p-value$	0.248	0.656
$AR(2)$	-1.540	-0.330
$p-value$	0.590	0.742

Note:

$$\triangle TFP^{nonfrontier}_{ijt} = \alpha_0 + \gamma_0 \triangle TFP^{nonfrontier}_{ijt-1} + \gamma_1 \triangle TFP^{frontier}_{jt} + \gamma_2 \triangle TFP^{frontier}_{jt-1}$$
$$- \Omega_0 \left(TFP^{Gap}_{ijt-2}\right) + \psi_0 Tech_{ijt-1} + \lambda X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates on the TFP convergence between the USA and selected non-frontier countries. Also, it repots the impact of the technology diffusion (measured as the technological goods imports ratio to value added) on the TFP growth of the non-frontier countries over the time period 1981-2008 . The dependent variable is TFP growth of eighteen manufacturing industries in the selected sample of non-frontier countries. Column 2 covers the estimates of the TFP convergence based on the first measure of technological diffusion i.e. industry specific imports of technological goods. Column 3 repeats the same exercise by using the alternative measure of technological diffusion. i.e. total imports of manufacturing industries. The sample of five emerging economies India, Indonesia, Malaysia, Philippines, and Singapore. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second-fifth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test instruments validity whereas autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. Real wages growth rate and capital-labor ratio of industries are used as control variables. ***,**, and * indicate level of significance at the 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

Table 4.4: GMM Estimates of the Conditional TFP Convergence, Conditional Uncertainty of Technology Diffusion

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Tech. Imports**		**Total Imports**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP^{gap}_{ij,t-1}$	-0.134	(0.062)**	-0.071	(0.042)*
$TFP^{nonfrontier}_{ij,t-1}$	-0.224	(0.076)**	-0.121	(0.069)*
$TFP^{frontier}_{ij,t}$	0.581	(0.235)**	0.329	(0.171)*
$TFP^{frontier}_{ij,t-1}$	0.226	(0.154)	0.149	(0.156)
$Tech.Diffusion_{ij,t-1}$	0.051	(0.041)	0.090	(0.155)
$\sigma^{2,Tech}_{ij,t-1}$	-0.012	(0.004)***	-0.101	(0.047)**
$Tech \times \sigma^{2,Tech}_{ij,t-1}$	-0.028	(0.016)*	-0.027	(0.015)*
$Tech_{ij,t-2} \times TFP^{Gap}_{ij,t-2}$	-0.016	(0.008)*	-0.006	(0.009)
$\sigma^{2,Tech}_{ij,t-2} \times TFP^{Gap}_{ij,t-2}$	0.065	(0.032)**	-0.035	(0.021)
$Wages^{nonfrontier}_{ij,t-1}$	0.337	(0.167)**	0.136	(0.059)**
$FI_{ij,t-1}$	0.167	(0.077)**	0.061	(0.035)*
Constant	-1.023	(0.529)*	0.061	(0.035)*
Year Fixed Effects	Yes		Yes	

Panel B: Diagnostic tests		
$Observations$	701.000	789.000
$J-Stat$	62.030	58.240
$p-value$	0.740	0.896
$AR(2)$	-0.700	-0.320
$p-value$	0.486	0.752

Note:

$$\begin{aligned}\triangle TFP^{nonfrontier}_{ijt} &= \alpha_0 + \gamma_0 \triangle TFP^{nonfrontier}_{ijt-1} + \gamma_1 \triangle TFP^{frontier}_{jt} + \gamma_2 \triangle TFP^{frontier}_{jt-1} \\ &- \Omega_0 \left(TFP^{Gap}_{ijt-2}\right) + \psi_0 Tech_{ijt-1} + \psi_1 \sigma^{Tech}_{ijt-1} + \psi_2 Tech_{ij,t-1} \times \sigma^{Tech}_{ij,t-1} \\ &+ \psi_3 Tech_{ij,t-2} \times TFP^{GAP}_{ij,t-2} + \psi_4 \sigma^{Tech}_{ijt-2} \times TFP^{GAP}_{ij,t-2} + \lambda X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}\end{aligned}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates on the TFP convergence between the USA and selected non-frontier countries. Also, it repots the impact of the technology diffusion (measured as the technological goods imports ratio to value added)on the TFP growth of the non-frontier countries over the time period 1981-2008 . The dependent variable is TFP growth of eighteen manufacturing industries in the selected sample of non-frontier countries. Column 2 covers the estimates of the TFP convergence based on the first measure of technological diffusion i.e. industry specific imports of technological goods. Column 3 repeats the same exercise by using the alternative measure of technological diffusion. i.e. total imports of manufacturing industries. The sample of five emerging economies India, Indonesia, Malaysia, Philippines, and Singapore. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second-fifth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test instruments validity whereas autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. Real wages growth rate and capital-labor ratio of industries are used as control variables. ***,**, and * indicate level of significance at the 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

Table 4.5: Percentiles of Total Effect:Conditional on Technology Diffusion

Panel A: Total Effect of Technology Diffusion's Uncertainty					
$P_{TechImports}$	0.753	1.937	6.166	15.927	36.931
F.O.D	-0018	0023	0.366*	1.278**	2.858**
S.E	(0.056)	(0.068)	(0.219)	(0.629)	(1.437)

Panel B: Total Effect of Industry Specific TFP Gap					
$P_{TechImports}$	0.753	1.937	6.166	15.927	36.931
F.O.D	-0.167***	-0.187***	-0.259***	-0.424***	-0.780***
S.E	(0.050)	(0.051)	(0.065)	(0.121)	(0.260)

Note: Panel A of the table reports the computation of the total effect of uncertainty of technology diffusion conditional on the level of technological diffusion. Panel A of the table reports the computation of the total effect of the TFP gap conditional on the technology diffusion. The dependent variable is the TFP growth of the eighteen manufacturing industries in the selected sample of five emerging economies in Asia. These countries include India, Indonesia, Malaysia, Philippines, and Singapore. The time period for estimation is 1981-2008. ***,**, and * indicate level of significance at the 1%, 5%, and 10% level of significance, respectively. F.O.D indicates first order derivative of dependent variable with respect to uncertainty of industry-specific technology diffusion and TFP gap. S.E shows Standard errors given in parenthesis.

Table 4.6: Percentiles of Total Effect:Conditional on Technology Diffusion Uncertainty

Total Effect of Industry Specific TFP Gap

	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}
$P_{Uncertainty}$	0.683	1.491	2.154	3.134	3.983
F.O.D	0.168	0.551*	0.864*	1.328**	1.730**
S.E	(0.144)	(0.319)	(0.466)	(0.684)	(0.873)

Note: Panel A of the table reports the computation of the total effect of TFP gap conditional on the technology diffusion uncertainty. The dependent variable is the TFP growth of the eighteen manufacturing industries in the selected sample of emerging economies. These countries include India, Indonesia, Malaysia, Philippines, and Singapore. The time period for estimation is 1981-2008. ***,**, and * indicate level of significance at the 1%, 5%, and 10% level of significance, respectively. F.O.D indicates first order derivative of dependent variable with respect to uncertainty of industry-specific technological goods' imports. S.E shows Standard errors given in parenthesis.

Figure 4.1: Uncertainty Impact of Technology Imports

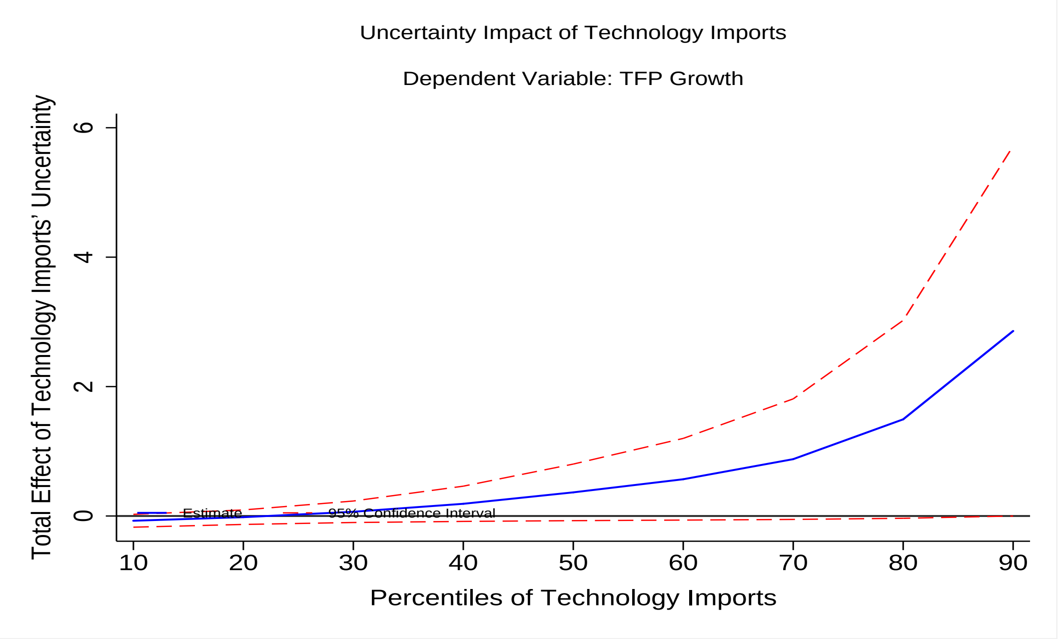


Figure 4.2: TFP Gap Convergence Through Technology Diffusion

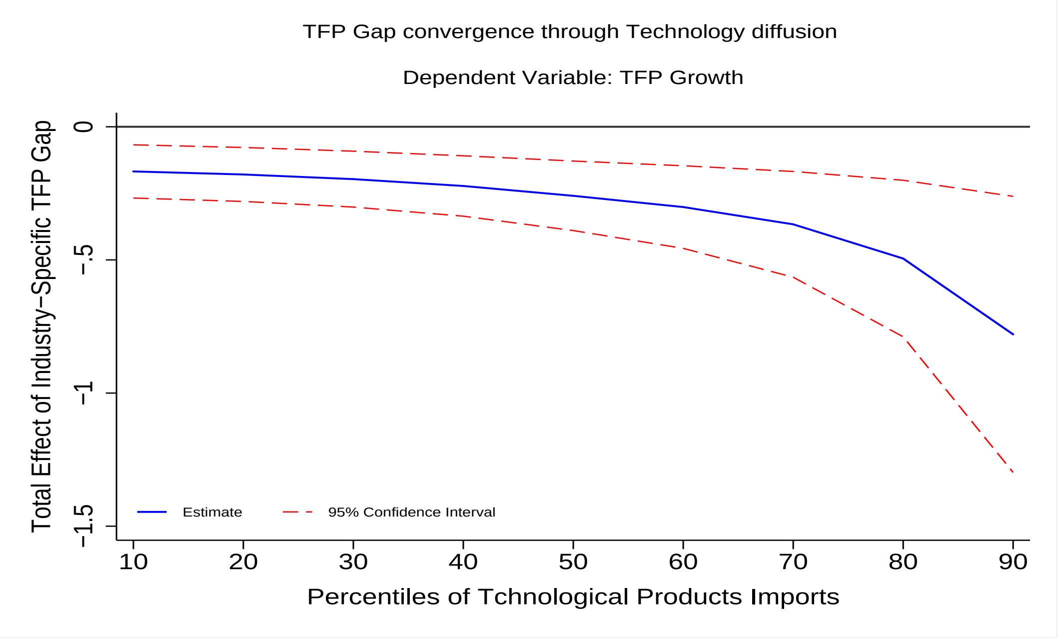
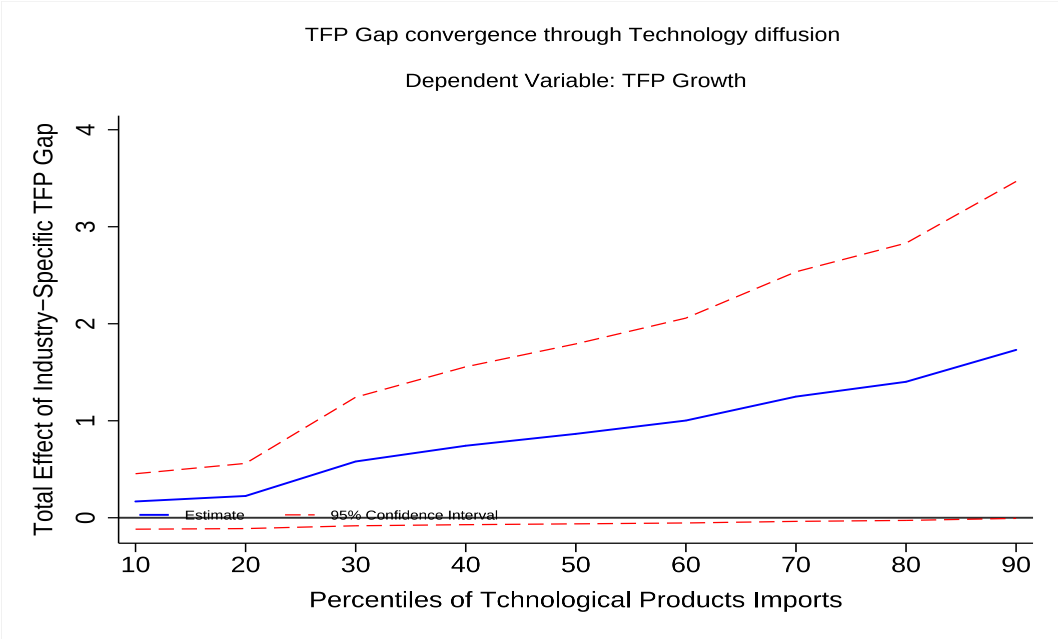


Figure 4.3: TFP Gap Convergence Through Technology Diffusion Uncertainty



Appendix A: Empirical Estimates based on Technological Diffusion

Table 4-A: GMM Estimates of the TFP Growth Convergence, Conditional Uncertainty, and TFP Gap through Technological Diffusion

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Tech. Imports** Coeff.	Std.Err.	**Total. Imports** Coeff.	Std.Err.
$TFP^{gap}_{ij,t-1}$	-0.116	(0.045)**	-0.053	(0.023)**
$TFP^{nonfrontier}_{ij,t-1}$	-0.156	(0.070)**	-0.140	(0.067)**
$TFP^{frontier}_{ij,t}$	0.502	(0.166)***	0.473	(0.200)**
$TFP^{frontier}_{ij,t-1}$	0.222	(0.205)	0.098	(0.138)
$Import^{Technology}_{ij,t-1}$	0.025	(0.013)*	0.020	(0.010)*
$\sigma^{2,Tech}_{ij,t-1}$	-0.006	(0.003)**	-0.008	(0.005)*
$Wages^{nonfrontier}_{ij,t-1}$	-0.046	(0.058)	0.400	(0.130)***
$FI_{ij,t-1}$	0.174	(0.054)***	0.053	(0.025)**
Constant	-1.187	(0.377)**	-0.409	(0.168)**
Year Fixed Effects	Yes		Yes	
Panel B: Diagnostic tests				
$Observations$	789.000		789.000	
$J-Stat$	66.430		65.900	
$p-value$	0.799		0.888	
$AR(2)$	-0.420		-0.460	
$p-value$	0.677		0.648	

Note:

$$\triangle TFP^{nonfrontier}_{ijt} = \alpha_0 + \gamma_0 \triangle TFP^{nonfrontier}_{ijt-1} + \gamma_1 \triangle TFP^{frontier}_{jt} + \gamma_2 \triangle TFP^{frontier}_{jt-1}$$
$$- \Omega_0 \left(TFP^{Gap}_{ijt-2}\right) + \psi_0 Tech_{ijt-1} + \psi_1 \sigma^{Tech}_{ijt-1} + \lambda X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates on the TFP convergence between the USA and selected non-frontier countries. Also, it repots the impact of the technology diffusion (measured as the technological goods imports ratio to value added)on the TFP growth of the non-frontier countries over the time period 1981-2008 . The dependent variable is TFP growth of eighteen manufacturing industries in the selected sample of non-frontier countries. Column 2 covers the estimates of the TFP convergence based on the first measure of technological diffusion i.e. industry specific imports of technological goods. Column 3 repeats the same exercise by using the alternative measure of technological diffusion. i.e. total imports of manufacturing industries. The sample of five emerging economies India, Indonesia, Malaysia, Philippines, and Singapore. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second-fifth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test instruments validity whereas autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. Real wages growth rate and capital-labor ratio of industries are used as control variables. ***,**, and * indicate level of significance at the 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

A.1 Empirical Estimates based on Technological Import

Table 4-A.1: GMM Estimates of the TFP Growth Convergence, Conditional Uncertainty, and TFP Gap through Technological Diffusion

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Tech.Imports**		**Total.Imports**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP^{gap}_{ij,t-1}$	-0.141	(0.055)**	-0.065	(0.030)**
$TFP^{nonfrontier}_{ij,t-1}$	-0.246	(0.084)***	-0.158	(0.078)**
$TFP^{frontier}_{ij,t}$	0.400	(0.195)**	0.454	(0.211)**
$TFP^{frontier}_{ij,t-1}$	0.091	(0.272)	0.167	(0.144)
$Import^{Technology}_{ij,t-1}$	0.022	(0.011)**	0.040	(0.021)*
$\sigma^{2,Tech}_{ij,t-1}$	-0.013	(0.006)**	-0.042	(0.020)**
$Tech \times \sigma^{2,Tech}_{ij,t-1}$	0.081	(0.039)**	-0.025	(0.009)***
$Wages^{frontier}_{ij,t-1}$	0.260	(0.104)**	0.417	(0.131)***
$FI_{ij,t-1}$	0.232	(0.083)***	0.054	(0.031)*
Constant	-1.500	(0.512)***	-1.432	(0.211)**
Year Fixed Effects	Yes		Yes	
Panel B: Diagnostic tests				
$Observations$	789.000		789.000	
$J-Stat$	57.100		67.380	
$p-value$	0.582		0.750	
$AR(2)$	-0.600		-0.440	
$p-value$	0.549		0.659	

Note:

$$\begin{aligned}\triangle TFP^{nonfrontier}_{ijt} &= \alpha_0 + \gamma_0 \triangle TFP^{nonfrontier}_{ijt-1} + \gamma_1 \triangle TFP^{frontier}_{jt} + \gamma_2 \triangle TFP^{frontier}_{jt-1} \\ &- \Omega_0 \left(TFP^{Gap}_{ijt-2}\right) + \psi_0 Tech_{ijt-1} + \psi_1 \sigma^{Tech}_{ijt-1} + \psi_2 Tech_{ij,t-1} \times \sigma^{Tech}_{ij,t-1} + \lambda X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}\end{aligned}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates on the TFP convergence between the USA and selected non-frontier countries. Also, it repots the impact of the technology diffusion (measured as the technological goods imports ratio to value added)on the TFP growth of the non-frontier countries over the time period 1981-2008 . The dependent variable is TFP growth of eighteen manufacturing industries in the selected sample of non-frontier countries. Column 2 covers the estimates of the TFP convergence based on the first measure of technological diffusion i.e. industry specific imports of technological goods. Column 3 repeats the same exercise by using the alternative measure of technological diffusion. i.e. total imports of manufacturing industries. The sample of five emerging economies India, Indonesia, Malaysia, Philippines, and Singapore. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second-fifth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test instruments validity whereas autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. Real wages growth rate and capital-labor ratio of industries are used as control variables. ***,**, and * indicate level of significance at the 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

A.2 Empirical Estimates based on Technological Diffusion

Table 4-A.2: GMM Estimates of the TFP Growth Convergence, Conditional Uncertainty, and TFP Gap through Technological Diffusion

Panel A: Estimation Results: Dependent Variable: TFP Growth				
Regressors.	**Tech.Imports**		**Total.Imports**	
	Coeff.	Std.Err.	Coeff.	Std.Err.
$TFP^{gap}_{ij,t-1}$	-0.112	(0.055)**	-0.071	(0.033)**
$TFP^{nonfrontier}_{ij,t-1}$	-0.203	(0.087)**	-0.114	(0.067)*
$TFP^{frontier}_{ij,t}$	0.537	(0.226)**	-0.047	(0.256)
$TFP^{frontier}_{ij,t-1}$	0.042	(0.205)	0.222	(0.103)**
$Import^{Technology}_{ij,t-1}$	-0.086	(0.052)	0.036	(0.021)*
$\sigma^{2,Tech}_{ij,t-1}$	-0.012	(0.004)***	-0.063	(0.031)**
$Tech \times \sigma^{2,Tech}_{ij,t-1}$	0.039	(0.021)*	-0.039	(0.002)
$Tech \times TFP^{Gap}_{ij,t-1}$	-0.020	(0.009)**	-0.040	(0.017)**
$Wages^{nonfrontier}_{ij,t-1}$	-0.115	(0.122)	0.257	(0.113)**
$FI_{ij,t-1}$	0.252	(0.105)**	0.065	(0.031)**
Constant	-1.575	(0.661)**	-0.476	(0.207)**
Year Fixed Effects	Yes		Yes	
Panel B: Diagnostic tests				
$Observations$	789.000		789.000	
$J-Stat$	60.760		58.310	
$p-value$	0.865		0.878	
$AR(2)$	-0.470		0.150	
$p-value$	0.636		0.877	

Note:

$$\begin{aligned}\triangle TFP^{nonfrontier}_{ijt} &= \alpha_0 + \gamma_0 \triangle TFP^{nonfrontier}_{ijt-1} + \gamma_1 \triangle TFP^{frontier}_{jt} + \gamma_2 \triangle TFP^{frontier}_{jt-1} \\ &- \Omega_0 \left(TFP^{Gap}_{ijt-2}\right) + \psi_0 Tech_{ijt-1} + \psi_1 \sigma^{Tech}_{ijt-1} + \psi_2 Tech_{ij,t-1} \times \sigma^{Tech}_{ij,t-1} \\ &+ \psi_3 Tech_{ij,t-2} \times TFP^{GAP}_{ij,t-2} + \lambda X_{ij,t} + f_{ij} + \zeta_t + \varepsilon_{ij,t}\end{aligned}$$

Panel A of the table reports the estimates obtained from robust two-step System-GMM estimations. This table presents the estimates on the TFP convergence between the USA and selected non-frontier countries. Also, it repots the impact of the technology diffusion (measured as the technological goods imports ratio to value added)on the TFP growth of the non-frontier countries over the time period 1981-2008 . The dependent variable is TFP growth of eighteen manufacturing industries in the selected sample of non-frontier countries. Column 2 covers the estimates of the TFP convergence based on the first measure of technological diffusion i.e. industry specific imports of technological goods. Column 3 repeats the same exercise by using the alternative measure of technological diffusion. i.e. total imports of manufacturing industries. The sample of five emerging economies India, Indonesia, Malaysia, Philippines, and Singapore. The one period lagged values of the first difference of the independent variables are used as instruments for the equations in levels whereas for the differenced equations, the second-fifth lag of the independent variables are used as instruments. Panel B reports the diagnostics test. J statistics is used to test instruments validity whereas autocorrelation in first differenced residuals is tested through the Arellano-Bond, AR(2) test. Real wages growth rate and capital-labor ratio of industries are used as control variables. ***,**, and * indicate level of significance at the 1%, 5%, and 10% level of significance, respectively. Standard errors are displayed in the parenthesis which are robust to the presence of serial correlation and heteroskedasticity within panels.

Chapter 5

Summary and Conclusions

This dissertation presents an empirical investigation on three important macroeconomic areas. The first study of this dissertation estimates the optimal policy reaction function accounting for asymmetric preferences concerning the fluctuations of inflation and output gap for their respective targets. We also allow optimal policy to respond to expected changes in real exchange rate.

We estimate optimal reaction function using quarterly data of four central banks namely, Canada, Japan, the UK, and the US over the period 1979q1-2007q4. Our estimates provide significant evidence in favor of asymmetric behavior of all the central banks towards changes in target variables i.e., inflation rate and output gap. This implies that central banks weigh the negative and the positive deviations of inflation and output gap from their respective targets differently. Specifically, we find that the coefficient of inflation volatility is positive suggesting that central banks change the nominal interest rate more when inflation exceeds the target level rather than when it falls below. Further, we also observe central banks have asymmetric preferences towards negative and positive deviations of output gap from its target. Although we expect to see that a central bank should be more concerned when output gap falls below the target, for some cases we find that the central bank can be more reactionary during periods of positive output gap. We address this observation arguing that the central banks may be inflation averse and may take a positive output gap as an indicator of future inflation. Further, we have found significant evidence that central banks pursue an active monetary policy as they increase the interest rate for more than one-to-one change in expected inflation.[1]We also observe that foreign policy variables have a significant impact on domestic monetary policy.[2] This view is based not only on the significant effect of real exchange rate and foreign real interest rate on domestic monetary policy but also on estimates of various closed economy models. We find that once we relax the open economy assumption, the sign of asymmetry parameters changes providing evidence of specification error, which might be driven by an omitted variable problem. Our empirical results suggest that domestic monetary authorities need to observe the changes in foreign monetary policy to avoid sudden capital inflows or outflows, which can further lead to exchange rate disturbances.

[1]Researchers such as Kydland and Prescott (1977), Barro and Gordon (1984), Blanchard and Fischer (1989), and Taylor (1993) have provided evidence on the effectiveness of monetary policy.

[2]Despite large number of studies on monetary policy asymmetries, there is lack of evidence on the asymmetric behavior of central banks in an open economy framework. Studies such as Ball (1999b), Svensson (2000), Leitemo et al. (2002), Leitemo and Söderström (2005), Dolado et al. (2005), and Adolfson et al. (2008) among others analyze the response of monetary policy towards changes in the international factors.

while this chapter has contributed in many important aspects to the literature of optimal monetary policy, there are yet some unexplored areas that could be further examined to provide a worthwhile extension to the existing work. We believe that it would be fruitful to model and empirically investigate the interest rate-smoothing hypothesis implementing a framework as in this paper. Also, expanding the set of countries under investigation can broaden our understanding. Finally, in line with the recommendation of Lubik and Marzo (2007b) one can pursue a multivariate approach by estimating the entire structural model using system GMM. Although,Lubik and Marzo (2007b) argue that full-information maximum likelihood exploits cross-equation restrictions, Ruge-Murcia (2007b) shows that limited information procedures are more robust to model misspecification. Ruge-Murcia (2007b) shows that GMM and simulated method of moment deliver more precise estimates than maximum likelihood. Thus, it would be useful to extend the current study employing system GMM approach to account both for the recommendations of Lubik and Marzo (2007b) and Ruge-Murcia (2007b).

Chapter three of this dissertation examines the role of different types of uncertainty on TFP growth of manufacturing industries of emerging economies over the period 1971-2008. A large number of studies empirically evaluate the impact of aggregate uncertainty on macroeconomic performance. However, there is not enough empirical evidence on how uncertainty originating from different sources affects TFP growth of manufacturing industries. Therefore, we estimate the impact of uncertainty stemming from industry, country, and world level on TFP growth. To proxy uncertainty, we have computed the time-varying measure of each type of uncertainty by using an AR (1) model. More concretely, we compute industry-specific uncertainty as the cumulative variance of industry-specific output ratio to manufacturing sector output, country-specific uncertainty as the cumulative variance of country investment ratio to country GDP, and world uncertainty as the cumulative variance of world inflation rate. We also estimate the impact of uncertainty on TFP growth conditional on other factors such as industry size, factor intensity, and the level series of each type of uncertainty. Hence, we not only instigate the direct impact of uncertainty on TFP growth but also the conditional impact.

To carry out our empirical estimation, we employ a two-step system GMM approach. Our empirical results suggest a statistically significant impact of each source of uncertainty on TFP growth. We have found that the impact of industry and country-specific uncertainty is positive whereas the impact of world uncertainty is negative on TFP growth. This implies that uncertainty forces industries towards more research and development activities. This increases the shock absorption capacity of industries: therefore TFP growth in following years will increase. This finding suggests that manufacturing industries need to increase their R&D activities in order to maintain a positive TFP growth in times of industry and country-specific uncertainty.

The empirical estimates of conditional impact of uncertainty through industry size show that as industry size increases, the positive impact of industry-specific uncertainty increases. However, the positive impact of country-specific uncertainty weakens as the industry size increases. Also, the negative impact of world uncertainty increases for larger industries. Turning towards the conditional impact of each type of uncertainty through factor intensity, we find that as factor intensity level increases, the positive impact of industry-specific uncertainty increases. Notably, the positive impact of country-specific uncertainty strengthens at higher levels of factor intensity. In contrast, the negative impact of world uncertainty monotonically increases as factor intensity increases. This finding suggests that inflation has more adverse impact on industries with higher capital-labor ratio.

The conditional impact of industry-specific uncertainty through manufacturing industries' output indicates that there is monotonic decrease in the positive impact of industry-specific uncertainty as we move on higher levels of industry output. The conditional impact of country-specific uncertainty through investment indicates that as the level of country investment increases the positive impact of country-specific uncertainty weakens. Finally, the interaction of world uncertainty with world inflation rate has shown a positive sign, which identifies that the negative impact of world uncertainty weakens at a higher level of world inflation.

Chapter three has pointed out the significant impact of industry, country, and world uncertainty on the TFP growth of manufacturing industries of emerging economies. This finding suggests that not only the domestic but also the international source of uncertainty influences the TFP growth. Therefore manufacturing industries, while making the investment decision, need to adopt measures that have built-in shock-resisting capacity particularly when the industries are confronted with negative shocks (either domestic or international). The empirical results from chapter three have also indicated that for industries with higher capital-labor ratio, the negative impact of global uncertainty is lower. This may suggest that manufacturing industries that lack the capital investment, may have to invest to increase physical capital relative to labor.

This chapter contributes to the existing literature in various aspects, yet we believe this analysis could be further extended as follows: In the third chapter, the focus of our analysis is to empirically evaluate the role of different types of uncertainties on TFP growth of manufacturing industries. As TFP growth is the sum of three different components namely, technical progress, technical efficiency, and scale component. It would be useful to conduct an in-depth analysis of how different types of uncertainty affect these components of TFP growth separately. Another extension to the present work could be done by estimating the impact of different sources of uncertainty on labor productivity. Finally, future research could be directed to examine the impact of different types of uncertainty on TFP growth of manufacturing industries under different classifications.

There is a growing body of literature that has explored the role of technology diffusion in convergence but overwhelmingly the focus of these studies remains the convergence among advanced economies or more precisely the OECD economies. There is not enough evidence on how and to what extent the technology diffusion has helped developing countries in their convergence process towards technological leader countries. Therefore, in the fourth chapter of this dissertation, we estimate the role of technology diffusion in the convergence process of manufacturing industries of emerging economies classified as non-frontier countries. Moreover, differing from the existing research, we also empirically test the impact of uncertainty of technology diffusion on TFP growth of manufacturing industries. Also, we test the convergence across different levels of technology diffusion and its uncertainty. This is examined by using an interaction of TFP gap with technology diffusion and its uncertainty. This interaction identifies whether technology diffusion (uncertainty of technology diffusion) strengthens (weakens) the convergence process. In doing so, we utilize three dimensional panel data of sixteen emerging economies and eighteen manufacturing industries over the period 1981-2008.

We compute TFP growth of manufacturing industries by employing superlative index number approach. Later, we compute TFP level of manufacturing industries of non-frontier countries relative to TFP level of manufacturing industries of the frontier country. This computation shows that manufacturing industries of non-frontier countries maintains low TFP levels relative to manufacturing industries of the frontier country. To carry out our empirical investigation, we have applied a two step system GMM estimator developed by Blundell and Bond (1998).

Our empirical estimates have confirmed that the further the country lies behind the technological frontier, the higher will be its growth and thus the faster will be the speed of convergence. Further, we observe a positive and statistically significant impact of technology diffusion on TFP growth of non-frontier countries. However, the uncertainty of technology diffusion, which we have computed through an AR(1) process of technology diffusion, has shown a negative impact on TFP growth. The conditional impact of technology diffusion uncertainty through technology diffusion appears as positive. This implies,though, that uncertainty has a negative impact on TFP growth; but as the level of technology diffusion increases, this negative impact of uncertainty weakens monotonically. While estimating the impact of TFP gap through technology diffusion, our results have confirmed earlier empirical findings that at higher levels of technology diffusion, the rate of convergence is higher. In contrast, we observe that uncertainty pertains a negative impact on TFP growth. Also, the negative impact strengthens at higher levels of uncertainty. Overall, our findings assist us to understand the convergence process in emerging economies particularly while taking uncertainty into consideration. This leads us to draw some important implications not only for manufacturing industries of these countries but also for effective policy formation.

Empirical results of chapter four help to identify the extent to which uncertainty affects TFP growth. In particular, we have computed the conditional impact of uncertainty through technology diffusion, which has identified the threshold level of technology diffusion where the negative impact of uncertainty turns to positive. This finding is of particular importance for industries that lie below or at the margin of the threshold point. Also, our findings suggest that uncertainty leads to divergence of TFP growth and it increases the technology gap between manufacturing industries of non-frontier and frontier countries. Since uncertainty attached to international trade involves many other international factors most importantly exchange rate changes, which are out-of-bounds of industries and more of the concern of the foreign exchange market. This implies that industries may plan strategies that increase their risk absorption capacity or help them to minimize the adverse effects of uncertainty not only related to trade but also to other macroeconomic shocks.

The empirical results of this chapter also suggest that manufacturing industries of emerging and developing countries not only focus on their own innovative technologies but also they should learn from the technological developments in advanced economies particularly the technology frontier. Also, they need to take into consideration to what extent the convergence process is sensitive with respect to technology diffusion and more importantly its uncertainty.

The analysis can be extended by including more emerging economies or developing countries and dividing them according to regional classification. It would be worthwhile to incorporate the role of macroeconomic uncertainty particularly exchange rate fluctuations and macroeconomic policies such as fiscal policy and monetary policy.

We have only taken the USA as the frontier country whereas one of the worthwhile contributions could be to identify the technology frontier among the emerging economies based on their TFP growth and then estimate the convergence process in these countries. This analysis will assist in understanding whether the emerging economies are converging towards the technology leader within their own group or not. We have carried out our analysis for overall manufacturing industries while a fascinating addition would be to investigate convergence of each industry of non-frontier countries with the respective industry of the frontier country. This extension may help to identify industries that are slow in the convergence process and thus these industries can specifically be improved through proper measures.

This dissertation has attempted to empirically contribute to the existing literature in various aspects. However, we have highlighted some points that could be explored and thus provided a detailed and in-depth analysis. This will complement earlier studies as well as reinforce our understanding not only on a deeper but also a wider scale.

References

Abel, A. (1983). Optimal investment under uncertainty. *American Economic Review 73*(1), 228–233.

Adolfson, M., S. Laséen, J. Lindé, and M. Villani (2008). Evaluating an estimated new keynesian small open economy model. *Journal of Economic Dynamics and Control 32*(8), 2690–2721.

Aghion, P., P. Bacchetta, R. Ranciere, and K. Rogoff (2009). Exchange rate volatility and productivity growth: The role of financial development. *Journal of Monetary Economics 56*(4), 494–513.

Aghion, P. and P. Howitt (1992). A model of growth through creative destruction. *Econometrica 60*(2), 323–351.

Aghion, P., P. Howitt, and C. García-Peñalosa (1998). *Endogenous Growth Theory*. The MIT Press.

Aigner, D., C. Lovell, and P. Schmidt (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics 6*(1), 21–37.

Aiyar, S. and J. Feyrer (2002). A contribution to the empirics of total factor productivity.

Aizenman, J. (1993). Policy uncertainty, persistence and growth. *Review of International Economics 1*(2), 145–163.

Aizenman, J. and N. Marion (1999). Volatility and investment: Interpreting evidence from developing countries. *Economica 66*(262), 157–1179.

Akinlo, A. (2005). Impact of macroeconomic factors on total factor productivity in subsaharan african countries. (2005/39).

Anderson, T. (1977). Asymptotic expansions of the distributions of estimates in simultaneous equations for alternative parameter sequences. *Econometrica 45*(2), 509–18.

Anderson, T. and H. Rubin (1950). The asymptotic properties of estimates of the parameters of a single equation in a complete system of stochastic equations. *The Annals of Mathematical Statistics 21*(4), 570–582.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies 58*(2), 277–297.

Arellano, M. and O. Bover (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics 68*(1), 29–51.

Ball, L. (1999a). Efficient rules for monetary policy. *International Finance 2*(1), 63–83.

Ball, L. M. (1999b). Policy rules for open economies. In *Monetary policy rules*, pp. 127–156. University of Chicago Press.

Banerjee, A., J. J. Dolado, J. W. Galbraith, and D. Hendry (1993). *Co-integration, Error Correction, and the Econometric Analysis of Non-Stationary Data.* OUP Catalogue. Oxford University Press.

Banerjee, A., J. Galbraith, and J. Dolado (1990). Practitioner's corner: Dynamic specification and linear transformations of the autoregressive-distributed lag model. *Oxford Bulletin of Economics and Statistics 52*(1), 95–104.

Barger, H. (1969). Growth in developed nations. *The Review of Economics and Statistics 51*(2), 143–148.

Barro, R. and D. Gordon (1984). Rules, discretion and reputation in a model of monetary policy. *NBER Working Paper* (w1079).

Barro, R. and N. Mankiw (1995). Capital mobility in neoclassical models of growth. *The American Economic Review 85*(1), 103–115.

Barro, R. J. and D. B. Gordon (1983). Rules, discretion and reputation in a model of monetary policy. *Journal of monetary economics 12*(1), 101–121.

Batini, N., R. Harrison, and S. Millard (2003). Monetary policy rules for an open economy. *Journal of Economic Dynamics and Control 27*(11-12), 2059–2094.

Batten, D. (1990). *The conduct of monetary policy in the major industrial countries: Instruments and operating procedures.* International Monetary Fund.

Bec, F., M. Ben Salem, and F. Collard (2002). Asymmetries in monetary policy reaction function: Evidence for US French and German central banks. *Studies in Nonlinear Dynamics & Econometrics 6*(2), 3.

Beck, T., R. Levine, and N. Loayza (2000). Finance and the sources of growth. *Journal of financial economics 58*(1), 261–300.

Ben-David, D. (1993). Equalizing exchange: Trade liberalization and income convergence. *The Quarterly Journal of Economics 108*(3), 653–679.

Ben-David, D. (1996). Trade and convergence among countries. *Journal of international Economics 40*(3-4), 279–298.

Ben-David, D. and M. Loewy (1998). Free trade, growth, and convergence. *Journal of economic growth 3*(2), 143–170.

Bergson, A. (1975). Index numbers and the computation of factor productivity. *Review of Income and Wealth 21*(3), 259–78.

Berkowitz, J. (2001). Testing density forecasts, with applications to risk management. *Journal of Business and Economic Statistics 19*(4), 465–474.

Bernanke, B. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics 98*(1), 85–106.

Bernanke, B. and I. Mihov (1998). Measuring monetary policy. *Quarterly Journal of Economics 113*(3), 869–902.

Bernard, A. and S. Durlauf (1996). Interpreting tests of the convergence hypothesis. *Journal of econometrics 71*(1), 161–173.

Bernard, A. and S. N. Durlauf (1991). Convergence of international output movements. *NBER Working Paper* (w3717).

Bernard, A. and J. Jensen (2001). Who dies? international trade, market structure, and industrial restructuring. *NBER Working Paper Series* (8327).

Bernard, A. and C. Jones (1996a). Comparing apples to oranges: Productivity convergence and measurement across industries and countries. *American Economic Review 86*(5), 1216–38.

Bernard, A. and C. Jones (1996b). Productivity acrossindustries: Time series theory and evidence. *Review of Economics & Statistics 78*(1), 135–146.

Bernard, A. and C. Jones (1996c). Technology and convergence. *The Economic Journal 106*(437), 1037–1044.

Berument, H., N. Dincer, and Z. Mustafaoglu (2011). Total factor productivity and macroeconomic instability. *Journal of International Trade & Economic Development 20*(5), 605–629.

Blackburn, K. and A. Pelloni (2004). On the relationship between growth and volatility. *Economics Letters 83*(1), 123–127.

Blanchard, O. and S. Fischer (1989). Lectures on macroeconomics.

Blundell, R. and S. Bond (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87*(1), 115–143.

Bond, S., A. Hoeffler, and J. Temple (2001). *GMM estimation of empirical growth models.* Number 3048. Centre for Economic Policy Research.

Bredin, D. and S. Fountas (2009). Macroeconomic uncertainty and performance in the European Union. *Journal of International Money and Finance 28*(6), 972–986.

Bruno, M. and W. Easterly (1998). Inflation crises and long-run growth. *Journal of Monetary Economics 41*(1), 3–26.

Bullard, J. and K. Mitra (2002). Learning about monetary policy rules. *Journal of Monetary Economics 49*(6), 1105–1129.

Cameron, G., J. Proudman, and S. Redding (2005). Technological convergence, R&D, trade and productivity growth. *European Economic Review 49*(3), 775–807.

Cameron, G., J. Proudman, S. Redding, and B. of England (1998). *Productivity convergence and international openness.* Bank of England.

Caves, D., L. Christensen, and W. Diewert (1982a). Multilateral comparisons of output, input, and productivity using superlative index numbers. *The economic journal 92*(365), 73–86.

Caves, D. W., L. R. Christensen, and W. E. Diewert (1982b). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica 50*(6), 1393–1414.

Chen, X. and R. MacDonald (2012). Realized and optimal monetary policy rules in an estimated markov-switching dsge model of the united kingdom. *Journal of Money, Credit and Banking 44*(6), 1091–1116.

Christoffersen, P. F. and F. X. Diebold (1998, October). Cointegration and long-horizon forecasting. *Journal of Business & Economic Statistics 16*(4), 450–58.

Clarida, R., J. Gali, and M. Gertler (1998). Monetary policy rules in practice: Some international evidence. *European Economic Review 42*(6), 1033–1067.

Clarida, R., J. Galí, and M. Gertler (1999). The science of monetary policy: A new keynesian perspective. *Journal of Economic Literature 37*(4), 1661–1707.

Clarida, R., J. Gali, and M. Gertler (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics 115*(1), 147–180.

Clarida, R., J. Gali, and M. Gertler (2001). Optimal monetary policy in open versus closed economies: An integrated approach. *The American Economic Review 91*(2), 248–252.

Clarida, R., J. Gali, and M. Gertler (2002). A simple framework for international monetary policy analysis. *Journal of Monetary Economics 49*(5), 879–904.

Clements, M. P. and J. Smith (2000). Evaluating the forecast densities of linear and non-linear models: applications to output growth and unemployment. *Journal of Forecasting 19*(4), 255–276.

Coe, D. and E. Helpman (1995). International R&D spillovers. *European Economic Review 39*(5), 859–887.

Coe, D., E. Helpman, and A. Hoffmaister (1997). North-South R&D Spillovres. *The Economic Journal 107*(440), 134–149.

Comin, D. (2000). An uncertainty-driven theory of the productivity slowdown: Manufacturing. CV Starr Center for Applied Economics, New York University.

Comin, D. (2006). Total factor productivity. *forthcoming in SN Durlauf and LE Blume, eds., The New Palgrave Dictionary of Economics, Second Edition, Palgrave Macmillan.*

Comin, D., B. Hobijn, and E. Rovito (2006). Five facts you need to know about technology diffusion. *NBER Working Papers No. W11928*.

Comin, D. and S. Mulani (2009). A theory of growth and volatility at the aggregate and firm level. *Journal of Monetary Economics 56*(8), 1023–1042.

Córdoba, J. and M. Ripoll (2008). Endogenous TFP and cross-country income differences. *Journal of monetary Economics 55*(6), 1158–1170.

Cororaton, C., T. Caparas, and S. Zingapan (1999). Recent TFP policy agenda for the Philippines. *APO productivity journal* (1), 88.

Costello, D. (1993). A cross-country, cross-industry comparison of productivity growth. *Journal of Political Economy 101*(2), 207–22.

Cragg, J. and S. Donald (1997). Inferring the rank of a matrix. *Journal of Econometrics 76*(1-2), 223–250.

Crespo, J., C. Martín, and F. Velázquez (2004). The role of international technology spillovers in the economic growth of the oecd countries. *Global Economy Journal 4*(2), 3.

Cukierman, A. and S. Gerlach (2003). The inflation bias revisited: Theory and some international evidence. *The Manchester School 71*(5), 541–565.

D'Adamo, G. (2011). Estimating central bank preferences in a small open economy: Sweden 1995-2009. WPAE Paper WPAE-11, Universitat De Valencia.

Davidson, J. et al. (1978). Econometric modelling of the aggregate time-series relationship between consumers' expenditure and income in the united kingdom. *Economic Journal 88*(352), 661–92.

De Andrade, J. and J. Divino (2005). Monetary policy of the Bank of Japan–inflation target versus exchange rate target. *Japan and the World Economy 17*(2), 189–208.

del Barrio-Castro, T., E. López-Bazo, and G. Serrano-Domingo (2002). New evidence on international R&D spillovers, human capital and productivity in the OECD. *Economics Letters 77*(1), 41–45.

Deliktas, E. and M. Balcilar (2005). A comparative analysis of productivity growth, catch-up, and convergence in transition economies. *Emerging Markets Finance and Trade 41*(1), 6–28.

Demir, F. and M. Caglayan (2012). Firm productivity, exchange rate movements, sources of finance and export orientation. MPRA Paper 37397, University Library of Munich, Germany.

Dennis, R. (2003). Exploring the role of the real exchange rate in Australian monetary policy. *Economic Record 79*(244), 20–38.

Derviş, K. (2012). World economy convergence, interdependence, and divergence. *MONEY 15*.

Diebold, F. X., T. A. Gunther, and A. S. Tay (1998). Evaluating density forecasts with applications to financial risk management. *International Economic Review 39*(4), 863–83.

Dixit, A. and R. Rob (1994). Switching costs and sectoral adjustments in general equilibrium with uninsured risk. *Journal of Economic Theory 62*(1), 48–69.

Dixit, A. K. and R. S. Pindyck (1994). Investment under uncertainty.

Dolado, J., R. Maria-Dolores, and M. Naveira (2005). Are monetary-policy reaction functions asymmetric?: The role of nonlinearity in the phillips curve. *European Economic Review 49*(2), 485–503.

Dolado, J., R. Pedrero, and F. Ruge-Murcia (2004). Nonlinear monetary policy rules: Some new evidence for the US. *Studies in Nonlinear Dynamics & Econometrics 8*(3), 2.

Dollar, D. and E. Wolff (1988). Convergence of industry labor productivity among advanced economies, 1963-1982. *The Review of Economics and Statistics 70*(4), 549–58.

Dollar, D. and E. Wolff (1994). Capital intensity and tfp convergence by industry in manufacturing, 1963-1985. *Convergence of Productivity: Cross-National Studies and Historical Evidence. Oxford University Press, Oxford*, 197–224.

Domar, E., S. Eddie, B. Herrick, P. Hohenberg, M. Intriligator, and I. Miyamoto (1964). Economic growth and productivity in the United States, Canada, United Kingdom, Germany and Japan in the post-war period. *The Review of Economics and Statistics 46*(1), 33–40.

Doornik, J. and H. Hansen (1994). A practical test for univariate and multivariate normality. Discussion Paper, Nuffield College.

Dougherty, C. and D. Jorgenson (1996). International comparisons of the sources of economic growth. *The American economic review 86*(2), 25–29.

Dougherty, C. and D. Jorgenson (1997). There is no silver bullet: investment and growth in the G7. *National Institute Economic Review 162*(1), 57–74.

Dowrick, S. (1989). Sectoral change, catching up and slowing down: Oecd post-war economic growth revisited. *Economics Letters 31*(4), 331–335.

Dowrick, S. and D. Nguyen (1989). OECD Comparative Economic Growth 1950-85: Catch-Up and Convergence. *American Economic Review 79*(5), 1010–30.

Easterly, W., N. Fiess, and D. Lederman (2003). NAFTA and convergence in North America: high expectations, big events, little time. *Economia: Journal of the Latin American and Caribb 4*(1), 1–53.

Edwards, S. (1998). Openness, productivity and growth: What do we really know? *The Economic Journal 108*(447), 383–398.

Fatás, A. and I. Mihov (2003). The case for restricting fiscal policy discretion. *Quarterly Journal of Economics 118*(4), 1419–1447.

Ferrett, B. (2004). Foreign direct investment and productivity growth: A survey of theory.

Fountas, S. and M. Karanasos (2007). Inflation, output growth, and nominal and real uncertainty: empirical evidence for the G7. *Journal of International Money and Finance 26*(2), 229–250.

Frankel, J. and D. Romer (1999). Does trade cause growth? *The American Economic Review 89*(3), 379–399.

Frantzen, D. (2000). R&d, human capital and international technology spillovers: A cross-country analysis. *The Scandinavian Journal of Economics 102*(1), 57–75.

Friedman, M. (1948). A monetary and fiscal framework for economic stability. *The American Economic Review 38*(3), 245–264.

Friedman, M. (1977). Nobel lecture: Inflation and unemployment. *Journal of Political Economy*, 451–472.

Friedman, M. and A. Schwartz (1963). A Monetary History of the United States, 1867-1960.

Gali, J. and T. Monacelli (2005, 07). Monetary policy and exchange rate volatility in a small open economy. *Review of Economic Studies 72*(3), 707–734.

Gouyette, C. and S. Perelman (1997). Productivity convergence in OECD service industries. *Structural Change and Economic Dynamics 8*(3), 279–295.

Granger, C., M. Pesaran, and U. of Cambridge. Dept. of Applied Economics (1996). A decision-theoretic approach to forecast evaluation. *DAE Working Papers*.

Greenspan, A. (2004). Risk and uncertainty in monetary policy. *The American Economic Review 94*(2), 33–40.

Gregory, A. and A. Head (1999). Common and country-specific fluctuations in productivity, investment, and the current account. *Journal of Monetary Economics 44*(3), 423–451.

Grier, K. and M. Perry (2000). The effects of real and nominal uncertainty on inflation and output growth: some GARCH-M evidence. *Journal of Applied Econometrics 15*(1), 45–58.

Grier, K. and G. Tullock (1989). An empirical analysis of cross-national economic growth, 1951–1980. *Journal of Monetary Economics 24*(2), 259–276.

Griffith, R., S. Redding, and J. Reenen (2004). Mapping the two faces of R&D: Productivity growth in a panel of OECD industries. *Review of Economics and Statistics 86*(4), 883–895.

Griliches, Z. (1980). Returns to research and development expenditures in the private sector. In *New Developments in Productivity Measurement*, pp. 419–462. University of Chicago Press.

Griliches, Z. (1996). The discovery of the residual: A historical note. *Journal of Economic Literature 34*(3), 1324–1330.

Griliches, Z. and F. Lichtenberg (1984a). Interindustry technology flows and productivity growth: A re-examination. *The Review of Economics and Statistics 66*(2), 324–29.

Griliches, Z. and F. Lichtenberg (1984b). R&D and productivity growth at the industry level: Is there still a relationship? In *R & D, Patents, and Productivity*, pp. 465–502. University of Chicago Press.

Grossman, G. and E. Helpman (1991). *Innovation and growth in the global economy.* Cambridge, The MIT Press.

Guariglia, A. (2008). Internal financial constraints, external financial constraints, and investment choice: Evidence from a panel of UK firms. *Journal of Banking & Finance 32*(9), 1795–1809.

Guellec, D. and B. Van Pottelsberghe de la Potterie (2001). The internationalisation of technology analysed with patent data. *Research Policy 30*(8), 1253–1266.

Guellec, D. and B. Van Pottelsberghe de la Potterie (2004). From R&D to productivity growth: Do the institutional settings and the source of funds of R&D matter? *Oxford Bulletin of Economics and Statistics 66*(3), 353–378.

Hall, B. and J. Mairesse (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of econometrics 65*(1), 263–293.

Hall, R. and C. Jones (1996). The productivity of nations. *NBER Working Paper Series 5812.*

Hall, R. and C. Jones (1997). Levels of economic activity across countries. *American Economic Review 87*(2), 173–77.

Hall, R. and C. Jones (1999). Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics 114*(1), 83–116.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica 50*(4), 1029–1054.

Hansen, L. P., J. Heaton, and A. Yaron (1996). Finite-sample properties of some alternative GMM estimators. *Journal of Business & Economic Statistics 14*(3), 262–280.

Hansson, P. and M. Henrekson (1994). Catching up in industrialized countries: a disaggregated study. *Journal of International Trade & Economic Development 3*(2), 129–145.

Harrigan, J. (1999). Estimation of cross-country differences in industry production functions. *Journal of International Economics 47*(2), 267–293.

Harris, R., C. I. Canada, and I. C. R. P. Program (1999). *Determinants of Canadian productivity growth: Issues and prospects*. Industry Canada Ottawa, ON.

Hendry, D. and G. Anderson (1977). Testing dynamic specification in small simultaneous systems: An application to a model of building society behavior in the United Kingdom. In *Frontiers of quantitative economics: papers invited for presentation at the Econometric Society third World Congress, Toronto, 1975*, Volume 1, pp. 361. North-Holland Pub. Co.

Hendry, D., A. Pagan, and J. Sargan (1984). Dynamic specification. *Handbook of econometrics 2*, 1023–1100.

Hodrick, R. and E. Prescott (1997). Postwar US business cycles: An empirical investigation. *Journal of Money, Credit, and Banking 29*(1), 1–16.

Howitt, P. (2000). Endogenous growth and cross-country income differences. *American Economic Review 90*(4), 829–846.

Ilbas, P. (2010). Revealing the preferences of the us federal reserve. *Journal of Applied Econometrics 27*(3), 440–473.

Imbs, J. (2007). Growth and volatility. *Journal of Monetary Economics 54*(7), 1848–1862.

Ireland, P. (1999). Does the time-consistency problem explain the behavior of inflation in the United States? *Journal of Monetary Economics 44*(2), 279–291.

Islam, N. (1995). Growth empirics: a panel data approach. *The Quarterly Journal of Economics 110*(4), 1127–1170.

Islam, N. (2001). Different approaches to international comparison of total factor productivity. In *New developments in productivity analysis*, pp. 465–508. University of Chicago Press.

Jajri, I. and R. Ismail (2007). Technical efficiency, technological change and total factor productivity growth in malaysian manufacturing sector. *The IUP Journal of Industrial Economics 4*(4), 63–75.

Jeong, H. and R. Townsend (2005). Discovering the sources of tfp growth: Occupational choice and financial deepening. *IEPR Working Paper No. 05-19*.

Jones, L., R. Manuelli, and E. Stacchetti (1999). Technology (and policy) shocks in models of endogenous growth. *NBER Working Paper Series 7063*.

Jorgenson, D. and M. Kuroda (1991). Productivity and international competitiveness in japan and the united states, 1960-1985. In *Productivity growth in Japan and the United States*, pp. 29–57. University of Chicago Press.

Jorgenson, D. W. and M. Nishimizu (1978). Us and japanese economic growth, 1952-1974: an international comparison. *The Economic Journal 88*(352), 707–726.

Judson, R. and A. Orphanides (1999). Inflation, volatility and growth. *International Finance 2*(1), 117–138.

Kao, C., M. Chiang, and B. Chen (1999). International R&D spillovers: an application of estimation and inference in panel cointegration. *Oxford Bulletin of economics and Statistics 61*(S1), 691–709.

Kasa, K. and H. Popper (1997). Monetary policy in Japan: A structural VAR analysis. *Journal of the Japanese and International Economies 11*(3), 275–295.

Keller, W. (1996). Absorptive capacity: On the creation and acquisition of technology in development. *Journal of Development Economics 49*(1), 199–227.

Keller, W. (1998). Are international R&D spillovers trade-related?: Analyzing spillovers among randomly matched trade partners. *European Economic Review 42*(8), 1469–1481.

Keller, W. (2000). Do trade patterns and technology flows affect productivity growth? *World Bank Economic Review 14*(1), 17.

Keller, W. (2002). Trade and the transmission of technology. *Journal of Economic Growth 7*(1), 5–24.

Kim, D., D. Osborn, and M. Sensier (2005). Nonlinearity in the Fed's monetary policy rule. *Journal of Applied Econometrics 20*(5), 621–639.

King, R., C. Plosser, and S. Rebelo (1988). Production, growth and business cycles: Ii. new directions. *Journal of Monetary Economics 21*(2), 309–341.

Kleibergen, F. and R. Paap (2006, July). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics 133*(1), 97–126.

Klenow, P. and A. Rodríguez-Clare (1997). The neoclassical revival in growth economics: Has it gone too far? *NBER Macroeconomics Annual*, 73–103.

Klenow, P. and A. Rodriguez-Clare (2005). Externalities and growth. *Handbook of economic growth 1*, 817–861.

Koren, M. and S. Tenreyro (2007). Volatility and development. *Quarterly Journal of Economics 122*(1), 243–287.

Kormendi, R. and P. Meguire (1985). Macroeconomic determinants of growth: cross-country evidence. *Journal of Monetary economics 16*(2), 141–163.

Kose, M., C. Otrok, and C. Whiteman (2003). International business cycles: World, region, and country-specific factors. *American Economic Review 93*(4), 1216–1239.

Kydland, F. and E. Prescott (1977). Rules rather than discretion: The inconsistency of optimal plans. *The Journal of Political Economy 85*(3), 473–491.

Kydland, F. and E. Prescott (1982). Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society 50*(6), 1345–1370.

Lawrence, R. and D. Weinstein (1999). *Trade and growth: import-led or export led?: evidence from Japan and Korea.* Number 7264. National Bureau of Economic Research.

Leahy, J. and T. Whited (1996). The effect of uncertainty on investment: Some stylized facts. *Journal of Money, Credit, Banking 28*(1), 64–83.

Lederman, D., W. F. Maloney, W. F. Maloney, and L. Servén (2005). *Lessons from NAFTA: for Latin America and the Caribbean.* Stanford Economics & Finance.

Lee, J. (2009). Trade, FDI, and productivity convergence: A dynamic panel data approach in 25 countries. *Japan and the World Economy 21*(3), 226–238.

Lee, J. (2010). The link between output growth and volatility: Evidence from a GARCH model with panel data. *Economics Letters 106*(2), 143–145.

Leitemo, K., Ø. Roisland, and R. Torvik (2002). Time inconsistency and the exchange rate channel of monetary policy. *Scandinavian Journal of Economics 104*(3), 391–397.

Leitemo, K. and U. Söderström (2005). Simple monetary policy rules and exchange rate uncertainty. *Journal of International Money and Finance 24*(3), 481–507.

Levine, R. and D. Renelt (1992). A sensitivity analysis of cross-country growth regressions. *American Economic Review 82*(4), 942–963.

Long Jr, J. B. and C. I. Plosser (1983). Real business cycles. *Journal of Political Economy 91*(1), 39–69.

Lubik, T. and F. Schorfheide (2004). Testing for indeterminacy: An application to US monetary policy. *The American Economic Review 94*(1), 190–217.

Lubik, T. A. and M. Marzo (2007a). An inventory of simple monetary policy rules in a new keynesian macroeconomic model. *International Review of Economics & Finance 16*(1), 15–36.

Lubik, T. A. and M. Marzo (2007b). An inventory of simple monetary policy rules in a new keynesian macroeconomic model. *International Review of Economics & Finance 16*(1), 15–36.

Lubik, T. A. and F. Schorfheide (2007, May). Do central banks respond to exchange rate movements? a structural investigation. *Journal of Monetary Economics 54*(4), 1069–1087.

Lucas, R. (1988). On the mechanics of economic development. *Journal of monetary economics 22*(1), 3–42.

Lumenga-Neso, O., M. Olarreaga, and M. Schiff (2001). *On" indirect" trade-related research and development spillovers*. World Bank, Development Research Group, Trade.

Madsen, J. (2007). Technology spillover through trade and TFP convergence: 135 years of evidence for the OECD countries. *Journal of International Economics 72*(2), 464–480.

Madsen, J. (2008). Economic Growth, TFP Convergence and the World Export of Ideas: A Century of Evidence. *The Scandinavian Journal of Economics 110*(1), 145–167.

Mandal, S. and S. Madheswaran (2012). Productivity growth in indian cement industry: A panel estimation of stochastic production frontier. *The Journal of Developing Areas 46*(1), 287–303.

Mankiw, N., D. Romer, and D. Weil (1992). A contribution to the empirics of economic growth. *The quarterly journal of economics 107*(2), 407–437.

Mansfield, E. (1980). Basic research and productivity increase in manufacturing. *American Economic Review 70*(5), 863–73.

Mascaro, A. and A. Meltzer (1983). Long-and short-term interest rates in a risky world. *Journal of Monetary Economics 12*(4), 485–518.

Mavroeidis, S. (2004). Weak identification of forward-looking models in monetary economics. *Oxford Bulletin of Economics and Statistics 66*, 609–635.

Mc Morrow, K., W. Röger, and A. Turrini (2010). Determinants of TFP growth: A close look at industries driving the EU–US TFP gap. *Structural Change and Economic Dynamics 21*(3), 165–180.

McCallum, B. T. and E. Nelson (2000, Winter). Monetary policy for an open economy: An alternative framework with optimizing agents and sticky prices. *Oxford Review of Economic Policy 16*(4), 74–91.

Meeusen, W. and J. van den Broeck (1977). Efficiency estimation from cobb-douglas production functions with composed error. *International Economic Review 18*(2), 435–44.

Miller, S. and M. Upadhyay (2000). The effects of openness, trade orientation, and human capital on total factor productivity. *Journal of development economics 63*(2), 399–423.

Miller, S. and M. Upadhyay (2002). Total factor productivity and the convergence hypothesis. *Journal of Macroeconomics 24*(2), 267–286.

Mirman, L. (1971). Uncertainty and optimal consumption decisions. *Econometrica 39*(1), 179–85.

Miyao, R. (2000). The Role of Monetary Policy in Japan: A Break in the 1990s? *Journal of the Japanese and International Economies 14*(4), 366–384.

Miyao, R. (2002). The effects of monetary policy in Japan. *Journal of Money, Credit and Banking 34*(2), 376–392.

Moomaw, R. and M. Williams (1991). Total factor productivity growth in manufacturing further evidence from the states. *Journal of Regional Science 31*(1), 17–34.

Morgan, D. (1993). Asymmetric effects of monetary policy. *Economic Review-Federal Reserve Bank of Kansas City 78*, 21–21.

Nelson, C. and C. Plosser (1982). Trends and random walks in macroeconmic time series: some evidence and implications. *Journal of monetary economics 10*(2), 139–162.

Newey, W. and K. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Nicoletti, G. and S. Scarpetta (2003). Regulation, productivity and growth: Oecd evidence. *Economic policy 18*(36), 9–72.

Nobay, A. and D. Peel (1998). Optimal monetary policy in a model of asymmetric central bank preferences. *LSE Financial Markets Group Discussion Paper Series*.

Nobay, A. and D. Peel (2000). Optimal monetary policy with a nonlinear phillips curve. *Economics Letters 67*(2), 159–164.

Nobay, A. and D. Peel (2003). Optimal discretionary monetary policy in a model of asymmetric central bank preferences. *The Economic Journal 113*(489), 657–665.

Norrbin, S. and D. Schlagenhauf (1990). The identification of the causes of business cycles across countries. *IMF Working Papers*.

Oikawa, K. (2010). Uncertainty-driven growth. *Journal of Economic Dynamics and Control 34*(5), 897–912.

Pagan, A. (1984, February). Econometric issues in the analysis of regressions with generated regressors. *International Economic Review 25*(1), 221–47.

Pagan, A. and A. Ullah (1988). The econometric analysis of models with risk terms. *Journal of Applied Econometrics 3*(2), 87–105.

Parente, S. and E. Prescott (1994). Barriers to technology adoption and development. *The Journal of Political Economy 102*(2), 298–321.

Park, W. (1995). International R&D spillovers and OECD economic growth. *Economic Inquiry 33*(4), 571–591.

Pindyck, R. (1982). Adjustment costs, uncertainty, and the behavior of the firm. *American Economic Review 72*(3), 415–27.

Pindyck, R. (1991). Ireversibility, Uncertainty, and Investment. *Journal of Economic Literature 29*(3), 1110–1148.

Ramey, G. and V. Ramey (1991). Technology commitment and the cost of economic fluctuations. *NBER Working Paper* (w3755).

Ramey, G. and V. Ramey (1995). Cross-country evidence on the link between volatility and growth. *American Economic Review 85*(5), 1138–1151.

Rebelo, S. (1991). Long-run policy analysis and long-run growth. *The Journal of Political Economy 99*(3), 500–521.

Rivera-Batiz, L. and P. Romer (1991). Economic integration and endogenous growth. *Quarterly Journal of Economics 106*(2), 531–555.

Robin, J. and R. Smith (2000). *Tests of Rank.* Cambridge University Press.

Romer, P. (1986). Increasing returns and long-run growth. *The Journal of Political Economy 94*(5), 1002–1037.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy 98*(5 pt 2).

Romer, P. (1993). Idea gaps and object gaps in economic development. *Journal of monetary economics 32*(3), 543–573.

Rudebusch, G. and L. Svensson (1999). Policy rules for inflation targeting. University of Chicago Press.

Ruge-Murcia, F. (2003a). Does the Barro-Gordon model explain the behavior of US inflation? A reexamination of the empirical evidence. *Journal of Monetary Economics 50*(6), 1375–1390.

Ruge-Murcia, F. (2003b). Inflation targeting under asymmetric preferences. *Journal of Money, Credit, and Banking 35*(5), 763–785.

Ruge-Murcia, F. J. (2004). The inflation bias when the central bank targets the natural rate of unemployment. *European Economic Review 48*(1), 91–107.

Ruge-Murcia, F. J. (2007a, August). Methods to estimate dynamic stochastic general equilibrium models. *Journal of Economic Dynamics and Control 31*(8), 2599–2636.

Ruge-Murcia, F. J. (2007b). Methods to estimate dynamic stochastic general equilibrium models. *Journal of Economic Dynamics and Control 31*(8), 2599–2636.

Russell, R. and S. Kumar (2002). Technological change, technological catch-up, and capital deepening: Relative contributions to growth and convergence. *American economic review 92*(3), 527–548.

Scarpetta, S. and T. Tressel (2002). Productivity and Convergence in a Panel of OECD Industries: Do Regulations and Institutions Matter? *OECD Economics Department Working Papers*.

Sharma, S., K. Sylwester, and H. Margono (2007). Decomposition of total factor productivity growth in US states. *Quarterly Review of Economics and Finance 47*(2), 215–241.

Solow, R. (1956). A contribution to the theory of economic growth. *The quarterly journal of economics 70*(1), 65–94.

Stehrer, R. and J. Wörz (2003). Technological convergence and trade patterns. *Review of World Economics 139*(2), 191–219.

Stock, J., J. Wright, and M. Yogo (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics 20*(4), 518–529.

Stockman, A. (1988). Sectoral and national aggregate disturbances to industrial output in seven european countries. *Journal of Monetary Economics 21*(2-3), 387–409.

Surico, P. (2003). Asymmetric reaction functions for the Euro Area. *Oxford Review of Economic Policy 19*(1), 44.

Surico, P. (2007a). The Fed's monetary policy rule and US inflation: The case of asymmetric preferences. *Journal of Economic Dynamics and Control 31*(1), 305–324.

Surico, P. (2007b). The monetary policy of the European Central Bank. *Scandinavian Journal of Economics 109*(1), 115–135.

Surico, P. (2008). Measuring the time inconsistency of US monetary policy. *Economica 75*(297), 22–38.

Svensson, L. (1997). Inflation forecast targeting: Implementing and monitoring inflation targets. *European Economic Review 41*(6), 1111–1146.

Svensson, L. (1999). Inflation targeting as a monetary policy rule. *Journal of Monetary Economics 43*(3), 607–654.

Svensson, L. (2000). Open-economy inflation targeting. *Journal of International Economics 50*(1), 155–183.

Tadesse, S. (2005). Financial development and technology. *William Davidson Institute Working Paper No. 749*.

Taylor, J. (1975). Monetary policy during a transition to rational expectations. *Journal of Political Economy 83*(5), 1009–21.

Taylor, J. (1993). Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy*, Volume 39, pp. 195–214. Elsevier.

Taylor, J. (1999a). The robustness and efficiency of monetary policy rules as guidelines for interest rate setting by the European central bank. *Journal of Monetary Economics 43*(3), 655–679.

Taylor, J. (2001a). *Monetary policy rules.* Number 31. University of Chicago Press.

Taylor, J. (2001b). The role of the exchange rate in monetary-policy rules. *The American Economic Review 91*(2), 263–267.

Taylor, J. B. (1999b). A historical analysis of monetary policy rules. In *Monetary policy rules*, pp. 319–348. University of Chicago Press.

Turnovsky, S. and P. Chattopadhyay (2003). Volatility and growth in developing economies: Some numerical results and empirical evidence. *Journal of International Economics 59*(2), 267–295.

Varian, H. (1974). *A Bayesian approach to real estate assessment.* North-Holland, Amsterdam. in Feinberg, S.E. and Zellner, A.: Studies in Bayesian Economics in Honour of L.J. Savage.

Ventura, L. and R. Zeidan (2000). Volatility and growth in developing countries.

Wolff, E. (1991). Capital formation and productivity convergence over the long term. *American Economic Review 81*(3), 565–79.

Zarnowitz, V. and L. Lambros (1987). Consensus and uncertainty in economic prediction. *The Journal of Political Economy 95*(3), 591–621.

Zarnowitz, V. and G. Moore (1986). Major changes in cyclical behavior. In *The American Business Cycle: Continuity and Change*, pp. 519–582. University of Chicago Press.

Zellner, A. (1986). Bayesian estimation and prediction using asymmetric loss functions. *Journal of the American Statistical Association*, 446–451.