Sell-side Analysts; Does their Gender Matter?

By

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Intellectual Property Statement

The candidate confirms that the work submitted is her own and that appropriate credit has been given where reference has been made to the work of others.

Dedication of this Thesis

To my mum, Maria, and my love, Steven.

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Abstract

Gender studies within the finance industry have received much attention from academics over the last decades, trying to determine whether the inclusion of more females would result in improved corporate outcomes (e.g. Francis et al., 2015). Specifically, the extant literature has considered gender differences in ethicality, risk attitude, and performance. However, the gender studies within the sell-side analyst profession are limited, due to data restrictions, and despite their limited number, their findings are mixed. For instance, Kumar (2010) found female sell-side analysts to be bolder and more accurate than their male counterparts, whereas Green et al. (2009) reported female sell-side analysts to be less optimistic and less accurate than males. Furthermore, the existing studies on sell-side analyst gender are limited to the U.S. market, hence their findings may not generalise to other markets with different institutional environments. Moreover, other than gender differences in risk attitude and performance, there is growing evidence that women exhibit greater moral reasoning than men (Emerson et al., 2007), which has resulted in improved quality of financial information (e.g. Chen et al., 2017). Within the sell-side analyst profession, the quality of sell-side analyst research is hindered by analyst bias when they are affiliated with the covering stock (Global Analyst Research Settlement), although, to date no study has tested for gender differences in the bias exhibited by affiliated sell-side analysts.

Consequently, this thesis provides three pieces of empirical evidence of the gender differences within the sell-side analyst profession across both Europe and/or the U.S. by answering the following questions: Does gender influence the way affiliated sell-side analysts respond to their conflicts of interest? Do male sell-side analysts issue more optimistic target prices than females? Is there gender heterogeneity in sell-side analyst forecasting skills?

The findings show that in the U.S., while affiliation bias is prevalent in the post regulatory period, there are no gender differences in the target price bias of affiliated sell-side analysts. Nevertheless, when female representation is higher within sanctioned banks, affiliated sell-side analysts exhibit less bias in their target price forecasts. Furthermore, male sell-side analysts issue more optimistic target price forecasts than their female counterparts across both Europe and the U.S. However, the documented gender difference in optimism does not persist in Europe when the endogenous decision to follow certain stocks is controlled for, suggesting that females appear less optimistic due to reverse causality. Lastly, there are no documented gender differences in sell-side analyst forecasting skills in Europe. Although, male sell-side analysts are more likely to issue bold forecasts while females are more likely to herd, implying that the latter has more reputational and career concerns.

The findings of this thesis have implications for regulators who need to address the bias in affiliated sell-side analyst target price forecasts by increasing female representation within the profession in the U.S. Furthermore, the findings have implications for gender studies in risk attitude since gender effect in optimism materialises differently in distinct markets (i.e. Europe and U.S.). Moreover, the findings have implications for policymakers and investment banks as the low female representation within the sell-side analyst profession in Europe is not justified by gender differences in forecasting skills.

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List of Abbreviations and Acronyms

Chartered Financial Analysts	CFA
Chartered Financial Planner	CFP
Chief Executive Officer	CEO
Chief Financial Officer	CFO
Committee on Uniform Securities Identification Procedures	CUSIP
Earnings per Share	EPS
European Union	EU
Financial Industry Regulatory Authority	FINRA
Institutional Brokers' Estimate System	I/B/E/S
Initial Public Offering	IPO
Institutional Investors All-America Research Team	All-star analyst
Markets in Financial Instruments Directive	MiFID
Mergers and Acquisitions	M&A
National Association of Securities Dealers Automated Quotations	NASDAQ
New York Stock Exchange	NYSE
Ordinary Least Squares	OLS
Regulation Analyst Certification	Regulation AC
Regulation Fair Disclosure	Reg FD
Seasoned Equity Offering	SEO
Securities Data Corporation platform	SDC platform
Self-regulatory organisation	SRO
Standards and Poor's	S&P
Target Price	TP

The Centre for Research in Security Prices	CRSP
The U.S. Securities and Exchange Commission	SEC
United States Dollar	USD
United States	U.S.
Wharton Research Data Services	WRDS

Chapter 1: Introduction

1.1 Introduction

The dot.com bubble, which led to the stock market crash in the early 2000s in the United States (U.S.), fuelled the concerns of regulators, the financial press, investors, and academics about bias in sell-side analysts' research due to potential conflicts of interest. Conflicts of interest are suggested to be inherent in the financial industry mainly because of the organisational structure of investment banks, which provide a variety of financial services to many different clients (Boatright, 2000, Palazzo and Rethel, 2008). Studies found that analysts' conflicts of interest exist and usually impede analysts from providing objective research reports (Lin and McNichols, 1998, Michaely and Womack, 1999, Hong and Kubik, 2003, O'Brien et al., 2005, Barber et al., 2007, Cliff, 2007, Kolasinski and Kothari, 2008, Bessler and Stanzel, 2009).

The literature has considered access to management, underwriting fees, and the affiliation as some of the most important sources of conflicts of interest within the analyst profession. Private communication with the management of a firm is considered an important input for analysts' earnings forecasts and stock recommendations (Francis and Philbrick, 1993, Das et al., 1998, Chan et al., 2007, Soltes, 2014, Brown et al., 2015). Consequently, analysts are often reluctant to downgrade a stock as they might be afraid of losing access to management (Francis and Philbrick, 1993, Lim, 2001, Chan et al., 2007). Furthermore, a good relationship with a firm's management might attract potential clients for the investment banks, implying that sell-side analysts employed at investment banks are more biased than analysts employed at brokerages or independent research firms (Dugar and Nathan, 1995, Clarke et al., 2004, Ljungqvist et al., 2006).

An extra layer of conflicts is created for affiliated sell-side analysts, whose employer provides underwriting or mergers and acquisition (M&A) advisory services to a client company. Affiliated sell-side analysts appear reluctant to issue negative reports about the client companies because that might negatively affect the revenues of their employer (Lin and McNichols, 1998, Michaely and Womack, 1999, O'Brien et al., 2005). Therefore, the findings of the extant literature support the allegations regarding sell-side analysts' conflicts of interest, reinforcing the need for regulatory reforms in the U.S. from 2000 onwards.

The documented conflicts of interest attracted the attention of regulators who, following the dot.com bubble period in the U.S., were called to address the bias in sell-side analyst research. The regulatory reforms and the Global Analyst Research Settlement agreement, led to twelve of the largest investment banks in the U.S. receiving fines of 1.4 billion dollars (USD) to address analysts' conflicts and the interdependence between research and investment banking departments (Global Analyst Research Settlement, NASD Rule 2711, NYSE Rule 472, Reg FD). In addition, the regulatory reforms include provisions such as disclosing conflicts and publishing rating distributions. The regulatory response in Europe subsequent to the dot.com bubble developed in a different way than in the U.S., with the regulatory regime being more of an oversight disciplinary mechanism and not a prescriptive approach, as it was the case in the U.S. (Moloney, 2014).

Within the U.S. context, the effectiveness of the regulatory reforms in the post-dot.com bubble era attracted the interest of academics. Studies that tested the impact of the settlement and the related regulations yield mixed results regarding the effectiveness of the reforms (Barber et al., 2006, Barber et al., 2007; Kadan et al., 2009, Barniv et al., 2009). More recent studies showed limited effectiveness of the regulations (Wu et al., 2015, Lu et al., 2016), whereas Corwin et al. (2017) found that the reforms have only been effective for the twelve sanctioned banks. In addition to the findings of the academic papers, the current fines by FINRA to investment banks regarding ongoing violations, highlight that the effectiveness of regulations is highly dependent on their enforcement. Furthermore, other than the regulations, the literature identifies other internal disciplinary mechanisms which can mitigate sell-side analysts' conflicts of interest, including internal factors such as personal reputation and the presence of institutional investors. However, none of them alone can effectively address sell-side analysts' conflicts of interest (Ljungqvist et al., 2007; Fang and Yasuda, 2009).

Conflicts of interest are inherent in the system and both regulations and internal moderating factors can partially mitigate them. As Reingold (2007) states, conflicts of interest will always exist in Wall Street, and the real issue is how individuals handle these conflicts. Therefore, it is important to understand how individual sell-side analysts respond when faced with ethical dilemmas and what factors affect their ethical decision-making. While there are many demographic characteristics that could affect moral reasoning, there is growing evidence that gender is an important determinant of moral reasoning.

The impact of gender on moral reasoning and decision-making has received much attention from academics in recent decades, suggesting that when gender-based differences exist regarding business ethical dilemmas, women tend to have higher ethical moral reasoning than men, supporting the gender socialisation theory. In particular studies found women to be more aware of unethical acts (Ameen et al., 1996, Singhapakdi, 1999), to judge situations as less ethical (Mason and Mudrack, 1996, Christie et al., 2003) and have fewer intentions to act unethically (Cohen et al., 2001) compared to men. However, other studies support the occupational socialisation theory, whereby gender based differences, if any, disappear once men and women enter the workplace as they both adapt to their organisation's culture (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001).

A priori, building on the gender socialisation theory, female analysts will be less likely to sacrifice the quality of their research when faced with conflicts of interest as opposed to men. While no research on analysts has yet considered the gender effect on the quality of sell-side analyst research when faced with conflicts, studies within the business sector have considered the impact of gender diversity on the quality of financial information.

Studies investigated the impact of gender diversity on earnings quality (Krishnan and Parsons, 2008, Srinidhi et al., 2011) and the quality of accruals (Barua et al., 2010), finding a positive association between female participation and the quality of financial statements. This is consistent with the notion that women are better at monitoring the boards and are more concerned with corporate governance issues (e.g. Francis et al., 2013, Frye and Pham, 2018). Further studies suggest that greater board gender diversity is associated with less environmental violations (Liu, 2018) and securities fraud (Cumming et al., 2015). This is consistent with the gender socialisation theory, which posits that women are more likely to stick to rules whereas men are more likely to break the rules (Roxas and Stoneback, 2004, Vermeir and Van Kenhove, 2008).

However, the main limitation of the above-mentioned studies is that other unobservable factors might drive the positive association between females and certain corporate outcomes. For instance, Garcia Lara et al. (2017) found that the firms which discriminate against women, provide lower quality financial statements than non-discriminating firms, which has implications for studies associating females with better quality financial information.

Furthermore, studies suggest that women's risk aversion might affect their decision-making. For instance, female chief financial officers (CFOs) and directors are more risk-averse compared to their male counterparts (Huang and Hung, 2013, Francis et al., 2014, Francis et al., 2015). Other researchers argue that generalisations from population characteristics can be misleading for high profile positions (Croson and Gneezy, 2009, Adams and Funk, 2012, Adams and Ragunathan, 2015, Sila et al., 2016). These studies imply that females entering highly competitive professions, usually with a high male presence, are not representative of the female population. Thus, women following risky finance careers are less risk-averse compared to the general population (e.g. Sapienza et al., 2009), so the findings of studies regarding females' risk attitude in the workplace are far from conclusive.

Within the sell-side analyst profession, the evidence regarding analyst's gender is also mixed. While Kumar (2010) argues that female analysts have personality traits similar to their male counterparts, since he finds females to be less risk-averse than males, by contrast, Green et al. (2009) and Li et al. (2013) consider female analysts to be more risk-averse than their male counterparts. Therefore, it remains unclear whether gender differences in risk attitude persist within the sell-side analyst profession in the U.S.

Regarding job performance, the studies on sell-side analyst gender are also inconclusive. Kumar (2010) reports that female sell-side analysts face discrimination in hiring decisions based on findings that show females outperform males in their earnings forecasts. Yet, other studies do not document any significant gender difference in analyst performance (Li et al., 2013, Fang and Huang, 2017) or document that females are less accurate than their male counterparts (Green et al., 2009).

Overall, the extant studies on sell-side analyst gender are limited, yielding mixed results on gender differences, thus more research needs to be done to shed further light on the gender effect within the sell-side analyst profession and extend the findings to markets with different institutional environments than the U.S.

1.2 Contribution of the Thesis

Although the gender effect within the finance industry has received much attention from academics over the last decades, there has been a limited number of studies investigating gender differences within the sell-side analyst profession. This is mainly attributed to gender data restrictions, since analyst gender is not readily available. Furthermore, the extant studies on analyst gender are implemented within the U.S. market. However, due to differences in the institutional environment, existing findings from the U.S. market cannot be generalised to other markets, as distinct institutional environments might affect the characteristics of female sell-side analysts.

Therefore, this thesis aims to provide evidence of the gender effect within the sell-side analyst profession across both the U.S. and Europe. The European market is large enough for comparison with the gender effect in the U.S. (Capstaff et al., 2001), thus provides an ideal setting to compare the extant findings from the U.S. market. Accordingly, Chapters 5, 6, and 7 provide unique evidence of the gender differences on analyst bias, optimism, and performance across Europe and/or the U.S.

1.2.1 Does Gender Influence the Way Affiliated Sell-side Analysts Respond to Their Conflicts of Interest?

To date, no research has considered the role of gender on sell-side analysts when faced with ethical dilemmas. Knowledge about gender effects has important implications for ethics training (Rest, 1986), hence such knowledge will assist both investment banks' and regulators' efforts to address analyst bias. Therefore, motivated by the importance of ethics within the sell-side analyst profession in the U.S., Chapter 5 investigates whether gender influences the way affiliated sell-side analysts respond to their conflicts of interest.

The research opinions of sell-side analysts provide an ideal setting to examine the role of gender in ethical decision-making. To address the research question, the chapter examines the gender heterogeneity in analysts' target price bias of the covering stocks when their employer was recently the lead underwriter of an equity issue. Target prices, like stock recommendations, represent a direct investment recommendation (Bradshaw, 2002, Brown et al., 2015, Bilinski et al., 2019) and are more granular than stock recommendations, allowing to more accurately measure changes in analysts' optimism bias.

Given the mixed results of the extant studies regarding gender differences in ethical decision-making, it is unclear whether gender influences the way affiliated sell-side analysts respond to their conflicts of interest. Building on the gender socialisation theory, it is expected that affiliated female sell-side analysts will be less likely to bias their research as opposed to their affiliated male counterparts. However, if male and female affiliated sell-side analysts are equally biased in their target prices, this will provide support for the occupational socialisation theory.

The findings of the chapter begin by showing that affiliated sell-side analysts issue more biased target prices than their unaffiliated counterparts, suggesting that, in line with prior studies (Barniv et al., 2009, Kadan et al., 2009), regulatory reforms have had a limited ability at mitigating this behaviour. This finding has implications for regulators' efforts to protect investors from biased analyst research in the U.S.

Next, it is documented that target price bias of affiliated female analysts is not significantly different from the target price bias exhibited by male analysts, which is consistent with the occupational socialisation theory, whereby gender differences do not persist in a professional environment where employees tend to develop similar moral reasoning as they adapt to the working environment and organisational culture of their chosen occupation (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001). This finding has implications for the male-dominated sell-side analyst profession. The proportion of males to females (86:14) is large enough to influence the organisational culture (Kanter, 1977) in which both male and female sell-side analysts are adapting to. Therefore, it is unclear if female sell-side analysts were more ethical prior to entering the profession, and once they have been employed, they adapted the ethical values underpinning the male dominated culture.

Although it is not possible to test the ethical behaviour of female sell-side analysts before entering the profession, it can be tested whether the organisational culture in which the sell-side analysts are adapting to is positively influenced by a higher proportion of females. In further analysis, it is reported that higher female representation is associated with less bias on affiliated sell-side analysts' target prices at sanctioned banks. Therefore, regulators should consider increasing female representation within the sell-side analyst profession in the U.S. to improve the ethical culture within investment banks.

Chapter 5 contributes to the literature on analysts in several ways. It complements the extant studies on analysts' conflicts of interest by showing that affiliated analysts exhibit more bias in their target price forecasts than unaffiliated analysts around equity issues in the post regulatory period. Next, it extends the studies on sell-side analyst gender in the U.S., by providing evidence of the gender effect in sell-side analyst bias. Lastly, it complements the existing studies on gender differences in ethical decision-making by providing support for the occupational socialisation theory.

Other than ethical decision-making, gender studies in the finance industry have considered gender differences in risk attitude. The extant studies on analyst gender provide mixed results of the gender effect in risk attitude, as well as being limited to the U.S. market. Differences in the institutional environments between distinct markets might affect the characteristics of female sell-side analysts, hence the findings from the U.S. market may not generalise in other markets. Thus, more research is needed to provide evidence of the gender differences in optimism within the sell-side analyst profession, therefore, Chapter 6 investigates gender differences in target price optimism across both the U.S. and Europe.

1.2.2 Do Male Sell-side Analysts Issue More Optimistic Target Prices than Females? Evidence from Europe and the United States

Chapter 6, motivated by the mixed results of the extant studies about the gender effect on sell-side analyst optimism in the U.S., tests whether male sell-side analysts issue more optimistic target prices than their female counterparts. Furthermore, given the lack of evidence from other markets, the research question is tested across both Europe and the U.S. The European market is large enough to bear comparison with the gender effect in the U.S. (Capstaff et al., 2001). In addition, U.S. and Europe have different institutional environments which might affect the characteristics of female sell-side analysts. Therefore, these two distinct markets are considered in this chapter to provide further insights of the gender effect within the sell-side analyst profession.

The results are important for market participants and regulators. For instance, if male analysts issue significantly more optimistic forecasts than females, investors need to be aware of this so that they can discount the forecasts issued by male sell-side analysts. Thus, the findings of this study will inform their investment decisions. Furthermore, the study will inform regulators if the gender effect, if any, is homogenous across the European and the U.S. market and whether the two markets should be treated homogenously in the issue of any potential future gender policies.

Target price forecasts were used to address the research question as they are more likely to be affected from sell-side analyst optimism than other measures (Bradshaw et al., 2006). There is no prior of the gender effect on sell-side analyst optimism given the mixed results of the extant studies. For instance, it is expected that more optimistic target price forecasts will be issued by male sell-side analysts if gender differences in risk attitude persist within the sell-side analyst profession. Yet, if gender differences are not prevalent in the male dominated sell-side analyst profession, it is expected that both male and female sell-side analysts will be equally optimistic in their target price forecasts.

In the first set of results, it is documented that across both Europe and the U.S., male sell-side analysts are significantly more optimistic than their female counterparts. However, when the sample was limited to stocks followed by both male and female sell-side analysts in the same year to control for endogeneity, there was no gender difference in sell-side analyst optimism for European stocks. Therefore, female sell-side analysts in Europe initially appear less optimistic due to reverse causality since they do not follow as risky stocks as their male counterparts. In the additional analysis, after controlling for the choice of the stock followed, there is no gender difference in target price forecast accuracy.

These findings have implications for previous gender studies in risk attitude, as the gender effect in optimism materialises differently in distinct markets; it might affect the choice of the stock followed (i.e. Europe) or it might affect the level of optimism documented in target prices (i.e. U.S.). Furthermore, there is no gender difference in the target price forecast accuracy in the European and the U.S. limited samples, suggesting that gender differences in optimism, if any, do not significantly affect the target price performance.

Overall, the findings of Chapter 6 contribute to the sell-side analyst literature by providing evidence of the gender effect on target price optimism from the U.S. and the European markets. In addition, the chapter complements the stream of literature testing for gender differences in risk attitude and corporate outcomes in high profile professions.

Unlike target prices, earnings forecasts are less likely to be affected from optimism bias (e.g. Bradshaw et al., 2006), therefore, earnings forecast accuracy proxy for analyst forecasting skill, so market participants systematically differentiate for analyst characteristics associated with greater earnings forecast accuracy (e.g. Bradley et al., 2017). In the U.S., Kumar (2010) found that female sell-side analysts are associated with greater forecast accuracy, but these findings are not generalisable to other markets with different institutional environment than in the U.S. Therefore, Chapter 7 investigated whether gender is a determinant of earnings forecast accuracy in Europe.

1.2.3 Is There Gender Heterogeneity in Sell-side Analyst Forecasting Skills? Evidence from Europe

Studies have extensively studied analyst characteristics that proxy for forecast accuracy (e.g. Clement, 1999), as accurate earnings forecasts are important for the sell-side analyst profession. For instance, market participants systematically differentiate for analyst characteristics that are associated with greater forecast accuracy (e.g. Bradley et al., 2017). Furthermore, analysts who issue more accurate earnings forecasts are more likely to have job promotions in the U.S. (e.g. Hong and Kubic, 2003) and less accurate analysts are more likely to exit the profession in Europe (e.g. Bolliger, 2004). Therefore, given the importance of accurate earnings forecasts, it would be expected that analysts with superior forecasting skills have a greater representation within the profession.

The sell-side analyst profession is male dominated which might be explained by the better forecasting skills that male analysts might have compared to their female counterparts. In his U.S. study however, Kumar (2010) found that female sell-side analysts are associated with higher forecast accuracy than males, which is surprising given the low female representation. Kumar (2010) suggests that this is explained by the discrimination female sell-side analysts face in hiring decisions. As the findings of Kumar's (2010) study might not generalise to markets with a different institutional environment than in the U.S., more research is required to explore any gender differences in earnings forecast accuracy across other markets.

Chapter 7, motivated by the low female representation within the sell-side analyst profession and the importance of earnings forecast accuracy to market participants, investigates whether there is gender heterogeneity in forecasting skills in Europe. The European market is a good setting to test for gender differences in earnings forecast accuracy, since it is large enough to bear comparison with the gender effect documented by Kumar (2010) in the U.S. To the best of my knowledge, no study has so far tested whether there is gender heterogeneity in the forecasting skills of analysts following European stocks.

The findings show that there is no gender heterogeneity in the earnings forecast accuracy across Europe. Therefore, low female representation in the sell-side analyst profession is not justified by lower forecasting skills. The different results between Kumar's (2010) study and the results of this chapter are explained by the different market examined in this study. Furthermore, despite the documented lack of gender difference in forecast accuracy, there are gender differences in forecasting characteristics. Specifically, male analysts are significantly more likely to issue bold forecasts whereas female analysts are more likely to herd, implying that females have more reputational and career concerns than their male counterparts.

The findings of this chapter have implications for policymakers and investment banks, since low female analyst representation is not justified by gender differences in forecasting skills. In addition, the results have implications for gender studies suggesting that females are less competent than males in highly competitive professions. Furthermore, the chapter contributes to the sell-side analyst literature, by providing evidence of the gender effect on earnings forecast accuracy within Europe. Finally, the chapter contributes to the stream of literature that tests for gender differences in performance within the finance industry.

1.3 Thesis Outline

The thesis is organised as follows:

- Chapter 2 discusses the institutional background of the sell-side analyst profession specifically providing an overview of the analyst industry, the sources of conflicts of interest within investment banks, and the regulatory reforms across both the U.S. and Europe.
- Chapter 3 is a literature review of the sell-side analyst conflicts of interest and the factors which moderate such conflicts. Furthermore, the role of gender within the finance industry is also discussed.
- Chapter 4 provides a detailed explanation of the gender identification process followed to obtain the core sample of matched analysts, as well as a set of descriptive statistics of the sample distribution.
- Chapter 5 presents the first empirical chapter of the thesis which tested whether gender influences the way affiliated sell-side analysts respond to their conflicts of interest.
- Chapter 6 presents the second empirical chapter of the thesis which investigated whether male analysts issue more optimistic target prices than females across Europe and the U.S.
- Chapter 7 presents the third empirical chapter of the thesis which addressed whether there is gender heterogeneity in sell-side analyst forecasting skills across Europe.
- Chapter 8 provides the thesis conclusion, summarising study background, key findings, policy implications as well as limitations and directions for further research.

Chapter 2: Institutional Background

2.1 Overview of Analysts' Industry

The role of research analysts in the stock market is important as they ease the flow of information to investors, therefore promote market efficiency (Schipper, 1991). Their main task is to issue research reports to help users to make informed investment decisions. Among their responsibilities, their job includes analysing companies and industries, evaluating historical and financial data, understanding regulations, policies, and economic as well as political trends. Depending on the nature of their employment, analysts fall into one of the three categories; sell-side, buy-side, and independent analysts.

2.1.1 Sell-side Analysts

Sell-side analysts are typically employed in the research department of full-service investment banks[1], distributing their research externally and their purpose is to provide their clients with objective research regarding the prospects of the stocks that they cover. Sell-side analysts' stock recommendations, target prices, and earnings forecasts are the most common outputs used by investors when evaluating investment decisions. The most important client for the sell-side research are the buy-side analysts who work for pension funds, mutual funds, etc. The costs of the sell-side research are hidden in the

[1] Full-service investment banks provide both research and investment banking services. Investment banking relates to the creation of capital for other companies, governments, and other entities through the underwriting of seasoned equity offerings, debt financing, and initial public offerings. Also, an investment bank acts as an adviser on mergers and acquisitions or performs general advisory services. In addition, among their services, investment banks facilitate broker trades for both institutions and private investors. In the research department, sell-side analysts review companies and issue reports about their prospects.

total trading commission costs charged by the investment banks thereby the buy-side firms do not pay directly for sell-side research[2].

Usually, sell-side analysts focus on a specific industry in which they have expertise. In many cases, sell-side analysts cover companies that are corporate clients of the investment bank in which they are employed. This relationship is often problematic because it creates conflicts of interest to the analyst, who might issue optimistically biased research to help the investment banking department generate more revenues at the expense of the objectivity of their research.

Furthermore, other than producing research reports, sell-side analysts are engaged in other activities within their firms. For instance, sell-side analysts might assist the investment banking department by providing their expertise to corporate finance transactions. In this situation, to avoid the leak of inside information, analysts are said to be brought over the 'Chinese Wall', an internal structure within the investment bank which attempts to prevent the flow of inside information by ensuring the independence of the research and investment banking departments. An analyst who is brought over the 'Chinese Wall' is temporarily considered part of the investment banking department and cannot use any new information for his/her research report. In addition, sell-side analysts could assist in securities marketing during 'road shows' where investment bankers hold presentations for potential institutional investors[3].

[2] While that is the case for the U.S., the MiFID II regulation in Europe enforced since January 2018 requires the unbundling of research costs and trading commissions.
[3] Since 2002, analysts in the U.S. have been prohibited from taking part in 'road shows' (FINRA Rule 2241 – Research Analyst Research Reports).

2.1.2 Buy-side Analysts

Buy-side analysts generally work for money managers such as mutual funds, hedge funds or pension funds. Buy-side analysts are the main users of the sell-side analyst research reports, their main task being to give advice to their clients about buying, selling, or holding a stock. Unlike the sell-side analyst reports which are publicly available, buy side analyst reports are distributed only to their clients.

The employer of the buy-side analysts is also their client which creates strong incentives for buy side analysts to perform well. For instance, buy-side analysts are assessed by their employer based on the performance of their analysis. Thus, if buy-side analysts bias their recommendations, hence hinder their performance, they might lose their job. By contrast, clients are different from the employers in the sell-side analyst profession. This distinction is important, as it is more likely to create misaligned incentives to sell-side analysts as opposed to buy-side analysts. For example, investment banks might want to favour a client company from the investment banking department, therefore create pressure on the sell-side analysts to issue biased research reports.

2.1.3 Independent Analysts

Independent analysts work for boutiques that sell research as a standalone product. These firms do not provide any investment banking services, so their only or main source of revenue comes from the sale of their research. Therefore, independent analysts have a strong incentive to provide objective research. Consistent with this argument was the requirement of the Global Analyst Research Settlement for the twelve sanctioned banks to provide independent research together with the sell-side research to their clients for a five-year period.

The implicit assumption of the requirement of Global Analyst Research Settlement for the twelve sanctioned banks was that independent research conveys less bias as opposed to sell-side research. Barber et al. (2007) who tested this implicit assumption, found that independent firms outperform investment banks during the period when the market was bearish. Other studies comparing independent analysts to sell-side analysts reported mixed results regarding differences in optimism and performance (Dugar and Nathan, 1995, Clarke et al., 2004, Cliff, 2007).

Overall, all the three types of analysts (i.e. sell-side, buy-side, and independent analysts) are likely to face some sort of conflicts of interest, due to their incentives to gain better access to a company's management. Favourable research might ease the access to a firm's management, which is an important source of information for analysts in generating their earnings forecasts and stock recommendations (Francis and Philbrick, 1993, Das et al., 1998, Chan et al., 2007, Soltes, 2014, Brown et al., 2015). Sell-side analysts though, are subject to higher conflicts of interest compared to independent and buy-side analysts, because investment banks are offering multiple services to many clients, which in many instances creates conflicting interests to the sell-side analysts.

2.2 Conflicts of Interest in Investment Banks

Using the definition suggested by Boatright (2000), conflicts of interest occur when:

> *'a personal or institutional interest interferes with the ability of an individual or institution to act in the interest of another party, when the individual or the institution has an ethical or legal obligation to act in that other party's interest'* (p. 202)

For instance, a person with conflicts of interest might choose to serve the interest of the firm over a client or to serve the interest of one client over other clients. Similarly, conflicts of interest might lead an employee to serve their own interest at the expense of their firm or their clients.

Within financial services, institutions usually perform many functions to multiple clients, thereby increasing the likelihood of conflicts of interest to emerge. Palazzo and Rethel (2008) suggest that conflicts are inherent in the system, hence both individuals and organisations need to make their own judgements to not turn potential conflicts into actual conflicts. Therefore, it is often appropriate to link conflicts of interest with ethical decision-making since when people are faced with conflicts, they can choose to either act or not act on such conflicts. In particular, in his book 'Confessions of a Wall Street Analyst', Reingold (2007) acknowledges that conflicts are inherent in Wall Street, but concludes that 'the real issue was how individuals chose to handle them' (pp. 275–276)[4].

Conflicts of interest usually evolve in unregulated areas where individuals and organisations find the opportunity to exploit these conflicts (Palazzo and Rethel, 2008). However, even in heavily regulated industries such as financial services, the failure of properly mitigating conflicts of interest played a key role in numerous financial crises and scandals. The market crash in the U.S. in 1929 and the subsequent banking crisis brought banks under scrutiny regarding their involvement in the securities markets. The Pecora hearings in the early 1930s revealed that conflicts of interest faced by banks and bank affiliates led them to abusive practices, such as the use of bank loans to support bank-affiliates and the underwriting of unstable securities to pay off bad bank loans (Florio, 2012). As a result, conflicts of interest led the former SEC Chairman Arthur Levitt to

[4] Dan Reingold was a top-ranked Wall Street telecom analyst from 1989 to 2003 at top investment banks such as Morgan Stanley, Merrill Lynch and Credit Suisse First Boston.

enact the Securities Act of 1933 and the Securities Exchange Act of 1934 as well as the Glass-Steagall Banking Act of 1933.

In the 1980s, conflicts of interest were the key player to insider trading scandals, for example, the Ivan Boesky and Dennis Levine scandals and the collapse of Drexel Burnham Lambert investment bank. In the late 1990s and early 2000s, the dot.com bubble in the U.S. revealed the severity of conflicts of interest within the sell-side analyst profession. Around that period, sell-side analyst profession came under severe public scrutiny and allegations regarding optimistically biased research reports proliferated. Thus, sell-side analyst conflicts were of particular interest in the post-dot.com bubble period, which led to regulatory reforms by FINRA and new provisions by Sarbanes-Oxley Act directly addressing those conflicts.

Sell-side analysts employed at investment banks are usually prone to personal-organisational conflicts of interest (Palazzo and Rethel, 2008). While all types of analysts are subject to conflicts of interest, arguably, sell-side analysts are prone to more severe conflicts due to the nature of their employment and the organisational structure of investment banks. According to their report, OICV-IOSCO (2003) outlined the most common scenarios where sell-side analysts are faced with conflicts of interest, which are discussed in the next section.

2.2.1 Investment Banking Clients and Sell-side Research Reports

The different incentives between investment banking and research departments within investment banks is a commonly cited source for creating conflicts of interests to sell-side analysts. Both research and banking departments work for the same investment bank and arguably, their goal should be to maximise the profits of their firm. Although the research department should provide objective research, their reports can sometimes impede the profits of the investment banking department. The services provided by the investment banking department represent the most important source of revenue for investment banks, whereas the research department does not produce any revenue. Therefore, lower profits from the investment banking department means lower overall profits for the firm. In his book 'Confessions of a Wall Street Analyst', Reingold (2007, p. 302) explains this problematic organisational structure from his own experience as a sell-side analyst:

'Eventually I started to see that the analyst's obligation to be independent, while ethically imperative, wasn't economically logical at all, given that he or she works for a firm whose primary purpose is to maximize fees' (Reingold, 2007, p. 302)

Therefore, sell-side analysts might be reluctant to publish a negative research report or express a negative opinion on certain stocks because that could harm the revenues, damaging the relationship with an existing or potential client of the investment banking department. Furthermore, an analyst's reluctance in conveying unfavourable news in their stock recommendations might provoke the use of a misleading 'coded' terminology in their research reports. For instance, analysts might issue a hold recommendation, instead of issuing a sell recommendation that might reflect their actual opinion about a stock.

Sophisticated investors who are more likely to be aware of analysts' conflicts of interest will often discount a hold recommendation and treat it as a sell recommendation instead (Lin and McNichols, 1998). However, retail investors who are perceived 'naïve' investors are more likely to follow the analyst's recommendation and hold the stock. This 'coded' terminology is arguably used by analysts as a way to keep good relations with the management of an existing or potential banking client. Furthermore, analysts might even stop the coverage of a stock to avoid publishing a negative research report.

In addition, given the conflicting incentives between the research and investment banking departments, the reporting lines between the two departments within the investment bank can be an important source of potential conflicts of interest. The interaction between research and investment banking department is sensitive to the essence that it might lead to the flow of important private information or it might also affect an analyst's objectivity. For instance, if personnel from the investment department intervenes with the research department, they might pressure an analyst to issue a favourable report or change a stock recommendation to benefit the investment banking department.

2.2.2 Trading Commissions and 'Venture Investing'

Another source of potential conflicts is when an analyst covers securities, which the investment bank that he/she is employed by is trading. The analyst's firm might trade securities for its own account or for clients, however, in either case, this situation creates conflicts to the analyst. An analyst report can affect the price of a company's securities, therefore, analysts might have the incentive to provide a favourable research report to benefit their firm or its clients who hold that company's securities.

Furthermore, investment banks provide brokerage services whereby the investment bank receives commissions for executing buy or sell orders from their clients. This again creates conflicts to the analysts who might improperly issue buy or sell recommendations on their research reports as an attempt to help their investment banks to earn commission revenue.

Another important source of conflict of interest is when an analyst covers a company for which significant positions are held by the same analyst or his/her firm or other colleagues. In the case of start-up companies, under 'venture investing', the analyst as well as the investment bank and its employees might buy pre-IPO shares at a discount price. This creates economic incentives to the analyst to issue a favourable research report for the covered company, or the investment bank might create pressure on the analyst to issue optimistically biased stock recommendations.

2.2.3 Compensation

Analyst compensation might also create important economic incentives to sell-side analysts in sacrificing the objectivity of their research to the extent that their remuneration has a direct relationship with the profits generated by the investment banking department. Based on the OICV-IOSCO (2003) report on analysts' conflicts of interest, they found that as of December 2002, in most jurisdictions, analysts were paid a combination of fixed salary and bonus. To what determinants the bonuses are based on differs across investment banks.

Compensation structures can be complex and many jurisdictions take into account many variables when deciding an analyst's compensation (OICV-IOSCO, 2003). Such variables might include the performance of analyst's stock recommendations, analyst's reputation, the investment banking department revenue attributable to the analyst, as well as the overall profitability of the investment bank (OICV-IOSCO, 2003). Consequently, if the investment bank links analyst's bonuses to the investment banking revenue generated by the analyst, it creates incentives to the analysts to issue favourable research to attract more investors to buy the stock of the company that they cover.

2.3 Regulatory Reforms Within the United States

The organisational structure of investment banks provokes the creation of conflicts of interest to sell-side analysts. However, regulators had not addressed these severe conflicts, which were inherent in the system, prior to the dot.com bubble period. As a result, the lack of sufficient rules to regulate the industry left the analysts and their investment banks plenty of room to act on their conflicts of interest. In the light of dot.com bubble and the subsequent stock market crash in the U.S., the need for new regulations directly addressing the conflicts of interest faced by sell-side analysts was revealed.

The current regulations in the pre-bubble period did not prohibit analysts from owning securities of companies they were covering or owning securities of companies their employer took public. In their examination of the largest full-service investment banks in the U.S. in 1999, the Office of Compliance Inspection and Examinations found poor compliance with the SRO rule which requires investment banks to monitor the private equity investment by employees (Richards, 2002). Furthermore, due to inconsistencies in the prior SRO rules, the disclosures of the examined firms regarding the analyst or firm positions in the recommended issuers were not clear or not disclosed at all (Richards, 2002). In addition, in their public appearances, analysts were often recommending stocks without mentioning the existence of any conflicts of interest (Richards, 2002). Another issue not addressed by the prior regulations was the confusing terminology of the stock recommendations used by analysts (Richards, 2002).

As a response to the inadequate rules, the regulatory reforms following the financial events in the U.S. intended to mitigate analyst conflicts of interest by increasing the independence between investment banking and research department (Global Analyst

Research Settlement, NASD Rule 2711, NYSE Rule 472, Reg FD)[5]. One of the first regulations enforced in response to the dot.com bubble issued in October 2000 was the Fair Disclosure Regulation (Reg FD) to address analyst conflicts regarding access to a company's management.

The Reg FD was issued by the SEC and mandated the concurrent disclosure of material information to all investors from all publicly traded companies. The regulation aims to prohibit selective disclosure to certain investors, usually large institutional investors, conveying material information at the expense of smaller, individual investors. Therefore, the prohibition of disclosure to selected investors also prohibits management from disclosing information to selected analysts.

Regarding the effectiveness of the Reg FD, recent studies suggest that the regulation is not effective in preventing access to management since it does not prohibit the disclosure of non-material information to selected market participants (Koch et al., 2013, Green et al., 2014, Soltes, 2014). Arguably, analysts are sophisticated investors and have superior skills than individual investors, therefore any disclosure of non-material information may assist the analysts to reach material conclusions.

Moreover, in an attempt to keep analysts more accountable in what they write and publicly say about a stock, the Regulation Analyst Certification (Regulation AC), which became effective on 14th April 2003, requires research analysts to certify that the views they express in their research reports and public appearances are truthful. In addition, research analysts must disclose whether they have received any compensation related to

[5] NASD Rule 2711 (Research Analysts and Research Reports) and NYSE Rule 472 (Communications with Public), which were formally accepted by the SEC on July 2003, were suspended by FINRA Rule 2241 (Research Analysts and Research Reports) adopted in 2015. The new FINRA rule addresses the same subject matter of regulations as the NASD Rule 2711 and NYSE Rule 472.

the specific recommendations or views expressed in those reports and appearances so that investors are aware of potential conflicts. This regulation is likely to make analysts more concerned about the quality of their research and stock recommendations[6].

A few days after the introduction of Regulation AC, on the 28th April 2003, a legal settlement was agreed with the twelve largest U.S. investment banks facing a $1.4 billion fine under the enforcement of the Global Analyst Research Settlement in 2003[7]. The allegation of the Global Analyst Research Settlement was that the twelve sanctioned banks[8] engaged in acts and practices that enabled investment banking to exert inappropriate influence over analysts and failed to manage analysts' conflicts of interest appropriately.

The twelve sanctioned banks should comply with undertakings including the independence between research and investment banking departments, enhanced disclosures, and the supply of independent third-party research. Specifically, the regulations include the complete separation of indirect or direct reporting from the research department to or through the investment banking department. In addition, physical separation of research and investment banking is required to prevent both intentional and unintentional flow of information.

[6] Reingold (2007) criticises this regulation in his book by arguing that dishonest analysts will have no trouble signing their names to anything, whereas analysts who are honest are already publishing objective research.
[7] Global Analysts Research Settlement was an enforcement agreement between the United States Securities and Exchange Commission (SEC), the Financial Industry Regulatory Authority (FINRA), the New York Stock Exchange (NYSE), and the twelve largest U.S. investment banks.
[8] Bear, Stearns & Co. Inc. (Bear Stearns), Credit Suisse First Boston LLC (CSFB), Goldman, Sachs & Co. (Goldman), Lehman Brothers Inc. (Lehman), J.P. Morgan Securities Inc. (J.P. Morgan), Merrill Lynch, Pierce, Fenner & Smith, Incorporated (Merrill Lynch), Morgan Stanley & Co. Incorporated (Morgan Stanley), Citigroup Global Markets Inc., f/k/a Salomon Smith Barney Inc. (SSB), UBS Warburg LLC (UBS Warburg), U.S. Bancorp Piper Jaffray Inc. (Piper Jaffray), Deutsche Bank Securities Inc., and Thomas Weisel Partners LLC Settle.

The Global Analyst Research Settlement also aimed at increasing the transparency of analysts' performance and to enhance disclosure requirements by clearly disclosing conflicts of interest faced by either the analysts or the investment bank. In addition, the twelve sanctioned investment banks are obligated to make available independent research to investors for five years by contracting at least three independent research firms.

While the provisions of the Global Analyst Research Settlement apply to the twelve sanctioned banks, new provisions and regulations aimed to address the gaps and/or inconsistencies of previous regulations in mitigating analysts' conflicts are applicable to all the investment banks within the U.S. The NASD Rule 2711 and NYSE Rule 472, which aimed to address sell-side analyst conflicts of interest, include provisions regarding:

2.3.1 Communication Between Investment Banking and Research Department

In an attempt to protect research analysts from any pressures or influences from the investment department, the reforms focus on decreasing the interdependence between the two departments. Personnel from the investment banking department are not allowed to supervise research analysts or discuss the research report with the analysts before its publication[9].

The prohibition also includes drafts of research reports which analysts are not allowed to share with the investment banking department unless the purpose of sharing the draft reports is to check facts. To proceed to any action of showing drafts of research

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[9] Even if research analysts do not report to anyone in the investment banking department, this might not solve the problem of conflicts of interest as the personnel within investment bank, such as the CEO and top executives, arguably want to maximise profits, which again might create pressures on the research department (e.g. Reingold, 2007).

reports or discussing the content of the research reports, investment banking and research department need approval from the firm's legal/compliance department.

2.3.2 Analyst Compensation

The regulatory reforms also prohibit investment banks from linking analyst's salary to specific investment banking transactions. This provision is likely to reduce an analyst's economic incentives to provide optimistic biased research reports. However, the prohibition does not restrict management to reward banker-friendly analysts by increasing their salary (Reingold, 2007).

In addition, investment banks need to disclose when an analyst's compensation is tied up on a specific recommendation or whether part of an analyst's remuneration is linked to other performance measures from the investment banking department. The additional disclosure requirements intended to make investors aware of the analyst's potential conflicts, so they can decide whether to discount the research report provided by the analyst.

2.3.3 Investment Banking Services

Analyst compensation is likely to be affected from the revenues produced by the investment banking services. Thus, analysts covering a stock whose employer acted as the underwriter or co-underwriter or as adviser of an M&A deal are usually referred to as affiliated analysts in the literature. Affiliated sell-side analysts are arguably subject to higher conflicts of interest than unaffiliated sell-side analysts or other types of analysts. Therefore, in the research reports, investment banks should disclose whether they acted as the underwriter or co-underwriter of an initial public offering (IPO) or seasoned equity offering (SEO) for the covered company in the past twelve months. Additionally, the firm should disclose the information if it expects to receive or intends to seek income revenue from the company during the next three months. Again, these disclosures aim to inform investors regarding potential conflicts of interest faced by the investment bank so that they are aware of the potential bias of the analyst research report.

Furthermore, during the IPO process, there is the implicit assumption that the underwriter will provide coverage of the newly issued security in the after-market. Positive research from the underwriter's analyst is important as it can improve the value of the securities in the market as well as attract more institutional investors. Therefore, to mitigate conflicts, the new provisions enforce 'quiet periods' which prohibit lead underwriter or co-underwriter analysts to issue a research report on the company within 40 days after the IPO. Thus, this rule limits the attractiveness of positive research coverage from the affiliated analyst because unaffiliated analysts will have the opportunity to issue their research reports first.

The recent example of Snapchat's IPO at the beginning of March in 2017 though shows that 'quiet periods' are not always effective since once the affiliated analysts can issue their recommendation, nothing can stop them from being biased and affect the value of the shares. In the case of Snapchat, the ten first research notes issued by the Wall Street analysts were either 'sell' or 'neutral' according to Bloomberg. However, by the end of the same month, on the 27th March 2017, analysts, including Morgan Stanley that led the $20 billion IPO, issued five buy ratings[10]. The 'quiet period' for the underwriters passed, therefore the 'bullish' reports managed to boost the worth of

[10] More information about Snapchat's IPO can be found at:https://www.ft.com/content/9323ef5e-1309-11e7-80f4-13e067d5072c?mhq5j=e2

Snapchat by 5% to almost $28 billion despite the fact that the unaffiliated analysts were bearish about the stock during the 'quiet period'.

2.3.4 Personal Trading

Furthermore, conflicts are created when an analyst or their employer and colleagues have economic incentives because they own big positions on a security covered by the analyst (OICV-IOSCO, 2003). The new rules restrict analysts and other employees of the investment bank to invest in a company's securities before the IPO if the company is in the business sector which the analyst covers (NASD Rule 2711).

In addition, when analysts issue research reports about a company, the 'blackout periods' ban those analysts from trading the securities for thirty days before and five days after the issue of their report (NASD Rule 2711). Analysts are also prohibited from trading contrary to their most recent stock recommendation (NASD Rule 2711).

2.3.5 Enhanced Disclosure Requirements

Regulatory reforms enhanced the disclosure requirements in analyst research reports in an attempt to make investors aware of potential conflicts of interest and to help them in their evaluation of analyst research reports. Among the provisions of the new rules, analysts are required to disclose whether they have any economic incentives in the covered firms. For instance, in their reports, analysts should disclose whether their investment bank owns 1% or more of a company's securities.

Furthermore, previous regulations did not address the issue of disclosing analysts' conflicts on public appearances. Therefore, new rules require analysts to disclose if they or their firms have positions in certain stocks. Also, during public appearances, analysts are required to disclose whether the company they are referring to is a client company of the investment banking department of their firm.

Another disclosure requirement under the new regulations relates to the terminology of stock recommendations as well as the rating distribution within the investment bank. Research reports should clearly explain the meaning of all rating terms they use, and investment banks should also make publicly available the percentage of all 'buy', 'hold' or 'sell' ratings they have issued. In addition to the overall rating distribution, investment banks should also provide information about the percentage of their investment banking clients in each rating category. These disclosure requirements are expected to benefit investors because it will provide them with a better view of how many 'buy' and 'sell' recommendations the investment bank issues. Besides, they will be aware of how the investment bank rates their investment banking clients compared to non-client firms; this information ultimately would assist investors in their decision-making.

Moreover, analysts are required to disclose information when they terminate the coverage of a stock, disclosing the exact reason for the termination. This action is likely to limit analysts from terminating the coverage of stocks because they do not want to issue an unfavourable report in their attempt to keep good relations with a company's management.

The main implication of the regulatory reforms regarding the enhanced disclosure requirements aiming to inform investors about potential conflicts of interest is to what extent investors read and understand such disclosures (Boni and Womack, 2003). In particular, institutional investors are more likely to read and understand the new disclosure requirements than retail investors (Boni and Womack, 2003), thus the positive effect of increased disclosures might not be exhibited equally to all investors.

Finally, the extant literature is not conclusive regarding the effectiveness of regulatory reforms for mitigating sell-side analysts' conflicts of interest (Barniv et al., 2009, Kadan et al., 2009, Wu et al., 2015, Lu et al., 2016, Corwin et al., 2017). Moreover, the ongoing violations of the regulations from investment banks and analysts highlight that compliance with the regulations is vital for the effectiveness of any regulatory reforms (Di Lorenzo, 2007).

2.4 Regulatory Reforms Within the European Union

In the post-dot.com bubble period, the regulatory regime in Europe around investment analysts was developed differently compared to the prescriptive approach under the Sarbanes Oxley Act in the U.S. (Moloney, 2014). The EU regulatory regime was generally supportive of a principles-based intervention which does not provide detailed regulations for the regulated parties to implement to achieve a certain outcome (Moloney, 2014).

In 2004, the Market in Financial Instruments Directive 2004/39/EC (MiFID) was created, but it was not implemented until November 2008. The key aims of MiFID, which was the cornerstone of the EU's financial markets, were to increase the competitiveness in the financial markets with the creation of a single market for investment services and to ensure consumer protection across the EU. The issue of conflicts of interest within the financial services was addressed by the MiFID, however it was a rather generic approach, where firms were required to take 'reasonable' steps to manage or prevent conflicts and disclose such conflicts. The MiFID was in force from the 31st January 2007 to the 2nd of January 2018.

MiFID II, which is the updated version of MiFID, came into force on 3rd January 2018 until today and extends and strengthens some of the conflict requirements found in the previous MiFID. For instance, under MiFID, firms were required to take 'reasonable' steps to prevent or manage conflicts, whereas under the MiFID II, firms are now required to take 'appropriate' steps, which requires a more active identification of conflicts. In addition, MiFID requirements for addressing conflicts of interest were overly reliant on disclosing such conflicts. However, disclosure of conflicts does not necessarily mean that the conflicts have been addressed. In MiFID II, it specifically states that firms 'should only use disclosure as a last resort' emphasising that disclosure of conflicts is not the same as managing conflicts.

Also, under MiFID II, fund managers need to unbundle the cost of investment research and advisory services from other products and services. To date, the costs of research were hidden since asset managers lumped trading and research costs into a single fee. This requirement is expected to change the sell-side analyst profession in Europe, since fund managers and investors may be unwilling to pay for sell-side research. In their study, Fang et al. (2019) found that since the implementation of MiFID II, the number of buy-side analysts has increased suggesting that European investment firms are more likely to produce in-house research. In addition, the authors found that the coverage of European firms by sell-side analysts has significantly dropped. However, the analysts who dropped coverage, had higher forecast error, greater optimism, and less experience in the profession. The remaining analysts have been found to issue more profitable stock recommendations than before the implementation of the MiFID II (Fang et al., 2019). Although, it has only been two years since the enforcement of MiFID II, therefore the effect of the new requirements might not yet be complete.

2.5 Summary and Conclusion

The role of research analysts in the stock market is important as they ease the flow of information to investors, thereby promoting market efficiency (Schipper, 1991). Depending on the nature of their employment, analysts fall into one of the three categories, sell-side, buy-side, and independent analysts. Sell-side analysts, who are employed at investment banks, are subject to conflicts of interest because investment banks offer multiple services to many clients which often creates conflicting interests to sell-side analysts.

The different incentives between investment banking and research departments within investment banks are the main source of conflicting interests to sell-side analysts. Another source of potential conflicts is when an analyst covers securities, which the investment bank that they are employed by is trading. Furthermore, analyst compensation might also create important economic incentives to sell-side analysts in sacrificing the objectivity of their research, to the extent that their remuneration has a direct relationship with the profits generated by the investment banking department.

Regulations in the U.S. have not properly addressed analyst conflicts of interest prior to the dot com bubble events. Therefore, following the financial events in the U.S., the regulatory reforms intended to mitigate analyst conflicts of interest by increasing the independence between investment banking and research department (Global Analyst Research Settlement, NASD Rule 2711, NYSE Rule 472, Reg FD). Furthermore, the regulations prohibit investment banks from linking analyst's salary to specific investment banking transactions. In the case of affiliated analysts, investment banks should disclose information as to whether they acted as the lead underwriter or co-underwriter of an IPO or an SEO for the covered company in the past twelve months. Moreover, the regulatory reforms restrict analysts and other employees of the investment bank to invest in a company's securities before the IPO if the company is in the business sector which the analyst covers. Lastly, the regulations increased the disclosure requirements to investors.

In Europe, analyst conflicts of interest initially were addressed in MiFID, however it was a rather generic approach, where firms were required to take 'reasonable' steps to manage or prevent conflicts and disclose such conflicts. MiFID II, which is the updated version of MiFID, came into force on 3rd January 2018 until today. MiFID II extends and strengthens some of the conflict requirements found in the previous MiFID. The most important requirement of MiFID II is that fund managers need to unbundle the cost of investment research and advisory services from other products and services.

Although the financial scandals over the past few decades encouraged the introduction of more regulations, their effect in mitigating conflicts of interest is limited. One reason might be that the current regulations are not enforced properly, which is supported by ongoing violations of the regulations[11]. Another reason might be that regulations simply cannot address all the existing conflicts because that might lead to an excessive amount of rules. Reingold (2007) emphasised in his book, that the conflicts are inherent in Wall Street, and that the real issue was how individuals choose to handle them. This suggests that regulation alone cannot fully mitigate these inherent conflicts, it all depends on how the individuals who are faced with such conflicts act on them.

[11] An example of violating the regulations can be found back in 2014 when Goldman Sachs, Citigroup and eight other investment banks were fined $43.5 m by FINRA facing allegations about issuing favourable research reports in an attempt to win underwriting fees around Toys 'R' IPO. A more recent example of weak monitoring within investment banks is the fine of $900,000 to Stephens Inc. by FINRA in May 2016 facing allegations regarding failure to supervise firm-wide internal 'flash' emails sent by the research department. This failure of supervision created the risk of the flow of important non-public information to sales and trading staff who might use such information for their advantage.

A study on how individual analysts handle such conflicts will shed further light on the issue of the conflicts. Research on business ethics has focused on the impact of gender in ethical decision-making, suggesting that women have generally higher ethical reasoning than men. This finding is particularly important for the male dominated sell-side analyst profession. For instance, a study on the impact of gender on analysts' conflicts of interest might inform regulators to issue regulations that are more effective for mitigating these conflicts.

The literature regarding sell-side analysts' conflicts of interest is reviewed in the next chapter, as well as the moderating factors that the literature has identified for analyst conflicts. Furthermore, the role of gender within the finance industry and the sell-side analyst profession is critically reviewed.

Chapter 3: Literature Review

3.1 Sell-side Analyst Conflicts of Interest

Analyst conflicts of interest were of particular interest in the post-dot.com bubble period and the subsequent crash of the U.S. stock market in the early 2000s. Allegedly, around that period analysts sacrificed the objectivity of their research in an attempt to help the investment banking department to generate higher revenues.

Research supports the notion that underwriting fees are an important source of conflict (Clarke et al., 2004, Ljungqvist et al., 2006). Indeed, both regulators and academics have shown particular interest in the conflicts created by the affiliation of the analyst with the covering stock. For instance, when the covering stock is a client of the investment banking department it has been argued to exacerbate analyst incentives to taint their research (Lin and McNichols, 1998, Michaely and Womack, 1999, Hong and Kubik, 2003, O'Brien et al., 2005, Barber et al., 2007, Cliff, 2007, Kolasinski and Kothari, 2008). Furthermore, the valuable information that can be obtained through the access to a firm’s management is another cited source that creates conflicts of interest to the analysts (Koch et al., 2013, Green et al., 2014, Soltes, 2014, Brown et al., 2015).

3.1.1 Access to Management

The evidence from the extant literature suggests that the access to a firm’s management is a valuable source of information for the analysts when they evaluate their forecasts and prepare stock recommendations (Francis and Philbrick, 1993, Das et al., 1998, Chan et al., 2007, Soltes, 2014, Brown et al., 2015). Private communication with a firm’s management is perceived by the analysts to be of high importance for the accuracy of their forecasts and stock recommendations (Brown et al., 2015).

One of the earliest papers linking analyst optimism and the incentive to maintain good management relations, is that of Francis and Philbrick (1993) who found more optimistic earnings forecasts for 'sell' and 'hold' stocks relative to 'buy' stocks, implying analyst efforts to maintain their relationship with the management of the firm. For instance, analysts tend to issue more optimistic earnings forecasts when they issue a negative stock recommendation. Another study by Das et al. (1998) during the years 1989 and 1993, suggests that when the earnings are not easily predictable, the analysts issue more optimistic forecasts in an attempt to obtain more information from the firm's management. This finding is consistent with Lim (2001), who highlighted the possibility that analysts intentionally bias their forecasts to assure management access and improve accuracy.

Chan et al. (2007) studied whether analysts bias their forecasts to help managers match or exceed their estimates, speculating that the bull market in the U.S. in the late 1990s enhanced analyst tendency towards positive earnings surprises. In fact, they found an increase of non-negative earnings surprises from 48.88% in the late 1980s to 75.59% in 1999 to 2000. One possible explanation for this finding might be that managers manipulate the earnings surprises rather than the analysts. However, the short time window between analyst estimates and the announcement date used in this study limits the possibility that managers adjusted the earnings to beat analyst forecasts (Chan et al., 2007).

More recently, Brown et al. (2015), in their survey of 365 analysts, emphasised how important private communication with the management is perceived by analysts as an input to their forecasts and stock recommendations. This evidence is consistent with the study of Soltes (2014), who also supports the notion that private communication with the management is a valuable source of information for the analyst profession. In addition, Brown et al. (2015) documented that while issuing unfavourable stock recommendations usually makes analysts appear more credible in the eyes of their investing clients, this might cost them access to the firm's management.

The evidence suggests that the relationship with a firm's management can be negatively affected by an analyst's negative report (e.g. Brown et al., 2015). In fact, when on 20th June 2001 Simon Flanner, a telecom analysts from Morgan Stanley downgraded Quest's rating to a hold and raised concerns about the accounting methods employed by the company, he was banned from visiting the company or talking to its executives, as well as being blocked from asking questions on Quest's investor calls (Reingold, 2007). This example reinforces the notion that analyst's incentives to uncover unfavourable news might be impeded due to their incentives to develop good relations with a firm's management and thus gain access to more information.

Besides using their research reports, analysts might use favourable language during earnings conference calls to secure better information from the management (Milian et al., 2016). In a sample of earnings conference calls from S&P 500 firms between 2004 and 2013, the authors found that analysts with a better tone during those calls were associated with more accurate quarterly earnings forecasts. This finding is interesting given that the sample period used in this study was after the enforcement of the Reg FD. However, the limitation of Reg FD is that it does not prohibit the disclosure of non-material information. Nonetheless, the disclosure of non-material information might assist an analyst to complete a 'mosaic' of information which taken together might lead to material conclusions (Koch et al., 2013).

Overall, given that access to a firm's management is an important input to analyst research reports (Soltes, 2014, Brown et al., 2015), all analysts have an incentive to maintain good relationship with the management of a firm. However, the allegations regarding analyst conflicts of interest highlight that the analysts employed by investment banks, providing both underwriting services and research, are subject to higher conflicts of interest. This is because analysts employed at investment banks, apart from desiring a good relationship with the management for having access to better information, they are also motivated to optimistically bias their reports in an attempt to win underwriting fees for their investment banks.

3.1.2 Underwriting Fees

In order to test the allegations that sell-side analysts exhibit more bias in their research reports due to higher conflicts of interest, Clarke et al. (2004) examine the performance of stock recommendations issued by analysts employed at investment banks compared to the stock recommendations of analysts employed at brokerages or independent firms. The authors, using a sample period of 1993–2002, found no significant difference in the long-term average abnormal returns for stock recommendation upgrades, thus, implying that the potential optimism of investment bank analysts, if any, does not hinder their competence relative to brokerages and independent firms.

An alternative explanation for the findings of Clarke et al. (2004) is proposed by the study of Lu et al. (2016), in which the authors suggest that in positive earnings surprises, the conflicts of interest do not play an important role in affiliated sell-side analyst conflicts of interest, as all analysts have incentives to uncover favourable news about the covering stock since both sets of analysts favour a good relationship with a firm's management.

While the allegations consider the bias in sell-side analyst research as a way to attract potential clients, Ljungqvist et al. (2006) attempted to test whether optimistic research reports affect the issuer's choice of investment bank. Their modelling approach sheds further light on the trade-off between analyst's career concerns, measured as the cost of losing their reputation, and the potential economic incentives they have from their banks to bias their research. Using a sample of 16,625 U.S. debt and equity offerings between 1993 and 2000, they found that although analyst recommendation behaviour was influenced by economic incentives, there was no evidence that such behaviour influenced the issuer's choice of the bank to proceed with either debt or equity offerings.

Ljungqvist et al. (2006) suggest that what appears to be more important for the choice of the underwriter is the strength of the previous relationship between the bank and the issuer, implying that affiliated analysts are motivated to optimistically bias their research in an attempt to win future underwriting fees. This is because, according to the evidence of Ljungqvist et al. (2006), their investment bank is more likely to be chosen given the pre-existing relationship between the bank and the issuer, hence reinforcing the arguments that the affiliation of analysts with investment banking clients is the most important source of conflicts of interest.

3.1.3 Affiliation

Affiliated analysts are defined by the literature as those issuing research reports for companies whose employer was either the lead and/or co-underwriter of an initial public offering (IPO), seasoned equity offering (SEO) or was a Mergers and Acquisition (M&A) adviser of the covering stock. Allegedly, affiliated analysts were more reluctant to downgrade stocks of client companies, especially during the bear market when the prospects of those stocks dimmed (Global Analyst Research Settlement).

In support of the allegations regarding affiliated analysts conflicts of interest, the extant literature documents greater conflicts faced by affiliated analysts compared to unaffiliated analysts (Dugar and Nathan, 1995, Lin and McNichols, 1998, Michaely and Womack, 1999, Hong and Kubik, 2003, O'Brien et al., 2005, Barber et al., 2007, Cliff, 2007, Kolasinski and Kothari, 2008, Bessler and Stanzel, 2009). An analyst affiliated with the underwriter is motivated to provide optimistically biased research as this might help the profits of his/her employer. For instance, in a 'firm commitment' deal, the underwriter bears all the risk of the issue, because the underwriter agrees to buy all the shares from the issuer and sell them to the market. Thus, if the analyst who is employed by the investment bank which underwrites the IPO of company X, issues negative reports about company's X stock prospects, their employer might occur loses as investors would not buy that stock.

The early study of Dugar and Nathan (1995) supports the argument that affiliation enhances analyst incentives to optimistically bias their reports. The authors, using data from 1980 to 1985, found that affiliated analysts make relatively more optimistic earnings forecasts and stock recommendations than unaffiliated analysts. They did not find any significant difference in the stock recommendation performance of the two sets of analysts, therefore, cannot make precise conclusions whether the relative optimism of the affiliated analysts is due to more favourable information or due to the investment banking relationship.

Likewise, the study of Lin and McNichols (1998) examined analyst earnings forecasts and stock recommendations between 1989 and 1994. The authors found that lead and co-underwriter analysts make significantly more favourable growth earnings forecasts and stock recommendations than unaffiliated analysts. In addition, they suggested that investors are probably aware of the conflicts faced by affiliated analysts since they expect that when a 'sell' recommendation is more appropriate, lead underwriter analysts are more likely to issue a 'hold' recommendation instead. However, the study did not provide any insights into whether these conflicts hinder affiliated analyst performance.

Michaely and Womack (1999) tested for the performance of affiliated analyst stock recommendations compared to the recommendations issued by unaffiliated analysts, using a sample of IPOs between 1990 and 1991. They conjectured that affiliated analysts have better access to the firm's management, hence they also have an information advantage compared to the other analysts, therefore, affiliated analysts performance should be better than that of unaffiliated analysts (Michaely and Womack, 1999). However, their findings support analyst conflicts of interest argument rather than the information advantage hypothesis, because the stock recommendations of affiliated analysts perform more poorly than 'buy' recommendations by unaffiliated analysts. They concluded that recommendations of affiliated analysts provide significant evidence of bias.

However, the evidence of Michaely and Womack (1999) is not consistent with the study of Dugar and Nathan (1995) who found no significant difference in the performance of stock recommendations between affiliated and unaffiliated analysts. The disparity between these studies is probably due to the different sample periods used since the sample period employed by Michaely and Womack (1999) is closer to the dot.com bubble period compared to the sample period used by Dugar and Nathan (1995). Furthermore, Michaely and Womack (1999) shed more light on the information advantage hypothesis by implying that the conflicts of interest which affiliated analysts are prone to, more than offset their superior information that they might have from better access to the firm's management.

Cliff (2007) compared the investment performance of stock recommendations of lead underwriter analysts using as a benchmark the analysts employed at banks which are independent of investment banking services. Based on their evidence, between the years 1994 and 2005, affiliated analysts underperformed the independent analysts in their 'buy' and 'hold' recommendations. However, the affiliated analysts' 'sell' recommendations yield significant abnormal returns, suggesting that investors might benefit from acting on affiliated analysts 'sell' recommendations rather than their 'buy' and 'hold' recommendations. However, Cliff (2007) documented an overreaction by the market to affiliated analysts 'buy' recommendations and an under reaction to their 'hold' and 'sell' recommendations, which is in line with Michaely and Womack (1999) who suggest that the market does not fully recognise the bias documented in the stock recommendations of affiliated analysts.

A different way of documenting bias on affiliated analyst research, other than the level of optimism and performance of their stock recommendations, was proposed by O'Brien et al. (2005). Using duration models of the time between an equity issue and the first downgrade, they examined the speed with which affiliated analysts convey unfavourable news. Using a sample period between 1994 and 2001, they found that affiliated analysts were slower to downgrade from 'buy' to 'hold' recommendations and faster to upgrade from 'hold' recommendations, in both within-analyst and within-issuer tests. Although the conflicts of interest hypothesis might explain their findings, the likelihood of selection bias still exists, that is, affiliated analysts might be slower at downgrades because they are more positive about the prospects of the covering stock, thus they might need more evidence to downgrade the stock.

Kolasinski and Kothari (2008) studied analysts affiliated with M&A advisers to address the problem of selection-bias. According to the authors, M&A is a setting that enables to distinguish between conflicts of interest and selection bias hypotheses[12]. The study supports that in all-cash deals, managers should not have any incentive to choose the most optimistic analyst since the stock performance is irrelevant in those deals. They concluded that the analyst conflicts of interest hypothesis can explain their findings, whereby affiliated analysts are more likely to upgrade the acquirer within 90 days of the M&A transaction in all-cash deals.

With regards to upgrades and downgrades, Lu et al. (2016) tested the impact of affiliation on analyst responses to earnings surprises, finding no significant difference between affiliated and unaffiliated analysts in response to positive earnings surprises. This finding is consistent with their conjecture that following good news, defined by positive earnings surprises, both sets of analysts are expected to upgrade their recommendations and respond in a similar way. However, in negative earnings surprises, affiliated analysts are expected to face greater conflicts of interest than unaffiliated analysts given that the former has closer ties with the covering stock than the latter. Lu et al. (2016) reported that affiliated analysts are more reluctant to downgrade their stock recommendations compared to unaffiliated analysts in response to negative earnings surprises. The findings

[12] Selection bias in this setting relates to the possibility that the management of a firm chooses the investment bank which has the most optimistic analyst, thus in this case, is not the affiliation that makes an analyst over optimistic but instead her/his optimistic views were honest in the first place.

of Lu et al. (2016) are consistent with Kadan et al. (2009) who found that affiliated analysts are still reluctant to issue pessimistic recommendations about the company they cover in the post regulatory period.

Studies so far have accounted for the impact of affiliation on analyst conflicts of interest within the U.S. Bessler and Stanzel (2009) focused on affiliated analysts' research quality for IPOs in the German universal banking system. Using a sample of 12,605 earnings forecasts and 6,209 stock recommendations during the years 1997 and 2004, they found that lead-underwriter analysts are on average inaccurate and biased compared to co-underwriter analysts and unaffiliated analysts. Specifically, they reported that around the IPOs, lead analysts issue optimistically biased stock recommendations and they have a long-run underperformance, whereas unaffiliated analysts perform better in their earnings forecasts and stock recommendations than affiliated analysts.

Bessler and Stanzel (2009) emphasised that an underwriting bias is sensitive to the definition of affiliation. For instance, the separation of lead underwriter analysts from co-underwriter analysts is important. Based on their sample, these two groups of analysts do not exhibit the same degree of bias, with co-underwriter analysts not having any significant difference in their optimism bias than unaffiliated analysts (Bessler and Stanzel, 2009).

The extant studies found evidence to support that analyst conflicts of interest can affect the objectivity of an analyst research report (Dugar and Nathan, 1995, Lin and McNichols, 1998, Michaely and Womack, 1999, Hong and Kubik, 2003, O'Brien et al., 2005, Barber et al., 2007, Cliff, 2007, Kolasinski and Kothari, 2008, Bessler and Stanzel, 2009). Although, studies found some external (e.g. regulations) and internal (e.g.

reputation) factors which acted as moderating factors in the documented analyst conflicts of interest.

3.2 Moderation of Analyst Conflicts

The dot.com bubble and the subsequent stock market crash in the U.S. alerted the need of a new regulatory environment within the finance industry. The regulatory reforms that took place in the U.S. since 2000 intended to mitigate sell-side analyst conflicts of interest by increasing the independence between the research and the investment banking departments (Global Analyst Research Settlement, NASD Rule 2711, NYSE Rule 472, Reg FD). Although regulations are perceived to be an external moderating factor for sell-side analyst conflicts of interest, other internal moderating factors also exist within the analyst profession, including the analyst and bank reputation as well as the presence of institutional investors (Hong and Kubik, 2003, Ljungqvist et al., 2007, Fang and Yasuda, 2009).

3.2.1 Effectiveness of Regulatory Reforms

Herrmann et al. (2008) investigated the adoption of Reg FD on analyst forecast accuracy on internationally diversified firms. The study was motivated by previous findings whereby analysts are more optimistically biased in their forecasts for internationally diversified firms because they have a greater need for information (Duru and Reeb, 2002). The authors found a reduction in analyst incentives to optimistically bias their earnings forecasts of internationally diversified firms in the post-Reg FD period. Similarly, Barniv et al. (2009) using a sample of stock recommendations between 1993 and 2005, examined the effect of the new regulations coupled with the introduction of Reg FD, reporting an increase in the usefulness of earnings forecasts to investors after the introduction of Reg

FD. However, prior studies found that in the post-Reg FD period, there was a decrease in the forecast accuracy and increased forecast dispersion (Bailey et al., 2003, Agrawal et al., 2006).

More recent studies examining the continuing private access to management, suggest that analysts can still benefit from meetings with a firm's management even after the implementation of Reg FD. For instance, Soltes (2014) found a more frequent issue of research reports from analysts who hold private meetings with top executives. In addition, Green et al. (2014) reported a larger immediate price impact for stock recommendation revisions made by analysts that host the firm at broker-sponsored investor conferences. Furthermore, they found more accurate, informative, and timely earnings forecasts issued by the conference-hosting brokers compared to non-hosts (Green et al., 2014). Moreover, Milian et al. (2016) reported more accurate quarterly earnings forecasts for analysts using more favourable language during earnings conference calls in a sample period after the introduction of Reg FD.

In addition to the enforcement of Reg FD in 2000, two years later, in 2002, the regulators proposed NASD Rule 2711(Research Analysts and Research Reports) and an amendment to NYSE Rule 472 (Communications with Public)[13]. The focus of the new regulations was primarily on stock recommendations given that the documented bias on stock recommendations is more severe than the bias in earnings forecasts (Lin and McNichols, 1998)[14].

[13] NASD Rule 2711 and NYSE Rule 472 were suspended by the FINRA Rule 2241 adopted in 2015 which addressed the same subject matter of regulations.

[14] In their study, they found that the earnings forecasts of affiliated analysts were not generally higher than unaffiliated analysts, as opposed to growth forecasts and recommendations, possibly because it is harder for investors to detect bias in growth forecasts and recommendations compared to earnings forecasts whose outcome is realised annually. Therefore, it is more difficult for analysts to bias earnings forecasts, as the investors will find out as opposed to overoptimistic growth forecasts and stock recommendations (Lin and McNichols, 1998).

In line with the argument of bias in analyst stock recommendations, Irvine (2004) found that by issuing optimistic stock recommendations, analysts increase their chances of gaining higher trading commissions than they would by issuing biased earnings forecasts. Likewise, Bradshaw (2004), using valuation models, concluded that investors can earn future excess returns by using earnings forecasts rather than stock recommendations in the U.S., because the former is a predictor of future excess returns, whereas the latter is a negative predictor of future excess returns. Within an international context, Barniv et al. (2010) reported consistent findings with Bradshaw (2004) for countries with a high rate of individual investor participation.

Barniv et al. (2009) investigated the impact of regulatory reforms in the documented negative relationship between stock recommendations and future returns. Although the negative relationship between stock recommendations and future returns is diminishing, it persists in the post regulatory period. Therefore, the authors concluded that regulations are effective in many ways in mitigating conflicts of interest, however, the effect on analysts' output may be incomplete.

Furthermore, Barber et al. (2006) assessed whether the NASD Rule 2711, which requires the disclosure of brokers' stock ratings, has affected the distribution of 'buys', 'holds', and 'sells' or the predictive value of such distributions, finding that since the middle of 2000, the percentage of 'buy' recommendations decreased steadily. In particular, by the end of June in 2013, 'buy' recommendations exceeded 'sells' by approximately 3:1 compared to 35:1 between the years 1996 and 2000 (Barber et al., 2006).

The substantial decrease in 'buy' recommendations found by Barber et al. (2006) could have been the outcome of a worsening economy coupled with a declining stock market. However, the authors suggest that their results strongly support that the implementation of NASD Rule 2711 has also played a key role. In addition, they suggest that the enforcement of NASD Rule 2711, besides affecting the distribution of analyst ratings, benefits investors in the sense that analyst rating distributions can predict recommendation profitability. For instance, upgrade to 'buy' (downgrades to 'hold' or 'sell') issued by analysts with the smallest percentage of buy recommendations significantly outperformed (underperformed) those upgrades from analysts with the greatest percentage of 'buys' (Barber et al., 2006).

Furthermore, Barber et al. (2007) attempted to test the effect of the requirement of the Global Analyst Research Settlement regarding the provision of independent research using a sample period during the years when the market was bull and bear, from January 1996 to June 2003. Their findings suggest that independent firms outperform investment banks only during the bear market, which is consistent with the allegations of the Global Analyst Research Settlement, whereby at least some investment banking analysts were reluctant to downgrade stocks whose prospects dimmed during the bear market (Barber et al., 2007). In the same year, Cliff (2007) compared the performance of analysts employed by the lead investment banks and independent research firms, showing that lead underwriter recommendations are viewed as more credible by the investors following the regulatory reforms as suggested by the announcement period returns.

Kadan et al. (2009) extended the study of Barber et al. (2007) by testing the overall effect of the Global Analyst Research Settlement and the related regulations on sell-side analyst stock recommendations. Kadan et al. (2009) suggest that affiliated analysts, defined as analysts employed by the lead investment bank, are as likely to issue an optimistic recommendation as unaffiliated analysts following the regulatory reforms.

However, affiliated analysts are still reluctant to issue pessimistic recommendations about the client companies that they cover (Kadan et al., 2009). Likewise, Lu et al. (2016) document that affiliated analysts are more reluctant to downgrade a stock in response to negative earnings surprises than unaffiliated analysts. The evidence suggests that the asymmetric responses of affiliated analysts have not been mitigated by the regulatory reforms. Therefore, Lu et al. (2016) concluded that bias on affiliated analyst stock recommendations was still prevalent in the post regulatory period.

Wu et al. (2015) examined the effectiveness of the Global Analyst Research Settlement on affiliated analyst optimism in an M&A context, showing limited benefits of the reform. Besides the reduction in affiliated analyst optimism documented over a 180-day period around the M&A announcement, the authors did not find any reduction in affiliated analyst bias when reducing the period to 90 days, suggesting that this is important since in a 90-day period after the M&A announcement, the investors do not know yet whether an analyst is affiliated, so may be misled by optimistically biased recommendations from affiliated analysts within this 90-day period following an M&A announcement.

Corwin et al. (2017) assessed the impact of the Global Analyst Research Settlement by comparing the sanctioned and the non-sanctioned banks, using a sample of common stock firms listed in the U.S. between 1999 and 2009. Their results showed that while the sanctioned banks had a substantial reduction in the bias of the stock recommendations issued by affiliated analysts, the concurrent regulations were ineffective for the non-sanctioned banks. In particular, they found strong evidence of bias on affiliated analyst stock recommendations employed by non-sanctioned banks in both the pre and post-Global Analyst Research Settlement period. Therefore, Corwin et al. (2017) provided evidence that regulations have been both effective and ineffective in mitigating sell-side analyst conflicts of interest.

More recently, Chen et al. (2018) provided evidence of the effectiveness of the NASD Rule 2711 using a sample period from 1994 to 2010. They examined the effect of the regulation on analysts' guidance in earnings forecasts and stock recommendations and corporate external financing, further assessing the effect of the regulation on the relation between external financing and future stock returns. Their findings showed a positive association between analysts' guidance in earnings forecasts and stock recommendation ratings and the external financing, although the relation was weaker after the implementation of the NASD Rule 2711. Similarly, they found that the negative association between external financing and future stock returns is weaker in the post regulatory period. Therefore, the authors concluded that the NASD Rule 2711 has some effect in mitigating analyst conflicts of interest.

In addition to the results regarding the effectiveness of regulatory reforms, the ongoing violations of the regulations from investment banks support the notion that regulations partially address sell-side analyst conflicts of interest, for example, the $43.5 m fine by FINRA in 2014 to Goldman Sachs, Citigroup, and eight other investment banks. The allegation was that these investment banks issued favourable stock research reports in an attempt to win underwriting business in Toys 'R' initial public offering[15]. Also, a more recent example is the FINRA fine of $900,000 to Stephens Inc. for inadequate supervision in the research department[16].

[15] More information can be found at: http://www.investmentnews.com/article/20141211/FREE/141219973/finra-fines-wall-street-banks-43-5m-for-pushing-analysts-on-ipos

[16] More information can be found at: http://www.finra.org/newsroom/2016/finra-fines-stephens-inc-900000-inadequate-supervision-research-department-flash

Overall, the results of the extant literature regarding the effectiveness of regulatory reforms are inconclusive (Kadan et al., 2009, Barniv et al., 2009, Lu et al., 2016, Wu et al., 2015, Corwin et al., 2017). Regulations have their own implications since regulatory reforms can only be effective if there is adequate enforcement from the investment banks. As Di Lorenzo (2007) suggests, the law does not necessarily determine corporate conduct, thus, the inconclusive results from the extant studies coupled with examples of violations show that sell-side analyst conflicts of interest persist and affect the objectivity of analyst research.

3.2.2 Internal Moderating Factors

Although the post regulatory period is expected to act as an external moderating factor on analyst conflicts, other internal moderating factors have been in place within the analyst profession. These internal moderating factors, which include career concerns, bank/personal reputation, and the presence of institutional investors, have been suggested to act against analyst propensity to bias their research. The general conclusion drawn from the extant studies regarding the effectiveness of internal moderating factors is that an internal moderating factor alone cannot always mitigate analyst conflicts of interest.

In their study, Fang and Yasuda (2009) found that both personal and bank reputation is associated with better quality earnings forecasts. They measured bank reputation using Carter-Manaster[17] ranks and personal reputation using the Institutional Investor All-

[17] Carter-Manaster (CM) is the ranking of investment banks and takes the value zero for the lowest reputation investment banks and nine for the highest reputation investment banks.

America (AA) awards[18]. According to their findings, personal reputation is an effective disciplinary device, while bank reputation alone cannot effectively moderate sell-side analyst conflicts of interest. Consistent with the evidence that bank reputation alone is not an effective disciplinary mechanism is the evidence of Lu et al. (2016), who document that in response to large earnings surprises, analysts at prestigious banks do not behave differently than analysts at less prestigious banks[19].

Hong and Kubik (2003) examined the relationship of earnings forecasts to analyst career concerns, measured as analyst job promotions or job terminations within their investment banks. One would expect career concerns to act as a disciplinary mechanism on analyst bias, ultimately enhancing their accuracy. However, the authors found that for affiliated analysts, job terminations depend less on accuracy and more on optimism (Hong and Kubik, 2003). More specifically, they found that during the market peak, job terminations were more sensitive to optimism rather than accuracy, reinforcing the allegations that analysts with investment banking ties face more severe conflicts of interests, which were exacerbated during the market bubble. Furthermore, they provided insight that besides analyst bias, conflicts of interest also affect the incentives of the investment banks.

The presence of institutional investors is usually linked to analyst career concerns since institutional investors affect sell-side analyst personal reputation through their votes on Institutional Investor (I.I) magazine. Ljungqvist et al. (2007) examined whether the

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[18] All-star analysts are the analysts elected by the institutional investors in the annual survey of the Institutional Investor magazine in the U.S. which is issued every October. Institutional investors evaluate the analysts against their industry knowledge, their timely and informative research reports, their earnings forecasts accuracy, and the profitability of their stock recommendations.
[19] In their study, the measure of prestigious banks is a binary variable taking the value one if the analyst work for one of the top 10 investment banks by market share. These include Goldman Sachs, Merrill Lynch, Morgan Stanley, Salomon Brothers, Credit Suisse, Lehman Brothers, JP Morgan, UBS, Barclay Capital or Citi.

presence of institutional investors is another moderating factor to sell-side analyst conflicts of interest, generally supporting this notion. They showed that firms which employ the most reputable investment banks and are primarily held by institutional investors, are associated with less optimistically biased recommendations, more accurate earnings forecasts, and more timely recommendation revisions compared to those firms which are served by smaller investment banks and are primarily held by retail investors. Another explanation for the association between institutional investors and less biased research might be that institutional investors are perceived sophisticated investors who have access to research reports from other analysts. Thus, it should be easier for institutional investors to assess for potential bias on analyst reports, therefore analysts are less likely to issue biased recommendations for stocks with high institutional investor ownership (Iskoz, 2003, Malmendier and Shanthikumar, 2007).

Overall, the extant literature suggests that sell-side analyst conflicts of interest are addressed partially by regulatory reforms (Barniv et al., 2009, Kadan et al., 2009, Wu et al., 2015, Lu et al., 2016), while personal reputation and the presence of institutional investors were not as effective in preventing the dot.com bubble in the late 1990s. This leaves open the possibility that there are other factors which are likely to moderate sell-side analyst conflicts of interest which have not yet been explored by researchers.

Conflicts of interest are inherent in the system and arguably, regulations cannot fully address every single conflict that exists within the industry. As Reingold (2007) states in his book Confessions of a Wall Street Analyst, 'the real issue was how individuals chose to handle them (conflicts to interest)' (pp. 275–276). Therefore, to fully appreciate the issue of sell-side analyst conflicts of interest, personal factors that are likely to affect ethical decision-making need be taken into account (Palazzo and Rethel, 2008). Gender has been the most common demographic independent variable examined in business ethics research and gender differences in ethical decision-making have been addressed in many empirical studies (Larkin, 2000, Christie et al., 2003).

3.3 The Role of Gender

Gender studies within the finance industry have considered gender to affect ethical decision-making, optimism, and performance. Indeed, the role of gender on business ethics has received a great amount of attention from academics over the past few decades. The studies support the occupational socialisation theory whereby gender does not have any effect on the moral reasoning of the employees, or that women are more likely to behave ethically than men supporting the gender socialisation theory (Roozen et al., 2001, Ross and Robertson, 2003). However, studies on business ethics are usually survey-based or they are based on hypothetical ethical dilemmas and vignettes, therefore, a common limitation of their findings is that they might not apply in real world situations where individuals have to make real decisions (Weber and Gillespie, 1998, Sheeran and Abraham, 2003).

Studies within the finance industry have attempted to identify whether women following finance careers possess their stereotypically gender traits or are similar to their male counterparts. To test for gender-based differences in the workplace, researchers assess the association between female participation and certain corporate outcomes, thereby drawing conclusions regarding female's monitoring role on the boards (Barua et al., 2010, Srinidhi et al., 2011, Frye and Pham, 2018) or their risk attitude (Matsa and Miller, 2013, Francis et al., 2015). The implication of these studies is that other unobservable factors, such as gender discrimination, might drive the association between female participation and certain corporate outcomes (Sila et al., 2016, Garcia Lara et al., 2017).

Within the analyst profession, studies have sought to determine whether there is gender discrimination in hiring decisions by comparing the forecast accuracy of the analysts (Green et al. 2009, Kumar, 2010). In addition, some inferences have been drawn about female analysts' risk attitude and performance, though the results are mixed (Green et al., 2009, Kumar, 2010, Li et al., 2013). The inconclusive findings regarding female analysts' risk attitude reflect the mixed results of the prior literature on risk attitude of female directors and chief financial officers (CFOs).

Overall, gender studies in the finance industry are far from conclusive regarding the gender effect, therefore, it is unclear whether gender differences within the sell-side analyst profession persist. The distinction is important for sell-side analyst profession since gender biases might affect the bias, optimism, and performance of female sell-side analysts and further research will shed light in our understanding whether the participation of females brings heterogeneity in the profession or whether they have homogenous characteristics with their male counterparts.

3.3.1 Gender Effect on Ethical Reasoning

Gender and occupational socialisation theories are two conflicting hypotheses regarding gender differences in ethical reasoning. The gender socialisation theory supports gender differences in ethical decision-making, regardless of whether an individual is a full-time employee or not (Betz et al., 1989, Ameen et al., 1996, Malinowski and Berger, 1996, Mason and Mudrack, 1996, Okleshen and Hoyt, 1996, Eynon et al., 1997, Glover et al., 1997, Singhapakdi, 1999, Larkin, 2000, Cohen et al., 2001, Ross and Robertson, 2003, Emerson et al., 2007), whereas the occupational socialisation theory hypothesises that when a female and a male enter the workplace, they both tend to develop similar moral reasoning as they adapt to the working environment and organisational culture of their chosen occupation (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001).

An alternative theory supported by a few studies is the situational theory under which gender-based differences are context specific (Dawson, 1997, Deshpande, 1997, Reiss and Mitra, 1998). Furthermore, other studies support the 'self-selection' theory, whereby women following business careers, which are often male dominated professions, are not representative of the female population and have personality traits similar to their male counterparts (Feldberg and Glenn, 1979, Lacy et al., 1983, Abdolmohammadi et al., 2003, Kumar, 2010, Adams and Funk, 2012, Sila et al., 2016). Overall, the extant literature provides mixed results and is inconclusive as to which theory is dominant regarding gender-based differences in ethical decision-making.

3.3.1.1 Gender Socialisation Theory

Betz et al. (1989) found evidence consistent with the gender socialisation theory. In their sample of 213 business students, they found men to be two times more likely to engage in unethical actions compared to women. Although relatively few men would engage in unethical actions, insider trading is the only exception since 50% of men have expressed willingness to buy stock using insider information (Betz et al., 1989). Likewise, Ameen et al. (1996), in their study of the ethical awareness between 285 male and female accounting students, found statistically significant gender-based differences in 17 out of 23 questionable activities.

Similarly, Glover et al. (1997) using a sample of 367 subjects including junior and senior business majors at a large western university, reported that women were more likely to make ethical choices compared to men. Furthermore, in their cross-cultural study of 341 business students from the U.S. and New Zealand, Okleshen and Hoyt (1996) found that women have higher mean scores in all constructs supporting the notion that women have higher ethical perspectives than men. Consistent with these findings is the study of Malinowski and Berger (1996), who investigate nine hypothetical marketing dilemmas using a sample of 403 undergraduate students, finding that the responses of the women in their sample were more ethical in all nine hypothetical dilemmas compared to the responses of their male counterparts.

Although the studies of Betz et al. (1989), Ameen et al. (1996), Glover et al. (1997), Okleshen and Hoyt (1996) and Malinowski and Berger (1996) are consistent with the gender socialisation theory, their samples are limited to students, so do not provide evidence as to whether the gender socialisation theory persists when business students enter the profession. Mason and Mudrack (1996) addressed this limitation by using a sample of 308 subjects consisting of both employees and non-employees. Consistent with the gender socialisation theory, the authors found gender differences in the ethical reasoning of full-time employees. Specifically, full time employed women were found to have lower tolerance for unethical behaviour, providing responses that were perceived more ethical compared to their male counterparts (Mason and Mudrack, 1996).

However, Mason and Mudrack (1996) did not find any gender differences in the ethical behaviour of the non-employed group, which is not consistent with the socialisation theory. The authors suggest that this might be due to the homogenous sample characteristics whereby individuals self-select into the business classrooms.

Furthermore, they explain that both genders might have similar characteristics before entering the workplace but the working environment could possibly make women more focused on ethical aspects (Mason and Mudrack, 1996).

Cohen et al. (2001), in their study of accounting students and accounting professionals, provided more consistent findings with the gender socialisation theory than Mason and Mudrack (1996). They found that in both sub samples, women perceived actions such as giving bribes, copying software, and charging family gifts to the company as more unethical and were less willing to act unethically compared to men. Moreover, Emerson et al. (2007) found that in both the accounting practitioner and the multidisciplinary student samples, males exhibit higher ethical tolerance on ethically charged vignettes compared to women.

Similarly, in support of the gender socialisation theory, Eynon et al. (1997) reported that female certified chartered accountants exhibited better moral reasoning abilities by scoring higher P-values than men. In the same vein, Singhapakdi (1999) documented gender based differences concerning the ethical intentions of marketing professionals. Specifically, they found that women, in their total sample of 453 U.S. practitioner members of the American Marketing Association, were more likely to have lower tolerance of unethical actions compared to men. In addition, using a sample of internal auditors in large financial services organisations, Larkin (2000) found that female internal auditors had a better ability to recognise ethical behaviour than men.

Furthermore, within the sales context, Ross and Robertson (2003) reported that females were more likely to behave ethically in a survey of 252 sales representatives. However, the study used only one unethical act scenario in their research, therefore the applicability of their findings might be limited to that specific scenario. Moreover, in their cross-cultural study of 345 business managers from India, Korea, and the U.S., Christie et al. (2003) found that besides culture, gender appears to have a strong impact on managers' ethical attitudes and their results generally support the gender socialisation theory.

According to the gender socialisation theory, it is expected that women are more likely to follow the rules, whereas men are more likely break the rules. For instance, within the finance industry, consistent with the gender socialisation theory, Liu (2018) reported that firms with greater board gender diversity are less likely to be sued for environmental violations. Similarly, Cumming et al. (2015) found that board gender diversity is associated with a reduced likelihood of securities fraud.

Nguyen et al. (2008) suggest that women are encouraged to follow their expected social traits and those who have traits similar to their male counterparts will possibly receive backlash. This is consistent with the recent study by Egan et al. (2017), who found that within the financial advisory industry, female advisers faced more severe punishment of misconduct than their male counterparts. This finding is also surprising given that female misconduct is less costly and female advisers are less likely to be repeat offenders than men (Egan et al., 2017). This suggests that even if women are not intrinsically morally superior to men, there is a greater amount of external pressure on them to behave ethically (Bossuyt and Van Kenhove, 2016).

3.3.1.2 Occupational Socialisation Theory

Although a considerable number of studies support the gender socialisation theory, other studies argue that gender is not an important factor for ethical decision-making in the workplace, consistent with the occupational socialisation theory (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001, Abdolmohammadi et al., 2003). Cole and Smith (1996) document in their student sample that in eight out of ten statements regarding ethical issues, female students perform better than men. However, in their sample of business professionals, they did not document any significant gender differences, in line with occupational socialisation theory.

Similarly, Wimalasiri et al. (1996) aimed to shed further light on the manager's reasoning process when faced with moral dilemmas in the work environment, finding that gender does not affect the moral reasoning of the subjects who participated in the sample. Nonetheless, the authors acknowledge that the participants were volunteers thus the sample might not be representative of the entire population. Furthermore, it is unclear whether findings on moral reasoning is a strong determinant of actual moral behaviour.

Moreover, Roozen et al. (2001) documented that gender has no significant impact on the ethical attitudes in their sample of 427 employees from several organisations. However, the study documented that on average, employees from banking and insurance organisations scored lower on the ethical dimensions as opposed to employees working at public services. The authors suggest that the highly competitive environment of the business sector might explain this finding. Consistent with these findings, Abdolmohammadi et al. (2003) found no gender differences in ethical reasoning in their sample of newly recruited professionals by Big Five accounting firms. The authors suggested that their results could be explained by the self-selection theory, whereby people with similar ethical reasoning self-select into the accounting profession[20].

[20] Self-selection theory is mainly supported by studies testing for gender differences in risk attitude, therefore I discuss this theory in section 3.3.3.

3.3.1.3 Situational Theory

An alternative theory to the gender and occupational socialisation theories is the situational theory which suggests that gender differences are significant to specific scenarios or situations. Consistent with the situational theory is the study of Deshpande (1997) who assessed 252 managers employed at a large non-profit organisation. The author reported that out of the 17 items included in the questionnaire covering various ethical situations, male and female managers were significantly different in only one ethical situation. Specifically, female managers found the acceptance of gifts/favours in exchange for preferential treatment significantly more unethical compared to men, implying that gender-based differences might be important in specific situations.

Similarly, in a sample of 209 subjects within the sales profession, Dawson (1997) found that while women scored higher in thirteen scenarios, they also scored lower in another seven scenarios than men. Thus, the results suggest that while on average the sample women appeared to have higher ethical attitudes than men, the gender-based ethical differences are specific to the situation. Likewise, Reiss and Mitra (1998) in a sample of 198 college students, found strong evidence showing that males tend to view extra-organisational behaviours of an uncertain ethical nature, such as staying at an expensive hotel on a company business trip, as more acceptable than females. The evidence though, does not support the intra-organisational hypothesis, emphasising that gender-based differences are not significant in every situation.

The studies of Mason and Mudrack (1996), Reiss and Mitra (1998), and Deshpande (1997) found significant gender-based differences in the acceptability of unethical behaviour in specific situations, supporting the situational theory. However, a common limitation of ethics research is that they are mainly survey-based or use hypothetical ethical dilemmas, thus responses might be affected by social desirability and self-reporting biases (Randall and Fernandes, 1991, Dalton and Ortegren, 2011, Sheeran and Abraham, 2003). Also, it can be argued that moral attitudes do not necessarily imply behaviour (Weber and Gillespie, 1998, Sheeran and Abraham, 2003). Thus, the applicability of the ethics research findings on real situations might be limited, highlighting the need for further studies testing actual behaviours rather than intentions (Bossuyt and Van Kenhove, 2016). Furthermore, research on actual behaviour can resolve the issue of self-reporting bias, whereby individuals believe to have higher ethical stances compared to other people.

The profession of sell-side analysts provides the opportunity to examine the behaviour of the analysts when faced with real ethical dilemmas. Within the sell-side analyst industry, ethical decision-making is a very important aspect of the profession since conflicts of interest are inherent within the system. For instance, an analyst's affiliation has been found to exacerbate incentives to bias sell-side research and hinder the quality of their research (e.g. Kolasinski and Kothari, 2008).

3.3.2 Gender Effect on the Quality of Financial Statements

A priori, building on the gender socialisation theory, is that female sell-side analysts will be less likely to sacrifice the quality of their research when faced with conflicts of interest as opposed to men. While no research on analysts has yet considered the gender effect on the quality of sell-side research when faced with conflicts, studies within the business sector have considered the impact of gender diversity on the quality of financial information. In particular, studies that tested the impact of gender diversity on earnings quality (Krishnan and Parsons, 2008, Srinidhi et al., 2011) and the quality of accruals

(Barua et al., 2010), found a positive association between female participation and the quality of financial statements.

Francis et al. (2013) also examined the impact of the CFO gender and the loan contracting, concluding that banks perceive female CFOs as more reliable for the provision of accounting information than male CFOs. Thus, the evidence implies that females are more effective in monitoring the boards, which ultimately results in better quality accounting numbers. Consistently, Frye and Pham (2018) found that firms with a female CEO have a greater board monitoring intensity. However, the study of Garcia Lara et al. (2017) has implications for the studies associating female participation with better board monitoring since previous studies do not account for gender discrimination in hiring decisions. According to the authors, gender differences do not exist in the absence of discrimination against women in hiring decisions.

In their study to investigate whether gender diversity in senior management is associated with better earnings quality, Krishnan and Parsons (2008) use data from 1996 to 2000 and a sample of 353 companies to distinguish between lower gender diversity and high gender diversity companies. In low gender diversity companies, women represent zero to 5.1 per cent of senior executives, whereas in high gender diversity companies, women represent 14.3 to 38.3 percent of senior executives. Overall, they identified a positive and significant correlation between earnings quality and high gender diversity in senior management. However, this does not necessarily imply that the participation of more women in senior management positions results in an increase of earnings quality.

In the same vein, Srinidhi et al. (2011), motivated by the increase of females on the boards within the U.S. corporations, investigated the association of gender diversity with higher earnings quality, finding that boards exhibit higher earnings quality when more women are included, thus reflecting a better corporate governance. The results of this study may not be generalised in different time periods or in different countries with different legislative, regulatory, and cultural institutions than in the U.S. (Srinidhi et al., 2011).

Srinidhi et al. (2011) also suggest that their findings might themselves be an implication for their study, because boards might include more women to achieve better governance. This assumption is consistent with research which shows females are more focused on corporate governance issues, monitoring, and corporate social responsibility within their companies compared to men (Adams and Ferreira, 2009, Gul et al., 2011, Shaukat et al., 2016, Chen et al., 2017, Frye and Pham, 2018). Therefore, it might be that when better monitoring of the board as well as better earnings quality are demanded by the investors, more women are included on the board to achieve this objective.

Barua et al. (2010) used accruals quality as a measure of the quality of financial reporting rather than earnings quality measures employed by Srinidhi et al. (2011) and Krishnan and Parsons (2008). In their study, they tested whether the gender of CFOs had an impact on accruals quality using a sample of 1559 and 1222 firms for the years 2005 and 2004 respectively. They hypothesised that female CFOs are associated with higher quality of accruals, providing evidence to support their hypothesis. However, even though the authors controlled for factors known to be associated with accruals quality, other unobservable factors might be correlated with female CFOs and accruals quality.

The evidence of the association between increased quality earnings and accruals with women participation is also supported by Francis et al. (2013). Instead of directly examining for earnings or accruals quality, they tested the impact of the CFOs gender on bank loan contracting, suggesting that female CFOs are perceived by banks to be more reliable in providing accounting information, given the 11% lower bank loan prices that female CFOs are entitled to compared to men. In line with the conclusion of Francis et al. (2013), Frye and Pham (2018) identified that public firms with a female CEO have greater board monitoring intensity in the U.S. over the sample period 1996–2016. Furthermore, to address reverse causality concerns the authors used the difference-in-difference technique to find that firms which transition from a male to a female CEO experience a higher increase in board monitoring than firms which transit from a male to male CEO.

Garcia Lara et al. (2017) re-examined the link between the participation of female directors, gender biases, and the quality of accounting statements in United Kingdom (UK) firms between 2003 and 2012. They found that a larger percentage of independent female directors is positively associated with better quality accounting information. However, this association did not persist after controlling for gender biases, such as gender discrimination in hiring decisions. The study showed that the quality of financial reporting is lower for the firms that discriminate against women. Specifically, in non-discriminating firms, there is no association between better accounting information and the inclusion of more independent female directors. Therefore, the authors concluded that in the absence of discrimination, there are no gender-based differences regarding the behaviour of men versus women in high profile jobs.

This conclusion is consistent with the studies of Croson and Gneezy (2009), Adams and Funk (2012) and Sila et al. (2016) who also suggest that gender differences documented in the general population do not exist in high profile positions. The study of Garcia Lara et al. (2017) has implications for the studies associating women with a better monitoring role on the boards and increased quality of the financial information, as this might be driven by discrimination against women. In addition, the studies acknowledge that other unobservable factors might be behind the documented positive correlation between female directors and accounting quality (Barua et al., 2010, Srinidhi et al., 2011).

3.3.3 Gender Effect on Risk Attitude and Corporate Outcomes

While studies have looked at the quality of financial statements to draw conclusions about female director's monitoring role on the boards, other studies examined corporate outcomes to assess the risk behaviour of women in the workplace. Typically, women are associated with higher levels of risk aversion (Olsen and Cox, 2001, Croson and Gneezy, 2009, Sapienza et al., 2009, Huang and Hung, 2013, Francis et al., 2014, Francis et al., 2015), whereas men are generally more competitive and overconfident (Barber and Odean, 2001, Gneezy et al., 2003, Niederle and Vesterlund, 2007, Sapienza et al., 2009). Another stream of literature argues that gender-based differences in risk attitude in high profile jobs are not consistent with the population characteristics (Adams and Funk, 2012, Matsa and Miller, 2013, Adams and Ragunathan, 2015, Sila et al., 2016). Furthermore, the studies of Berger et al. (2014), Adams and Funk (2012) and Kumar (2010) found that the women in their samples were less risk-averse than men. Thus, the literature is far from conclusive regarding gender differences in risk attitude and corporate outcomes.

Barber and Odean (2001) assessed whether men are trading more than women in common stock investments in a sample of over 35,000 households between 1991 and 1997, finding that men are traded 45% more than women, consistent with men being more confident than women. They also found that men performed worse than women, possibly because their overconfidence led them to overestimate the precision of their information, thus the expected returns from trading (Barber and Odean, 2001).

Olsen and Cox (2001) aimed to identify whether gender differences in risk aversion affect the way professional female investors perceive and respond to investment risk compared to their male counterparts. In their paper, they employed two groups of professional investors: the first group consisted of 209 Chartered Financial Analysts (CFA) with women representing 20% of the total sample, while the second group comprised of 274 Certified Financial Planners (CFP), of which 36% were women. They used survey questionnaires specifically formed to mitigate response bias, finding that in an investment setting, female financial professionals tended to put more emphasis on downside or loss potential than men. In addition, they suggested that women are more concerned with security as opposed to gain, consistent with the notion that women tend to be more risk-averse than men.

In contrast, Atkinson et al. (2003) found no significant difference in investment behaviour and performance between female and male fund managers, suggesting that differences in investment behaviour between men and women are not necessarily gender based, rather they might be attributed to finance knowledge or wealth constraints. In addition, they identified differences in the way mutual fund investors make their investment allocations towards female and male fund managers, for instance, investors put less money into funds managed by females compared to the funds managed by males. This reflects a gender-based stereotype that women are less competent managers than men (Atkinson et al., 2003).

Likewise, the study of Mohan and Chen (2004) reported no gender differences between male and female CEOs leading an initial public offering between 1999 and 2001.

The authors suggested that gender did not have a significant impact on CEOs risk behaviour. However, due to data restrictions, the sample of female CEOs was relatively small, hence any generalisations should be made with caution.

Niederle and Vesterlund (2007) conducted laboratory experiments involving men and women of similar abilities, concluding that men tended to embrace competition while women shied away from it. Similarly, Croson and Gneezy (2009) reviewed experimental evidence on gender differences in preferences, finding that women are more risk-averse compared to men as well as being more averse to competition. In addition, Niederle and Vesterlund (2007) do not find any gender differences in performance despite the different preferences for competition among men and women. This contrast with the findings of Gneezy et al. (2003), who reported that women were less competent than men when competition increases.

The conclusions drawn from the studies associating women with risk aversion and men with overconfidence, may not generalise to high profile professions within the finance industry (Croson and Gneezy, 2009, Adams and Funk, 2012, Adams and Ragunathan, 2015), because self-selection might drive women who are more competitive than the general population to pursue jobs in a competitive working environment like the finance industry.

Sapienza et al. (2009) found within their sample of Masters Business Administration students from Chicago University that while 57% of male students choose a risky finance career, such as investment banking, only 36% of the sample women would do the same. They suggest that this difference might be attributed to biological reasons, for example, high testosterone and low levels of risk aversion make a risky career in finance more appealing. Therefore, Sapienza et al. (2009) postulated that women choosing to follow risky careers have lower levels of risk aversion and have higher testosterone than the women in the general population, suggesting that women in competitive and male dominated professions, have personality traits similar to their male counterparts. Extending the results of Sapienza et al. (2009), Adams and Ragunathan (2015) showed that after controlling for the choice of a finance career, women do not have higher levels of risk aversion than men.

The conclusion of Adams and Ragunathan (2015) has implications for many recent studies that use corporate outcomes to draw inferences about gender-based differences in risk attitude. One such study is that of Huang and Kisgen (2013) who showed that female executives make different financial and investment decisions than male executives. In particular, they reported that firms having female executives make fewer acquisitions and issue less debt compared to their male counterparts. The authors attribute the documented corporate decision differences to women's higher levels of risk aversion as opposed to their male counterparts. Another study supporting women's risk aversion is that of Francis et al. (2014) who examined the gender effect on tax aggressiveness, finding that female CFOs are associated with less tax aggressiveness and that gender is a strong determinant of tax aggressiveness.

Similarly, Francis et al. (2015) in their study of 1500 S&P companies between 1988 and 2007, reported that the level of accounting conservatism significantly increases when a female CFO is recruited to replace a male CFO. Thus, the gender-based differences in the choice of accounting conservatism suggest that women are more risk-averse than men and that different risk attitude leads to different corporate outcomes. However, in their study of 359 CFOs across several firms, Ge et al. (2011) found that gender has limited effect on the accounting choices of CFOs, contrasting the findings of Francis et al. (2015).

In their large survey of directors of all public and private firms in Sweden in 2005, Adams and Funk (2012) found that unlike the female population characteristics, the women in their study were less concerned with security and were more risk-taking compared to their male counterparts. Therefore, the authors concluded that the participation of women in the boardroom does not necessarily lead to more risk-averse decision making.

Similarly, Matsa and Miller (2013) regarding the effectiveness of the Norwegian gender quota on corporate decision making, suggest that the implementation of the gender quota on the boards did not have any effect on most corporate decisions. However, consistent with the population characteristics Adams and Funk (2012) found that their sample female participants were more kind and concerned about others compared to men. However, they suggested a different institutional environment across countries might affect female directors' characteristics, thus their results are not generalisable to countries other than Norway.

This is supported by the study of Berger et al. (2014) who documented higher risk in German banks with more women in the composition of the executive teams. Specifically, using portfolio risk to measure the risk attitude of 3,525 banks between 1994 and 2010, they found that in the three years following a higher participation of women on the board, the portfolio risk increased. However, the authors suggest that this finding might be explained by the fact that female executives in their sample had less working experience than men.

A recent study by Sila et al. (2016) offers further insight into our understanding of the mixed results documented by prior studies regarding women's risk aversion. The paper examined the effect of boardroom gender diversity on a firm's risk and found no evidence that the participation of women within the boardroom has any impact on the equity risk. They specifically addressed endogeneity concerns which are likely to bias the findings regarding the association of gender and firm risk, explaining that two sources of endogeneity can possibly bias their findings. The first relates to omitted unobservable firm characteristics which might affect the appointment of directors and the firm risk. Second, female directors may self-select into lower risk firms given their risk aversion. Thus, in this case, reverse causality can better explain the negative association between female directors and firm risk (Sila et al., 2016).

Overall, the literature regarding gender-based differences in risk attitude is mixed. While studies document a gender effect on risk behaviour which in turn affects the corporate outcomes, other studies support the self-selection theory whereby women entering highly male dominated industries are not representative of the female population, thereby gender differences in terms of risk attitude are not significant (Kumar, 2010, Ge et al., 2011, Adams and Funk, 2012, Adams and Ragunathan, 2015, Sila et al., 2016). Therefore, it is not clear whether females in competitive and male dominated professions exhibit lower optimism than their male counterparts.

3.3.4 Sell-side Analysts and Gender

To date, studies on sell-side analyst gender are limited and yield mixed results regarding female analysts' performance and risk attitude (Green et al., 2009, Kumar, 2010, Li et al., 2013, Fang and Huang, 2017). Furthermore, studies on sell-side analyst gender have attempted to determine whether women entering the analyst profession have superior skills due to discrimination in hiring decisions or whether they are subject to affirmative action plans (i.e. Green et al., 2009, Kumar, 2010, Li et al., 2013).

The gender discrimination in the workplace suggests that if a man and a woman have equal qualifications, the man would always be chosen by the employers (Olson and Becker, 1983, Jones and Makepeace, 1996, Winter-Ebmer and Zweimüller, 1997, Kumar, 2010). Thus, women need to be more qualified than men in order to be selected to enter the profession. The second scenario which relates to affirmative action plans suggests that employers strive for gender equality, thus they may set a lower hurdle for women in their hiring decisions (Glazer, 1975, Coate and Loury, 1993, Epstein, 1995).

Green et al. (2009), using a sample of sell-side analyst's earnings forecasts during the period 1995 and 2005, found that brokerages neither systematically discriminate against women nor set lower hurdles to promote gender diversity in the workplace. They reported that although female analysts exhibit significantly less optimism bias compared to men, the former issues less accurate earnings estimates. However, they suggested that women perform better than men in other job aspects, such as industry knowledge and responsiveness, since they are more likely to be designated as All-star analysts than their male counterparts. Furthermore, Li et al. (2013) who examined stock recommendations between 1994 and 2005 showed that female analysts exhibit lower risk, in line with Green et al.'s (2009) conclusion that male analysts exhibit significantly more optimism than their female counterparts. Moreover, regarding stock recommendation profitability, Li et al. (2013) reported that the abnormal returns of analyst stock recommendations are similar for both male and female analysts.

Nonetheless, Kumar (2010) found that female analysts have superior skills than their male counterparts due to gender discrimination in hiring decisions. Specifically, using a sample period from 1983 to 2005, he showed female analysts are more accurate and more likely to issue bold forecasts, the latter being consistent with his prediction that female analysts are not representative of the female population, therefore are likely to have similar risk preferences to their male counterparts. Kumar (2010) controlled for factors that are likely to affect analyst earnings forecast accuracy suggested by prior studies such as firm-specific experience (e.g. Mikhail et al., 1997), analyst portfolio complexity (e.g. Clement, 1999) and forecast frequency (Jacob et al. 1999). However, other unobservable factors might drive Kumar's (2010) documented positive association between females and earnings accuracy.

In addition, Kumar (2010) found that the market assigns greater importance to the opinions of female analysts implying that the market is aware of this female-male skill difference. This is consistent with studies showing investors to systematically differentiate for analyst characteristics which proxy for forecast accuracy (e.g. Stickel, 1997, Bradley et al., 2017).

More recently, Fang and Huang (2017) using a sample period from 1993 to 2009, examined for gender differences in the way alumni ties with corporate boards affect analyst's job performance and career outcomes. The authors found that connections in the Wall Street are more beneficial for males than females, both in terms of performance and career advancement. However, even though men benefit more than women from connections, there was no significant gender difference in analyst performance.

The above-mentioned studies yield mixed results regarding gender differences in analyst performance. For instance, Green at al. (2009) found that female analysts issue less accurate earnings forecasts than their male counterparts whereas Kumar (2010) showed females to be significantly more accurate in their earnings forecasts.

Furthermore, Fang and Huang (2017) did not document any significant gender differences in earnings forecast accuracy. These inconsistent findings might be due to the different sample periods used by the studies. For instance, Kumar (2010) used an extensive sample period starting from 1983 to 2005, whereas Green at al. (2009) employed a sample period from 1995 to 2005 and Fang and Huang (2017) sampled the period between 1993 and 2009. Therefore, it might be that gender discrimination in hiring decisions, was more prevalent in Kumar's (2010) sample.

Furthermore, while Kumar (2010) found women to issue bolder forecasts, Green et al. (2009) showed females to be less optimistic in their forecasts, while Li et al. (2013) reported that females were more risk-averse in their stock recommendations. Again, the studies yield mixed results regarding female analysts' risk attitude. The study of Li et al. (2013) employed stock recommendations, which are more susceptible to biases than earnings forecasts, therefore, the different dependent variables might explain the inconsistent results between Kumar (2010) and Li et al. (2013). However, the inconsistent findings regarding risk attitude between Kumar (2010) and Green et al (2009) cannot be due to different dependent variables since both studies use earnings forecasts, so the reason must rest with the different sample periods.

Concerning female analyst's career outcomes, studies document that women are more likely to be designated as an All-star analyst compared to men (Kumar, 2010, Green et al., 2009, Li et al., 2013, Fang and Huang, 2017). The All-star indicator usually reflects an analyst's reputation and could capture some of the key qualitative aspects, including qualitative characteristics voted by institutional investors in the Institutional Investor magazine such as industry knowledge, integrity, responsiveness, and management access.

Hong and Kubic (2003) reported that in the U.S., the analysts who issue more accurate earnings forecasts are rewarded with better career outcomes. Thus, this is consistent with Kumar's finding that females, who issue more accurate earnings forecasts, have better career outcomes than their male counterparts. However, Green et al. (2009) attribute the better career outcomes of female analysts to their outperformance on other job aspects, other than job performance. This suggests that female analysts have different attitudes and perspectives, which are perceived more favourably by the institutional investors. Therefore, given the findings regarding female analyst's job performance and career outcomes, their low representation within the analyst profession is surprising.

Although only the study of Kumar (2010) supports gender discrimination in hiring decisions whereby females need to be more qualified than males in order to enter the profession, it provides some explanation of female analysts' low presence. A counter argument is that women are less likely to follow risky finance careers as opposed to men because they are less competitive and more risk-averse than men (Sapienza et al., 2009) or because they are less competent in highly competitive professions (Gneezy et al., 2003). This might also suggest that women who enter highly male dominated professions, such as sell-side analyst profession, are not representative of the female population characteristics due to self-selection (Kumar, 2010, Adams and Ragunathan, 2015).

Overall, studies on analysts are inconclusive regarding gender differences in risk attitude, which is consistent with the mixed results of prior literature examining the impact of gender on risk attitude within the finance sector (Atkinson et al., 2003, Adams and Funk, 2012, Sila et al., 2016). Furthermore, the findings on gender differences in sell-side analyst performance are also mixed. Specifically, Kumar (2010) suggests that females outperform their male counterparts, which is not supported by other studies on analyst gender (e.g. Fang and Huang, 2017). However, due to data restrictions, studies on analyst gender are limited and more research is needed to shed further light on the findings of the extant studies. Moreover, research on sell-side analyst gender has provided evidence only from the U.S. market and other markets, have a different institutional environment than the U.S., which might affect the characteristics of female sell-side analysts. Therefore, further studies on sell-side analyst gender are required to provide evidence of gender differences from other markets besides the U.S.

3.4 Summary and Conclusion

Sell-side analyst conflicts of interest have received much attention from academics and regulators, particularly after the dot.com bubble in the U.S. The literature has considered access to management (e.g. Brown et al., 2015), underwriting fees (e.g. Clarke et al., 2004), and analyst affiliation (e.g. Kolasinski and Kothari, 2008) as some of the most important sources of conflicts of interest within the analyst profession. In the light of the dot.com bubble events, analyst affiliation was identified as the main source of bias behind the irrational exuberance of financial analysts touting internet stocks underwritten by their investment banking colleagues (Global Analyst Research Settlement).

In response, regulatory reforms (Global Analyst Research Settlement, NASD Rule 2711, NYSE Rule 472, Reg FD) tried to increase the independence between the research and the investment baking departments. Nonetheless, studies have yielded mixed results regarding the overall effectiveness of these regulatory reforms in mitigating analysts' conflicts of interest (Barniv et al., 2009, Chen and Chen, 2009, Kadan et al., 2009, Guan et al., 2012, Corwin et al., 2017, Chen et al., 2018).

Other than the regulatory reforms, the literature has identified some internal factors which are likely to moderate analysts' conflicts of interest. For instance, career concerns, bank/personal reputation, and the presence of institutional investors have been suggested to act against an analyst's propensity to bias their research (e.g. Hong and Kubik, 2003, Ljungqvist et al., 2007, Fang and Yasuda, 2009). Although, the studies suggest that these internal moderating factors can partially address analyst conflicts of interest.

Conflicts of interest are inherent in the system and arguably, regulations cannot fully address every single conflict that exists within the industry. Reingold (2007) states that conflicts are inherent in Wall Street, therefore what really matters is how individuals responds to such conflicts. This implies that individual analysts can choose how they act when faced with potential conflicts of interest, therefore personal characteristics that are likely to affect ethical decision-making, need to be taken into account (Palazzo and Rethel, 2008).

There is growing evidence that women exhibit greater moral reasoning than men (e.g. Emerson et al., 2007) and that this has resulted in improved outcomes on corporate boards (e.g. Chen et al., 2017). According to the gender socialisation theory, women are more ethical than men (e.g. Cohen at al., 2001). However, the extant literature on gender differences in ethical decision making is far from conclusive with occupational socialisation theory hypothesising that gender differences do not persist in the workplace as both men and women tend to develop similar moral reasoning as they adapt to the working environment and organisational culture of their chosen occupation (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001).

While no research has yet considered the gender effect on the quality of sell-side analyst research when faced with conflicts, studies within the business sector have considered the impact of gender diversity on the quality of financial information. Specifically, studies tested the impact of gender diversity on earnings quality (Krishnan and Parsons, 2008, Srinidhi et al., 2011) and the quality of accruals (Barua et al., 2010), finding a positive association between female participation and the quality of financial statements.

The quality of sell-side analyst research is hindered by analyst affiliation (Global Analyst Research Settlement). However, to date no study has tested for gender differences in the bias exhibited by affiliated sell-side analysts. Such a study would be important since knowledge about gender effects has important implications for ethics training (Rest, 1986), hence will assist both investment banks' and regulators' efforts to address analyst bias. Therefore, the first empirical chapter of this thesis (i.e. Chapter 5), tests whether gender influences the way affiliated analysts respond to their conflicts of interest.

The extant studies on sell-side analyst gender have considered gender differences on analyst performance, risk attitude, and alumni ties (Green et al., 2009, Kumar, 2010, Li et al., 2013, Fang and Huang, 2017), but due to data restrictions, the studies on analyst gender are limited and yield mixed results regarding female analysts risk attitude. Similarly, within the finance industry, studies also yield mixed results regarding the gender differences on risk attitude (e.g. Adams and Funk, 2012; Sila et al., 2016). Generally, males are less risk-averse (e.g. Francis et al., 2014) and more competitive (e.g. Niederle and Vesterlund, 2007) than females. Such differences in risk attitude have been shown to affect corporate outcomes, for instance, Francis et al. (2015) found females CFOs to exhibit more accounting conservatism than their male counterparts. Yet, other studies do not document any gender differences in the risk-taking behaviour in high profile professions, which is consistent with the self-selection theory, whereby females choosing risky finance careers are more competitive and risk-taking than the average female population (e.g. Sapienza et al., 2009). Therefore, the literature is far from conclusive regarding gender difference in risk attitude.

Within the sell-side analyst profession, Kumar (2010) suggests that female sell-side analysts issue more bold earnings forecasts whereas Green et al. (2009) and Li et al. (2013) found female analysts are less optimistic than their male counterparts. Furthermore, the studies provide evidence of the gender effect in the U.S., hence the generalisability of their results do not necessarily apply to other markets with different institutional environment than the U.S. Therefore, motivated by the mixed results of the gender effect on analyst optimism in the U.S. and the lack of studies outside the U.S, the second empirical chapter (i.e. Chapter 6), tests whether male sell-side analysts are more optimistic than their female counterparts across both the U.S. and the European markets.

Furthermore, the sell-side analyst profession is male dominated and the extant studies on analyst gender have tried to identify whether this is explained by differences in analyst forecasting skills. Kumar (2010) found that females outperform male analysts in their earnings forecast. Therefore, since differences in forecasting skills do not justify female analyst low presence, Kumar (2010) argues that female analysts face discrimination in hiring decisions (Olson and Becker, 1983, Jones and Makepeace, 1996, Winter-Ebmer and Zweimüller, 1997). However, gender discrimination in hiring decisions within the sell-side analyst profession is not supported by other studies (Green et al., 2009; Li et al., 2013; Fang and Huang, 2017). Again, the findings of the existing studies are mixed, and their limited number does not enable to reach to a consensus. Moreover, the findings of the extant studies are limited to the U.S., therefore their findings do not apply to other markets with a different institutional environment.

In Europe, like in the U.S., the sell-side analyst profession is also male dominated, hence a study testing for gender differences in analyst forecasting skill in Europe will provide interesting results to regulators and market participants. For instance, market participants systematically differentiate for analyst characteristics which proxy for forecast accuracy (e.g. Bradley et al., 2017). Thus, if female analysts are positively associated with forecast accuracy, that will be useful information for the market participants in the European market. Furthermore, if female analysts are subject to discrimination in hiring decisions it will inform regulators that action is needed in establishing equal entry requirements for both male and female sell-side analysts. Therefore, the third empirical chapter of this thesis (i.e. Chapter 7), tests whether there is gender heterogeneity in analyst forecasting skills in Europe.

The next chapter provides a detailed explanation of the gender identification process followed to obtain the core sample of matched analysts used in the subsequent empirical chapters, as well as descriptive statistics of the gender distribution across countries and years.

Chapter 4: Sample Selection and Descriptive Statistics

The purpose of this chapter is to describe the gender identification process followed in this thesis to obtain the core sample of matched analysts before applying any filtering criteria applicable to the methodology used by subsequent empirical chapters. Furthermore, a discussion of the descriptive statistics is also provided for the gender distribution of the core sample across Europe and the U.S. Consequently, this chapter presents an overview of the core sample of matched analysts while Chapter 5, 6, and 7 discuss more detailed descriptive statistics of the samples used in each chapter.

4.1 Gender Identification Process

The Institutional Brokers' Estimate System (I/B/E/S) Detail files was the main dataset used to address the research questions in the three empirical chapters as it provides analyst forecasts for the covering stocks. Amongst other information, the I/B/E/S Detail files provide a unique identifier for each analyst, their current employer, as well as the analyst surname and the first initial of their name. Analyst gender, which is the key variable in this thesis, is not readily available and the I/B/E/S Detail files alone do not enable for gender identification of the analysts. Therefore, supplementary data was collected from the S&P Global Market Intelligence database which provides the full name of the analysts as well as job history, biographies, and a prefix specifying their title, hence their gender (i.e., Mr, Mrs, and Ms)[21]. In certain cases, the prefix includes Dr, Prof,

[21] The S&P Global database was used by Lourie (2018), who utilised equity analyst employment history to test for analyst bias.

or it is blank, so analyst gender was identified by reading the biographies of the analysts provided by S&P Global. As there was no common unique analyst identifier across the two databases, the first initial and last name of the analysts was extracted from S&P Global and merged with the I/B/E/S sample analysts[22], which were collected from both the I/B/E/S Target Price and Stock Recommendation Detail files[23], to create a comprehensive list of the analysts appearing on the I/B/E/S.

Once the I/B/E/S and S&P Global samples were merged based on an analyst's surname and first initial, the job histories were compared between the two databases to check their compatibility[24]. In those instances where analysts with unique names based on surname and first initial were matched between the two databases, at least one job compatible between the two job histories was required for the analyst to be considered a valid match. If unique analysts matched, but there was no common job between the two job histories, a further research was conducted mainly through the Broker Check provided by FINRA to update the job history in S&P Global. In other cases where there were duplicate names based on surname and first initial, the I/B/E/S analyst with the most similar job history with the S&P Global analyst was assigned, defined as the 'best match'. In cases where there was ambiguity as to which analyst was the 'best match', the analyst was removed from the sample.

[22] In certain cases, S&P Global provides middle names and nicknames of the analysts, so the first letter of those names was further extracted to achieve a better match.

[23] For the empirical analysis in this thesis, the I/B/E/S Target Price Detail files (Chapter 5 and 6) and the I/B/E/S EPS Detail files (Chapter 7) were utilised. However, the I/B/E/S EPS Detail files do not provide the first initial and the surname of the analysts, therefore the I/B/E/S EPS Detail files were not used for the gender identification process. The I/B/E/S Stock Recommendation Detail files together with the I/B/E/S Target Price Detail files were used to create a comprehensive list of the analysts appearing on the I/B/E/S.

[24] Whilst the S&P Global provides the job history of the analyst, the I/B/E/S provides the current employer of the analyst as of the date they submitted a forecast on the I/B/E/S. In order to create a job history for the analysts who appear on I/B/E/S, a unique code was used for each analyst, which stays the same and does not change even if an analyst moves to a new employer, thereby allowing identification of the brokers for which an analyst has worked over the years.

Overall, the gender of 7,962 unique analysts of the 9,717 valid analysts[25] was identified in Europe, which represents a match of 82%, while the gender of 9,753 analysts out of 10,488 valid analysts was identified in the U.S., representing a match of 93%. Sections 4.1.1 and 4.1.2 provide details of gender identification process for the U.S. and Europe respectively.

4.1.1 Gender Identification in the United States

The initial sample exported from the I/B/E/S Target Price and Stock Recommendation Detail files over the sample period 1st January 2003 to 31st December 2014[26] consisted of 11,597 unique analysts by ID. Analyst IDs which related to teams and research departments, or had missing first initial were excluded as the gender identification was impossible in those instances (Sonney, 2007), leaving 10,488 valid analysts in the sample. Overall, the gender of 9,753 analysts was successfully identified, which represents a match of 93% of the valid analysts (i.e. analysts with surname and first initial).

Within the 9,753 matched analysts, 8,546 analysts were unique based on surname and first initial on the I/B/E/S sample, with the remaining 1,207 analysts having duplicate last names and first initials. Among the 8,546 matched unique analysts, 6,743 analysts were unique across both databases. To ensure a valid match the job histories of the matched analysts were checked. If at least one job compatible was not identified, even after additional research, then the analyst was removed from the list. The remaining 1,803

[25] As in Kumar's (2010) study, the present study refers to valid analysts as those analysts who have a surname and a first initial and do not relate to teams or research departments in the I/B/E/S Detail files.
[26] The gender identification of sell-side analysts appearing on the I/B/E/S starts from 2003 to limit the effect of the disruptions caused to the analysts' industry before that period. Also, the study ends the gender identification in 2014, as the sample period is large enough with large number of observations for performing a panel data analysis (e.g. Kennedy, 2003). If the sample is to be extended beyond 2014, then the new analysts appearing on the I/B/E/S need to be hand matched with the S&P Global analysts by following the same matching approach described in this chapter.

analysts with unique names from the I/B/E/S sample were matched to many S&P Global analysts, so the S&P Global analyst with the most similar job history to the I/B/E/S analyst was assigned as the 'best match'. However, when duplicate analysts from the S&P Global were equally compatible with the analyst on the I/B/E/S and it was not possible to determine the 'best match', these analysts were excluded. This matching procedure led to the removal of 437 sample analysts.

In addition, 1,207 of the matched analysts were duplicates based on the surname and first initial on the I/B/E/S sample and were mapped onto multiple analysts on the S&P Global sample. Again, in this case, the analysts who shared the most similar job history between the two databases were matched. If an analyst was not the 'best match' or if there was ambiguity regarding which analyst was the 'best match', they were excluded from the sample, which led to the exclusion of another 298 analysts. Panel A of Table 1 provides a summary of the gender identification process in the U.S. and Panel B of Table 1 shows the distribution of the matched analysts across the I/B/E/S Target Price and Stock Recommendation Detail files.

Table 1: *Gender Identification in the United States*

Panel A: Gender identification	
	Unique Analysts
Initial sample	**11,597**
Drop teams/Departments/Without first initial	1,109
Valid analysts	**10,488**
Drop unique analysts - Not matched	437
Drop duplicate Analysts - Not matched	298
Matched analysts	**9,753**
Unique analysts - Matched	8,546
Duplicate analysts - Matched	1,207

Table 1 *(continued)*

Panel B: Matched analysts	
	Unique Analysts
Matched analysts appearing only in the I/B/E/S Target Price Detail file	126
Matched analysts appearing only in the I/B/E/S Stock Recommendation Detail file	1,222
Matched analysts appearing on both files	8,405
Matched analysts	**9,753**
Matched analysts appearing on I/B/E/S Target Price Detail file	**8,531**
Matched analysts appearing on I/B/E/S Stock Recommendation Detail file	**9,627**

Table 1 presents the number of unique matched analysts in the U.S. Panel A shows the gender identification of unique analysts issuing target prices and/or stock recommendations over the sample period 1st January 2003 to 31st December 2014. Panel B shows the distribution of unique matched analysts across the I/B/E/S Target Price Detail file and the I/B/E/S Stock Recommendation Detail file.

4.1.2 Gender Identification in Europe

The initial sample extracted from the I/B/E/S Target Price and Stock Recommendation Detail files of the 14 European (EU) countries[27] over the sample period 1st January 2003 to 31st December 2014 consisted of 13,353 unique analysts by ID. After excluding teams and research departments, 9,717 analysts with surname and first initial remained. The I/B/E/S sample analysts were merged with the S&P Global sample analysts, successfully matching 7,962 analysts, which represents an 82% match of the valid analysts.

Within the 7,962 matched analysts, 6,705 analysts were unique, and 1,257 analysts were duplicates based on surname and first initial on the I/B/E/S sample. Among the 6,705 unique matched analysts, 5,981 analysts were unique based on surname and first initial across both databases. To consider the analyst assigned as a valid match, the job histories of the matched analysts were checked to ensure that there is at least one job compatible. The remaining 724 matched analysts were unique based on surname and first initial on the I/B/E/S sample, but they mapped onto multiple analysts in the S&P Global sample, hence the S&P Global analyst who has the most similar job history with the

[27] I refer to these countries as Europe (EU): Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom.

I/B/E/S analyst was assigned. The matching process led to the exclusion of 1,247 unique I/B/E/S analysts because they were not the 'best match' with the S&P Global analyst, they did not appear on the S&P database, or they did not have any job compatible with the S&P Global analysts.

Moreover, 1,257 matched analysts were duplicates based on surname and first initial on the I/B/E/S sample and 'best match' S&P Global analyst was assigned, leading to the removal of 508 duplicate analysts because the analysts were not the 'best match' or because it was ambiguous which I/B/E/S analyst was the 'best match' for the S&P Global analyst. Panel A of Table 2 provides a summary of the gender identification process in Europe, with Panel B showing the distribution of the matched analysts in Europe across the I/B/E/S Target Price and Stock Recommendation Detail files.

Table 2: *Gender Identification in Europe*

Panel A: Gender identification	
	Unique Analysts
Initial sample	**13,353**
Drop teams/departments/Without first initial	3,636
Valid analysts	**9,717**
Drop unique analysts - Not matched	1,247
Drop duplicate analysts - Not matched	508
Matched analysts	**7,962**
Unique analysts - Matched	6,705
Duplicate analysts - Matched	1,257
Panel B: Matched analysts	
	Unique Analysts
Matched analysts appearing only in the I/B/E/S Target Price Detail file	469
Matched analysts appearing only in the I/B/E/S Stock Recommendation Detail file	1,203
Matched analysts appearing on both files	6,290
Matched analysts	**7,962**
Matched analysts appearing on I/B/E/S Target Price Detail file	**6,759**
Matched analysts appearing on I/B/E/S Stock Recommendation Detail file	**7,493**

Table 2 presents the unique matched analysts in Europe. Panel A shows the gender identification of unique analysts issuing target prices and/or stock recommendations over the sample period 1st January 2003 to 31st December 2014. Panel B shows the distribution of unique matched analysts across the I/B/E/S Target Price Detail file and the I/B/E/S Stock Recommendation Detail file.

4.2 Summary Statistics of Gender Distribution

This section provides the summary statistics of the gender distribution across both Europe and the U.S. using the core sample of the matched analysts from sections 4.1.1. and 4.1.2. The summary statistics are provided for the sample matched analysts, before applying the filtering criteria used in the subsequent empirical chapters.

Table 3 shows the number of unique female and male matched analysts over the sample period 1st January 2003 to 31st December 2014. Overall, in the U.S. sample, there were more unique analysts (i.e. 9,753) than in the European sample (i.e. 7,962). In Europe, unique female analysts represented 17% of the total analysts, which was higher than in the U.S., where only 14% of unique analysts were female. However, in Table 4 it is shown that female analyst representation varied across Europe, with Italy having the highest average female analyst representation at 19% and Norway scoring the lowest average female representation at 9% over the sample period 2003 to 2014. Furthermore, in the European sample, United Kingdom (UK) had the highest number of analysts following stocks traded in the UK market, with 3,962 analysts, whereas Portugal had the lowest number of unique analysts, with just 379 analysts over the sample period 1st January 2003 to 31st December 2014.

An important distinction is that by female representation, the thesis refers to the female representation in the stock market of a certain country, not to the country of domicile of the analyst. For example, 19% female representation in Italy, means that among all the analysts following stocks traded in Italy, 19% were females. Therefore, analysts who have their portfolio firms headquartered in distinct countries will appear in more than one country.

Table 3: *Gender Distribution*

	Europe		United States	
	Unique Analysts	%	Unique Analysts	%
Males	6,628	83	8,374	86
Females	1,334	17	1,379	14
Total	7,962	100	9,753	100

Table 3 presents the gender distribution of the unique matched analysts issuing target prices and/or stock recommendations for stocks trading in Europe and the U.S. over the sample period 1st January 2003 to 31st December 2014.

Table 4: *Gender Distribution by Country*

	Males		Females		Total
	Unique Analysts	%	Unique Analysts	%	Unique Analysts
Austria	640	86	102	14	742
Denmark	679	85	124	15	803
Finland	803	88	112	12	915
France	2,355	83	472	17	2,827
Germany	2,257	86	377	14	2,634
Ireland	392	85	68	15	460
Italy	1,181	81	279	19	1,460
Netherlands	1,338	86	214	14	1,552
Norway	965	91	95	9	1,060
Portugal	320	84	59	16	379
Spain	988	83	200	17	1,188
Sweden	1,265	87	185	13	1,450
Switzerland	1,314	84	245	16	1,559
United Kingdom	3,305	83	657	17	3,962
United States	8,374	86	1,379	14	9,753

Table 4 presents the distribution of unique male and female analysts issuing target prices and/or stock recommendations for stocks trading in each country, over the sample period 1st January 2003 to 31st December 2014.

Panel A of Table 5 shows the number of unique male analysts by country and per year, with the U.S. having the most male analysts in each year during the sample period 2003 to 2014. Across the Europe, the UK had the highest number of male analysts over the years, whereas Ireland and Portugal had the least number of male analysts over the sample period. The same pattern applies to the number of unique female analysts, which reflects the market size pattern (Panel B of Table 5). For instance, UK has the biggest market in Europe and therefore the highest number of analysts. Consequently, given the differences in market sizes across Europe, it would be more appropriate to check the percentage representation of male and female analysts across the countries.

Table 5: *Analysts' Distribution by Country per Year*

Panel A: Male analysts' distribution

	2003	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
	N	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**
Austria	69	76	96	122	162	182	207	214	241	207	209	203
Denmark	150	144	140	129	173	184	195	211	242	232	214	222
Finland	178	175	177	206	223	253	234	278	282	264	233	217
France	762	754	713	708	675	746	728	800	806	764	733	731
Germany	682	642	627	670	720	794	768	843	898	848	794	790
Ireland	67	67	76	66	79	101	98	113	119	114	103	102
Italy	323	306	289	303	328	356	355	363	390	356	328	350
Netherlands	417	395	373	376	390	400	396	407	424	398	392	387
Norway	156	170	188	206	282	308	316	333	363	316	310	319
Portugal	53	55	67	63	71	95	101	109	122	109	103	110
Spain	253	247	234	248	247	297	283	317	352	295	289	314
Sweden	333	325	315	335	363	362	358	385	431	404	385	393
Switzerland	361	349	322	331	354	409	411	456	497	478	441	422
United Kingdom	930	999	1,026	1,066	1,061	1,127	1,164	1,244	1,351	1,244	1,166	1,129
United States	3,026	3,189	3,275	3,301	3,291	3,207	3,029	3,321	3,443	3,375	3,215	3,237

Table 5 *(continued)*

Panel B: Female analysts' distribution												
	2003	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
	N	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**
Austria	10	9	6	14	22	26	24	26	38	30	31	39
Denmark	26	14	22	21	23	22	24	32	35	38	33	33
Finland	20	22	17	24	37	33	32	35	38	36	28	28
France	151	135	136	134	130	146	142	154	160	141	129	131
Germany	107	95	80	79	97	102	111	126	134	121	108	114
Ireland	11	11	13	14	15	15	16	18	23	20	18	17
Italy	92	80	68	77	83	91	93	89	96	102	88	80
Netherlands	58	46	41	38	42	45	48	56	50	47	44	53
Norway	14	12	17	10	21	25	27	25	28	28	34	30
Portugal	15	11	12	10	12	17	21	19	21	18	13	14
Spain	56	56	43	50	49	51	58	67	70	66	63	60
Sweden	41	35	33	36	38	41	42	44	44	47	47	46
Switzerland	59	54	52	51	52	64	71	83	89	78	67	70
United Kingdom	143	152	160	156	146	176	181	197	214	213	195	217
United States	453	449	486	499	499	485	422	430	425	404	394	378

Table 5 presents the distribution of unique analysts (N) issuing target prices and/or stock recommendations over the sample period 1st January 2003 to 31st December 2014. Panel A shows the distribution of unique male analysts by country per year. Panel B shows the distribution of unique female analysts by country per year.

Panel A of Table 6 presents the unique male analyst percentage representation by country and per year, which ranged from 78% to 95%. Over the years, Italy had the lowest male analyst representation ranging from 78% to 81%, whereas Norway had the highest male analyst representation ranging from 90% to 95%. In the U.S., male analyst representation ranged from 87% to 90%. Overall, the male analyst representation did not change significantly over the years, with the percentages of male analyst representation being in line with the male dominance within the sell-side analyst profession in all the sample countries used in this study over the years 2003–2014.

Panel B of Table 6 presents the unique female analyst percentage representation by country and per year. Over the sample period and the sample countries, the percentage of female analyst representation ranged from 5% to 22%, with Italy having the highest female representation among the sample countries over the whole sample period. The lowest female representation was observed in Norway, which has a small number of total analysts. In larger markets, such as the U.S. and UK, female representation ranged from 10% to 13% and from 12% to 16% respectively. Overall, the descriptive statistics of female representation show that female sell-side analysts are underrepresented within the profession in all the sample countries across the whole sample period.

Table 6*: Analysts' Representation by Country per Year*

Panel A: Male analysts' representation

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	%	%	%	%	%	%	%	%	%	%	%	%
Austria	87	89	94	90	88	88	90	89	86	87	87	84
Denmark	85	91	86	86	88	89	89	87	87	86	87	87
Finland	90	89	91	90	86	88	88	89	88	88	89	89
France	83	85	84	84	84	84	84	84	83	84	85	85
Germany	86	87	89	89	88	89	87	87	87	88	88	87
Ireland	86	86	85	83	84	87	86	86	84	85	85	86
Italy	78	79	81	80	80	80	79	80	80	78	79	81
Netherlands	88	90	90	91	90	90	89	88	89	89	90	88
Norway	92	93	92	95	93	92	92	93	93	92	90	91
Portugal	78	83	85	86	86	85	83	85	85	86	89	89
Spain	82	82	84	83	83	85	83	83	83	82	82	84
Sweden	89	90	91	90	91	90	90	90	91	90	89	90
Switzerland	86	87	86	87	87	86	85	85	85	86	87	86
United Kingdom	87	87	87	87	88	86	87	86	86	85	86	84
United States	87	88	87	87	87	87	88	89	89	89	89	90

Table 6 *(continued)*

Panel B: Female analysts' representation

	2003	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
	%	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**
Austria	13	11	6	10	12	13	10	11	14	13	13	16
Denmark	15	9	14	14	12	11	11	13	13	14	13	13
Finland	10	11	9	10	14	12	12	11	12	12	11	11
France	17	15	16	16	16	16	16	16	17	16	15	15
Germany	14	13	11	11	12	11	13	13	13	12	12	13
Ireland	14	14	15	18	16	13	14	14	16	15	15	14
Italy	22	21	19	20	20	20	21	20	20	22	21	19
Netherlands	12	10	10	9	10	10	11	12	11	11	10	12
Norway	8	7	8	5	7	8	8	7	7	8	10	9
Portugal	22	17	15	14	14	15	17	15	15	14	11	11
Spain	18	18	16	17	17	15	17	17	17	18	18	16
Sweden	11	10	9	10	9	10	11	10	9	10	11	10
Switzerland	14	13	14	13	13	14	15	15	15	14	13	14
United Kingdom	13	13	13	13	12	14	13	14	14	15	14	16
United States	13	12	13	13	13	13	12	11	11	11	11	10

Table 6 presents the representation (%) of unique analysts issuing target prices and/or stock recommendations over the sample period 1st January 2003 to 31st December 2014. Panel A shows the representation of unique male analysts by country per year. Panel B shows the representation of female analysts by country per year.

Chapter 5: Does Gender Influence the Way Affiliated Sell-side Analysts Respond to Their Conflicts of Interest?

5.1 Introduction

Eventually I started to see that the analyst's obligation to be independent, while ethically imperative, wasn't economically logical at all, given that he or she works for a firm whose primary purpose is to maximise fees'. (Reingold, 2007, p. 302)

One of the biggest culprits behind the dot.com bubble was the irrational exuberance of financial analysts touting internet stocks underwritten by their investment banking colleagues (Global Analyst Research Settlement). In response, a barrage of regulatory requirements (Global Analyst Research Settlement, NASD Rule 2711, NYSE Rule 472, Reg FD) were issued to increase the impartiality of sell-side analysts' research reports and create a 'Chinese wall' between equity research and investment banking departments. Nonetheless, studies yield mixed results regarding the overall effectiveness of these regulatory reforms in mitigating analysts' conflicts of interest (Barniv et al., 2009, Chen and Chen, 2009, Kadan et al., 2009, Guan et al., 2012, Corwin et al., 2017, Chen et al., 2018).

Jennings (2013) argues that regulation alone cannot deal with the complex ethical issues faced by sell-side analysts, because ethics, which are defined as the principles of conduct governing an individual or group, are a highly personal matter (Caccese, 1997). Although an individual's ethics can depend on several personal factors, gender has been suggested by researchers as one factor that shapes people's moral reasoning. For sell-side analysts, who are subject to conflicts of interest, being ethical is imperative (Reingold, 2007). However, studies on analyst gender, have not answered whether gender is a personal factor that influences a sell-side analyst's ethical decision-making. This is an interesting issue, since knowledge about gender effects has important implications for ethics training (Rest, 1986), hence such knowledge will assist both investment banks' and regulators' efforts to address analyst bias. Therefore, motivated by the importance of ethics within sell-side analyst profession, I test whether gender influences the way affiliated analysts respond to their conflicts of interest. However, the extant literature regarding gender effects in ethical decision-making in the workplace is far from conclusive, with gender and occupational socialisation being the two main contradicting theories.

According to the gender socialisation theory, women exhibit superior moral reasoning and they are more likely to obey regulations compared to men (Larkin, 2000, Cohen et al., 2001, Glover et al., 2002, Emerson et al., 2007). In support of this theory, finance studies found females in high profile positions (i.e., CEO, CFO, board of directors) were associated with better quality financial information, as well as more focused on corporate governance issues, monitoring, and corporate social responsibility (Adams and Ferreira, 2009, Gul et al., 2011, Srinidhi et al., 2011, Liu, 2018, Chen et al., 2017, Frye and Pham, 2018). Yet, occupational socialisation theory posits there should be no gender differences in the workplace as men and women adapt to the working environment and organisational culture by adopting informal work norms, attitudes, and behaviours of their chosen occupation (Wimalasiri et al., 1996, Cole and Smith, 1996, Roozen et al., 2001). Similarly, other finance studies have documented no gender differences in terms of the quality of financial information or risk attitude in high profile professions (Croson and Gneezy, 2009, Adams and Funk, 2012, Sila et al., 2016, Garcia Lara et al., 2017).

The research opinions of affiliated sell-side analysts provide an ideal setting to examine the role of gender in ethical decision-making. To test the research question, the gender heterogeneity in analysts' target price bias of the covering stocks when their employer was recently the lead underwriter of an equity issue, was examined. Unlike earnings forecasts, target prices represent a direct investment recommendation (Bradshaw, 2002, Brown et al., 2015, Bilinski et al., 2019). In addition, target prices are more granular than stock recommendations, allowing to measure more accurately changes in analysts' optimism bias. If the gender socialisation theory holds, affiliated women should issue less biased target prices than their affiliated male counterparts. Alternatively, according to the occupational socialisation theory, there should be no gender difference in the bias exhibited by affiliated sell-side analysts if both male and female analysts adapt to the culture underpinning their organisation.

The present study starts by showing that affiliated analysts issue more biased target prices than their unaffiliated counterparts, suggesting that, in line with prior studies (Barniv et al., 2009, Kadan et al., 2009), regulatory reforms have had a limited ability at mitigating this behaviour. Next, to test whether gender has a significant impact on this bias, the sample was limited to affiliated analysts. Based on the results, the target price bias of affiliated female sell-side analysts was not significantly different from the target price bias exhibited by affiliated male sell-side analysts. This finding is consistent with the occupational socialisation theory whereby analysts adapt to their organisation's culture thus gender differences do not persist.

The findings have implications for regulators and investment banks. The first finding of the documented bias on affiliated analysts' target prices has implications for regulators' efforts to protect investors from biased analyst research. The second finding, which suggests analysts adopt the values of their organisation's culture, has implications for the male dominated analyst profession. The proportion of male analysts is high enough to impact the culture within the sell-side analyst profession[28], hence the culture of the research departments at investment banks, so female analysts adopt the values of the male dominated culture. However, it was not clear if female analysts were more ethical before adopting the ethical values underpinning the male dominated culture. Nevertheless, it was possible to test whether the organisational culture in which the analysts are adapting to, is positively influenced by a higher proportion of females. Further analysis revealed that higher female representation is associated with less bias on affiliated sell-side analysts' target prices, at sanctioned banks. Therefore, the sell-side analyst profession can benefit from the inclusion of more females, as a higher proportion of females within an investment bank can positively impact the organisational culture to which both male and female sell-side analysts adapt.

The findings of this chapter contribute to the literature on analysts in several ways. First, it complements the extant studies on analysts' conflicts of interest by showing that affiliated analysts exhibit more bias in their target price forecasts than unaffiliated analysts around equity issues. Second, the sample period was up to 2014, which is the most recent sample period examining sell-side analysts' conflicts of interest affiliated with equity issues in the post regulatory period. Third, the limited studies on analyst gender were extended by considering a different perspective of gender differences (i.e., ethical

[28] For instance, Kanter (1977) suggests that with a proportion of 85:15, dominants can influence the culture of the group in many ways. Male analysts represent 85% within the sell-side analyst profession.

decision-making). Fourth, the extant studies on gender differences in ethical decision-making were complemented by providing evidence in support of the occupational socialisation theory.

This chapter is organised as follows: Section 5.2 discusses the motivation of the research question; Section 5.3 explains the research design; Section 5.4 describes the sample selection and descriptive statistics; Section 5.5 examines the impact of gender on affiliated sell-side analyst conflicts of interest; Section 5.6 provides a robustness analysis of the results, with conclusion provided in section 5.7.

5.2 Motivation and Research Question

5.2.1 Sell-side Analysts' Conflicts of Interest

The regulatory reforms in the U.S. following the dot.com bubble, were mainly introduced to decrease the interdependence between the research and the investment banking departments (Global Analyst Research Settlement). Analysts have an incentive to optimistically bias their research reports for stocks that their employer has provided investment banking services (e.g., M&A, underwriting, etc.). Therefore, affiliated analysts face potential conflicts of interest because issuing an optimistic research report can assist the profits of their employer. In support of these allegations, research has documented that before the regulatory reforms, affiliated analysts issued more optimistic earnings forecasts, growth earnings forecasts, and stock recommendations, than unaffiliated analysts (Dugar and Nathan, 1995, Lin and McNichols, 1998, Michaely and Womack, 1999).

Furthermore, O'Brien et al. (2005) documented that affiliated analysts are faster at upgrades and slower at downgrades than unaffiliated analysts. However, it might be that a company's management chooses as the underwriter, the investment bank with the most optimistic analysts about their company's prospects (selection bias). Therefore, affiliated analysts might be slower at downgrades because they are more positive about the future prospects of the covering stock. However, Ljungqvist et al. (2006) did not find any evidence that the optimism on analyst reports influences the issuer's choice of the bank to proceed with either debt or equity offering. In addition, Kolasinski and Kothari (2008) suggest that in all-cash deals within an M&A context, a company's managers do not have any incentive to choose the most optimistic analyst because the stock performance is irrelevant in such deals. Therefore, the authors concluded that analysts' conflicts of interest hypothesis, rather than selection bias, explains their finding whereby affiliated analysts are more likely to upgrade the acquirer within 90 days in an all-cash deal.

More recent studies on analyst affiliation focus on the impact of the regulatory reforms introduced in 2003 in mitigating the documented bias on analysts' research. The results of the extant literature regarding the overall effect of the regulations are mixed (Barniv et al., 2009, Chen and Chen, 2009, Kadan et al., 2009, Guan et al., 2012, Corwin et al., 2017, Chen et al., 2018). Examining analysts' recommendations and earnings forecasts studies found that the NASD Rule 2711, which aimed to increase the independence of analysts' research, was effective in mitigating sell-side analysts' bias in the post regulatory period (Chen and Chen, 2009, Chen et al., 2018).

However, Barniv et al. (2009) found that the negative relationship between stock recommendations and future returns persisted in the post regulatory period. In addition, Kadan et al. (2009) reported that even though both affiliated and unaffiliated analysts are equally likely to issue optimistic recommendations in the post regulatory period, affiliated analysts are still reluctant to issue pessimistic recommendations about the covering stocks. Moreover, Guan et al. (2012) documented that regulatory reforms reduced the relative optimism of analysts' stock recommendations at sanctioned banks[29]. However, the authors did not report any change in the relative optimism of their earnings forecasts in the post regulatory period.

Similarly, Corwin et al. (2017) found that the bias of affiliated analysts' stock recommendations at sanctioned banks significantly decreased in the post regulatory period, whereas the bias of affiliated analysts at non-sanctioned did not. Therefore, the authors concluded that regulations did not have the same effect across investment banks. Overall, the studies on the effectiveness of the regulatory reforms show that regulations had some effect on mitigating analysts' conflicts of interest, however the effect on analysts' output may be incomplete (Barniv et al., 2009).

Regulations, as Jennings (2013) suggests, are mainly introduced to cover ethical lapses in the financial markets. However, history showed that regulation fails and ethical lapses continue, then new regulations are introduced, and then again, ethical lapses continue (Jennings, 2013). This pattern is repetitive, so the focus needs to be on understanding the determinants of ethical decision-making of the people who are working within the sell-side analyst profession. Rest (1986) proposed that successful ethics training requires a good understanding of the people involved, because ethics are the principles of conduct governing an individual or a group (Caccese, 1997). Therefore, beyond regulations, personal factors of the individual analysts can influence their ethical decision-making.

[29] All U.S. investment banks were subject to the new SRO rules, however the twelve sanctioned banks included in the Global Analyst Research Settlement faced a $1.4 billion fine coupled with more requirements aiming to enhance the independence of the research department. Initially the Global Settlement included ten banks, however two more banks were added in 2004.

For instance, analyst personal reputation has been suggested as a moderating factor for sell-side analysts' conflicts of interest (Ljungqvist et al., 2007, Fang and Yasuda, 2009).

Although several personal factors might affect an individual analyst's ethics, it is almost impossible to observe all of them. Moreover, it would be difficult for investment banks and regulators to address conflicts of interest based on each individual's ethical stances. Nevertheless, studies usually infer generalisations about individual's ethics based on their culture, age, gender, etc. (Christie et al., 2003). Indeed, researchers have suggested a possible link between gender and moral development (Gilligan, 1982, Cohen et al., 2001). Given the importance of ethics within the sell-side analyst profession, it would be interesting to determine whether gender differences in ethics are prevalent within the profession. Such research, would offer regulators and investment banks a better understanding of the ethical values underpinning sell-side analysts' decision-making, thus improve ethics training (Rest, 1986) or potential future regulations.

5.2.2 Gender Differences in the Financial Industry

The role of gender in ethical decision-making has received a great amount of attention from academics over the past few decades. There has been particular interest in the finance industry, in which males dominate, to test whether female participation is associated with different corporate decisions. The two main contradicting theories underpinning gender differences in ethical decision-making in the workplace are the gender and occupational socialisation theories.

According to the gender socialisation theory, gender differences in ethical decision-making are prevalent, regardless of whether an individual is a full-time employee or not (Betz et al., 1989, Ameen et al., 1996, Malinowski and Berger, 1996, Mason and Mudrack, 1996, Okleshen and Hoyt, 1996, Eynon et al., 1997, Glover et al., 1997, Singhapakdi, 1999, Larkin, 2000, Cohen et al., 2001, Ross and Robertson, 2003, Emerson et al., 2007). More specifically, the gender socialisation theory suggests that women are more likely to stick to rules, whereas men are more likely to break the rules (Roxas and Stoneback, 2004, Vermeir and Van Kenhove, 2008). This is because studies found women to be more aware of unethical acts (Ameen et al., 1996, Singhapakdi, 1999), to judge situations as less ethical (Mason and Mudrack, 1996, Christie et al., 2003) and have fewer intentions to act unethically (Cohen et al., 2001) compared to men.

Other studies within the finance industry use corporate outcomes, such as the quality of financial information, to infer conclusions about gender differences, rather than interviews or surveys. In particular, studies that tested the impact of gender diversity on earnings quality (Krishnan and Parsons, 2008, Srinidhi et al., 2011) and the quality of accruals (Barua et al., 2010), found a positive association between female participation and the quality of financial information. Furthermore, Francis et al. (2013) who examined the impact of the CFO's gender and the loan contracting, concluded that banks perceive female CFOs as more reliable for the provision of accounting information than male CFOs.

Moreover, studies suggest that females are more concerned with corporate governance issues, monitoring, and corporate social responsibility within their companies, than men (Adams and Ferreira, 2009, Gul et al., 2011, Shaukat et al., 2016, Frye and Pham, 2018). In addition, the studies suggested that greater board gender diversity is associated with less environmental violations (Liu, 2018) and securities fraud (Cumming et al., 2015). Thus, the findings of the above-mentioned finance studies, are consistent with the gender socialisation theory. However, research regarding gender differences in the workplace is far from conclusive.

Unlike gender socialisation, the occupational socialisation theory hypothesises that when a female and a male enter the workplace, they both tend to develop similar moral reasoning as they adapt to the working environment and organisational culture of their chosen occupation (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001). In line with this theory, recent finance studies do not document gender differences in corporate decisions, for instance, Garcia Lara et al. (2017) showed that the quality of financial reporting is lower for the firms that discriminate against women in their hiring decisions. Specifically, in non-discriminating firms, there is no association between better accounting information and the inclusion of more independent female directors. Therefore, the authors concluded that in the absence of discrimination, there are no gender-based differences in high profile jobs. In addition, the studies of Croson and Gneezy (2009), Adams and Funk (2012) and Sila et al. (2016) also suggest that gender differences documented in the general population do not exist in high profile and often male dominated professions.

Within the analyst profession, the studies have tested for gender differences in terms of performance (Green et al., 2009, Kumar, 2010, Li et al., 2013) or for gender heterogeneity in alumni connections (Fang and Huang, 2017). The extant studies on sell-side analysts yield mixed results regarding gender differences in performance. For instance, Kumar (2010) supports that female analysts face discrimination in hiring decisions, because he found that female analysts outperform their male counterparts[30],

[30] The gender discrimination in workplace suggests that women need to be more qualified than men in order to be chosen to enter a male dominated profession.

whereas Green et al. (2009) reported that female analysts' earnings forecasts are less accurate than their male counterparts, thus they do not support gender discrimination. Also, Li et al. (2013) found no significant difference in the stock recommendation performance between male and female sell-side analysts. More recently, Fang and Huang (2017) identified no gender difference in the forecasting accuracy, however they showed that connections through alumni ties improve analyst performance, and the effect is two to three times greater for men than for women. The number of extant studies testing for gender differences within the sell-side analyst profession is limited, mainly because data on analyst gender is not readily available and not easy to collect, so it is not clear whether gender differences in ethical decision-making is prevalent within the sell-side analyst profession.

Ethics are imperative for sell-side analyst profession. In the meantime, there is an increasing amount of interest in recent years as to whether gender leads to different decision-making within the male dominated finance industry. Thus, studying gender differences in the bias exhibited by affiliated analysts will determine whether male and female analysts respond differently to their conflicts of interest. Furthermore, the outcome of the study will be important for regulators and investment banks aiming to address analysts' bias, since as Cohen et al. (2001) and Rest (1986) suggest, knowledge about gender effects has important implications for ethics training.

This chapter is motivated by the importance of ethics within the sell-side analyst profession, as well as the evidence regarding gender effect on ethics. Using analysts' target prices, the study tested for gender heterogeneity in the bias exhibited by affiliated analysts. There is no prior of the expected result, given the vast amount of studies supporting either of the two contradicting theories. To determine which theory holds within the sell-side analyst profession (i.e., gender or occupational socialisation theory), the following research question was empirically addressed in the U.S. market:

Research Question: Does gender influence the way affiliated sell-side analysts respond to their conflicts of interest?

5.3 Research Design

Target prices were used to measure the bias of sell-side analyst's research. Arguably, target prices represent a better measure of bias than earnings forecasts, and stock recommendations (Bilinski et al., 2019). For instance, target prices provide a direct investment recommendation whereas earnings forecasts are used as inputs in analysts' valuation models (Bradshaw, 2002, Brown et al., 2015, Bilinski et al., 2019). Furthermore, research found that earnings forecasts do not suffer from severe bias as opposed to stock recommendations, implying that is easier for analysts to bias stock recommendations whose outcome is not realised as often (Lin and McNichols, 1998, Bradshaw, 2004). Stock recommendations though are stale, especially in the post regulatory period when most investment banks shifted into a three-tier system, thus making it more difficult to measure an increase in analysts' bias (Kadan et al., 2009, Bilinski et al., 2019). Target prices are more granular than stock recommendations, hence allowing to more accurately capture changes in analysts' bias.

Furthermore, both the analysts and the investment banks face less reputational costs when biasing target prices, compared to biased earnings forecasts or stock recommendations (Bilinski et al., 2019), because target prices do not count in the Institutional Investor, The Wall Street Journal, and StarMine rankings for analysts and brokers (Brown et al., 2015). Lastly, the focus of the regulatory reforms was mainly on reducing bias on stock recommendations, hence most of the papers have used that measure to test the impact of the reforms. Instead, by using target prices, this chapter sheds further light on whether affiliated analysts' target prices are subject to bias in the post regulatory period.

5.3.1 Dependent Variables

Following Bradshaw et al. (2013), four target price measures were used to capture analyst bias. The first measure is the target price forecast error (TPE) which is calculated as $(P_{t+12} - TP_t)/P_{t-3}$, where P_{t+12} is the stock price 12 months following the target release date, TP_t is the target price forecast with a 12-month horizon, and the P_{t-3} is the stock price three days before the target price release date. Negative values of TPE show that an analyst's forecast error is due to their optimistic biased target price since the actual stock price did not exceed the analyst's expectations.

The second measure is the target price divided by the current stock price, TP_t/P_t ratio, which captures an analyst's optimism bias about the covering stock; values higher than one indicate an analyst's optimism bias and the higher the ratio the more optimistic the analyst is about the stock's prospects[31]. For the third measure, like Bradshaw et al. (2013), the indicator variable (0, 1) equal to one if an analyst's target price is equal or lower than the stock price at the end of the 12-month forecast horizon (TPMETEND) was used. Furthermore, the last measure used to measure analyst bias, TPMETANY, is an indicator variable (0, 1) equal to one if the maximum stock price over the 12-month forecast horizon is equal or higher than the target price. The measures of TPMETEND

[31] The TP_t/P_t can also be calculated as (TP_t/P_t)-1 where positive values of that measure indicate an analyst's optimism for the covering stock (e.g. Bradshaw et al., 2019). However, this chapter follows Bradshaw's et al. (2013) definition to allow for comparison with their study which, like in this chapter, is conducted in the U.S. market.

and TPMETANY when equal to one show that the analyst's target price was either met or exceeded by the actual stock price. Optimistically biased target price forecasts are expected to exceed the stock price at the end of the 12-month forecast horizon and/or the maximum stock price over the 12-month forecast horizon, thus taking a value of zero based on TPMETEND and TPMETANY.

5.3.2 Explanatory Variables and Model Specification

5.3.2.1 Affiliation

The research question tests for gender differences when the sell-side analysts are faced with conflict, so one of the main independent variables is analyst affiliation. Following the studies of Kadan et al. (2009) and O'Brien et al. (2005), the affiliation setting was frame worked based on firms that issued equity, either through an IPO or an SEO, during the sample period 1st January 2003 to 31st December 2014.

While some studies argue that analysts employed from either the lead underwriter or the co-manager of an equity issue exhibit significant bias in their research (O'Brien et al., 2005, Bradley et al., 2008, Kadan et al., 2009), other studies acknowledge that lead underwriters are subject to greater conflicts (Michaely and Womack, 1999, Ellis et al., 2000, Cliff, 2007). For instance, the lead underwriter is responsible for the due diligence process in an IPO issue, in addition to the IPO price setting as well as the after-market price support (Michaely and Womack, 1999). More specifically in their study Ellis et al. (2000) found that the lead underwriter plays the most significant role as the market maker, whereas the co-managers role in the after-market trading of the IPO is negligible. Thus, even though all affiliated sell-side analysts are likely to have an incentive to provide optimistic research, the analysts employed by the lead underwriter in an equity issue face a greater conflict than the rest of the analysts. Therefore, in this chapter, affiliated analysts are identified as those affiliated with the lead underwriter of an equity issue.

Furthermore, other papers use a wider definition of affiliation including M&A, equity, and debt issues (Lu et al., 2016, Corwin et al., 2017). This study departs from this approach by limiting the affiliation setting on equity issues since only one affiliation setting is needed to test the research question, and arguably, the equity setting is one that exacerbates analysts' conflicts. For instance, the dot.com bubble in the early 2000s was primarily caused by analyst's optimism on IPOs, therefore, in this chapter, the affiliation variable is an indicator variable (0, 1) equal to one if an analyst is affiliated with the lead underwriter of either an IPO or SEO issue within a two-year window and zero otherwise (*Aff*). Therefore, any target prices issued by an affiliated analyst about a client company take the value one.

When regressing the TPE dependent variable, the coefficient of the *Aff* independent variable is expected to be negative, implying that affiliated analysts are less accurate than unaffiliated analysts due to more optimistically biased target prices. For the TP_t/P_t measure, it is also expected that the coefficient of the *Aff* variable will be significantly positive. Similarly, it is expected that affiliated analysts' optimistically biased target price forecasts would be less likely to be met or exceeded by the stock prices following the 12-month forecast horizon in both TPMETANY and TPMETEND measures.

5.3.2.2 Analyst and Broker Characteristics

The main analyst characteristic in this study is gender, thus an indicator variable was included (0, 1), equal to one if an analyst is female and zero otherwise, GENDER, which captures the instance when a sell-side analyst is a female including both affiliated and unaffiliated analysts. Moreover, to capture the impact of gender on affiliated analyst's bias, the sample was limited to affiliated analysts and the GENDER independent variable captures the instance when a female sell-side analyst is affiliated. There is no prior on this variable's coefficient direction because the extant literature yields mixed results on the presence of gender differences within the sell-side analyst industry and other high-profile male dominated professions. If gender differences are prevalent in the analyst profession, then it is expected the GENDER coefficient to be significant and have the opposite direction to the *Aff* coefficient when using the four target price bias (TP bias) measures. Otherwise, if the gender differences do not hold, an insignificant coefficient of the GENDER variable is expected when using the four TP bias measures.

In addition, other analyst characteristics, such as analyst general experience, were included to capture the forecasting skills and knowledge that an analyst has, logGEXP, measured as the natural logarithm of an analyst's years of experience (Clement, 1999). Moreover, to measure analyst expertise on a specific company, the natural logarithm of the number of years an analyst has followed the covering stock, logFEXP, was included. It is expected that analysts with greater general and firm experience will issue more accurate target price forecasts. In addition, analyst coverage was controlled for, measured as the natural logarithm of the number of companies an analyst is following, logCOVERAGE, since it is less likely for an analyst to be as active and accurate when following many firms (Clement, 1999). In addition, to proxy for analyst reputation, ALL_STAR indicator variable (0, 1) was included, which takes the value one if an analyst is identified as an 'all-star' in the issue of the Institutional Investor magazine in the previous year and 0 otherwise (Fang and Yasuda, 2009).

To capture the resources available to the analyst when doing their research, brokerage size was controlled for, logBROKERSIZE, measured as the natural logarithm of the number of analysts employed by an investment bank. It is anticipated broker size will have a positive impact on analyst target price accuracy, since analysts from larger investment banks will have better access to a company's management, thus access to superior information. Furthermore, an indicator variable was included (0, 1), SANCTIONED, which equals to one if the bank is one of the twelve sanctioned banks included in the Global Settlement, to account for the distinct regulatory environments between the investment banks (Corwin et al., 2017). According to Corwin et al. (2017), it is expected that analysts employed by the sanctioned investment banks will exhibit less bias in their target price forecasts than analysts employed by the non-sanctioned banks.

5.3.2.3 Firm Characteristics and Model Specification

Firm characteristics might also affect the accuracy and the bias of analyst target prices, therefore there is a need to control for them. Consequently, a price momentum control variable, PRCMOM, measured as the six-month buy-and-hold return ending three days before the target price release date, was included. It is anticipated that analysts will issue more accurate target prices for stocks with more predictable price patterns (Bilinski et al., 2012). Furthermore, to proxy for a stock's visibility and information environment, the size of the company was measured as the natural logarithm of the company's market value, three days before the target price release day (LOGMV). It is expected that analysts will be less biased and accurate for stocks with high market value because of the richer information environment associated with larger firms (Bradshaw et al., 2013). Also, to control for stock price variability, the STDPRC variable was included, which is the standard deviation of stock prices over the 12 months before the target price release date. Higher optimism for more volatile and risky stocks is expected.

In addition, studies found institutional ownership to moderate bias on analyst's research (e.g. Ljungqvist et al., 2007), thus Inst_own variable measured as the percentage of quarterly institutional ownership at the current quarter was included. It is expected stocks with a high percentage of institutional ownership will have less biased target prices. Lastly, the market return (MRKRET) was controlled for, measured as the buy-and-hold value weighted market return over the 12-month forecast horizon following the target price release date.

The empirical specification of the multivariate regressions for target price (TP) bias is:

(5.1) $$TP\_bias = \beta_0 + \beta_1 Aff + \beta_2 \text{GENDER} + \beta \text{CONTROLS} + \sum \text{IND} + \sum \text{TIME} + \varepsilon$$

(5.2) $$TP\_bias = \beta_0 + \beta_1 \text{GENDER} + \beta \text{CONTROLS} + \sum \text{IND} + \sum \text{TIME} + \varepsilon$$

Where, TP_bias is a measure of target price bias, measured as TPE, TP_t/P_t, TPMETEND or TPMETANY. OLS regressions were used for the dependent variables TPE and TP_t/P_t and logistic regressions for the dependent variables TPMETEND and TPMETANY. All continuous dependent and independent variables were winsorised at the 1 percent level. Furthermore, year and industry fixed effects were controlled for, as well as the cross-sectional dependence of observations with standard errors being clustered at the analyst and firm-level (Petersen, 2009). Equation (5.1) includes both affiliated and unaffiliated analysts whereas equation (5.2) is limited to affiliated analysts. Table 7 provides a summary of the dependent and independent variables used in Chapter 5.

Table 7: *Variable Definitions for Chapter 5*

Variable	Definition
Dependent Variables	
TPE	Defined as the actual 12-month-ahead closing stock price minus the target price forecast scaled by the closing price 3 days before the target price release date, $(P_{t+12} - TP_t)/P_{t-3}$ *Sources: I/B/E/S Detail Target Price file, CRSP*
TP_t/P_t	Defined as the target price forecast divided by the current stock price *Sources: I/B/E/S Detail Target Price file, CRSP*
TPMETANY	An indicator variable (0, 1) equal to 1 if the maximum closing price during the 12-month forecast horizon is greater than or equal to the target price forecast and 0 otherwise *Sources: I/B/E/S Detail Target Price file, CRSP*
TPMETEND	An indicator variable (0, 1) equal to 1 if the actual 12-month-ahead closing stock price is greater or equal to the target price forecast, P12>= TP, and 0 otherwise *Sources: I/B/E/S Detail Target Price file, CRSP*
Analyst and Broker Characteristics	
Aff	An indicator variable (0, 1) equal to 1 if an analyst is affiliated through either an IPO and/or SEO issue with the covering stock within a 2-year window and 0 otherwise *Sources: I/B/E/S Detail Target Price file, SDC*
GENDER	An indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise *Sources: I/B/E/S Detail Target Price file, S&P Global Market Intelligence*
ALL_STAR	An indicator variable (0, 1) equal to 1 if an analyst was elected to the All-America Research Team by the Institutional Investor magazine in the previous year; the magazine is issued annually in October *Source: Institutional Investor Magazine*
logGEXP	Defined as the log number of years an analyst has submitted reports to I/B/E/S measured at the target price release date *Source: I/B/E/S Detail Target Price files*
logFEXP	Defined as the log number of years an analyst has followed a specific company measured at the target price release date *Source: I/B/E/S Detail Target Price file*
logCOVERAGE	Defined as the log number of firms an analyst has followed over the previous 12 months at the target price release date *Source: I/B/E/S Detail Target Price files*

Table 7 *(continued)*

Variable	Definition
logBROKERSIZE	Defined as the log number of analysts employed by the investment bank in the previous year *Source: I/B/E/S Detail Target Price file*
SANCTIONED	An indicator variable (0, 1) equal to 1 if the investment in which the analyst is employed is one of the 12 sanctioned banks included in the Global Analyst Research Settlement *Source: https://www.sec.gov/litigation/litreleases/lr18438.htm*
Qrtl_Female	A categorical variable, defined as the previous year's number of unique females divided by the total number of unique analysts per broker per year, ranked in quartiles, with 1 being the lowest and 4 being the highest based on the female representation within investment banks *Source: I/B/E/S Detail Target Price file*
Firm Characteristics	
LOGMV	Defined as the market value of the firm measured as the natural logarithm of market value 3 days before the target price release date, calculated as the log value of the share price multiplied by shares outstanding *Source: CRSP*
PRCMOM	Defined as the 6-month buy-and-hold return ending 3 trading days before the target price release date *Source: CRSP*
STDPRC	Defined as the standard deviation of stock prices over the 12 months before the target price release date *Source: CRSP*
Instown_perc	Defined as the percentage of quarterly institutional ownership, measured at the current quarter of the target price release date *Source: 13f Filings*
Other Controls	
MRKRET	Defined as the buy-and-hold value weighted market return over the 12-month forecast horizon following the target price release date *Source: CRSP*
Industry effect	12 industry dummies based on Fama and French 12 industry definitions
Year effect	A set of annual dummies for the target price issue year

5.4 Sample and Descriptive Statistics

5.4.1 Sample Selection

To identify analysts affiliated through an equity issue, data was first collected from the SDC platform of all companies that had an equity issue, IPO or an SEO, in the U.S. during the sample period 1st January 2003 to 31st December 2014[32]. The sample period starts in 2003 because after the dot.com bubble in the early 2000s, the regulatory environment in the U.S. underwent many reforms during 2000 to 2002, so by starting the sample in 2003, the effect of the disruptions caused to the analysts' industry before that period was limited.

The SDC platform gives information about the lead underwriters of an equity issue, the offering technique (e.g., firm commitment, best efforts, etc.) and the date of issue. In cases where an equity issue has more than one lead underwriter, the analysts employed by all the lead underwriters are equally defined as affiliated[33]. The initial sample downloaded from SDC over the sample period 1st January 2003 to 31st December 2014 included 4,544 IPO deals and 15,543 SEO deals. Following previous literature, financial, and utility firms identified through the issuer's main SIC code, as well as foreign companies were excluded. Also, deals whose security type is other than Common Shares, Class A shares, Ordinary Shares and Ord. /Common Shares were not included. To ensure that the equity issues in the sample were complete, deals with missing or zero principal amount were removed. Moreover, given that the incentives of the investment bank which underwrites equity issues are subject to the underwriting method, only firm

[32] Although data on equity issues are available after the 2014, the sample ends in 2014 because the analyst gender was not identified after that year.
[33] For instance, in the IPO of Groupon in 2011, eleven lead underwriters were involved, whereas in Google's IPO in 2004, the number of lead underwriters was ten.

commitment deals were included. After applying these criteria, there were 1,108 IPOs and 2,643 SEO deals over the sample period 1st January 2003 to 31st December 2014.

Furthermore, the I/B/E/S Detail files were used to collect data on analyst target price forecasts. When the SDC equity sample was merged with the I/B/E/S sample of analyst target price forecasts, there were 966 IPO deals (87% match) and 2,571 SEO deals (97% match) matched based on CUSIP[34]. Following Kadan et al. (2009), the I/B/E/S sample was limited to the sample firms that issued equity and had analyst coverage.

The unique identifier (CUSIP) of the issuer and the name of the lead underwriter from the SDC were used to identify affiliated analysts. The name of the broker, labelled as 'estimid' on I/B/E/S and 'bookrunners' on SCD, is not consistent between the two databases, therefore after I trimmed for broker name variations, the underwriter names were manually matched. In the event of mergers between two investment banks, following Corwin et al. (2017), it was assumed that investment banking relationships from both predecessor banks were retained by the combined bank.

Moreover, following Kadan et al. (2009), affiliated and unaffiliated analysts were identified based on a two-year time window after an IPO or SEO issue. Therefore, if an analyst was employed by the lead underwriter of an equity issue and issued a target price for that stock within the two-year time window, they were identified as an affiliated analyst. Otherwise, if the analyst issued a target price within the same two-year time window, but was not employed by the lead underwriter, they were identified as an

[34] Other studies included only one SEO per firm over their sample period (e.g. O'Brien et al. 2005), however in this study all the subsequent SEO of the firms were included because in some cases the broker changes. Also, some firms have multiple SEO within the same year, in those cases if the lead underwriter is the same in all SEO issues, which is usually the case, the latest SEO of that year was kept, that is underwritten by the same lead underwriter.

unaffiliated analyst. In addition, equity issues were collected starting from 2001 to include the affiliated analysts in 2003 (Kadan et al., 2009). Moreover, unaffiliated analysts were included only for those stocks for which an affiliated analyst is identified (Corwin et al., 2017).

After merging the SDC with the I/B/E/S database for the affiliation variable, then the sample was merged with CRSP daily data and the Institutional Ownership data from 13f Filings to construct the dependent and control variables. This reduced the final sample to 780 IPO deals and 1,853 SEO deals. In total both IPO and SEO deals represented 1,481 unique stocks by CUSIP. Overall, the final sample of equity deals included 58 unique investment banks involved in an IPO underwriting, 80 unique investment banks involved in an SEO underwriting, and 365 unique investment banks that employed the sample of analysts. Table 8 provides an overview of the sample selection process of the equity deals.

Table 8: *Sample Selection*

Equity Deals over the sample period 1st January 2003 to 31st December 2014	**IPO**	**SEO**
Initial sample	4,544	15,543
Remove financial and utility firms	1,815	4,916
Remove issues other than common stock, Class A shares, Ord.Shares, Ord./Common Shares	170	2,191
Remove foreign stock (ADRs), Common stock withdrawn from registration and US Private Stock	684	4,555
Remove issuers with public status other than public, private, and subsidiary	6	85
Remove deals with missing Principal Amount information	130	36
Remove deals other than firm commitment	628	1,062
Remove deals with missing Lead Underwriter Information	3	55
Deals not matched with IBES (based on CUSIP)	142	72
Deals with missing CRSP and 13F information	186	718
Final sample of equity deals	780	1,853

The comprehensive analyst gender list created in section 4.1.1 by merging I/B/E/S and S&P Global Market Intelligence databases was used to identify the gender of the analysts who have issued target price forecasts for the final equity sample[35] in Table 8. The number of matched analysts appearing on the I/B/E/S Target Price Detail file over the sample period 1st January 2003 to 31st December 2014, found in section 4.1.1, was 8,531 (Panel B of Table 1). After keeping only those analysts who issued target price forecasts for the final sample of the firms with equity deals, the number of unique analysts reduced to 3,443 with 64,490 target price observations, with unique females accounting for 12% of the final sample (Table 9).

Table 9: *Unique Analysts*

	Unique Analysts	Target Price forecasts
Matched analysts appearing in the I/B/E/S Target Price Detail file from section 4.1.1	8,531	980,172
Drop analysts not issuing target prices for sample equity deals	5,088	915,682
Matched analysts issuing target prices for sample equity deals	**3,443**	**64,490**
Males	3,039	58,543
Females	404	5,947

Table 9 presents the number of unique matched analysts and the number of their target price forecasts issued for the final sample of equity deals, as well as their gender distribution over the sample period 1st January 2003 to 31st December 2014.

[35] A comprehensive analyst gender list was created using all analysts from the I/B/E/S Target Price and Stock Recommendation Detail files starting from 2003 to 2014 (section 4.1.1), rather than directly identifying the gender of the unique analysts in the final sample, because by using a limited sample of analysts covering certain stocks, other analysts appearing on the I/B/E/S database that are a 'better match' with the S&P Global sample analysts might be excluded, thereby assigning the wrong analyst from the I/B/E/S to the S&P Global.

5.4.2 Descriptive Statistics

Panel A of Table 10 provides the descriptive statistics of the final sample of 64,490 firm-analyst observations (affiliated and unaffiliated analysts) who issued target prices during the sample period 1st January 2003 to 31st December 2014 for firms who had an equity issue in the U.S. Overall, firm observations from affiliated analysts represented 22% of the total firm-analyst observations. Similar to Bradshaw et al. (2013), the mean target price forecast error was -15% and on average, 36% (64%) of target prices are met or exceeded by the stock price using TPMETEND (TPMETANY), with the TP_t/P_t ratio of the total sample being 1.21(Panel A of Table 10).

The four target price (TP) bias measures differed across affiliated and unaffiliated analysts, with the average TPE of unaffiliated analysts being -14.1%, which was lower than the average TPE of the total sample (Panel A of Table 10), because affiliated analysts increased the total sample TPE average by scoring a mean TPE of -16.8%. Therefore, affiliated analysts were on average 2.7% more biased than unaffiliated analysts in their target price forecasts and the difference in their mean values is statistically significant. Moreover, unaffiliated analysts met, on average, 65 % (36%) of the TPMETANY (TPMETEND) whereas affiliated analysts met 64% (34%) of the TPMETANY (TPMETEND). Also, affiliated analysts were, on average, more optimistically biased in their TP_t/P_t ratio (1.23) than unaffiliated analysts (Panel A of Table 10). The t-value suggests that there is statistical difference in the mean values of TPMETEND and TP_t/P_t ratio between unaffiliated and affiliated sell-side analysts.

Female analysts had a TPE of -14.5% compared to -14.7% for males (Table B of Table 10). Therefore, females had, on average, less error from issuing optimistic prices compared to their male counterparts however there is no statistical difference between their mean values. Also, on average, stock prices met or exceeded 65% (37%) of female analysts' target prices using TPMETANY (TPMETEND). Similarly, male analysts' target prices were, on average, 65% (36%) likely to be met or exceeded by the stock price at the end of (during) the 12-month forecast horizon. Furthermore, female analysts were, on average, less optimistic than males based on their TP_t/P_t ratio, with statistical significance in the difference between their mean values. Moreover, the average market return (MRKRET) and the average price variability (STDPRC) is the same for both females and males (Panel B of Table 10). However, the average price momentum (PRCMOM) of the female analyst sample was lower than that of male analysts, implying that, on average, it would have been harder for females to forecast target prices.

Panel C of Table 10 limits the sample to affiliated analysts. Affiliated male analysts had the most optimistically biased TP_t/P_t ratio of 1.23 than any other analyst sub-sample (i.e full sample, affiliated, unaffiliated, males, and affiliated females). Affiliated female analysts had a TP_t/P_t ratio of 1.21 which conveys less bias than the TP_t/P_t ratio of their affiliated male counterparts who score on average 1.23, with statistical significance in the difference between their mean values (Panel C of Table 10). Regardless of the difference in optimism, both affiliated male and female analysts scored, on average, a similar TPE of -0.17 (Panel C of Table 10). Furthermore, the TPMETEND and TPMETANY measures were similar across both affiliated males and affiliated females.

Regarding other analyst characteristics, affiliated analysts have on average more experience and cover more stocks than unaffiliated analysts (Panel A of Table 10). Also, affiliated analysts are employed by larger investment banks compared to unaffiliated analysts which is not surprising given that larger and more prestigious investment banks are more likely to be the underwriters of an equity issue. In addition, female analysts' firm observations represent 11% within affiliated analysts and 9% within the unaffiliated analyst sample (Panel A of Table 10), therefore, female analysts are, on average, more likely to issue target price as affiliated.

Moreover, the total firm observations of female analysts represent 9% of the total sample, which is lower than their representation of 12% based on their unique ID, which means that female analysts issue less frequent target price forecasts than their male counterparts. Furthermore, females are on average more likely to be employed by larger investment banks, than male analysts (Panel B of Table 10). Also, male analysts have on average more general and firm experience, tending to cover more stocks compared to female analysts.

Table 10: *Descriptive Statistics*

Panel A: Firm-analyst observations split by affiliation				
	Full Sample	Affiliated	Unaffiliated	
	Mean	Mean	Mean	t-value
TPE	-0.147	-0.168	-0.141	5.667***
TP_t/P_t	1.211	1.226	1.207	-6.349***
TPMETANY	0.646	0.641	0.648	1.601
TPMETEND	0.358	0.343	0.363	4.246***
Aff	0.218	1.000	0.000	N/A
GENDER	0.092	0.105	0.089	-6.071***
ALL_STAR	0.07	0.165	0.044	-50.324***
logGEXP	2.228	2.35	2.193	-19.244***
logFEXP	0.835	0.762	0.856	14.793***
logCOVERAGE	2.649	2.77	2.614	-26.764***
logBROKERSIZE	3.772	4.649	3.528	-0.013
SANCTIONED	0.326	0.752	0.207	-0.014
LOGMV	14.181	14.004	14.23	17.532***
PRCMOM	0.119	0.108	0.123	4.808***
STDPRC	0.027	0.027	0.028	7.370***
MRKRET	0.118	0.114	0.119	3.705***
Instown_perc	0.731	0.691	0.742	13.789***
N	64,490	14,053	50,437	

Panel B: Firm-analyst observations split by gender			
	Males	Females	
	Mean	Mean	t-value
TPE	-0.147	-0.145	-0.221
TP_t/P	1.212	1.202	2.212**
TPMETANY	0.646	0.648	-0.305
TPMETEND	0.358	0.367	-1.511
Aff	0.215	0.249	-6.071***
ALL_STAR	0.068	0.093	-7.175***
logGEXP	2.242	2.082	13.777***
logFEXP	0.839	0.798	4.554***
logCOVERAGE	2.669	2.448	21.870***
logBROKERSIZE	3.762	3.871	-7.623***
SANCTIONED	0.319	0.394	-11.828***
LOGMV	14.190	14.096	5.101***
PRCMOM	0.120	0.113	1.605
STDPRC	0.027	0.027	3.654***
MRKRET	0.118	0.118	-0.052
Instown_perc	0.729	0.748	-3.647***
N	58,543	5,947	

Table 10 *(continued)*

Panel C: Affiliated firm-analyst observations split by gender

	Affiliated Males	Affiliated Females	
	Mean	Mean	t-value
TPE	-0.167	-0.172	0.341
TP_t/P_t	1.229	1.207	2.568**
TPMETANY	0.641	0.639	0.130
TPMETEND	0.344	0.337	0.523
ALL_STAR	0.161	0.200	-3.869***
logGEXP	2.352	2.335	0.804
logFEXP	0.763	0.748	0.931
logCOVERAGE	2.804	2.684	6.484***
logBROKERSIZE	4.641	4.718	-4.581***
SANCTIONED	0.745	0.814	-5.762***
LOGMV	14.008	13.975	0.895
PRCMOM	0.109	0.105	0.476
STDPRC	0.027	0.027	1.102
MRKRET	0.114	0.117	-0.749
Instown_perc	0.688	0.714	-2.561**
N	12,573	1,480	

Table 10 presents the mean values of the dependent and control variables measured at each target price issue. Panel A shows the firm-analyst observations of the full sample and by affiliation. Panel B shows the firm-analyst observations by gender. Panel C shows the affiliated firm-analyst observations by gender. The t-value is obtained from independent t-tests in the mean values of the variables between unaffiliated-affiliated, male-female, and affiliated male-affiliated female analysts. N is the number of target price forecasts. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 7.

Dependent Variables
TPE defined as the actual 12-month-ahead closing stock price minus the target price forecast scaled by the closing stock price 3 days before the target price release date, $(P_{t+12} - TP_t)/P_{t-3}$.
TP_t/P_t defined as the target price divided by the current stock price.
TPMETANY an indicator variable (0, 1) equal to 1 if the maximum stock price over the 12-month forecast horizon is equal to or higher than the target price.
TPMETEND an indicator variable (0, 1) equal to 1 if an analyst's target price is equal to or lower than the stock price at the end of the 12-month horizon.

Main Independent Variables
Aff an indicator variable (0, 1) equal to 1 if an analyst is affiliated through an IPO and/or SEO issue with the covering stock within a 2-year window and 0 otherwise.
GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

5.5 Results

This section starts by testing for differences in target price bias between affiliated and unaffiliated analysts to establish bias in affiliated sell-side analysts target price forecasts in equation (5.1). Next, to test the research question, whether gender influences the way affiliated sell-side analysts respond to their conflicts of interest, the sample was limited to affiliated sell-side analysts to estimate the model in equation (5.2). In both equations the four TP bias measures are used as the dependent variables, identified in section 5.3.1, as well as the same set of independent variables from section 5.3.2.

5.5.1 Affiliated Analysts' Target Price Bias

The regression results from equation (5.1) presented in Panel A of Table 11 show that affiliated sell-side analysts are more biased than the unaffiliated in all four TP bias measures, at the 1% level of significance. More specifically, affiliated sell-side analysts' target prices are 5% less accurate (TPE) and 4% more optimistic (TP_t/P_t) than those issued by their unaffiliated counterparts. Furthermore, affiliated sell-side analysts' target prices are significantly less likely to be met or exceeded by the maximum stock price than unaffiliated sell-side analysts during the 12-month forecast horizon (TPMETANY). Similarly, affiliated sell-side analysts' target prices are significantly less likely to be met or exceeded by the stock price than unaffiliated sell-side analysts at the end of the 12-month forecast horizon (TPMETEND).

In terms of analyst characteristics, analyst general experience (logGEXP) improved the accuracy of the TPE measure (at the 10% level of significance). For instance, one year of additional experience improved analyst accuracy by 1%. However, analyst coverage (logCOVERAGE) decreased the accuracy of the TPE measure (at the 10%

level of significance). This is consistent with studies supporting that the more stocks the analysts cover the more inaccurate they are because of the their portfolio complexity (Clement, 1999). Similarly, the more stocks an analyst covers (logCOVERAGE) and the more years they follow a company (logFEXP), the less likely they are to meet the TPMETANY measure. However, one year of general experience increases an analyst's chances to meet the TPMETANY measure by 5% (at the 5% level of significance).

Likewise, for TPMETEND measure, general experience (logGEXP) and coverage (logCOVERAGE) have a positive and a negative effect respectively (Panel A of Table 11). In addition, being an All-Star analyst is associated with increased accuracy for both TPE and TPMETEND measures, consistent with prior studies (Fang and Yasuda, 2009, Kumar, 2010). However, analyst characteristics did not have a significant impact on reducing analyst optimism (TP_t/P_t). In addition, the GENDER variable was not significant in any of the four TP bias measures, showing that there are no gender differences in target price forecasting skill or optimism between the sample analysts. This is consistent with the studies of Li et al. (2013) and Fang and Huang (2017), who also documented no significant gender differences in terms of sell-side analyst performance, using stock recommendations and earnings forecasts.

Broker characteristics, such as the size (logBROKERSIZE), improved analysts' accuracy and reduced their optimism, in line with the literature. Furthermore, the SANCTIONED variable reduced analyst optimism bias and increased accuracy, consistent with Corwin et al. (2017) who suggested that in the post regulatory period, analysts at sanctioned banks had significantly less bias than analysts at non-sanctioned banks.

Regarding stock characteristics, as expected, the price momentum (PRCMOM), firm size (LOGMV), and institutional ownership (Instown_perc), reduced analyst optimism at the 1% level of significance. Also, price variability (STDPRC) reduced accuracy on TPE, TPMETANY, and TPMETEND and increased optimism on TP_t/P_t ratio at the 1% level of significance, consistent with the literature.

In their paper, using stock recommendations, Corwin et al. (2017) found an insignificant affiliation bias around equity issues at sanctioned banks in the post regulatory period. In Panels B and C of Table 11, the sample was split into sanctioned and non-sanctioned banks, and there was still a significant bias in the affiliated sell-side analysts' target prices employed at both sanctioned and non-sanctioned banks[36]. These findings differ from those of Corwin et al. (2017) mainly because target prices rather than stock recommendations were used in the present study. This reinforces the notion that regulations, which primarily aim to mitigate bias on sell-side analyst stock recommendations, have had an incomplete impact on reducing affiliation bias on other analysts' outputs such as target prices which, like stock recommendations, represent a direct investment recommendation. However, it is difficult to determine whether regulations have decreased the bias on sell-side analysts' target prices in the post regulatory period because sell-side analyst target price bias in the pre regulatory period was not examined in this study. Nevertheless, the finding that the bias in affiliated sell-side analysts' target prices is still prevalent and significant in the post regulatory period is important.

[36] The twelve sanctioned banks are; Bear, Stearns & Co. Inc. (Bear Stearns), Credit Suisse First Boston LLC (CSFB), Goldman, Sachs & Co. (Goldman), Lehman Brothers Inc. (Lehman), J.P. Morgan Securities Inc. (J.P. Morgan), Merrill Lynch, Pierce, Fenner & Smith, Incorporated (Merrill Lynch), Morgan Stanley & Co. Incorporated (Morgan Stanley), Citigroup Global Markets Inc., f/k/a Salomon Smith Barney Inc. (SSB), UBS Warburg LLC (UBS Warburg), U.S. Bancorp Piper Jaffray Inc. (Piper Jaffray), Deutsche Bank Securities Inc., and Thomas Weisel Partners LLC Settle.

Table 11: *Regression Analyses for Affiliation Bias*

Panel A: Regression results for differences in the bias exhibited between affiliated and unaffiliated analysts

VARIABLES	(1) TPE	(2) TP_t/P_t	(3) TPMETANY	(4) TPMETEND
Aff	**-0.050*****	**0.040*****	**-0.200*****	**-0.164*****
GENDER	-0.011	-0.007	-0.053	-0.005
ALL_STAR	0.019*	-0.004	0.083	0.143***
logGEXP	0.010*	0.000	0.049**	0.047**
logFEXP	-0.004	0.006	-0.045**	0.006
logCOVERAGE	-0.011*	0.005	-0.047**	-0.063***
logBROKERSIZE	0.025***	-0.018***	0.100***	0.069***
SANCTIONED	0.025**	-0.026***	0.172***	0.105**
LOGMV	0.034***	-0.042***	0.065***	0.096***
PRCMOM	0.108***	-0.196***	0.515***	0.307***
STDPRC	-6.871***	6.520***	-13.436***	-20.149***
MRKRET	1.025***	0.230***	2.162***	4.432***
Instown_perc	0.036***	-0.026***	0.141***	0.091***
Constant	-0.564***	1.510***	0.112	-1.516***
Observations	64,490	64,490	64,490	64,490
R^2/ Pseudo R^2	0.162	0.179	0.053	0.071
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel B: Regression results for differences in the bias exhibited between affiliated and unaffiliated analysts at sanctioned banks

VARIABLES	(1) TPE	(2) TPt/Pt	(3) TPMETANY	(4) TPMETEND
Aff	**-0.052*****	**0.048*****	**-0.220*****	**-0.187*****
GENDER	-0.021	-0.005	-0.109	-0.057
ALL_STAR	0.011	-0.000	0.064	0.101*
logGEXP	0.011	0.002	0.044	0.017
logFEXP	0.009	-0.004	-0.027	0.054
logCOVERAGE	-0.013	0.005	-0.042	-0.037
logBROKERSIZE	0.039***	-0.033***	0.168***	0.103*
LOGMV	0.014**	-0.024***	-0.034	0.009
PRCMOM	0.112***	-0.183***	0.638***	0.344***
STDPRC	-5.223***	5.063***	-14.698***	-20.875***
MRKRET	1.132***	0.152***	2.599***	4.618***
Instown_perc	0.060***	-0.033***	0.228***	0.162*
Constant	-0.460***	1.410***	1.082**	-0.582
Observations	21,017	21,017	21,017	21,017
R^2/ Pseudo R^2	0.166	0.143	0.056	0.071
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 11 *(continued)*

Panel C: Regression results for differences in the bias exhibited between affiliated and unaffiliated analysts at non-sanctioned banks

VARIABLES	(1) TPE	(2) TP_t/P_t	(3) TPMETANY	(4) TPMETEND
Aff	**-0.061*** **	**0.043*** **	**-0.232*** **	**-0.197*** **
GENDER	-0.002	-0.009	-0.007	0.041
ALL_STAR	0.054***	-0.026*	0.186*	0.306***
logGEXP	0.011*	-0.002	0.056**	0.066***
logFEXP	-0.010*	0.011**	-0.052**	-0.019
logCOVERAGE	-0.010	0.005	-0.048*	-0.074***
logBROKERSIZE	0.023***	-0.017***	0.093***	0.067***
LOGMV	0.042***	-0.049***	0.103***	0.134***
PRCMOM	0.106***	-0.203***	0.461***	0.289***
STDPRC	-7.743***	7.337***	-12.811***	-19.726***
MRKRET	0.967***	0.273***	1.932***	4.337***
Instown_perc	0.026***	-0.022***	0.102***	0.060*
Constant	-0.592***	1.541***	-0.283	-1.944***
Observations	43,473	43,473	43,473	43,473
R^2/ Pseudo R^2	0.162	0.193	0.052	0.074
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 11 presents the regression results of equation (5.1). Panel A shows the regression results of the target price bias exhibited by affiliated and unaffiliated analysts. Panel B shows the regression results of the target price bias exhibited by affiliated and unaffiliated analysts employed by the 12 sanctioned banks. Panel C shows the regression results of the target price bias exhibited by affiliated and unaffiliated analysts employed by the non- sanctioned banks. The model includes industry fixed effects based on Fama-French 12-industry classification and time fixed effects. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 7.

Dependent Variables

TPE defined as the actual 12-month-ahead closing stock price minus the target price forecast scaled by the closing stock price 3 days before the target price release date, $(P_{t+12} - TP_t)/P_{t-3}$.

TP_t/P_t defined as the target price divided by the current stock price.

TPMETANY an indicator variable (0, 1) equal to 1 if the maximum stock price over the 12-month forecast horizon is equal to or higher than the target price.

TPMETEND an indicator variable (0, 1) equal to 1 if an analyst's target price is equal to or lower than the stock price at the end of the 12-month horizon.

Main Independent Variables

Aff an indicator variable (0, 1) equal to 1 if an analyst is affiliated through an IPO and/or SEO issue with the covering stock within a 2-year window and 0 otherwise.

GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

5.5.2 Does Gender Influence the Way Affiliated Sell-side Analysts Respond to Their Conflicts of Interest?

When regressing equation (5.2), the sample was limited to the target prices issued by affiliated sell-side analysts to test the research question. The results presented in Panel A of Table 12 show that GENDER is not significant in any of the four TP bias measures, therefore, gender does not play a significant role in the way affiliated sell-side analysts respond to their conflicts of interest. Thus, both affiliated male and affiliated female sell-side analysts are equally optimistically biased in their target price forecasts. In addition, in Panels B and C of Table 12, the sample was split into sanctioned and non-sanctioned banks, and again no gender effect was documented in the biased exhibited by the affiliated sell-side analysts.

These findings are consistent with the occupational socialisation theory, whereby gender differences do not hold in a professional environment where employees tend to develop similar moral reasoning as they adapt to the working environment and organisational culture of their chosen occupation (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001). Therefore, employees develop common ethical values within the same organisation, hence sell-side analysts adopt the values of their employer investment banks, in essence, the values of their profession.

However, the sell-side analyst profession is male dominated and the proportion of males to females (86:14) is large enough to influence the organisational culture (Kanter, 1977). Therefore, is unclear if female analysts were more ethical prior entering the profession, and employed, they adopted the ethical values underpinning the male dominated culture. The next section investigated this issue further.

Table 12: *Regression Analyses for Gender Differences within an Affiliation Setting*

Panel A: Gender differences in target price bias exhibited by affiliated analysts

VARIABLES	(1) TPE	(2) TP_t/P_t	(3) TPMETANY	(4) TPMETEND
GENDER	**-0.028**	**-0.011**	**-0.093**	**-0.106**
ALL_STAR	0.007	-0.005	0.070	0.128*
logGEXP	-0.007	0.004	-0.035	-0.058
logFEXP	-0.003	0.009	-0.148***	-0.016
logCOVERAGE	-0.008	0.008	-0.007	-0.041
logBROKERSIZE	0.055***	-0.041***	0.207***	0.135**
SANCTIONED	0.026	-0.022	0.150*	0.110
LOGMV	0.023***	-0.031***	0.049*	0.059**
PRCMOM	0.118***	-0.211***	0.603***	0.349***
STDPRC	-7.741***	6.478***	-14.270***	-27.396***
MRKRET	1.071***	0.186***	2.489***	4.574***
Instown_perc	0.080***	-0.046***	0.390***	0.261*
Constant	-0.574***	1.558***	-0.490	-1.254**
Observations	14,053	14,053	14,053	14,053
R^2/ Pseudo R^2	0.171	0.185	0.061	0.071
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel B: Gender differences in target price bias exhibited by affiliated analysts at sanctioned banks

VARIABLES	(1) TPE	(2) TP_t/P_t	(3) TPMETANY	(4) TPMETEND
GENDER	**-0.027**	**-0.020**	**-0.110**	**-0.154**
ALL_STAR	0.005	-0.005	0.068	0.120
logGEXP	-0.013	0.007	-0.033	-0.083*
logFEXP	0.003	0.005	-0.148**	0.008
logCOVERAGE	-0.007	0.007	-0.007	-0.019
logBROKERSIZE	0.034*	-0.018	0.126	0.069
LOGMV	0.013*	-0.024***	-0.011	0.018
PRCMOM	0.115***	-0.195***	0.720***	0.335***
STDPRC	-6.930***	5.683***	-16.542***	-27.137***
MRKRET	1.159***	0.157***	2.740***	4.939***
Instown_perc	0.061***	-0.030**	0.357***	0.171
Constant	-0.340**	1.356***	1.212	-0.163
Observations	10,574	10,574	10,574	10,574
R^2/ Pseudo R^2	0.164	0.133	0.061	0.069
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 12 *(continued)*

Panel C: Gender differences in target price bias exhibited by affiliated analysts at non-sanctioned banks

	(1)	(2)	(3)	(4)
VARIABLES	TPE	TP_t/P_t	TPMETANY	TPMETEND
GENDER	**-0.028**	**0.023**	**-0.060**	**0.068**
ALL_STAR	0.025	-0.007	0.108	0.184
logGEXP	0.008	-0.003	-0.053	0.041
logFEXP	-0.024	0.025*	-0.152	-0.092
logCOVERAGE	-0.016	0.012	-0.022	-0.182*
logBROKERSIZE	0.060**	-0.053**	0.226***	0.178
LOGMV	0.048***	-0.049***	0.208***	0.167***
PRCMOM	0.130***	-0.265***	0.343**	0.403**
STDPRC	-10.413***	8.790***	-14.589*	-30.295***
MRKRET	0.654***	0.353***	1.630**	2.723***
Instown_perc	0.146***	-0.102***	0.323	0.599**
Constant	-0.837***	1.776***	-2.993***	-2.966***
Observations	3,479	3,479	3,479	3,479
R^2/ Pseudo R^2	0.192	0.313	0.063	0.092
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 12 presents the results of equation (5.2). Panel A shows the regression results of the gender differences in the target price bias exhibited by affiliated analysts. Panel B shows the regression results of the gender differences in the target price bias exhibited by affiliated analysts employed by the 12 sanctioned banks. Panel C shows the regression results of the gender differences in the target price bias exhibited by affiliated analysts employed by the non-sanctioned banks. The model includes industry fixed effects based on Fama-French 12-industry classification and time fixed effects. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 7.

Dependent Variables
TPE defined as the actual 12-month-ahead closing stock price minus the target price forecast scaled by the closing stock price 3 days before the target price release date, $(P_{t+12} - TP_t)/P_{t-3}$.
TP_t/P_t defined as the target price divided by the current stock price.
TPMETANY an indicator variable (0, 1) equal to 1 if the maximum stock price over the 12-month forecast horizon is equal to or higher than the target price.
TPMETEND an indicator variable (0, 1) equal to 1 if an analyst's target price is equal to or lower than the stock price at the end of the 12-month horizon.

Main Independent Variable
GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

5.5.3 Does Higher Female Representation Positively Influence the Bias Exhibited by Affiliated Sell-side Analysts?

So far, it has been documented that sell-side analysts adopt the values of their organisation, but it is unclear whether female analysts were more ethical prior entering the sell-side analyst profession and adopt the values of a male-dominated culture. Nevertheless, it can be tested whether females can positively impact the male-dominated culture within investment banks when their representation is higher. For instance, Kanter (1977) suggests that with a proposed ratio of 65:35, minority members can affect the culture of the group. Consequently, it would be expected that if females were more ethical than males before entering the sell-side analyst profession, a higher proportion of females within an investment bank could positively impact the organisational culture in which both male and female sell-side analysts adapt to.

For this analysis, the sample was split into sanctioned and non-sanctioned banks to account for the differences of the distinct regulatory environments, to avoid falsely associate female participation with better organisational culture[37]. Furthermore, the sample was split into affiliated and unaffiliated analysts, because I expect the impact of higher female representation to be prevalent in the sample of affiliated analysts where conflicts of interest, hence bias, are higher.

Female representation is defined as the previous year's number of unique female sell-side analysts divided by the total number of unique sell-side analysts employed each year

[37] For instance, Corwin et al. (2017) suggest that the decreased bias documented within sanctioned banks might be due to a change of the culture within those banks.

by a certain investment bank[38], reported in percentages. Then, the investment banks were ranked into quartiles based on their female representation in each year, with one being the lowest and four being the highest in the ranking. Accordingly, banks in the fourth quartile are those with the highest female representation for that year whereas banks in the first quartile are those with the lowest female representation in a specific year; banks can go up or down in the ranking each year depending on their female representation.

Panel A of Table 13 shows that the average female representation at sanctioned banks is 14%, whereas it is 9.5% at non-sanctioned banks, however, the maximum female representation at non-sanctioned banks is 67% compared to 24% at sanctioned banks. Panel B of Table 13, which presents the average number of analysts employed by the investment banks in each quartile, shows that larger investment banks within the sanctioned group are in the fourth quartile meaning that female representation is higher for those banks. Within the non-sanctioned group, the proportion of females is higher at smaller banks, implying that non-sanctioned banks reach a higher proportion of females because they employ fewer analysts and not necessarily because they tend to hire more women. Therefore, the higher proportion of females as shown in Panel C of Table 13, for non-sanctioned banks, is driven by the lower number of employees. For sanctioned banks though, the high proportion of female participation is not driven by fewer employees, as the largest banks are in the fourth quartile.

[38] Analysts employed by investment banks were counted based on the number of unique analysts submitting a forecast on the I/B/E/S database. Thus, the percentage of female analysts was calculated based on the number of analysts working at the research department, rather than the number of employees within the whole investment bank. Therefore, when referring to organisational culture, the chapter refers to the culture of the research department that employs the sell-side analysts. Arguably, regulations attempted to increase the independence of research department from the other departments within the investment bank, which might shape differently the culture of the research department.

Table 13: *Female Representation*

Panel A: Female representation

	N	Mean	Std. Dev.	Min	Max
Sanctioned Banks	21,017	0.141	0.038	0.061	0.244
Non-Sanctioned Banks	43,473	0.095	0.079	0.000	0.667
All Banks	64,490	0.110	0.071	0.000	0.667

Panel B: Average number of unique analysts employed at investment banks in each quartile

Quartiles	1	2	3	4
Sanctioned				
Affiliated	95	139	137	197
Unaffiliated	86	111	139	172
Non-Sanctioned				
Affiliated	40	52	46	28
Unaffiliated	15	34	26	17

Panel C: Average female representation within investment banks in each quartile

Quartiles	1	2	3	4
Sanctioned				
Affiliated	10%	14%	17%	20%
Unaffiliated	9%	13%	15%	19%
Non-Sanctioned				
Affiliated	3%	9%	11%	17%
Unaffiliated	0%	7%	11%	24%

Table 13 presents the descriptive statistics of the female representation over the sample period 1st January 2003 to 31st December 2014. Female representation is defined as the previous year's number of unique females divided by the total number of unique analysts per broker per year, reported in percentages. Quartiles represent the ranking of investment banks, with 1 being the lowest and 4 being the highest, based on the percentage of females employed. Panel A shows the statistics of the female representation at sanctioned and non-sanctioned banks. Panel B shows the average number of analysts employed by investment banks in each quartile rank at sanctioned and non-sanctioned banks. Panel C shows the average female representation in each quartile rank at sanctioned and non-sanctioned banks.

Table 14 presents the regression results of the four sub-samples based on analyst-firm observations (i.e. affiliated analysts at sanctioned banks, unaffiliated analysts at sanctioned banks, affiliated analysts at non-sanctioned banks, unaffiliated analysts at non-sanctioned banks). The main independent variable is the Qrtl_Female, a categorical variable taking values one to four, depending on the female representation that the investment banks have on a particular year. Female representation is measured as the previous year's number of unique female sell-side analysts divided by the total number of unique sell-side analysts for each investment bank.

Panel A of Table 14 shows that affiliated sell-side analysts at sanctioned banks exhibit a significant reduction in their bias in all four TP bias measures when female representation is higher. The effect is not significant in the unaffiliated group within sanctioned banks (Panel B of Table 14). This is consistent with the prediction that if female participation positively influences the organisational culture, the effect will be prevalent in the sub sample of affiliated analysts where conflicts are greater.

Furthermore, within non-sanctioned banks, there is significance in one measure within the affiliated group (Panel C of Table 14) and in two measures within the unaffiliated group (Panel D of Table 14). The results for non-sanctioned banks are not consistent with those of sanctioned banks, mainly because there are 54 non-sanctioned investment banks within the affiliated group and 273 within the unaffiliated group, therefore different investment banks appear in each sample, unlike in the case of sanctioned banks.

Table 14: *Regression Analyses of the Female Representation Effect on Analyst Bias*

Panel A: Affiliated analysts employed at sanctioned banks				
	(1)	(2)	(3)	(4)
VARIABLES	TPE	TP_t/P_t	TPMETANY	TPMETEND
Qrtl_Female	**0.014***	**-0.010***	**0.107*****	**0.074****
ALL_STAR	0.001	-0.003	0.043	0.100
logGEXP	-0.013	0.007	-0.033	-0.083*
logFEXP	0.003	0.004	-0.149***	0.007
logCOVERAGE	-0.005	0.007	0.004	-0.008
logBROKERSIZE	0.019	-0.009	0.012	-0.012
LOGMV	0.012*	-0.023***	-0.016	0.015
PRCMOM	0.116***	-0.196***	0.727***	0.339***
STDPRC	-6.934***	5.682***	-16.664***	-27.161***
MRKRET	1.162***	0.156***	2.768***	4.957***
Instown_perc	0.060***	-0.030**	0.348***	0.164
Constant	-0.297*	1.317***	1.595**	0.073
Observations	10,574	10,574	10,574	10,574
R^2/ Pseudo R^2	0.165	0.133	0.063	0.070
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel B: Unaffiliated analysts employed at sanctioned banks				
	(1)	(2)	(3)	(4)
VARIABLES	TPE	TP_t/P_t	TPMETANY	TPMETEND
Qrtl_Female	-0.006	-0.003	-0.014	0.010
ALL_STAR	0.021	0.008	0.055	0.083
logGEXP	0.032**	-0.003	0.116**	0.106*
logFEXP	0.012	-0.008	0.062	0.079
logCOVERAGE	-0.017	0.000	-0.070	-0.046
logBROKERSIZE	0.045***	-0.036***	0.194**	0.094
LOGMV	0.015*	-0.025***	-0.059*	-0.001
PRCMOM	0.101***	-0.168***	0.531***	0.339***
STDPRC	-3.212**	4.260***	-12.963**	-14.256**
MRKRET	1.099***	0.152***	2.498***	4.350***
Instown_perc	0.065**	-0.043**	0.093	0.178
Constant	-0.614***	1.483***	0.954	-0.896
Observations	10,443	10,443	10,443	10,443
R^2/ Pseudo R^2	0.169	0.149	0.054	0.075
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel C: Affiliated analysts employed at non-sanctioned banks				
	(1)	(2)	(3)	(4)
VARIABLES	TPE	TP_t/P_t	TPMETANY	TPMETEND
Qrtl_Female	0.014	-0.006	0.070	**0.109***
ALL_STAR	0.023	-0.011	0.080	0.158
logGEXP	0.008	-0.001	-0.045	0.041
logFEXP	-0.022	0.025*	-0.131	-0.074
logCOVERAGE	-0.011	0.004	-0.021	-0.172
logBROKERSIZE	0.063**	-0.043***	0.275***	0.229*
LOGMV	0.048***	-0.050***	0.216***	0.166***
PRCMOM	0.125***	-0.258***	0.317**	0.394**
STDPRC	-10.216***	8.558***	-13.871*	-28.388***
MRKRET	0.677***	0.331***	1.792**	2.873***
Instown_perc	0.142***	-0.100***	0.290	0.585**
Constant	-0.912***	1.779***	-3.516***	-3.508***
Observations	3,461	3,461	3,461	3,461
R^2/ Pseudo R^2	0.190	0.304	0.064	0.094
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 14 *(continued)*

Panel D: Unaffiliated analysts employed at non-sanctioned banks				
	(1)	(2)	(3)	(4)
VARIABLES	TPE	TP_t/P_t	TPMETANY	TPMETEND
Qrtl_Female	0.003	-0.001	**0.032****	**0.028***
ALL_STAR	0.040	-0.021	0.109	0.289**
logGEXP	0.011*	-0.002	0.068***	0.073***
logFEXP	-0.011*	0.010**	-0.051*	-0.019
logCOVERAGE	-0.010	0.005	-0.058**	-0.071**
logBROKERSIZE	0.022***	-0.016***	0.094***	0.063***
LOGMV	0.040***	-0.048***	0.091***	0.128***
PRCMOM	0.106***	-0.199***	0.472***	0.284***
STDPRC	-7.656***	7.136***	-13.707***	-19.920***
MRKRET	0.975***	0.257***	1.975***	4.403***
Instown_perc	0.020**	-0.018**	0.091**	0.041
Constant	-0.573***	1.531***	-0.104	-1.930***
Observations	38,793	38,793	38,793	38,793
R^2/ Pseudo R^2	0.162	0.183	0.053	0.075
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 14 presents regression analyses of the female representation effect on analyst bias. Panel A shows the regression results of the female representation effect at the target prices issued by affiliated analysts at the 12 sanctioned banks. Panel B shows the regression results of the female representation effect at the target prices issued by unaffiliated analysts at the 12 sanctioned banks. Panel C shows the regression results of the female representation effect at the target prices issued by affiliated analysts at non-sanctioned banks. Panel D shows the regression results of the female representation effect at the target prices issued by unaffiliated analysts at non-sanctioned banks. The model includes industry fixed effects based on Fama-French 12-industry classification and time fixed effects. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only while the definition of the remaining variables can be found in Table 7.

Dependent Variables

TPE defined as the actual 12-month-ahead closing stock price minus the target price forecast scaled by the closing stock price 3 days before the target price release date, $(P_{t+12} - TP_t)/P_{t-3}$.

TP_t/P_t defined as the target price divided by the current stock price.

TPMETANY an indicator variable (0, 1) equal to 1 if the maximum stock price over the 12-month forecast horizon is equal to or higher than the target price.

TPMETEND an indicator variable (0, 1) equal to 1 if an analyst's target price is equal to or lower than the stock price at the end of the 12-month horizon.

Main Independent Variable

Qrtl_Female defined as the previous year's number of unique females divided by the total number of unique analysts per broker per year, converted in quartiles, representing the ranking of investment banks, with 1 being the lowest and 4 being the highest, based on the percentage of females employed.

5.6 Robustness Analysis

To add more validity to the findings of section 5.5.2, the sample was limited to those stocks which have at least one affiliated female and male analyst in a certain year covering the same stock, and equation (5.2) was applied. In this way affiliated sell-side analysts who cover the same stocks were compared, controlling for the endogenous decision of female analysts to follow certain stocks. By doing this, the sample was limited to 4,197 analyst-firm observations, with unique females representing 27% of the total sample and their firm-analyst observations representing 35% of the total sample.

Consistent with the findings in section 5.5.2, there was no gender difference in the bias exhibited between affiliated analysts. Therefore, the robustness analysis in Table 15 supports that gender differences in ethical decision-making do not hold within the sell-side analyst profession. This is in line with occupational socialisation theory whereby all analysts adapt to the culture within their organisations, hence adopt similar values. Furthermore, analyst characteristics are not significant, suggesting that the affiliated analysts of the limited sample have similar characteristics in terms of years of experience, firm experience, coverage, and broker size.

Table 15: *Robustness Analysis*

VARIABLES	(1) TPE	(2) TP_t/P_t	(3) TPMETANY	(4) TPMETEND
GENDER	-0.019	-0.005	-0.103	-0.098
ALL_STAR	-0.022	0.005	-0.148	-0.022
logGEXP	-0.019	0.001	-0.088	-0.037
logFEXP	0.002	0.004	-0.030	-0.020
logCOVERAGE	0.006	0.011	-0.001	-0.070
logBROKERSIZE	-0.011	0.013	-0.028	-0.065
SANCTIONED	0.040	-0.071**	0.200	0.244
LOGMV	0.021**	-0.020***	0.030	0.025
PRCMOM	0.074**	-0.160***	0.352**	0.225
STDPRC	-3.224*	4.685***	-7.206	-5.928
MRKRET	0.991***	0.147	3.042***	5.227***
Instown_perc	0.199***	-0.121***	0.632***	0.754***
Constant	-0.325	1.229***	1.762*	-0.609
Observations	4,197	4,197	4,197	4,197
R^2/ Pseudo R^2	0.168	0.163	0.078	0.076
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 15 presents the robustness analysis by limiting the sample to stocks that have at least one affiliated female and male analyst in a certain year covering the same stock. The model includes industry fixed effects based on Fama-French 12-industry classification and time fixed effects. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 7.

Dependent Variables
TPE defined as the actual 12-month-ahead closing stock price minus the target price forecast scaled by the closing stock price 3 days before the target price release date, $(P_{t+12} - TP_t)/P_{t-3}$.
TP_t/P_t defined as the target price divided by the current stock price.
TPMETANY an indicator variable (0, 1) equal to 1 if the maximum stock price over the 12-month forecast horizon is equal to or higher than the target price.
TPMETEND an indicator variable (0, 1) equal to 1 if an analyst's target price is equal to or lower than the stock price at the end of the 12-month horizon.

Main Independent Variable
GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

5.7 Conclusion

Sell-side analysts' conflicts of interest is an important issue within financial industry, since bias in sell-side analyst research can impose severe negative economic effects, such as the dot.com bubble and the subsequent stock market crash in the late 1990s in the U.S. Following these events, regulators aimed to address analysts' conflicts, but studies yield mixed results regarding the effectiveness of the regulations in addressing sell-side analysts' conflicts of interest (Barniv et al., 2009, Chen and Chen, 2009, Kadan et al., 2009, Guan et al., 2012, Corwin et al., 2017, Chen et al., 2018).

The main implication of the regulations, is that regulation alone cannot deal with the complex ethical issues faced by sell-side analysts (Jennings, 2013). Ethics are a highly personal matter, thus when faced with conflicts, an individual analyst can choose to behave ethically or unethically. Several personal factors can affect an individual's moral reasoning, however, is almost impossible to observe all of them and difficult to draw generalisations. Researchers though, have suggested a possible link between gender and moral reasoning (Gilligan, 1982, Cohen et al., 2001). However, the extant studies on gender differences in the workplace are far from conclusive.

According to the gender socialisation theory, gender differences do exist in the workplace and females tend to behave more ethically than men (Mason and Mudrack, 1996, Cohen et al., 2001, Glover et al., 2002, Cumming et al., 2015). Furthermore, studies within the finance industry associate female participation with increased quality of financial statements (Barua et al., 2010, Srinidhi et al., 2011, Francis et al., 2013) and better board monitoring (Frye and Pham, 2018). A conflicting theory is the gender occupational theory which suggests that gender differences, if any, disappear once men and women enter the workplace, as they both adapt to their organisation's culture (Cole and Smith, 1996, Wimalasiri et al., 1996, Roozen et al., 2001). Similarly, other finance studies do not document any gender differences in the quality of financial information or decision-making (Adams and Funk, 2012, Sila et al., 2016, Garcia Lara et al., 2017) .

Gender differences within the sell-side analyst profession have attracted little attention from the researchers, mainly because of data availability. The extant studies have focused on gender differences in terms of performance or connections through alumni ties (Green et al., 2009, Kumar, 2010, Li et al., 2013, Fang and Huang, 2017). Therefore, it is not yet known whether gender differences influence the way affiliated sell-side analysts respond to their conflicts of interest. Such a study would be interesting, as knowledge about gender effects has important implications for ethics training (Rest, 1986), thus this knowledge will be useful for both investment banks' and regulators' efforts to address analyst bias. Consequently, this chapter tested whether gender influences the way affiliated sell-side analysts respond to their conflicts of interest.

To test for gender heterogeneity in affiliated sell-side analysts' bias, target price forecasts were used. Target prices, like stock recommendations, represent a direct investment recommendation (Bradshaw, 2002, Brown et al., 2015, Bilinski et al., 2019), but are more granular than stock recommendations, allowing to more accurately measure changes in analysts' optimism bias. Given the mixed results of the extant studies regarding gender differences in ethical decision-making, there is no prior as to whether gender influences the way affiliated sell-side analysts respond to their conflicts of interest. For instance, building on the gender socialisation theory, one would expect female affiliated sell-side analysts to exhibit less bias than their affiliated male counterparts. However, according to the occupational socialisation theory, one would expect all analysts to adopt the values of their working environment, hence gender differences should not persist.

The results revealed that although affiliated sell-side analysts are significantly more biased than unaffiliated sell-side analysts in their target prices forecasts, gender does not play a significant role in the way affiliated sell-side analysts respond to their conflicts of interest. The latter finding is consistent with the occupational socialisation theory whereby employees tend to develop similar moral reasoning as they adapt to the same working environment and organisational culture. Nonetheless, the sell-side analyst profession is male dominated and the proportion of males to females (86:14) is large enough to influence the organisational culture (Kanter, 1977). Further analysis, to test whether higher female representation can positively affect the values and the culture of the organisation, showed affiliated analysts exhibit less bias in their target prices when the percentage of females is higher within the sanctioned banks.

These findings contribute to the extant literature in several ways. First, complementing the extant literature on affiliated sell-side analysts' conflicts of interest by documenting bias on affiliated analysts' target price forecasts. Second, the study examines a sample period up to 2014, which is the most recent period testing for bias of sell-side analysts affiliated with an equity issue, in the post regulatory period. Third, the chapter adds to the extant studies on analyst gender by examining a different dimension of gender differences within the profession, by testing for gender differences in ethical decision-making. Fourth, using an affiliation setting for examining gender differences in ethical decision-making, the chapter provides support for the occupational socialisation theory.

While Chapter 5 determined for gender differences in the bias exhibited by affiliated sell-side analysts, gender studies within the finance industry have identified a potential link between gender and risk attitude. Although, the existing studies on sell-side analyst gender provide mixed results of the gender effect in risk attitude. In addition, the results are limited to the U.S. and may not generalise to markets with different institutional environments, therefore more research is necessary to shed further light about the gender differences in risk attitude within sell-side analyst profession. Accordingly, Chapter 6 assesses gender differences in target price optimism across both the U.S. and Europe.

Chapter 6: Do Male Sell-side Analysts Issue More Optimistic Target Prices than Females? Evidence from Europe and the United States

6.1 Introduction

Gender studies within the finance industry have identified a potential link between gender and risk attitude (e.g. Barber and Odean, 2001). In particular, males are found to be less risk-averse (e.g. Francis et al., 2014) and more competitive (e.g. Niederle and Vesterlund, 2007) than females, with such differences in risk attitude to affect corporate outcomes. For instance, Francis et al. (2015) found female CFOs exhibited more accounting conservatism than their male counterparts. Yet, other studies do not document any gender differences in risk-taking behaviour in high profile professions, suggesting that this might be explained by the self-selection theory, whereby females choosing risky finance careers are more competitive and risk-taking than the average female population (e.g. Sapienza et al., 2009).

Within the sell-side analyst profession, the findings regarding gender differences in risk attitude are also mixed, and due to data restrictions, the studies on analyst gender are limited. Kumar (2010) suggested that female sell-side analysts are more optimistic in their earnings forecasts, whereas Green et al. (2009) and Li et al. (2013) found that female analysts were less optimistic than their male counterparts. To capture differences in risk attitude, the studies used earnings forecasts (i.e. Green et al., 2009; Kumar, 2010) and stock recommendations (i.e. Li et al., 2013). However, literature suggests that target prices is a better measure to capture analyst optimism compared to earnings forecasts and stock recommendations (e.g. Bradshaw et al., 2006). Furthermore, the extant studies on sell-side analyst profession provide evidence of the gender effect in the U.S., hence the generalisability of their results does not necessarily apply to other markets outside the U.S. with different institutional environment.

Motivated by the mixed results of the extant studies regarding the gender effect on analyst optimism in the U.S., as well as the lack of studies outside the U.S, the present study tested whether male sell-side analysts are more optimistic than their female counterparts across both the U.S. and European markets. The European market is large enough to bear comparison with the gender effect in the U.S. (Capstaff et al., 2001). In addition, the U.S. and Europe have different institutional environments which might affect the characteristics of female sell-side analysts. Therefore, these two distinct markets were used in this study to provide further insights of the gender effect within the sell-side analyst profession.

This study is important for market participants since it will provide them with knowledge to help them make more informed investment decisions. If, for example, male analysts issue significantly more optimistic forecasts than females, investors need to be aware of this so that they can discount the forecasts issued by male sell-side analysts. Furthermore, a gender study providing results from two distinct markets will provide evidence of whether the gender effect, if any, is homogenous across the European and the U.S. market. This will inform regulators whether the two markets should be treated homogenously regarding the issue of any potential future gender policies within the profession.

Target price forecasts were used to test whether sell-side analysts have gender differences in optimism, as they are more likely to be affected by analyst optimism (Bradshaw et al., 2006). Given the mixed results of the extant studies on analyst gender in the U.S., there is no prior of the gender effect in either the U.S. or Europe. It is expected that more optimistic target price forecasts will be issued by male analysts, if gender differences in risk attitude persist within their profession. Yet, if gender differences in risk attitude are not prevalent in the highly male dominated analyst profession, it is anticipated that male and female analysts will be equally optimistic in their target price forecasts.

The findings of this study suggest that in the U.S., female sell-side analysts are less optimistic in their target price forecasts compared to their male counterparts, but gender differences in optimism do not result in gender differences in the target price forecast accuracy, after controlling for the endogenous decision to follow certain stocks. In Europe, while males initially appear to be more optimistic than females, the effect disappears once the sample was limited to stocks followed by both men and women in the same year to control for endogeneity. This implies that, in Europe, males initially appear more optimistic because of reverse causality as they follow, on average, riskier stocks than females, which explains their greater optimism. Furthermore, after controlling for the choice of the stock followed, gender differences in optimism, if any, do not affect analyst's target price performance in Europe.

The findings of the present study contribute to the sell-side analyst literature by providing evidence of the gender effect on target price optimism from the U.S. and the European markets. Also, the paper complements the stream of literature testing for gender differences in risk attitude in high profile professions. The findings also have implications for the previous gender studies in risk attitude, as the gender effect materialises differently in distinct markets, it might affect the choice of the stock followed (i.e. Europe) or it might affect the level of optimism documented in target prices (i.e. U.S.). For instance, female analysts following European stocks, follow, on average, less risky stocks than males, which is a gender effect, whereas in the U.S. the gender effect in risk attitude is reflected in the optimism of target price forecasts, rather than the stock followed, since female analysts in the U.S. follow, on average, more risky stocks than their male counterparts. Furthermore, another implication of these findings is that there was no gender difference in the target price forecast accuracy in the European and the U.S. limited samples, suggesting that gender differences in optimism, if any, do not significantly affect the target price performance.

This chapter is organised as follows: Section 6.2 discusses the motivation of the research question; Section 6.3 explains the research design; Section 6.4 describes the sample selection and descriptive statistics; Section 6.5 examines whether there is gender effect on target price optimism across Europe and the U.S; Section 6.6 provides an additional analysis and the conclusion is presented in section 6.7.

6.2 Literature Review

Compared to men, women are typically more risk-averse (Olsen and Cox, 2001, Croson and Gneezy, 2009, Sapienza et al., 2009, Huang and Hung, 2013, Francis et al., 2014, Francis et al., 2015) and less competitive (Barber and Odean, 2001, Gneezy et al., 2003, Niederle and Vesterlund, 2007). However, other studies argue that gender-based differences in risk attitude in high profile professions are not consistent with the population characteristics (Adams and Funk, 2012, Matsa and Miller, 2013, Adams and Ragunathan, 2015, Sila et al., 2016). Furthermore, the studies of Kumar (2010), Adams and Funk (2012), and Berger et al. (2014) found that women are less risk-averse than men. Thus, while some studies suggest a link between gender and risk-taking behaviour, other studies suggest that such a link does not persist in high profile professions.

Within the U.S. households, Barber and Odean (2001) report that, compared to women, men are 45% more likely to be trading equity investments, but when women traded, they earned significantly higher stock returns compared to men. Interpreting these findings, the authors concluded that men show signs of overconfidence when trading equity investments, ultimately leading to their lower performance compared to their female counterparts. Alternatively, women may be simply more risk-averse. For example, Olsen and Cox (2001), in their survey of professional investors found that females tend to put more emphasis on downside risk, compared to men. Moreover, Niederle and Vesterlund (2007), in their laboratory experiments showed that men tend to embrace competition whilst women tend to shy away from it. Similarly, Croson and Gneezy (2009) reviewed experimental evidence on gender differences in preferences, finding that women are more risk-averse than men, and that the former is more averse to competition than the latter. Although Niederle and Vesterlund (2007) found different preferences for competition among men and women, they did not document any gender differences in performance. This differs with the finding of Gneezy et al. (2003) who found in their laboratory experiment that women are less competent than men when competition increases.

Within the sell-side analyst profession in the U.S., Green et al. (2009) documented that females exhibit significantly less optimism in their earnings forecasts than their male counterparts. Similarly, Li et al. (2013) showed that female sell-side analysts exhibit lower risk in their stock recommendations compared to males by issuing less sell recommendations. In a more recent study, Huang and Kisgen (2013) reported that female executives make different financial and investment decisions than their male counterparts. In particular, consistent with studies associating females with risk aversion, they show that firms with female executives make fewer acquisitions and issue less debt than men. In line with this conclusion, Francis et al. (2014) found that female CFOs are associated with less tax aggressiveness than males, concluding that gender is a strong determinant of tax aggressiveness. In the same vein, Francis et al. (2015) found that the level of accounting conservatism significantly increases when a female CFO replaces a male CFO, supporting the notion that females are associated with risk aversion.

While the above-mentioned studies document a gender effect on risk-taking behaviour, with women being more risk-averse than men, other studies do not report a gender effect on risk-taking behaviour. For instance, Atkinson et al. (2003) found no significant gender difference in investment behaviour and performance of fund managers, suggesting that differences in investment behaviour between men and women are not necessarily gender-based; they might be attributed to finance knowledge or wealth constraints. Likewise, Mohan and Chen (2004) did not find any gender differences in the risk-taking behaviour of CEOs leading an initial public offering between 1999 and 2001. Furthermore, Ge et al. (2011) reported that gender has a limited effect on the accounting choices of CFOs, contrasting the findings of Francis et al. (2015). Similarly, regarding the effectiveness of the Norwegian gender quota on corporate decision making, Matsa and Miller (2013) suggest that the implementation of the gender quota on the boards did not have any effect on most corporate decisions, implying that that there are no gender differences in risk attitude, hence corporate decisions.

A more recent study by Sila et al. (2016) offered further insights into our understanding of the mixed results documented by prior studies regarding women's risk aversion. They examined the effect of boardroom gender diversity on a firm's risk and found no evidence that the participation of women in the boardroom has any impact on the equity risk. Sila et al. (2016) specifically addressed endogeneity concerns, which are likely to bias the findings regarding the association of gender and firm risk, explaining that two sources of endogeneity can possibly bias their findings. The first relates to omitted unobservable firm characteristics, which might affect the appointment of directors and the firm risk. Second, female directors may self-select into lower risk firms given their risk aversion, thus in this case, reverse causality can better explain the negative association between female directors and firm risk (Sila et al., 2016).

Other studies suggest that the documented deviations from the general population characteristics are attributed to the self-selection theory. In their sample of MBA students from Chicago University, Sapienza et al. (2009) reported that while 57% of male students choose a risky finance career, such as investment banking, only 36% of their sample women would do the same. The authors suggested that this difference might be attributed to biological reasons, for instance, high testosterone and low levels of risk aversion can make a risky finance career more appealing. Consequently, Sapienza et al. (2009) concluded that women who choose to follow risky careers have lower levels of risk aversion and higher testosterone than other women, suggesting that women entering highly male dominated professions within the finance industry have different personality traits than those characteristics of the general female population. Extending the results of Sapienza et al. (2009), Adams and Ragunathan (2015) showed that after controlling for the choice of a finance career, women do not have higher levels of risk aversion than men.

Within the sell-side analyst profession, Kumar (2010) documented that female sell-side analysts in the U.S. issue more bold earnings forecasts than their male counterparts, contrasting the findings of Green et al. (2009). Therefore, Kumar (2010) concluded that this is attributed to the self-selection theory, whereby females who enter the profession have similar characteristics to their male counterparts. Within the European context, Adams and Funk (2012) surveyed directors of all public and private firms in Sweden in 2005, revealing that unlike the female population characteristics, the women in their study were less concerned with security and were more risk-taking, compared to males. They concluded that the participation of women in the boardroom does not necessarily lead to more risk-averse decision making. Likewise, Berger et al. (2014) documented higher risk in German banks when the executive comprised more women. In particular, they found that in the three years following higher participation of women on the boards, the portfolio risk increases, however, they suggested that this might be explained by the lower working experience that females had compared to men.

Overall, the results of the extant studies on gender differences in risk attitude in high profile professions are mixed across both the U.S. and Europe. Within the sell-side analyst profession, the number of studies testing for gender differences is limited, mainly because of gender data restrictions, and their results are inconclusive (Green et al., 2009, Kumar, 2010, Li et al., 2013). Furthermore, the extant studies regarding the sell-side analyst profession are limited to the U.S. market, thus their findings do not necessarily generalise to other markets. For instance, Europe and the U.S. have different institutional environments which might affect the characteristics of female sell-side analysts. In addition, the European market is large enough to bear comparison with the findings in the U.S., therefore a study conducted across both the U.S. and Europe will allow a comparison of the gender effect in optimism, if any, across the two markets.

Therefore, motivated by the mixed results on analyst optimism in the U.S., as well as the lack of studies in Europe, this study tested whether gender differences in risk attitude within the sell-side analyst profession are prevalent across both the U.S. and the European market. Given the mixed results of the prior literature, there is no prior of the gender effect on risk attitude within the sell –side analyst profession, thus the following research question was addressed for both the U.S. and European market:

Research Question: Do male sell-side analysts issue more optimistic target prices than females?

6.3 Research Design

Target price forecasts were used to address the research question as they are more likely to convey optimism compared to other analyst measures. In their study for instance, Bradshaw et al. (2006) found that target prices exhibit the highest level of optimism among earnings forecasts and stock recommendations. More recent studies, interested in examining the determinants of analyst optimism or bias, have also used target prices, since they are more susceptible to optimism than other analyst measures (Bilinski et al., 2019, Bradshaw et al., 2019). Consequently, it is anticipated that gender differences in optimism, if any, will have a greater effect on target prices than earnings forecasts and stock recommendations. Following previous literature, this study focused on target prices with a 12-month forecast horizon (e.g. Bradshaw et al., 2013).

6.3.1 Dependent Variables

A well-documented target price optimism measure in the literature (e.g. Bradshaw et al. 2013; Bradshaw et al., 2019), is the target price to price ratio, which captures the distance between an analyst's target price forecast (TP_t) and the current stock price (P_t). More specifically, TP_t/P_t ratio is defined as an analyst's target price forecast divided by the stock price at the target price issue date, minus one, with positive and higher values of TP_t/P_t indicating more optimism[39]. Also, to adjust for potential risks associated with each stock, as in Bradshaw et al. (2019), the TP_t/P_t_Rank was used, which is defined as the percentile rank of TP_t/P_t within its two-digit SIG sector in each year, coded between 0 and 99, with higher values of TP_t/P_t_Rank indicating more optimism in an analyst's target price forecast. The optimism measures TP_t/P_t and TP_t/P_t_Rank capture the degree of optimism documented in target price forecasts at the date of issue.

If male sell-side analysts are more optimistic than their female counterparts, higher scores are expected than the latter in TP_t/P_t and TP_t/P_t_Rank optimism measures. Alternatively, if gender differences in optimism are not prevalent, then no significant differences between male and female sell-side analyst's target price optimism measures are expected.

6.3.2 Explanatory Variables and Model Specification

To explain the variation in target price optimism, several control variables were included. More specifically, the control variables were divided into three categories: (1) analyst and broker characteristics, (2) firm characteristics, (3) and other controls.

[39] The definition of TP_t/P_t is slightly different than that used in chapter 5, although both are valid measures. Chapter 6 follows Bradshaw's et al. (2019) definition of TP_t/P_t in order to allow for comparison with their study which is conducted in an international context.

6.3.2.1 Analyst and Broker Characteristics

The main explanatory variable in the study was analyst gender (GENDER), therefore an indicator variable (0, 1) was included, equal to one if an analyst is female and zero otherwise. This variable is expected to capture any gender differences in analyst target price optimism. Furthermore, in line with previous literature (e.g. Clement, 1999, Bilinski et al., 2012, Bradshaw et al., 2013, Bradshaw et al., 2019) additional analyst characteristics were included, which are expected to affect analyst target price performance, such as an analyst's general experience, firm experience, number of countries and firms followed[40]. An analyst's general experience (General_exp) for instance, is expected to proxy for the forecasting skills and knowledge that an analyst has (Clement, 1999). General_exp variable is defined as the natural logarithm of the number of years that an analyst has submitted reports to the I/B/E/S, measured at the target price issue date. An analyst's firm experience (Firm_exp) is a proxy of analyst expertise on a specific company and is defined as the natural logarithm of the number of years an analyst has followed the covering stock, measured at the target price issue date. It is expected that firm-specific experience will have a stronger positive association with analyst accuracy than general experience (Clement, 1999).

In addition, studies show a negative association between portfolio complexity and analyst accuracy (e.g. Clement, 1999), so analyst firm coverage (Firm_coverage) and country coverage (Country_coverage) were controlled to proxy for the complexity of an analyst's portfolio. Firm_coverage is defined as the natural logarithm of the number of

[40] Although chapter 5 showed that analyst affiliation significantly affects an analyst's optimism bias, chapter 6 does not control for analyst affiliation. That is because controlling for analyst affiliation is expected to have little or no effect in the sample used in chapter 6 as it employs all the firms covered by the analysts during the sample period (427,654 observations) without restricting the sample to firms that had an equity issue, as in chapter 5 (64,490 observations). In un-reported results, controlling for analyst affiliation for the U.S. analysis does not affect the results in Chapter 6.

firms an analyst has followed over the previous 12 months measured at the target price issue date. Similarly, Country_coverage is defined as the natural logarithm of the number of countries an analyst has followed over the previous 12 months measured at the target price issue date. Based on previous research, a negative relationship between analyst accuracy and portfolio complexity (e.g. Clement, 1999) is expected.

Furthermore, following Bilinski et al. (2012), to proxy for analyst accuracy, the earnings per share (EPS) forecast error (aEPS) was controlled for, which is defined as the absolute difference between the actual and the forecasted EPS, scaled by the stock price. In addition, following Bradshaw et al. (2019), an analyst's EPS optimism (EPS_optimism) was controlled to account for the level of optimism exhibited by the individual analysts. The EPS_optimism variable is defined as the difference between the forecasted and the absolute EPS, divided by the stock price and multiplied by 100. In both aEPS and EPS_optimism variables, the nearest annual earnings forecast by the same analyst for the same firm was used, either at the target price issue date or within 90 days prior to the target price issue date (Bilinski et al., 2012). It is anticipated that a more competent analyst would issue more accurate EPS, hence issue more accurate target prices[41]. Also, it is intuitive that analysts who are more optimistic in their EPS forecasts will issue more optimistic target prices. Similar to the findings of Bradshaw et al. (2019), the present study documented a very low correlation between the TP_t/P_t ratio and the EPS_optimism, suggesting a distinct optimism between target prices and EPS forecasts[42]. Lastly, to proxy for the resources available to the analysts, the brokerage size (Broker_size) was controlled for, which is defined as the natural logarithm of the number

[41] An EPS forecast is an important input into analyst's valuation models which are used to produce their target price forecasts (Bilinski et al., 2012).

[42] Bradshaw et al. (2019) found a correlation of 0.05 between TP/P ratio and EPS optimism. Similarly, in this study, there was a correlation of 0.04 between the two variables.

of analysts employed by an investment bank in the previous year. It is expected that broker size will have a positive impact on analyst performance because analysts who are working for larger investment banks have access to more resources.

6.3.2.2 Firm Characteristics

Firm characteristics can also affect the accuracy and optimism of analyst target prices. The size of the company (Firm_size) was used, to proxy for a stock's visibility and information environment, defined as the natural logarithm of the company's market value three days before the target price issue date (Bradshaw et al., 2013). It is anticipated that analysts will issue more accurate target prices for larger companies because there is a richer information environment around larger companies compared to smaller companies.

Furthermore, prior studies documented a positive association between past momentum and analyst recommendation profitability (e.g. Jegadeesh et al., 2004, Bradshaw et al., 2013). Therefore, following Bradshaw et al. (2013), a price momentum (PRCMOM) control variable was included, measured as the 90 days buy-and-hold raw return ending three days before the target price release date. Predictable price patterns, hence a continuation in price momentum, are expected to increase an analyst's target price accuracy, and vice versa (Bilinski et al., 2012). In addition, to control for a firm's total risk, the stock price volatility (STDPRC) was measured, which is defined as the standard deviation of stock prices over 90 days before the target price release date, scaled by the mean price level over this period[43]. Analysts are expected to issue less accurate target prices for more volatile and hence less predictable stocks.

Moreover, following Bradshaw et al. (2019), the market to book ratio (MB_ratio) was controlled for, which was measured at the target price issue date. Analysts are expected to issue less (more) optimistic target prices for stocks with high (low) market to book ratio, as this would signal an overvalued (undervalued) stock. The percentage change of a company's revenue (Revenue_%growth) between the current and the previous fiscal year (Bradshaw et al., 2019) was also controlled for. It is anticipated that analysts will be more optimistic for stocks with a higher percentage increase in their revenue, as this signifies potential growth.

6.3.2.3 Other Controls and Model Specification

Following prior studies, the market return in the country where the stock is trading (e.g. Bilinski et al., 2012, Bradshaw et al., 2019) was controlled for by including the MRKRET variable, which is the buy-and-hold value-weighted market return over the 12 months following the target price release date. A higher ex-post market return is expected to be positively associated with target price optimism. Also, to account for target price revisions, the target price change between the previous and the current target price for the same firm within a year, scaled by the previous forecast, $\Delta TP/TP$, was controlled for, as well as the cumulative market-adjusted abnormal return during the current and the previous target price issue (Return_rev) (Bradshaw et al., 2019).

[43] The STDPRC was scaled by the mean price level, to adjust for differences in price level across firms caused by the differences in currencies, creating a STDPRC variable comparable across countries (Bilinski et al., 2012).

Furthermore, to control for the higher forecasting uncertainty and the unexpected poor stock market performance during and after the financial crisis (Post_Fin_crisis), an indicator variable (0, 1) was used, equal to one if the period of the target price forecast is later than September 2007 (Bilinski et al., 2012). In addition, the time and industry fixed effects were controlled for, by using year dummies of the target price issue year (Year FE) and ten industry dummies (Industry FE) based on the two-digit sector SIG code from the I/B/E/S. Lastly, to control for the differences in institutional and regulatory characteristics and other unobserved factors across countries in the European sample, the country fixed effects (Country FE) was included. A summary of the variable definitions can be found in Table 16.

The empirical specification of the multivariate regressions for the target price optimism is:

(6.1) $$TP\_optimism = \beta_0 + \beta_1\text{GENDER} + \beta\text{CONTROLS} + \sum\text{IND} + \sum\text{TIME} + \sum\text{COUNTRY} + \varepsilon$$

Where, the $TP\_optimism$ is either the TP_t/P_t or TP_t/P_t_Rank target price optimism measures. Furthermore, to control for the cross-sectional dependence of observations, standard errors were clustered at the analyst and firm-level (Petersen, 2009). All continuous dependent and independent variables were winsorised at the 1 percent level.

Table 16: *Variable Definitions for Chapter 6*

Variable	Definition
Dependent Variables	
TP_t/P_t	Defined as an analyst's target price forecast divided by the stock price at the target price issue date, minus 1 *Sources: I/B/E/S Detail Target Price file, CRSP, Compustat – Capital IQ*
TP_t/P_t_Rank	Defined as the percentile rank of TP_t/P_t , coded from 0 to 99, within its two-digit SIG sector in each year *Sources: I/B/E/S Detail Target Price file, CRSP, Compustat – Capital IQ*
aTPE	Defined as the natural logarithm of the absolute value of $(P_{t+12} - TP_t)/P_{t-3}$, where P_{t+12} is the stock price 12 months following the target release date, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price 3 days before the target price release date *Sources: I/B/E/S Detail Target Price file, CRSP, Compustat – Capital IQ*
aTPE_rev	Defined as the natural logarithm of the absolute value of $(P_{rev} - TP_t)/P_{t-3}$, where P_{rev} is the stock price at the date of the target price revision, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price 3 days before the target price release date *Sources: I/B/E/S Detail Target Price file, CRSP, Compustat – Capital IQ*
Analyst and Broker Characteristics	
GENDER	An indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise *Sources: I/B/E/S Detail Target Price file, S&P Global Market Intelligence*
General_exp	Defined as the natural logarithm of the number of years an analyst has submitted reports to the I/B/E/S, measured at the target price issue date *Sources: I/B/E/S Detail EPS file*
Firm_exp	Defined as the natural logarithm of the number of years that an analyst has followed the covering stock, measured at the target price issue date *Sources: I/B/E/S Detail EPS file*
Firm_coverage	Defined as the natural logarithm of the number of firms an analyst has followed over the previous 12 months, measured at the target price issue date *Sources: I/B/E/S Detail EPS file*
Country_coverage	Defined as the natural logarithm of the number of countries an analyst has followed over the previous 12 months, measured at the target price issue date *Sources: I/B/E/S Detail EPS file*

Table 16 *(continued)*

Variable	**Definition**
aEPS	Defined as the absolute difference between the actual and the forecasted EPS, scaled by the stock price. I use the nearest annual earnings forecast by the same analyst for the same firm at the target price issue date or within 90 days before the target price issue date *Sources: I/B/E/S Detail EPS file, CRSP, Compustat – Capital IQ*
EPS_optimism	Defined as the difference between the forecasted and the absolute EPS, divided by the stock price and multiplied by 100, using the nearest annual earnings forecast by the same analyst for the same firm at the target price issue date or within 90 days before the target price issue date *Sources: I/B/E/S Detail EPS file, CRSP, Compustat – Capital IQ*
Broker_size	Defined as the natural logarithm of the number of analysts employed by an investment bank over the previous year *Source: I/B/E/S Detail Target Price file*
Firm Characteristics	
Firm_size	Defined as the natural logarithm of the company's market value 3 days before the target price issue date *Sources: CRSP, Compustat – Capital IQ*
PRCMOM	Defined as the 90 days buy-and-hold raw return ending 3 days before the target price release date *Sources: CRSP, Compustat – Capital IQ*
STDPRC	Defined as the standard deviation of stock prices over 90 days before the target price release date, scaled by the mean price level over this period *Sources: CRSP, Compustat – Capital IQ*
MB_ratio	Defined as the market to book ratio measured at the target price issue date *Sources: CRSP, Compustat – Capital IQ*
Revenue_%growth	Defined as the percentage change of revenue over the previous fiscal year *Source: Compustat – Capital IQ*
Other Controls	
MRKRET	Defined as the buy-and-hold value-weighted market return over the 12 months following the target price release date. *Sources: CRSP, World Indices by WRDS*
$\Delta TP/TP$	Defined as the target price change between the previous and the current target price issue, scaled by the previous forecast *Source: I/B/E/S Detail Target Price file*
Return_rev,	Defined as the cumulative market-adjusted abnormal return during the current and the previous target price issue *Sources: CRSP, Compustat – Capital IQ, World Indices by WRDS*
Post_Fin_crisis	An indicator variable (1,0), equal to 1 if the period of the target price forecast is later than September 2007
Year FE	A set of annual dummies for the target price issue year

Table 16 *(continued)*

Variable	**Definition**
Industry FE	Ten industry dummies based on the sector code from I/B/E/S SIG code
Country FE	A set of country dummies for the target price issue date

6.4 Data and Sample Selection

Target price data was collected for firms domiciled in 14 European countries[44] and in the U.S. from the I/B/E/S Target Price International and U.S. Detail files from 1st January 2003 to 31st December 2014[45]. For analyst gender, supplementary information was used from the S&P Global Market Intelligence database. For analyst characteristics the I/B/E/S EPS Detail files were used, starting from January 1982 to produce more reliable measures (Clement, 1999). Firm characteristics were constructed using daily stock prices and shares outstanding, from Compustat - Capital IQ for EU and CRSP for the U.S. Also, the value-weighted market return was obtained from the CRSP for the U.S. and from the World Indices by WRDS for Europe. In addition, under the Fundamentals Annual in Compustat – Capital IQ, the revenue variable for the sample companies was obtained. Furthermore, to convert the market value into U.S. dollars (USD), when necessary, the Daily Exchange Rate file from the I/B/E/S on the issue date was used (Bilinski et al., 2012).

The first criterion for the sample selection process was analyst gender. Therefore, the initial sample exported from the I/B/E/S Target Price International and U.S. Detail files was limited to the matched analysts issuing target prices identified in sections 4.1.1 and

[44] The thesis refers to these countries as Europe (EU); Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom.
[45] The I/B/E/S Target Price International Detail file is scarcely populated prior to 2002. Also, the sample ends in 2014 because analyst gender was not identified after that year.

4.1.2 for the U.S. and Europe respectively. After limiting the initial sample extracted for the U.S. from the I/B/E/S Target Price Detail file to the matched analysts issuing target prices, the sample consisted of 8,531 unique analysts with 980,172 observations (Table 17). Similarly, for Europe, the unique matched analysts issuing target prices was 6,759 with 634,470 observations (Table 17).

Next, the sample was reduced by the observations that were not matched with Compustat - Capital IQ for EU, and CRSP for the U.S. because the daily stock prices were required to construct the dependent and some of the control variables. Then, any observations where the stock traded at a different currency than the company's default currency[46] were removed (Bilinski et al., 2012). Furthermore, following Bilinski et al. (2012), the target price forecasts accompanied by one-year-ahead earnings per share (EPS) forecasts were retained. The accompanying EPS should be issued within the past 90 days of the target price issue to eliminate stale EPS forecasts. In addition, the target price issue date was required to be before the EPS review date as this implies that the latest EPS forecast is considered by the analyst to be still outstanding (Bilinski et al., 2012). In line with Clement (1999), those EPS forecasts which were issued within 30 days and 330 days prior to the fiscal year-end were retained to eliminate observations from analysts that are less likely to follow the stock closely.

Moreover, following Bradshaw et al. (2013), any observations with TP/P ratio greater than four, as well as stocks followed by less than three analysts were removed. Lastly, the observations with missing dependent or control variables were removed. After applying the sample selection criteria, the final sample consisted of 199,345 observations with

[46]I/B/E/S Detail history user guide states that all target prices are reported in the company's default reporting currency. If an analyst submits a target price in other currency, the I/B/E/S converts the analyst's estimate to the company's default currency using the exchange rate file on the activation date.

4,807 unique analysts from the EU, and 427,654 observations with 6,222 unique analysts from the U.S. Table 17 provides a summary of the sample selection process.

Table 17: *Sample Selection Process*

	Europe		United States	
Sample Period: 1st January 2003 to 31st December 2014	**N**	**Unique Analysts**	**N**	**Unique Analysts**
I/B/E/S sample restricted to 14 EU countries / U.S.	783,943	11,085	1,041,519	9,881
Drop analysts without gender identification	149,473	4,326	61,347	1,350
Matched Analysts issuing target prices from sections 4.1.1 and 4.1.2	**634,470**	**6,759**	**980,172**	**8,531**
Drop observations not matched with Compustat/CRSP	134,572	282	63,286	360
Drop observations with different currency	51,685	288	0	0
Drop observations without an EPS issued within the past 90 days	91,251	550	197,243	396
Drop observations if TP issue date not prior to EPS review date	29,753	29	38,406	21
Drop observations if the EPS is not issued within 30-330 days	69,888	138	107,753	153
Drop observations if TPtoP > 4	731	5	5,030	6
Drop observations if stocks are followed by less than 3 analysts	414	4	388	3
Drop observations with missing control variables	56,831	656	140,412	1,367
Final sample	199,345	4,807	427,654	6,222

6.4.1 Summary Statistics of Gender Distribution

Panel A of Table 18 shows the gender distribution across Europe and the U.S. over the sample period 1st January 2003 to 31st December 2014, with unique female analysts representing 15% and 13% of the sample analysts in Europe and the U.S., respectively. This low female representation across Europe and the U.S. is not surprising in the male dominated sell-side analyst profession (Kumar, 2010).

Panel B of Table 18 presents unique female analysts by country. Across Europe, Norway scores the lowest percentage of female representation at 8%, whereas Ireland and Italy have the highest female representation at 21%, followed by France at 17%, with the remaining sample European countries having a female representation between 12% and 15%. It should be noted that the European countries in the sample do not represent the country of domicile of the analysts, but rather the country in which the stock is headquartered. Therefore, when referring to female representation, this is the number of unique females covering stocks that are operating in each of the sample European countries.

Furthermore, Panel C of Table 18 presents the unique female representation by year across Europe and the U.S. In Europe, female representation ranged from 13% to 15% over the sample period, while in the U.S. ranged from 9% to 11%. Therefore, Europe had a higher female representation than the U.S. over the years. Even though the number of unique female analysts issuing target prices in Europe has increased from 66 in 2003 to 245 in 2014, representing an increase of 371%, their percentage representation ranged only from 13% to 15%. Therefore, overall, the female analyst representation did not change significantly over the years across both the U.S. and Europe, with the female analyst representation being in line with their underrepresentation within the sell-side analyst profession.

Table 18: *Unique Analyst Gender Distribution*

Panel A: Gender distribution		
	N	%
Europe		
Males	4,068	85
Females	739	15
Total	4,807	100
United States		
Males	5,423	87
Females	799	13
Total	6,222	100

Table 18 *(continued)*

Panel B: Gender distribution by country

	Fem_N	Fem_%	Male_N	Male_ %
Austria	56	12	407	88
Denmark	62	15	354	85
Finland	69	12	525	88
France	274	17	1,377	83
Germany	227	14	1,443	86
Ireland	30	21	112	79
Italy	159	21	612	79
Netherlands	83	12	616	88
Norway	54	8	586	92
Portugal	33	14	199	86
Spain	99	15	568	85
Sweden	90	12	648	88
Switzerland	117	15	670	85
United Kingdom	289	15	1,675	85
United States	799	13	5,423	87

Panel C: Gender distribution by year

	Europe				**United States**			
	Fem_N	Fem_%	Male_N	Male_%	Fem_N	Fem_%	Male_N	Male_%
2003	66	15	371	85	208	11	1,612	89
2004	113	13	731	87	215	10	1,838	90
2005	134	13	912	87	224	11	1,893	89
2006	175	13	1,195	87	252	11	1,964	89
2007	222	14	1,411	86	244	11	1,998	89
2008	259	13	1,742	87	261	11	2,012	89
2009	285	14	1,785	86	245	11	2,036	89
2010	319	14	1,949	86	242	10	2,185	90
2011	325	14	2,053	86	247	10	2,354	90
2012	293	13	1,904	87	241	10	2,249	90
2013	270	13	1,792	87	228	9	2,225	91
2014	245	13	1,651	87	237	10	2,213	90

Table 18 presents the distribution of the unique male and female sample analysts over the sample period 1st January 2003 to 31st December 2014. Panel A shows the number (N) and the percentage (%) of unique male and female analysts in Europe and in the United States. Panel B shows the gender distribution of unique analysts by country. Panel C shows the gender distribution of unique analysts by year. Fem_N is the number of unique female analysts; Male_N is the number of unique male analysts; Fem_% is the percentage of unique female analysts; Male_% is the percentage of unique male analysts.

6.4.2 Summary Statistics of Target Price Optimism

Table 19 reports the summary statistics of the two dependent variables, which measure an analyst's target price optimism. In Europe, the mean value of the optimism measures TP_t/P_t and TP_t/P_t_Rank was 0.16 and 49.44 respectively (Panel A of Table 19), while analysts in the U.S. market exhibited more optimism than the analysts covering European stocks, with a mean value of 0.20 for TP_t/P_t and 49.62 for TP_t/P_t_Rank (Panel B of Table 19). Similarly, Bradshaw et al. (2019) reported a documented mean value of 0.20 for TP_t/P_t and 50.96 for TP_t/P_t_Rank in the U.S. market.

Panel C of Table 19 presents the summary statistics of target price optimism measures by gender, with female analysts exhibiting lower optimism compared to male analysts, which is consistent in both target price optimism measures across both Europe and the U.S. Regarding the mean values of the two target price optimism measures, male analyst's average optimism was slightly higher than the mean value of the full sample, whereas female analyst's average optimism was below the sample average. For instance, in Europe, the average TP_t/P_t was 0.156 with male and female analysts having a mean value of 0.157 and 0.146 respectively. Therefore, on average, female sell-side analysts issue less optimistic target prices than their male counterparts across both Europe and the U.S., with statistical significance in the difference between their sample means, in line with theories associating females with risk aversion and males with overconfidence. However, descriptive statistics do not control for other variables expected to affect analyst optimism, which will be explored in the results section.

Table 19: *Summary Statistics of Target Price Optimism*

Panel A: Summary statistics for Europe					
	N	Mean	Std. Dev.	Min	Max
TP_t/P_t	199,345	0.156	0.247	-0.368	1.350
TP_t/P_t_Rank	199,345	49.448	28.479	1	99

Panel B: Summary statistics for the United States					
	N	Mean	Std. Dev.	Min	Max
TP_t/P_t	427,654	0.204	0.286	-0.770	1.692
TP_t/P_t_Rank	427,654	49.628	27.581	1	99

Panel C: Summary statistics by gender			
	N	TP_t/P_t	TP_t/P_t_Rank
Europe			
Males	172,784	0.157	49.548
Females	26,561	0.146	48.798
t-value		6.953***	3.378***
United States			
Males	389,021	0.206	49.785
Females	38,633	0.181	48.043
t-value		16.551***	11.842***

Table 19 presents the summary statistics of the target price optimism measures over the sample period 1st January 2003 to 31st December 2014. Panel A shows the summary statistics of the target price optimism measures in Europe. Panel B shows the summary statistics of the target price optimism measures in the U.S. Panel C shows the mean values of the target price optimism measures, by gender across Europe and the U.S. The t-value is obtained from independent t-tests in the mean values of the dependent variables between male and female analysts. N is the number of target price forecast observations. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively.

Variable Definitions

TP_t/P_t ratio defined as an analyst's target price forecast divided by the stock price at the target price issue date, minus 1.

TP_t/P_t_Rank defined as the percentile rank of TP_t/P_t within its two-digit SIG sector in each year, coded between 0 and 99.

6.4.3 Summary Statistics of Control Variables

Table 20 presents the descriptive statistics of the control variables. The log form of analyst and broker characteristics (i.e. General_exp, Firm_exp, Firm_coverage, Country_coverage) and firm characteristics (i.e. Firm_size) were not used for a more meaningful interpretation of the numbers, but the log form of the above-mentioned control variables were used for the regression analysis because these variables were expected to have a diminishing effect on target price performance. For instance, it was expected the effect on target price performance from an additional year of general experience to be larger for analysts with less general experience than analysts with greater general experience. Also, to allow for comparison between these results and other studies (e.g. Kumar, 2010, Bilinski et al, 2012), the averages were calculated based on the control variables measured at each target price issue. For instance, if an analyst issued five target prices within a year, the analyst average general experience was calculated based on analyst general experience measured at each target price forecast issue. Furthermore, the summary statistics of the control variables presented in Table 20 were also split by gender to provide insight regarding gender characteristics.

On average, in Europe, both male and female analysts had seven years of experience, with men having, on average, three months more experience than females, whereas in the U.S. analysts had, on average, six years of experience and men were, on average, four months more experienced than their female counterparts. This result is similar to Bradley et al. (2017), who found the U.S. analysts to have, on average, an experience of 6.7 years. Moreover, the statistics of analyst experience across Europe and the U.S. show that there is a slightly lower turnover in Europe for both male and female analysts compared to the U.S. analysts. In an earlier study, Bolliger (2004) suggested that there is higher turnover in the analyst profession across Europe than in the U.S., however, this difference is attributed to the different sample period used by the author (i.e. 1990 – 1999) compared to the present study (i.e. 2003-2014). In addition, male analysts had on average slightly more firm experience (Firm_exp) than females in both Europe and the U.S. samples, of three months and one month respectively. This reflects the pattern documented in the general experience, as it is more likely that analysts who stay longer in the sample will have more firm experience. Overall, the findings that females have on average less general and firm experience than their male counterparts are consistent with the findings of Kumar (2010).

Regarding portfolio complexity (i.e. Firm_coverage and Country_coverage), although the analysts covering European stocks follow on average fewer firms than the U.S. analysts, the former tend to have higher country diversification than the latter, in line with the international study of Bilinski et al. (2012). Furthermore, in line with Bilinski et al. (2012), the average broker size (Broker_size) was found higher in Europe that in the U.S. Moreover, consistent with Kumar's (2010) study, female analysts in the U.S. were, on average, employed by larger investment banks compared to their male counterparts. Also, analysts' EPS were less accurate and more optimistic for European stocks compared to U.S. firms.

In addition, for stock and market characteristics, female analysts in the U.S cover larger firms, measured by market value in USD millions (Firm_size) than their male counterparts, whereas in Europe, males covered, on average, slightly larger firms than female analysts. Furthermore, female analysts following European stocks tend to cover companies with less volatile stock prices (i.e. STDPRC) than their male counterparts, whereas in the U.S., females tend to follow, on average, stocks with more volatile target prices than their male counterparts. Also, male analysts following European stocks issue target prices for firms with 2% higher revenue growth compared to their female counterparts, while females in the U.S. follow, on average, stocks with higher revenue growth than males.

The descriptive statistics of the control variables, suggest that there are, on average, some differences between female analyst characteristics across Europe and the U.S., adding validity to the study for examining gender differences in optimism, across both Europe and the U.S. Specifically, in most of the control variables, there is statistical significance in the difference of the mean values between male and female sell-side analysts.

Table 20: *Summary Statistics of Control Variables*

Panel A: Summary Statistics of Control Variables in Europe			
	Males	Females	t-value
General_exp	6.992	6.742	8.567***
Firm_exp	3.423	3.152	12.076***
Firm_coverage	10.792	10.228	13.171***
Country_coverage	3.106	2.999	7.004***
aEPS	0.033	0.029	3.930***
EPS_optimism	1.232	0.987	2.068**
Broker_size	98.062	97.796	0.444
Firm_size	12168.450	11224.030	6.672***
PRCMOM	0.067	0.062	0.893
STDPRC	0.080	0.078	6.437***
MB_ratio	18.476	19.096	-3.119***
Revenue_%growth	8.007	6.310	4.948***
MARKRET	0.055	0.051	3.108***
$\Delta TP/TP$	0.015	0.013	1.896*
Return_rev	0.000	0.000	-0.121
Post_Fin_crisis	0.856	0.868	-5.202***
N	172,777	26,558	

Table 20 *(continued)*

Panel B: Summary Statistics of Control Variables in the United States

	Males	Females	t-value
General_exp	6.468	6.039	21.587***
Firm_exp	3.274	3.151	7.660***
Firm_coverage	18.574	15.658	65.842***
Country_coverage	1.294	1.243	11.252***
aEPS	0.019	0.018	1.084
EPS_optimism	0.443	0.405	0.543
Broker_size	62.229	71.376	-32.168***
Firm_size	9234.470	9592.192	-4.726***
PRCMOM	0.070	0.066	2.566**
STDPRC	0.089	0.091	-4.238***
MB_ratio	17.496	16.869	3.378***
Revenue_%growth	14.733	15.379	-2.771***
MARKRET	0.112	0.112	0.266
$\Delta TP/TP$	0.029	0.026	3.810***
Return_rev	-0.001	-0.001	-0.410
Post_Fin_crisis	0.741	0.719	9.601***
N	389,021	38,633	

Table 20 presents the mean values of the control variables, over the sample period 1st January 2003 to 31st December 2014. The mean values are calculated based on control variables measured at each target price issue. The t-value is obtained from independent t-tests in the mean values of the control variables between male and female analysts. N is the number of the target price forecast observations. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively.

Variable Definitions

General_exp defined as the number of years an analyst has submitted reports to the I/B/E/S measured at the target price issue date.

Firm_exp defined as the number of years an analyst has followed the covering stock measured at the target price issue date.

Firm_coverage defined as the number of firms an analyst has followed over the previous 12 months measured at the target price issue date.

Country_coverage defined as the number of countries an analyst has followed over the previous 12 months measured at the target price issue date.

aEPS defined as the absolute difference between the actual and the forecasted EPS, scaled by the stock price, using the nearest annual earnings forecast by the same analyst for the same firm at the target price issue date or within 90 days before the target price issue date.

EPS_optimism defined as the difference between the forecasted and the absolute EPS, divided by the stock price and multiplied by 100, using the nearest annual earnings forecast by the same analyst for the same firm at the target price issue date or within 90 days before the target price issue date.

Broker_size defined as the number of analysts employed by an investment bank in the previous year.

Firm_size defined as the company's market value 3 days before the target price issue date expressed in USD millions.

PRCMOM defined as the 90 days buy-and-hold raw return ending 3 days before the target price release date.

STDPRC defined as the standard deviation of stock prices over 90 days before the target price release date, scaled by the mean price level over this period.

MB_ratio defined as the market to book ratio measured at the target price issue date.

Revenue_%growth defined as the percentage change of revenue over the previous fiscal year.

MRKRET defined as the buy-and-hold value-weighted market return over the 12 months following the target price release date.

$\Delta TP/TP$ defined as the target price change between the previous and the current target price for the same firm within a year, scaled by the previous forecast.

Return_rev defined as the cumulative market-adjusted abnormal return during the current and the previous target price issue.

Post_Fin_crisis an indicator variable (1,0), equal to 1 if the period of the target price forecast is later than September 2007.

6.5 Results

Panel A of Table 21 presents the regression results for Europe, with the GENDER variable being significant in both target price optimism measures. In particular, female analysts had significantly less optimism in their target prices compared to males, at the 5% level of significance. Similarly, in the U.S., GENDER was significant in both optimism measures, at the 1% level of significance (Panel B of Table 21). Therefore, female analysts issue significantly less optimistic target prices than their male counterparts across both Europe and the U.S., which is in line with studies associating females with risk aversion and males with overconfidence (e.g. Barber and Odean, 2001).

Female analysts' risk aversion might affect the choice of the stocks followed, for instance, the documented gender difference in optimism might be driven by the fact that female analysts follow, on average, less risky stocks than their male counterparts. This seems to be the case for Europe, where females cover, on average, less risky stocks, measured by STDPRC, than their male counterparts (Panel A of Table 20). In the U.S. though, female analysts tend to follow, on average, more risky stocks than their male counterparts, measured by STDPRC.

To test whether the results in Table 21 are driven by the endogenous decision to follow certain companies and control for the possibility of reverse causality[47] (e.g. Sila et al., 2016), the sample was limited to stocks followed by both men and women in the same year, as shown in Table 22. In the U.S., the results stay the same, however, in Europe, GENDER is no longer significant in any of the target price optimism measures. This shows that in Europe, the lower optimism documented in female analysts' target prices

[47] Female sell-side analysts might self-select into lower risk stocks given their risk-aversion, therefore reverse causality can better explain the lower optimism exhibited by female sell-side analysts.

is driven by reverse causality whereby females follow, on average, less risky stocks than their male-counterparts. The choice of the stocks followed can still be a gender effect (i.e. female analysts choose to follow less risky stocks because they are risk-averse), however, differences in optimism are not robust in the choice of the stocks followed for Europe.

Other analyst characteristics that affect analyst optimism include analyst general experience, firm experience, the number of countries followed, analyst EPS accuracy and EPS optimism (Table 21). In line with Bradshaw et al. (2019), analyst general experience increased an analyst optimism across both the U.S. and Europe. However, unlike Bradshaw et al. (2019), firm experience in the present study was associated with less optimistic target prices in both the target price optimism measures. This difference in the sign of the coefficient is likely to be explained by the different sample countries used in Bradshaw et al.'s (2019) study. The present results are more consistent with the study of Bilinski et al. (2012), who documented that firm experience was associated with less error in target price forecasts.

Furthermore, the more countries an analyst follows, the more optimistic target prices they issue, in agreement with Bilinski et al. (2012), who reported a positive association between the number of countries followed and an analyst's target price error. In addition, consistent with Bilinski et al. (2012) and Bradshaw et al. (2019), in Europe, higher EPS error and optimism lead to more optimistic target price forecasts, whereas in the U.S., the effect of aEPS and EPS_optimism variables was not consistent across the two dependent variables, which may be explained by the higher correlation between the two variables in the U.S. compared to Europe. In unreported results, I re-ran the equation (6.1) for the U.S. excluding one of the two variables each time and obtained consistent results. Also, broker characteristics, such as the broker size, are associated with less optimistic target prices across both Europe and U.S., in line with prior literature (i.e. Bradshaw et al., 2019).

In line with the extant studies, Firm_size, PRCMOM and MB_ratio, had a negative association with the target price optimism (e.g. Bradshaw et al., 219). Furthermore, as expected, STDPRC and Revenue_%growth had a positive association with analyst optimism. Moreover, the ex-post MRKRET was positively associated with optimism measures, as it was anticipated that analysts would be more optimistic when they expect a higher market return. This finding was consistent across both Europe and the U.S. Also, in line with Bradshaw et al. (2019), the $\Delta TP/TP$ was positively associated and Return_rev negatively associated with target price optimism. Lastly, the Post_Fin_crisis variable was associated with more optimism, reflecting the higher forecasting uncertainty and the unexpected poor stock market performance in the post financial crisis period.

Overall, female analysts were significantly less optimistic in their target price forecasts across both Europe and the U.S. However, the gender effect does not hold in Europe when the choice of the stocks followed was controlled for, suggesting that the gender effect is not homogenous across the two markets (i.e. EU and U.S). Furthermore, to provide a more complete picture of the gender effect on target price optimism, additional analysis tested whether the documented optimism materialises ex-post, thus whether it affects target price accuracy.

Table 21: *Regression Results of Target Price Optimism*

Panel A: Regression results for Europe

VARIABLES	(1) TP_t/P_t	(2) TP_t/P_{t}_Rank
GENDER	**-0.010****	**-1.155*****
General_exp	0.006***	0.862***
Firm_exp	-0.009***	-1.138***
Firms_coverage	-0.001	-0.036
Countries_coverage	0.006***	0.280
aEPS	0.022**	-0.531
EPS_optimism	0.000	0.011
Broker_size	-0.009***	-0.812***
Firm_size	-0.016***	-1.421***
PRCMOM	-0.015***	-1.436***
STDPRC	0.238***	11.167***
MB_ratio	-0.000***	-0.024***
Revenue_%growth	0.000***	0.014***
MARKRET	0.126***	12.547***
$\Delta TP/TP$	0.099***	13.992***
Return_rev	-0.334***	-40.535***
Post_Fin_crisis	0.094***	13.039***
Constant	0.230***	63.101***
Observations	199,335	199,335
R^2	0.090	0.048
Industry FE	YES	YES
Year FE	YES	YES
Country FE	YES	YES

Panel B: Regression results for the United States

VARIABLES	(1) TP_t/P_t	(2) TP_t/P_{t}_Rank
GENDER	**-0.020*****	**-1.622*****
General_exp	0.014***	2.301***
Firm_exp	0.000	-0.794***
Firms_coverage	-0.017***	-2.526***
Countries_coverage	0.002	0.187
aEPS	0.032*	-0.801
EPS_optimism	-0.000***	-0.005
Broker_size	-0.021***	-2.735***
Firm_size	-0.012***	-0.852***
PRCMOM	-0.218***	-20.905***
STDPRC	0.208***	19.136***
MB_ratio	-0.000***	-0.036***
Revenue_%growth	0.000***	0.034***
MARKRET	0.149***	12.067***
$\Delta TP/TP$	0.139***	14.200***
Return_rev	-0.398***	-47.413***
Post_Fin_crisis	0.063***	5.500***
Constant	0.322***	69.606***
Observations	427,654	427,654
R^2	0.107	0.090
Industry FE	YES	YES
Year FE	YES	YES

Table 21 *(continued)*

Table 21 presents the regression results of equation (6.1). Panel A shows the regression results for Europe. Panel B shows the regression results for the United States. Year, industry, and country fixed effects were used in Panel A and year and industry fixed effects in Panel B. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 16.

Dependent Variables

TP_t/P_t ratio defined as an analyst's target price forecast divided by the stock price at the target price issue date, minus 1.

TP_t/P_t_Rank defined as the percentile rank of TP_t/P_t within its two-digit SIG sector in each year, coded between 0 and 99.

Main Independent Variables

GENDER is an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

Table 22: *Regression Results of Target Price Optimism – Limited Sample*

Panel A: Regression results for Europe		
	(1)	(2)
VARIABLES	TP_t/P_t	TP_t/P_t_Rank
GENDER	0.001	0.042
General_exp	0.003	0.484
Firm_exp	-0.004**	-0.544**
Firms_coverage	0.003	0.424
Countries_coverage	0.001	-0.210
aEPS	0.023	-0.623
EPS_optimism	-0.000	0.006
Broker_size	-0.005***	-0.411***
Firm_size	-0.008***	-0.595***
PRCMOM	-0.015***	-1.535***
STDPRC	0.263***	14.859***
MB_ratio	-0.000***	-0.026***
Revenue_%growth	0.000***	0.009***
MARKRET	0.119***	12.664***
$\Delta TP/TP$	0.086***	12.811***
Return_rev	-0.344***	-42.907***
Post_Fin_crisis	0.085***	12.261***
Constant	0.153***	53.649***
Observations	134,304	134,304
R^2	0.085	0.042
Industry FE	YES	YES
Year FE	YES	YES
Country FE	YES	YES

Table 22 *(continued)*

Panel B: Regression results for the United States		
VARIABLES	(1) TP_t/P_t	(2) TP_t/P_t_Rank
GENDER	-0.010***	-0.783**
General_exp	0.011***	1.629***
Firm_exp	0.001	-0.397**
Firms_coverage	-0.007**	-0.818***
Countries_coverage	0.007*	0.492
aEPS	0.043*	-3.511**
EPS_optimism	-0.000*	0.014
Broker_size	-0.020***	-2.616***
Firm_size	-0.006***	-0.335***
PRCMOM	-0.215***	-21.566***
STDPRC	0.214***	19.487***
MB_ratio	-0.000***	-0.034***
Revenue_%growth	0.000***	0.033***
MARKRET	0.151***	12.638***
$\Delta TP/TP$	0.140***	14.920***
Return_rev	-0.388***	-47.989***
Post_Fin_crisis	0.059***	5.143***
Constant	0.229***	59.926***
Observations	243,739	243,739
R^2	0.113	0.084
Industry FE	YES	YES
Year FE	YES	YES

Table 22 presents the regression results of equation (6.1) of the limited sample of stocks followed by both male and female analysts in a year. Panel A shows the regression results for Europe. Panel B shows the regression results for the United States. Year, industry, and country fixed effects were used in Panel A and year and industry fixed effects in Panel B. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 16.

Dependent Variables

TP_t/P_t ratio defined as an analyst's target price forecast divided by the stock price at the target price issue date, minus 1.

TP_t/P_t_Rank defined as the percentile rank of TP_t/P_t within its two-digit SIG sector in each year, coded between 0 and 99.

Main Independent Variable

GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

6.6 Additional Analysis

To test whether target price optimism affected analyst target price accuracy, the absolute value of an analyst's target price forecast error (aTPE) was measured. Following prior literature (e.g. Bilinksi et al, 2012, Bradshaw et al.,2013), aTPE was defined as the natural logarithm of the absolute value of $(P_{t+12} - TP_t)/P_{t-3}$, where P_{t+12} is the stock price 12 months following the target release date, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price three days before the target price release date[48]. Higher values of aTPE indicate less accuracy.

In addition, Bilinski et al. (2012) suggested that when a revision is made to a target price prior to the end of the 12-month forecast horizon, the preceding target price becomes stale. Therefore, to control for the effect of target price revisions, the revision adjusted target price forecast error, aTPE_rev, was included, which was defined as the natural logarithm of the absolute value of $(P_{rev} - TP_t)/P_{t-3}$, where P_{rev} is the stock price at the date of the target price revision, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price three days before the target price release date[49]. If an analyst does not revise their target price forecast during the 12-month forecast horizon, then aTPE = aTPE_rev. Higher values of aTPE_rev indicate more

[48] Please note that TPE measure used in chapter 5 is almost identical in construct with aTPE measure. However, the TPE in chapter 5 does not use the absolute value of the error as in chapter 6 (aTPE), since the aim is to capture the bias rather than the accuracy of the analysts (e.g. Merkley et al., 2017).

[49] For instance, on the 9th June 2014 analyst A issued a target price forecast of 105 USD for EXXON MOBIL GROUP with a 12 month forecast horizon, on that date, the stock price of EXXON MOBIL was 101.52 USD and the stock price at the end of the 12-month forecast horizon was 84.58 USD. The stock price three days before the target price release date (i.e. P_{t-3}) was 100.04 USD. The same analyst revised her forecast on the 16th July 2014 for EXXON MOBIL to 111 USD, on that date, the stock price of EXXON MOBIL was 103.77 USD and the stock price at the end of the 12-month forecast horizon was 82.91 USD. The stock price three days before the target price release date (i.e. P_{t-3}) was 101.74 USD. Based on the aTPE measure, the analyst error would be as follows: on the 9th June 2014, the analyst error would be log(|84.58-105|/100.04) and similarly on the 16th July 2014 the analyst error would be log(|82.91-111/101.74). When taking into account the target price revisions, the analyst error on the 9th June 2014 would be log(|103.77-105/100.04).

error, hence less accuracy. To test whether gender affects target price accuracy equation (6.2) was run.

The empirical specification of the multivariate regressions for the target price accuracy is:

(6.2) $$TP\_accuracy = \beta_0 + \beta_1 \text{GENDER} + \beta \text{CONTROLS} + \sum \text{IND} + \sum \text{TIME} + \sum \text{COUNTRY} + \varepsilon$$

Where, the $TP\_accuracy$ is measured as aTPE and aTPE_rev and the standard errors are clustered at the analyst and firm-level (Petersen, 2009).

Table 23 presents the regression results of equation (6.2) for target price accuracy. In Europe, the higher optimism of male analysts documented in Panel A of Table 21 materialises ex-post since there is no gender difference in the earnings forecast accuracy based on the aTPE in Panel A of Table 23. However, when considering the target price revisions (aTPE_rev), females outperformed their male counterparts at the 10% level of significance. In the limited sample (Panel A of Table 23) of stocks followed by both males and females, there was no significance in any of the two accuracy measures. This is not surprising, as there were no significant gender differences in the optimism measures in the European limited sample (Panel A of Table 22). Similarly, in the U.S., female analysts were significantly more accurate than males in their target price revisions (i.e. aTPE_rev) at the 5% level of significance (Panel B of Table 23). In the U.S. limited sample, even though there was a significant gender difference in the optimism measures (Panel B of

Table 22), this did not significantly affect the target price accuracy. An illustration of how greater optimism might not result in higher error is provided in Appendix.

Table 23: *Regression Results of Target Price Accuracy*

Panel A: Regression results for Europe				
	Full Sample		**Limited Sample**	
VARIABLES	aTPE	aTPE_rev	aTPE	aTPE_rev
GENDER	**-0.001**	**-0.004***	**-0.001**	**-0.001**
General_exp	0.001	0.001	0.001	0.000
Firm_exp	-0.003**	-0.003***	-0.002*	-0.002
Firm_coverage	-0.006***	-0.005***	-0.005***	-0.004***
Country_coverage	0.008***	0.009***	0.004**	0.006***
aEPS	0.086***	0.075***	0.150***	0.101***
EPS_optimism	-0.000	-0.000	-0.000**	-0.000
Broker_size	-0.002***	-0.004***	-0.001	-0.003***
Firm_size	-0.019***	-0.017***	-0.017***	-0.013***
PRCMOM	-0.006***	-0.007***	-0.007***	-0.007***
STDPRC	0.655***	0.499***	0.632***	0.493***
MB_ratio	0.000	0.000	0.000	0.000
Revenue_%growth	0.000**	0.000***	0.000	0.000**
MARKRET	-0.131***	-0.047***	-0.144***	-0.045***
$\Delta TP/TP$	-0.023***	-0.003	-0.026***	-0.004
Return_rev	-0.076***	-0.136***	-0.069***	-0.146***
Post_Fin_crisis	0.088***	0.084***	0.084***	0.083***
Constant	0.333***	0.304***	0.320***	0.279***
Observations	199,335	199,335	134,304	134,304
R^2	0.152	0.144	0.148	0.137
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES

Table 23 *(continued)*

Panel B: Regression results for the United States				
	Full Sample		**Limited Sample**	
VARIABLES	aTPE	aTPE_rev	aTPE	aTPE_rev
GENDER	**-0.000**	**-0.005****	**-0.003**	**-0.003**
General_exp	0.006***	0.005***	0.004**	0.003**
Firm_exp	-0.005***	0.001	-0.004***	0.001
Firm_coverage	-0.014***	-0.012***	-0.009***	-0.007***
Country_coverage	0.016***	0.014***	0.019***	0.016***
aEPS	0.134***	0.064***	0.324***	0.163***
EPS_optimism	-0.001**	-0.000	-0.001***	0.000
Broker_size	-0.004***	-0.008***	-0.005***	-0.009***
Firm_size	-0.020***	-0.016***	-0.020***	-0.015***
PRCMOM	-0.072***	-0.097***	-0.068***	-0.096***
STDPRC	0.423***	0.305***	0.519***	0.350***
MB_ratio	-0.000***	-0.000***	-0.000***	-0.000***
Revenue_%growth	0.000***	0.000***	0.000***	0.000***
MARKRET	-0.120***	-0.007***	-0.121***	-0.007***
$\Delta TP/TP$	0.003	0.019***	0.003	0.018***
Return_rev	-0.092***	-0.150***	-0.088***	-0.147***
Post_Fin_crisis	0.080***	0.072***	0.075***	0.066***
Constant	0.430***	0.340***	0.404***	0.305***
Observations	427,654	427,654	243,739	243,739
R^2	0.149	0.138	0.171	0.153
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 23 presents the regression results of equation (6.2), for both the full and the limited samples. The limited sample comprised stocks followed by both male and female analysts, in a year. Panel A shows the regression results for Europe. Panel B shows the regression results for the United States. Year, industry, and country fixed effects were used in Panel A and year and industry fixed effects in Panel B. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 16.

Dependent Variables

aTPE defined as the natural logarithm of the absolute value of $(P_{t+12} - TP_t)/P_{t-3}$, where P_{t+12} is the stock price 12 months following the target release date, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price three days before the target price release date.

aTPE_rev defined as the natural logarithm of the absolute value of $(P_{rev} - TP_t)/P_{t-3}$, where P_{rev} is the stock price at the date of the target price revision, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price 3 days before the target price release date.

Main Independent Variable

GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

6.7 Conclusion

A link between gender and risk-taking behaviour has been identified, which often affects corporate outcomes (e.g. Francis et al., 2015), however, the literature is far from conclusive with studies suggesting that gender differences in risk attitude to do not persist in high profile professions (e.g. Sapienza et al., 2009). Indeed, within the sell-side analyst profession, the findings regarding the gender effect on analyst optimism are mixed. Furthermore, due to data restrictions, studies on analyst gender are limited, only providing evidence from the U.S. market to date.

This chapter, motivated by the mixed results of the extant studies on sell-side analyst gender in the U.S., attempted to provide further insights regarding the gender effect on analyst optimism by using a more suitable measure than the prior studies to capture analyst optimism. More specifically, target price forecasts were used, which are more susceptible to optimism than other analyst measures (Bradshaw et al., 2006). To shed further light on the gender effect on analyst optimism, the research question was also tested in the European market. The U.S. and Europe are distinct markets and the different institutional environments might affect the characteristics of female sell-side analysts. In addition, the European market is large enough for comparison with the U.S. market.

The findings of the present study showed that male sell-side analysts are significantly more optimistic than their female counterparts across both Europe and the U.S., however, gender differences in optimism do not persist in Europe when the endogenous decision to follow certain stocks was controlled for. Therefore, female analysts in Europe initially appear less optimistic because of reverse causality as they do not follow the same stocks as their male counterparts, which are on average, riskier stocks. In the U.S., the results remain the same, suggesting that the documented differences in optimism are not driven by the choice of the stock followed. Furthermore, in the additional analysis, there was no gender difference in the accuracy of target prices across both the European and the U.S. limited samples. Thus, gender differences in optimism, if any, do not affect an analyst's target price performance.

The results of Chapter 6 have implications for gender studies in risk attitude because gender effect materialises differently in distinct markets (i.e. Europe and the U.S.). In Europe females initially appear less optimistic than males because of reverse causality, since after the sample was limited to stocks followed by both males and females, to control for endogeneity, there were not documented any significant gender differences in optimism. In the U.S., female analysts exhibited lower optimism and the results were robust when controlling for endogeneity. Furthermore, the findings are important to market participants. For instance, female analysts in the U.S. issue less optimistic target prices than males, therefore market participants might adopt a strategy where they discount male analysts target prices or add to the target prices issued by female analysts.

Overall, the results show that gender differences in risk attitude materialise differently in Europe than in the U.S., therefore, the findings of the extant studies on analyst gender in the U.S. do not necessarily generalise to the European market. In his U.S. study, Kumar (2010) suggests that due to discrimination in hiring decisions, female analysts are associated with superior forecast accuracy. The determinants of earnings forecast accuracy are important for market participants, hence a study extending the findings of Kumar (2010) to Europe would be useful to both market participants and regulators. For instance, if female analysts are positively associated with forecast accuracy, that will be useful information for the market participants in the European market. Furthermore, if a study on a European market, reinforces Kumar's (2010) findings of gender discrimination in the hiring decision of sell-side analyst profession, it will highlight the need for regulators to establish equal entry requirements for both male and female sell-side analysts. Therefore, the third empirical chapter of this thesis (i.e. Chapter 7) tests whether there is gender heterogeneity in analyst earnings forecast accuracy in Europe.

Chapter 7: Is There Gender Heterogeneity in Sell-side Analyst Forecasting Skills? Evidence from Europe

7.1 Introduction

Accurate earnings forecasts are important for the sell-side analyst profession since analysts who issue more accurate earnings forecasts are more likely to be promoted in the U.S. (e.g. Hong and Kubic, 2003) and less accurate analysts are more likely to exit the profession in Europe (e.g. Bolliger, 2004). The determinants of earnings forecast accuracy are also important for market participants, who systematically differentiate for analyst characteristics that are associated with greater forecast accuracy (e.g. Bradley et al., 2017). Furthermore, studies have extensively studied analyst characteristics that proxy for forecast accuracy (e.g. Clement, 1999). Therefore, given the importance of accurate earnings forecasts within the sell-side analyst profession, analysts with superior forecasting skills are likely to have a greater representation within the profession compared to those with poor forecasting skills.

As mentioned, the sell-side analyst profession is male dominated, which raises the question of whether this male dominance is explained by the better forecasting skills that male analysts might have compared to their female counterparts. For instance, Gneezy et al. (2003) argued that women are less competent than men in competitive environments. Surprisingly, Kumar (2010) found that female sell-side analysts issue more accurate earnings forecasts compared to males, which does not justify their low representation. Kumar (2010) explains this is because of gender discrimination in hiring decisions, whereby female analysts need to be more qualified than their male counterparts to enter the profession, however, the study of Kumar (2010) is limited to the U.S., therefore his findings do not necessarily generalise to other markets outside the U.S. Bolliger (2004) suggests that the distinct incentives between analysts covering the U.S. and European market to issue accurate earnings forecasts, hinder the generalisability of the results from the U.S. studies to the European market, thereby reinforcing the importance of investigating gender differences in earnings forecast accuracy outside the U.S.

This study, motivated by the low female representation within the sell-side analyst profession and the importance of the earnings forecast accuracy to market participants, tested whether there is gender heterogeneity in forecasting skills in Europe. The European market is a good setting to test for gender differences in earnings forecasts, since it is large enough to bear comparison with the gender effect documented by Kumar (2010) in the U.S. To the best of my knowledge, no study has so far tested whether there is gender heterogeneity in the forecasting skills of analysts following European stocks. Such a study will be important first to market participants who are interested in analyst characteristics that proxy for earnings forecast accuracy. Second, the results of the study will complement prior studies examining gender differences in earnings forecast accuracy, by providing evidence from the European market. Third, the study will inform policymakers in Europe whether the low female representation in the sell-side analyst profession is justified by their underperformance.

The findings show that there is no gender heterogeneity in the earnings forecast accuracy across Europe, therefore, low female representation in the sell-side analyst profession is not justified by lower forecasting skills. Moreover, the present findings do not support Kumar's (2010) conclusion of gender discrimination in hiring decisions, as females do not have superior forecasting skills than their male counterparts, hence they do not need to be more qualified than men to enter the profession. This difference in findings can be explained from the different markets examined in each study. Furthermore, there was no significant gender difference in the earnings forecast's performance in the country regressions in thirteen out of the fourteen European countries. Denmark was the only European sample country where female analysts were more accurate than males following stocks headquartered in Denmark. Despite the documented lack of gender difference in forecast accuracy across the overall sample, there were gender differences in the forecasting characteristics. For instance, male analysts were significantly more likely to issue bold forecasts, whereas female analysts were more likely to herd, implying that females have more reputational and career concerns.

The findings of this study have implications for policymakers and investment banks since low female analyst representation is not justified by their skills. In addition, the results have implications for gender studies suggesting that females are less competent than males within highly competitive professions. Furthermore, the study contributes to the sell-side analyst literature, by providing evidence of the gender effect on earnings forecast accuracy within Europe. Finally, the paper contributes to the stream of literature that tests for gender differences in performance within the finance industry.

This chapter is organised as follows: Section 7.2 discusses the motivation of the research question; Section 7.3 explains the research design; Section 7.4 describes the sample selection and descriptive statistics; Section 7.5 examines whether there is gender heterogeneity in analyst forecasting skills; Section 7.6 provides an additional analysis, with the conclusion provided in section 7.7.

7.2 Literature Review

Analyst characteristics, which are associated with higher forecasting skills, have attracted much attention from academics. The earliest study investigating the characteristics of U.S. analysts who produce more accurate forecasts than their peers is that of Mikhail et al. (1997), who found a positive association between earnings forecast accuracy and firm-specific experience. Two years later, Clement (1999) suggested that besides firm experience, analyst portfolio complexity is another determinant of forecast accuracy. Specifically, they found that portfolio complexity, measured as the number of firms and industries followed by the analyst, is negatively associated with earnings forecast accuracy. In addition, the authors documented that the size of the broker, which proxies for the resources available to the analyst, is associated with better forecast accuracy. Furthermore, Jacob et al. (1999) found a positive association between forecast frequency and forecast accuracy.

Within the European context, Bolliger (2004) has documented that, in line with the U.S., analyst firm-specific experience is positively associated with earnings forecast accuracy, whereas the age of the forecast and portfolio complexity is negatively associated with forecast accuracy. However, unlike in the U.S. market, Bolliger (2004) did not identify a relationship between forecast accuracy and analyst general experience and the size of the analyst employer. Bolliger (2004) suggests that these differences across the U.S. and the European markets might be attributed to the distinct incentives that analysts have in providing accurate earnings forecasts. For example, in the U.S., analysts are rewarded with better career outcomes when producing accurate earnings forecasts (Hong and Kubik, 2003) whereas analysts are not rewarded for their better forecasting skills in Europe (Bolliger, 2004).

Furthermore, Malloy (2005) suggests that geographically proximate analysts have an information advantage, hence perform better than other analysts. Similarly, Bae et al. (2008), using a sample of 32 countries, found that local analysts issue more accurate earnings forecasts that foreign analysts. O'Brien and Tan (2015) also suggest that in the U.S., the proximity of the analyst influences the choice of the stocks that they follow. In addition, cultural proximity, which is distinct from geographical proximity, has been suggested to influence analyst forecast accuracy (Du et al., 2017). Analyst industry expertise acquired from pre-analyst work experience has also been associated with superior forecasting skills (Bradley et al., 2017). Recently, Hirshleifer et al. (2019) showed that decision fatigue, measured by the number of forecasts issued by an analyst during the day, is negatively associated with forecast accuracy.

The determinants of earnings forecast accuracy are important for investors as they systematically differentiate between analyst characteristics that proxy for forecast accuracy (e.g. Stickel, 1995, Kumar, 2010, Bradley et al., 2017). As a result, earnings forecast accuracy is important for sell-side analyst profession, since lower-performing analysts are more likely to leave the profession than those who perform well (Bolliger, 2004). Therefore, it is intuitive to expect that within the sell-side analyst profession, competent analysts are more likely to survive in the profession than less competent analysts. The sell-side analyst profession is male dominated, thus differences in forecasting skills might be a reason behind this gender representation imbalance. For instance, in their laboratory experiments, Gneezy et al. (2003) found that females are less competent in competitive environments than males. Therefore, if female analysts issue less accurate earnings forecasts than their male counterparts, this might provide some explanation for their low representation within the profession.

However, Kumar (2010) found that being a female sell-side analyst is positively associated with earnings forecast accuracy in the U.S., which is puzzling given that female analysts are under-represented in the profession. Kumar (2010) explains that low female representation is likely to be the outcome of discrimination in the hiring decisions that female sell-side analysts are subject to. Gender discrimination in hiring decisions suggests that women need to be more qualified than men to be chosen to enter the profession, and if a man and a woman have equal qualifications, the man would always be chosen by the employers (Olson and Becker, 1983, Jones and Makepeace, 1996, Winter-Ebmer and Zweimüller, 1997, Kumar, 2010).

Nonetheless, Kumar's (2010) argument of gender discrimination in hiring decisions is not supported by the study of Green et al. (2009), who found that female sell-side analysts' earnings forecasts are less accurate than their male counterparts and by Fang and Huang (2017) who documented no gender difference in earnings forecast accuracy. The findings of the extant studies of the gender effect on sell-side analyst earnings forecast accuracy are mixed and limited to the U.S., hence they may not generalise to other markets with different institutional environments. For instance, Bolliger (2004) suggests that the distinct incentives between analysts covering the U.S. and European market to issue accurate earnings forecasts, hinders the generalisability of the determinants of earnings forecast accuracy documented in the U.S. to the European market. Therefore, further research needs to complement the findings of the extant studies and provide further insight of the gender effect from the European market.

Motivated by the underrepresentation of female sell-side analysts and the importance of earnings forecast accuracy to market participants, this study examined whether there is gender heterogeneity in sell-side analysts forecasting skills in Europe. The findings will be important to European market participants who are interested in analyst characteristics that are associated with superior forecasting skills. Also, the findings will allow for a comparison with Kumar's (2010) argument of gender discrimination in the hiring decision within the sell-side analyst profession in the U.S. market. There is no prior of the gender effect in earnings forecast accuracy for the European market, mainly because the findings of the extant studies are mixed and limited to the U.S., thus may not generalise in the European market. Therefore, this chapter tests the following research question for Europe:

Research Question: Is there gender heterogeneity in sell-side analyst forecasting skills?

7.3 Research Design

Earnings forecasts were used to test whether there is gender heterogeneity in sell-side analyst forecasting skills. It is anticipated that the accuracy of the earnings forecasts will reflect an analyst's forecasting skill, because the earnings forecasts outcome is realised often, which makes them less susceptible to biases than other analyst measures (McNichols and O'Brien, 1997). Furthermore, Bradshaw (2004), using valuation models concludes that in the U.S., investors can earn future excess returns by using earnings forecasts rather than stock recommendations, supporting the notion that stock recommendations are subject to greater bias as opposed to earnings forecasts. Within an international context, Barniv et al. (2010) reported consistent results with Bradshaw (2004) for countries with a high rate of individual investor participation. In addition, analysts have greater incentives to issue accurate earnings forecasts given that investors systematically differentiate for analyst characteristics that are associated with greater forecast accuracy (e.g. Stickel. 1995)

7.3.1 Dependent Variables

Following previous studies (e.g. Bradley et al., 2017), to measure analyst earnings forecast accuracy, the relative earnings forecast accuracy measure was used, constructed as the proportional mean absolute forecast error $(PMAFE_{ijt})$ developed by Clement (1999). This measure captures an analyst's forecast accuracy relative to all analysts covering a given firm, allowing to control for differences across companies, time, and industries (Ke and Yu, 2006, Bradley et al., 2017). The proportional mean absolute forecast error, is the difference between the absolute forecast error (AFE_{ijt}) of analyst *i* for firm *j* at time *t* and the mean absolute forecast error for firm *j* at time *t*. To reduce heteroscedasticity, the difference was further scaled by the mean absolute forecast error for firm *j* at time *t*, specifically, $PMAFE$ was calculated as:

(7.1) AFE_{ijt} = Absolute (ForecastEPS_{ijt} - ActualEPS_{ijt}),

(7.2) $PMAFE_{ijt}$ = (AFE_{ijt} - $MAFE_{jt}$)/ $MAFE_{jt}$

Where, AFE_{ijt} is the absolute forecast error of analyst *i* for firm *j* at time *t*, and $MAFE_{jt}$ is the mean absolute forecast error for all analysts who cover firm *j* within the same fiscal year, excluding analyst's i forecasts. The lower the value of $PMAFE$, the more accurate the analyst forecast. Following Bradley et al. (2017), to account for outliers, AFE_{ijt} and $PMAFE_{ijt}$ were winsorised at the 1 percent level.

7.3.2 Explanatory Variables and Model Specification

The main explanatory variable in this study is analyst gender (GENDER), which is an indicator variable (0, 1) equal to one if an analyst is female and zero otherwise. The variable is expected to capture any gender differences in analyst earnings forecast performance. Given the mixed results regarding gender differences in performance in the U.S. (e.g. Green et al., 2009, Kumar et al., 2010), and the differences between the U.S. and the EU markets, there is no prior for the effect of gender on earnings forecasts accuracy.

Furthermore, following Clement (1999) and others (e.g. Bradley et al., 2017), other analyst characteristics expected to affect an analyst's ability to issue accurate earnings forecasts were controlled for. Analyst firm and general experience are expected to have a positive impact on analyst's forecast accuracy (e.g. Bradley et al., 2017). Therefore, the General_exp variable was included, which is defined as the number of years that an analyst has submitted reports to the I/B/E/S, measured at the earnings forecast date. Also, to control for an analyst's firm experience, the Firm_exp control variable was included, which is defined as the number of years an analyst has followed the covering stock, measured at the earnings forecast date. It is expected that analyst general and firm experience are positively associated with an analyst's forecasting skills (e.g. Clement, 1999).

The timeliness of the earnings forecasts is also important, according to Clement (1999), who showed a positive association between the forecast error and the number of days between the earnings forecast and the earnings announcement date. Therefore, to control for the forecast timeliness, the Age_forec control variable was included, which measures the number of days between the forecast and the earnings announcement date. In addition, following Clement and Tse (2005), the number of forecasts an analyst issued for a company over the previous year (Forec_frequency) was controlled for. It is expected that analysts who more closely follow a company will issue more accurate forecasts.

Furthermore, previous studies suggest a negative association between portfolio complexity and analyst accuracy (e.g. Clement, 1999), so to account for analyst portfolio complexity, the Firm_coverage variable was included, defined as the number of firms an analyst has followed over the previous year, and Country_coverage variable, the number of countries an analyst has followed over the previous year. Also, following Bradley et al. (2017), the number of industries followed by an analyst, SIG2, was controlled for, defined as the number of two-digit SIGs that an analyst followed over the previous year. Moreover, to proxy for the resources available to the analysts, their employer size was controlled for, including the Top10 variable, which is an indicator variable (0, 1) equal to one if an analyst works at a top decile investment bank and zero otherwise (i.e. Bradley et al., 2017). The top decile was constructed based on the number of analysts working for the specific investment bank over the previous year. All the control variables for the analyst and broker characteristics (i.e. General_exp, Firm_exp, Forec_frequency, Age_forec, Firm_coverage, Country_coverage, SIG2, Top10) were firm-year mean adjusted[50] (e.g. Clement, 1999, Bradley et al., 2017).

[50] For instance, firm-year mean adjusted value for General_exp, is DGeneral_exp, which is defined as the number of years analyst *i* has submitted reports on the I/B/E/S minus the average tenure of analysts submitting earnings forecast for firm *j* at time *t*, excluding analyst *i* from the mean.

Although the firm-year mean adjusted dependent variable, $PMAFE_{ijt}$, was used which controls for differences across companies, time and industries, following Bradley et al. (2017), several firm characteristics were also included, controlling for the size of the firm (Firm_size), which is defined as the natural logarithm of the company's market value three days before the earnings forecast date. It is expected that the size of the company will proxy for the visibility and information environment of the company, hence analysts are expected to issue more accurate forecasts for larger companies. Furthermore, the book to market ratio (MB_ratio) was controlled for, which is measured as the market value scaled by the book value of a company, measured at the earnings forecast date. In addition, the price momentum (PRCMOM) was controlled for, measured as buy-and-hold raw return over the 90 days ending three days before the earnings forecast date. Lastly, to capture the level of competition among analysts, the Analysts_follow variable was included, which is defined as the number of analysts following a stock over the previous year. Higher competition among analysts is expected to result in more accurate earnings forecasts.

Furthermore, to control for the higher forecasting uncertainty and the unexpected poor stock market performance during the financial crisis, an indicator variable (0, 1), equal to one if the period of the target price forecast is later than September 2007 was used (Bilinski et al., 2012). In addition, the time fixed effects were controlled for using year dummies of the target price issue year (Year_FE) and industry fixed effects using ten industry dummies (Industry_FE) based on the two-digit sector SIG code from the I/B/E/S. Lastly, to control for the differences in institutional and regulatory characteristics and other unobserved factors across the European countries, the country fixed effects (Country_FE) were inlcuded. All continuous explanatory variables were winsorised at the 1 percent level. Table 24 provides a summary of the dependent and explanatory variables.

The empirical specification of the multivariate regression for earnings forecast accuracy is:

$$(7.3)\ PMAFE_{ijt} = \beta_0 + \beta_1(\text{GENDER}) + \beta_2(\text{DGeneral\_exp}) + \beta_3(\text{DFirm\_exp}) + \beta_4(\text{DAge\_forec}) + \beta_5(\text{DForec\_frequency}) + \beta_6(\text{DFirm\_coverage}) + \beta_7(\text{DCountry\_coverage}) + \beta_8(\text{DSIG2}) + \beta_9(\text{DTop10}) + \beta_{10}(\text{Firm\_size}) + \beta_{11}(\text{MB\_ratio}) + \beta_{12}(\text{PRCMOM}) + \beta_{13}(\text{Analysts\_follow}) + \beta_{13}(\text{Fin\_crisis}) + \sum\text{IND} + \sum\text{TIME} + \sum\text{COUNTRY}\ \varepsilon$$

Where, analyst and broker characteristics are firm year mean-adjusted (D stands for cross sectionally-centred). Furthermore, standard errors were clustered at analyst and firm-level (Petersen, 2009).

Table 24: *Variable Definitions for Chapter 7*

Variable	**Definition**
Dependent Variables	
PMAFE	Proportional mean absolute forecast error defined as the difference between the absolute forecast error (AFE) for analyst *i* on firm *j* and the mean absolute forecast error (MAFE) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t* *Source: I/B/E/S Detail EPS file*
Bold	An indicator variable (0, 1) equal to 1 if analyst's *i* forecast is above (below) the prevailing consensus for firm *j* at time *t*, and above (below) the most recent forecast issued by the analyst for the firm *j* *Source: I/B/E/S Detail EPS file*
Bold_positive	An indicator variable (0, 1) equal to 1 if analyst's *i* forecast is above the prevailing consensus for firm *j* at time *t*, and above the most recent forecast issued by the analyst for the firm *j* *Source: I/B/E/S Detail EPS file*
Bold_negative	An indicator variable (0, 1) equal to 1 if analyst's *i* forecast is below the prevailing consensus for firm *j* at time *t*, and below the most recent forecast issued by the analyst for the firm *j* *Source: I/B/E/S Detail EPS file*
Herding_postive	An indicator variable (0, 1) equal to 1 if analyst's *i* forecast is not below or above the prevailing consensus for firm *j* at time *t*, but it is revised above the analyst's most recent forecast for firm *j* *Source: I/B/E/S Detail EPS file*
Herding_negative	An indicator variable (0, 1) equal to 1 if analyst's *i* forecast is not below or above the prevailing consensus for firm *j*, but it is revised below the analyst's most recent forecast for firm *j* *Source: I/B/E/S Detail EPS file*
Analyst and Broker Characteristics	
GENDER	An indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise *Sources: I/B/E/S Detail EPS file, S&P Global Market Intelligence*
DGeneral_exp	Defined as total number of years that analyst *i* has submitted reports to the I/B/E/S, minus the average tenure of analysts issuing earnings forecasts for firm *j* at time *t* *Source: I/B/E/S Detail EPS file*
DFirm_exp	Defined as the number of years analyst *i* has followed firm *j* at time *t*, minus the average number of years I/B/E/S analysts have been issuing earnings forecasts for firm *j* at time *t* *Source: I/B/E/S Detail EPS file*

Table 24 *(continued)*

Variable	**Definition**
DForec_frequency	Defined as the number of forecasts that analyst *i* issued for company *j* over the previous year, minus the average number of forecasts issued by analysts following firm *j* over the previous year *Source: I/B/E/S Detail EPS file*
Ddays_elapsed	Defined as the number of days elapsed since the most recent forecast issued for company *j* by analyst *i*, minus the average number of days elapsed of the analysts following the company *j* at time *t* *Source: I/B/E/S Detail EPS file*
lag_PMAFE	The analyst's *i* promotional mean absolute forecast error for company *j* over the previous year *Source: I/B/E/S Detail EPS file*
DFirm_coverage	Defined as the number of firms that analyst *i* has followed over the previous year for firm *j*, minus the average number of firms followed by the analysts issuing earnings forecasts for firm *j* over the previous year *Source: I/B/E/S Detail EPS file*
DCountry_coverage	Defined as the number of countries that analyst *i* has followed over the previous year for firm *j*, minus the average number of countries followed by analysts issuing earnings for firm *j* over the previous year *Source: I/B/E/S Detail EPS file*
DSIG2	It is defined as the number of two-digit SIGs that analyst *i* follows over the previous year for firm *j*, minus the average number of industries followed by analysts issuing earnings forecasts for firm *j* over the previous year *Source: I/B/E/S Detail EPS file*
DTOP10	An indicator variable (0, 1) equal to 1 if analyst *i* works at a top decile investment bank for firm *j* at time *t*, minus the average value of top decile investment banks indicators for analysts following firm *j* at time *t*. The top decile is constructed based on the number of analysts working for the specific investment bank over the previous year *Source: I/B/E/S Detail EPS file*
Firm Characteristics	
Firm_size	Defined as the natural logarithm of the company's market value three days before the earnings forecast date *Source: Compustat – Capital IQ*
MB_ratio	Defined as the market to book ratio measured at the earnings forecast date *Source: Compustat – Capital IQ*
PRCMOM	Defined as the 90 days buy-and-hold raw return ending three days before the earnings forecast date *Source: Compustat – Capital IQ*

Table 24 *(continued)*

Variable	Definition
Analysts_follow	Defined as the number of analysts following a stock over the previous year *Source: I/B/E/S Detail EPS file*
Other Controls	
Fin_crisis	An indicator variable (1,0), equal to 1 if the period of the earnings forecast is later than September 2007
Year FE	A set of annual dummies for the earnings forecast year
Industry FE	Ten industry dummies based on the sector code from I/B/E/S SIG code
Country FE	A set of country dummies for the earnings forecast date

7.4 Data and Sample Selection

Target price data was collected for firms domiciled in 14 European (EU) countries[51] from the I/B/E/S Detail EPS file, from 1st January 2003 to 31st December 2014[52]. To identify analyst gender, supplementary information was collected from I/B/E/S Target Price and Stock Recommendation Detail files and S&P Global Market Intelligence database. Analyst and broker characteristics were constructed using I/B/E/S Detail EPS, starting from January 1982 to produce more reliable measures (Clement, 1999). Firm characteristics were constructed using daily stock prices and shares outstanding, from Compustat – Capital IQ. Further, to ensure comparability of the firm size across the countries, the market value was converted into U.S. dollars (USD), by using the Daily Exchange Rate file from the I/B/E/S on the earnings forecast date (Bilinski et al., 2012).

The first criterion of the sample selection process was the identification of the analyst gender. The I/B/E/S Detail files, among other information, provide a unique identifier for each analyst (i.e. amaskcd or id_analyst) as well as the surname and first initial of the

[51] The thesis refers to these countries as Europe (EU); Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom.
[52] Although data on EPS are available prior to 2003 on I/B/E/S Detail files, the sample period was limited from 2003 to 2014 because the analyst gender was not identified prior to 2003 or later than 2014.

analysts (i.e. analyst or alysnam). However, the I/B/E/S EPS Detail file does not provide the information regarding the analyst's first initial and surname as in the stock recommendation and target price detail files. Nevertheless, the unique analyst code is available in all the three files, therefore, the comprehensive list of analyst gender created in section 4.1.2 was used and merged across to the I/B/E/S EPS Detail file[53]. Consequently, the matched analysts issuing target price and stock recommendations from section 4.1.2 (Table 2) were merged with the EPS file using the analyst ID which is common across the files. From the initial sample of 7,962 matched analysts, 305 analysts do not appear on the EPS file, leaving 7,657 matched analysts in the EPS file (Panel A of Table 25).

Next, firms that were not matched with the Compustat-Capital IQ were removed during the sample selection process, as well as those firms which traded in a different currency in the Compustat-Capital IQ than the company's default currency in the I/B/E/S EPS Detail file (Panel B of Table 25). Also, following the earnings forecasts literature (e.g., Clement, 1999, Bradley et al., 2017), EPS forecasts issued within 30 days and 330 days before the fiscal year-end were retained to exclude forecasts from analysts who are less likely to follow the stock closely.

Furthermore, following Clement (1999) and others (e.g. Bradley et al., 2017), the latest EPS issued by each analyst for a certain firm during the fiscal year was kept. Moreover, stocks followed by less than three analysts were removed to be able to compare analysts providing forecasts for a particular firm, during a year (Clement and Tse, 2005). Moreover, observations with any missing dependent or control variables were

[53] For more details about the gender identification process in Europe, please refer to section 4.1.2.

excluded. The final sample had 156,013 EPS forecast observations from 6,721 unique analysts. Table 25 provides a summary of the sample selection process.

Table 25: *Sample Selection Process*

Panel A: Matched analysts appearing on I/B/E/S International EPS Detail file	
	Unique Analysts
Matched analysts issuing either target prices or stock recommendations from section 4.1.2	7,962
Matched analysts not appearing on I/B/E/S International EPS Detail file	305
Matched analysts appearing on I/B/E/S International EPS Detail file	7,657

Panel B: Sample selection of EPS for Europe		
Sample period: 1st January 2003 to 31st December 2014	**EPS forecasts**	**Unique Analysts**
I/B/E/S EPS sample restricted to matched analysts	853,351	7,657
Drop observation not matched with Compustat	178,796	245
Drop observations with different currency	57,529	253
Keep EPS forecasts issued within 30-330 days of the fiscal year-end	130,750	131
Keep the latest forecast issued by an analyst for a firm in the fiscal year-end	283,766	0
Drop observations of stocks followed by less than 3 analysts	85	6
Drop observations with missing control variables	46,412	301
Final sample	156,013	6,721

7.4.1 Summary Statistics of Sample Distribution

Panel A of Table 26 presents the gender distribution of the unique analysts in the final sample. The final sample comprised 6,721 unique analysts, of which, 1,109 were female, representing 17% of the sample. The sell-side analyst profession is male dominated, and the low female representation is consistent with other gender studies in the U.S. (e.g. Kumar, 2010).

Panel B of Table 26 shows the number of unique female and male analysts in each country and their representation within each country. It should be noted that unique analysts could appear in more than one country since the country represents the country where a firm is headquartered, not the location of the analyst. Therefore, analysts who have their portfolio firms headquartered in distinct countries will appear in more than one country. Regarding raw numbers, the number of unique females in each country was higher in the United Kingdom, France, and Germany. The same pattern applies to the number of unique male analysts. In percentage terms, female representation within each country was higher for Italy at 21%, which exceeds the sample average of 17%, with Norway having the lowest female representation at 9%.

Panel C of Table 26 presents the gender distribution across the years, as well as the percentage representation of female and male analysts in each year. Over the sample period, the number of female analysts ranged from 299 (2014) and 390 (2011), with female representation relatively constantly ranging from 13% to 15%. Furthermore, Table 27 presents the sample distribution of the 156,013 observations across countries, with 24% of the sample observations from the UK, accounting for most of the European sample. Ireland and Portugal have the lowest sample representation, at 1%.

Table 26: *Unique Analyst Gender Distribution*

Panel A: Gender distribution

	N	%
Males	5,612	83
Females	1,109	17
Total	6,721	100

Panel B: Gender distribution by country

	Fem_N	Fem_%	Male_N	Male_%
Austria	79	13	509	87
Denmark	93	16	504	84
Finland	109	13	754	87
France	430	17	2,108	83
Germany	350	15	2,052	85
Ireland	43	17	209	83
Italy	238	21	911	79
Netherlands	158	14	993	86
Norway	78	9	798	91
Portugal	50	15	276	85
Spain	162	16	838	84
Sweden	141	13	952	87
Switzerland	194	16	1,022	84
United Kingdom	458	16	2,355	84

Panel C: Gender distribution by year

	Fem_N	Fem_%	Male_N	Male_%
2003	389	15	2,132	85
2004	366	15	2,083	85
2005	351	14	2,114	86
2006	371	14	2,269	86
2007	382	14	2,39	86
2008	388	14	2,463	86
2009	383	14	2,312	86
2010	394	14	2,398	86
2011	390	14	2,456	86
2012	366	14	2,281	86
2013	322	13	2,113	87
2014	299	14	1,905	86

Table 26 presents the gender distribution of the unique analysts over the sample period 1st January 2003 to 31st December 2014. Panel A shows the number (N) and the percentage (%) of unique male and female analysts. Panel B shows the gender distribution of unique analysts by country. Panel C shows the gender distribution of unique analysts by year. Fem_N is the number of unique female analysts; Male_N is the number of unique male analysts; Fem_% is the percentage of unique female analysts; Male_% is the percentage of unique male analysts.

Table 27: *Sample Distribution*

	N	%
Austria	2,717	2
Denmark	2,913	2
Finland	8,242	5
France	24,165	15
Germany	27,122	17
Ireland	1,061	1
Italy	10,403	7
Netherlands	7,841	5
Norway	6,576	4
Portugal	1,450	1
Spain	8,459	5
Sweden	7,839	5
Switzerland	9,215	6
United Kingdom	38,010	24
Total	156,013	100

Table 27 presents the distribution of the final sample by country, over the sample period 1st January 2003 to 31st December 2014. N is the number of EPS forecast observations for stocks operating in each country; % denotes the percentage representation of each country based on the country EPS forecast observations, relative to the final sample.

7.4.2 Summary Statistics of Earnings per Share Accuracy

Table 28 presents the summary statistics of the earnings forecast accuracy variables (i.e. PMAFE and Forec_error). On average, analysts following European stocks have a PMAFE of 0.039 (Panel A of Table 28), which is higher than the mean PMAFE of -0.13 in the U.S. documented by Bradley et al. (2017). This might be explained by the different incentives that the analysts have at issuing accurate earnings forecasts across Europe and the U.S. For instance, Bolliger (2004) found that in Europe, accurate earnings forecasts are not rewarded by better career outcomes, whereas in the U.S., accurate earnings forecasts are more likely to experience favourable career outcomes (Hong and Kubik, 2003).

Furthermore, male analysts have, on average, more absolute forecast error (i.e. Forec_error) than females, with statistical significance in the difference of their means.

However, in the PMAFE measure, which controls for differences across companies, time, and industries, male analysts are on average more accurate than their female counterparts, although with no statistical significance in the t-value. This pattern applies for Finland, France, Germany, Netherlands, Sweden (Panel B of Table 28). In the remaining European countries, the mean gender forecast accuracy varies, with females being less accurate in both PMAFE and Forec_error measures (Panel B of Table 28) in Austria, Ireland, and the United Kingdom, whereas in Denmark, Italy, Norway, and Switzerland, females have on average less error in both PMAFE and Forec_error variables (Panel B of Table 28). Spain is the only sample country where females have on average more error in the Forec_error measure, but they are on average more accurate in the PMAFE measure than their male counterparts. Overall, gender differences across Europe in the mean values of forecast accuracy measures (i.e. PMAFE and Forec_error) are not homogenous.

Table 28: *Summary Statistics of Earnings Forecast Accuracy*

Panel A: Summary statistics by gender				
	N	Mean	Median	Std. Dev.
Full Sample:				
PMAFE	156,013	0.039	-0.150	0.922
Forec_error	156,013	0.022	0.007	0.047
Females:				
PMAFE	20,301	0.049	-0.150	0.937
Forec_error	20,301	0.020	0.006	0.045
Males:				
PMAFE	135,712	0.038	-0.150	0.920
Forec_error	135,712	0.022	0.007	0.048
t-value (PMAFE)		-1.582		
t-value (Forec_error)		6.289***		

Table 28 *(continued)*

Panel B: Summary statistics by Country

	Females			Males		
	N	PMAFE	Forec_error	N	PMAFE	Forec_error
Austria	325	0.084	0.034	2,392	0.050	0.028
Denmark	293	-0.013	0.021	2,620	0.060	0.022
Finland	1,051	0.117	0.021	7,191	0.030	0.022
France	4,399	0.030	0.019	19,766	0.024	0.021
Germany	2,650	0.057	0.026	24,472	0.031	0.028
Ireland	135	0.168	0.013	926	0.100	0.017
Italy	2,725	0.046	0.024	7,678	0.052	0.027
Netherlands	636	0.036	0.017	7,205	0.027	0.024
Norway	344	-0.036	0.027	6,232	0.059	0.039
Portugal	248	0.095	0.027	1,202	0.042	0.026
Spain	1,280	0.025	0.020	7,179	0.028	0.022
Sweden	625	0.089	0.015	7,214	0.056	0.019
Switzerland	1,053	0.011	0.016	8,162	0.043	0.021
United Kingdom	4,537	0.062	0.014	33,473	0.041	0.015

Table 28 presents the summary statistics of the earnings forecast accuracy measures over the sample period 1st January 2003 to 31st December 2014. Panel A shows the summary statistics of the accuracy measures of the sample and split by gender. Panel B shows the mean values of the earnings forecast accuracy measures by country. The t-value is obtained from independent t-tests in the mean values of the variables between male and female analysts. N is the number of analyst-firm observations. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively.

Variable Definitions
PMAFE proportional mean absolute forecast error defined as the difference between the absolute forecast error (AFE) for analyst *i* on firm *j* and the mean absolute forecast error (MAFE) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*.
Forec_error absolute forecast error defined as the absolute difference between analyst *i* earnings forecast minus the actual earnings scaled by the stock price for firm *j* at time *t*.

7.4.3 Summary Statistics of Control Variables

Table 29 shows the mean values of the control variables of the final sample and by gender, also providing the t-values of independent t-tests in the mean values of the control variables between male and female analysts. The raw number, not the firm-year mean adjusted values, were used for analyst characteristics, as it is difficult to interpret the differenced variables used in the regressions.

The sample analysts have, on average, 11 years of experience, almost double the mean general experience documented by Bradley et al. (2017) of 6.7 years for the U.S. This might be attributed to the sample selection process, where less experienced analysts (i.e. less than 5 years of experience) issue, on average, one earnings forecast for each firm, and in most cases that earnings forecast falls out of the 30-330 day range used in the sample selection process. As a result, the exclusion of those analysts increases the general experience sample mean[54].

On average, male analysts were more experienced than females, by one year, which was reflected in the firm experience, where males have, on average, 3 years of general experience, which is higher than the female analysts' mean firm experience of 2.7 years. The t-value suggests that there is a statistical difference between the mean values of the general and firm experience between the two groups.

Furthermore, the sample mean of the forecast age is 118 days, which is similar to the mean of 105 days documented by Bolliger (2004), in his European study. On average, female analysts' earnings forecasts are older by 2 days compared to male analysts, and this difference in their mean value is statistically significant. Regarding portfolio complexity, male analysts follow, on average, two more firms than their female counterparts, within a year. In addition, male analysts follow, on average, stocks headquartered in more countries, and more industries, than female analysts. However, female analysts follow, on average, larger firms than their male counterparts and the difference in the mean values of the above-mentioned control variables is statistically significant.

[54] In unreported results, the GEXP was calculated before applying the restriction of 30–330 day range, and analyst general experience was 7.18 years.

Also, differences in the mean values of PRCMOM and Analyst_follow variable between male and female analysts were not statistically different from zero. While the descriptive statistics provide some insights into the gender differences in earnings forecast accuracy and analyst characteristics, regression analysis will provide a clearer picture of the gender effect on forecast accuracy.

Table 29: *Summary Statistics of Control Variables*

	Final Sample	Females	Males	t-value
General_exp	11.143	10.155	11.290	21.379***
Firm_exp	2.976	2.739	3.011	11.174***
Age_forec	117.890	119.604	117.634	-3.329***
Forec_frequency	2.406	2.240	2.430	9.865***
Firm_coverage	11.410	10.173	11.595	29.216***
Country_coverage	2.842	2.680	2.866	11.235***
SIG2	2.461	2.344	2.479	12.453***
Top10	0.093	0.112	0.091	-9.784***
Firm_size	12,165.790	12,179.070	12,163.800	5.474***
MB_ratio	18.312	19.316	18.162	-5.638***
PRCMOM	0.065	0.070	0.065	-0.835
Analysts_follow	20.059	20.000	20.068	0.759
N	156,013	20,301	135,712	

Table 29 presents the mean values of the control variables of the final sample and by gender over the sample period 1st January 2003 to 31st December 2014. The t-value is obtained from independent t-tests in the mean values of the control variables between male and female analysts. N is the number of observations. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively.

Variable Definitions

General_exp defined as the number of years analyst *i* has submitted reports to the I/B/E/S, measured at the earnings forecast date.

Firm_exp defined as the number of years analyst *i* has followed firm *j* at the earnings forecast date.

Age_forec defined as the number of days between analyst *i* forecast for firm *j* and the earnings announcement date at time *t*.

Forec_frequency defined as the number of forecasts that analyst *i* issued for firm *j* over the previous year.

Firm_coverge defined as the number of firms analyst *i* has followed for firm *j* over the previous year.

Country_coverage defined as the number of countries analyst *i* has followed for firm *j* over the previous year.

SIG2 defined as the number of two-digit SIGs (sector classification) that analyst *i* follows for firm *j*, over the previous year.

TOP10 an indicator variable (0, 1) equal to 1 if analyst *i* works at a top decile investment bank, for firm *j* over the previous year. The top decile is constructed based on the number of analysts working for the investment bank over the previous year.

Firm_size defined as the company's market value three days before the target price issue date, expressed in USD millions.

MB_ratio defined as the market to book ratio measured at the earnings forecast date.

PRCMOM defined as the 90 days buy-and-hold raw return ending three days before the earnings forecast date.

Analysts_follow defined as the number of analysts following a stock over the previous year.

7.5 Results

Panel A of Table 30 presents the regression results of the gender effect on the earnings forecast accuracy (i.e. PMAFE). GENDER variable is not statistically significant, suggesting that overall, there is no gender heterogeneity in the forecasting skills of analysts covering European stocks. Other studies on sell-side analyst gender conducted in the U.S. documented different results, for instance, Green et al. (2009) found female analysts to issue less accurate earnings forecasts, whereas Kumar (2010) reported that female analysts issue more accurate earnings forecasts than their male counterparts. Also, the findings of the present study do not support Kumar's argument of gender discrimination in hiring decisions since no gender heterogeneity was found in analyst forecasting skills, adding more validity to the motivation behind this research given the different findings between the European and the U.S. markets. Although, the findings of the present study are more consistent with the study of Fang and Huang (2017), who documented no gender difference in earnings forecasts accuracy in their U.S. sample of sell-side analysts. Furthermore, in a broader context, these findings are in line with the laboratory study of Niederle and Vesterlund (2007) who reported that despite gender differences in the level of competition, there is no such difference in performance.

The effect of the remaining control variables on analyst forecast accuracy is consistent with prior studies on earnings forecasts. For instance, the age of the forecast significantly increases the forecast error, consistent with Clement (1999) and Bradley et al. (2017). Furthermore, in line with Clement and Tse (2005), the number of earnings forecasts issued by an analyst for a specific firm over the prior year increases an analyst's accuracy. In addition, portfolio complexity (i.e. DCountry_coverage, and DSIG2) increases an analyst's forecast error (Clement, 1999). Furthermore, the size of the broker which proxies for the resources available to the analyst is positively associated with analyst earnings forecast accuracy (e.g. Bradley et al., 2017).

In the summary statistics section, it is reported that the average accuracy of PMAFE between male and female analysts is not homogenous across the sample of European countries, therefore, country regressions were performed to check whether there are any differences in the gender effect on the earnings forecast accuracy across the sample European countries, as shown in Panels B of Table 30.

GENDER was only statistically significant in Denmark, at the 10% level of significance, therefore, female analysts who follow stocks headquartered in Denmark issue more accurate earnings forecasts than their male counterparts. Female analysts account for the 16% (Panel B of Table 27) of the analysts following stocks headquartered in Denmark, with Denmark accounting for 2% (Table 27) of the total sample. Denmark's low representation in the final sample (i.e. 2%) explains the documented no gender difference in PMAFE in the overall European sample, as in the rest of the sample European countries, which account for the 98% of the sample, gender variable is not statistically significant.

Even though GENDER is not statistically significant in most of the sample, other control variables affect earnings forecast accuracy across the European countries. For instance, the age of the forecast variable (DAge_forec) is significant across all the sample European countries; older forecasts are associated with increased forecast error. An analyst general experience (DGeneral_exp) is statistically significant only for the UK, where more experienced analysts have less error in the earnings forecasts.

Forecast frequency (DForec_frequency) is significant across France, Germany, Sweden and the UK. Surprisingly, the coefficient for Sweden does not have the expected sign; however, this is due to the high correlation between firm experience and forecast frequency variables[55]. Regarding portfolio complexity, analysts following greater numbers of firms, tend to be less accurate in Portugal, but are more accurate in Finland. In addition, the more countries analysts are following, the less accurate earnings forecasts they produce for firms domiciled in Austria and the UK.

Furthermore, analysts who follow many industries have a higher error in their earnings forecasts when following stocks operating in France, Ireland, and Switzerland. The size of the analyst employer is statistically significant for stocks operating in Denmark, France, Netherlands, Spain, Switzerland and the UK, where analysts tend to produce more accurate forecasts when they are employed by larger brokers. Regarding stock characteristics, the number of analysts following a stock, was statistically significant in eight out of the fourteen sample European countries (i.e. France, Germany, Ireland, Italy, Norway, Spain, Switzerland, and the UK), where the higher the competition, measured by the number of analysts following the stock, the more accurate the earnings forecasts.

These results suggest that there are no significant gender differences in terms of forecasting skills in thirteen out of the fourteen European countries, with female analysts being more accurate in their earnings forecast than their male counterparts only in Denmark. Other analyst characteristics that affect earnings forecast accuracy, include analyst general and firm experience as well as portfolio complexity. Overall, the results

[55] In the un-tabulated results, the regressions were re-run including one variable at a time (i.e. DForec_frequency or DFirm_exp) and the expected sing of the coefficients was obtained.

of the study are in line with studies supporting no gender differences in performance in competitive environments (e.g. Niederle and Vesterlund, 2007).

Table 30: *Regression Results of Earnings Forecast Accuracy*

Panel A: Final sample regression	
	PMAFE
GENDER	**0.010**
General_exp	-0.000
DFirm_exp	-0.000
DAge_forec	0.003***
DForec_frequency	-0.006***
DFirm_coverage	0.000
DCountry_coverage	0.005***
DSIG2	0.007***
DTOP10	-0.044***
Analysts_follow	-0.003***
Firm_size	-0.004
MB_ratio	-0.000
PRCMOM	0.003*
Fin_crisis	0.024*
Constant	0.110***
Observations	156,013
R-squared	0.046
Industry FE	YES
Year FE	YES
Country FE	YES

Panel B: Country regressions					
	(1) Austria	(2) Denmark	(3) Finland	(4) France	(5) Germany
GENDER	**0.054**	**-0.100***	**0.037**	**0.013**	**0.015**
DGeneral_exp	-0.003	0.000	-0.001	0.001	0.000
DFirm_exp	-0.004	-0.005	-0.007	0.003	0.002
DAge_forec	0.003***	0.003***	0.004***	0.002***	0.003***
DForec_frequency	0.003	-0.001	0.004	-0.011**	-0.009*
DFirm_coverage	-0.004	-0.001	-0.003*	0.001	-0.001
DCountry_coverage	0.022**	-0.008	0.004	-0.003	0.002
DSIG2	0.023	0.020	0.003	0.019***	0.008
DTOP10	-0.002	-0.111**	-0.034	-0.057***	-0.003
Firm_size	-0.027	-0.020	-0.008	0.001	0.006
MB_ratio	-0.000	0.000	-0.000	-0.000	0.000
PRCMOM	0.003	0.062	0.021	-0.018	0.026**
Analysts_follow	-0.006	-0.003	-0.001	-0.004***	-0.004***
Fin_crisis	-0.042	0.045	0.017	0.033	0.037
Constant	0.307	0.257	0.072	0.117*	0.047
Observations.	2,717	2,913	8,242	24,165	27,122
R-squared	0.078	0.083	0.095	0.029	0.055
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 30 *(continued)*

Country regressions					
	(6) Ireland	(7) Italy	(8) Netherlands	(9) Norway	(10) Portugal
GENDER	**0.074**	**-0.013**	**0.009**	**-0.060**	**0.014**
DGeneral_exp	0.004	0.002	0.001	-0.001	-0.003
Dfirm_exp	-0.005	-0.002	-0.001	-0.002	-0.016
Dage_forec	0.003***	0.002***	0.002***	0.003***	0.002***
Dforec_frequency	-0.003	-0.008	-0.001	0.006	0.015
Dfirm_coverage	-0.002	0.000	0.000	0.001	0.002*
Dcountry_coverage	0.013	0.000	-0.002	0.006	0.023
DSIG2	0.075**	-0.009	-0.001	-0.004	0.020
DTOP10	0.109	-0.038	-0.202***	-0.042	0.035
Firm_size	-0.013	-0.000	0.005	-0.005	-0.026
MB_ratio	-0.000	0.000	-0.000	0.000	-0.001
PRCMOM	0.147	0.000	0.035	0.055	0.098
Analysts_follow	-0.013	-0.004***	-0.003	-0.003*	-0.001
Fin_crisis	-0.023	0.042	0.083	0.021	-0.137
Constant	0.268	0.137	-0.049	0.119	0.384
Observations.	1,061	10,403	7,841	6,576	1,450
R-squared	0.081	0.033	0.028	0.078	0.035
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Country regressions				
	(11) Spain	(12) Sweden	(13) Switzerland	(14) United Kingdom
GENDER	**0.003**	**0.017**	**-0.034**	**0.020**
DGeneral_exp	-0.001	-0.002	-0.001	-0.001*
DFirm_exp	-0.005	-0.015**	-0.003	0.004
DAge_forec	0.002***	0.004***	0.002***	0.003***
DForec_frequency	-0.000	0.016*	-0.003	-0.013***
DFirm_coverage	0.001	0.002	-0.001	0.000
DCountry_coverage	0.006	-0.003	-0.002	0.013***
DSIG2	0.010	-0.002	0.021**	0.006
DTOP10	-0.106***	-0.032	-0.088***	-0.028*
Firm_size	0.012	-0.048***	0.003	-0.007
MB_ratio	0.000	0.000	-0.000	-0.000
PRCMOM	-0.007	-0.018	0.000	0.015
Analysts_follow	-0.003*	0.002	-0.004***	-0.004***
Fin_crisis	0.015	-0.073	0.076	0.009
Constant	-0.032	0.422***	0.095	0.153***
Observations	8,459	7,839	9,215	38,010
R-squared	0.021	0.098	0.047	0.049
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 30 presents the regression results of the equation (7.3). Panel A shows the regression results of the earnings forecast accuracy measure, PMAFE, in the final sample. Panels B shows the country regressions of the earnings forecast accuracy measure, PMAFE. Year, industry, and country fixed effect were used for Panel A and year and industry fixed effects for Panel B. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 24.

Dependent Variable
PMAFE the proportional mean absolute forecast error defined as the difference between the absolute forecast error (AFE) for analyst *i* on firm *j* and the mean absolute forecast error (MAFE) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*.
Main Independent Variable
GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

7.6 Additional Analysis

7.6.1 Are There Gender Differences in Forecasting Characteristics?

Trueman (1994) suggests that analysts who are more concerned about their reputation are more likely to herd in their earnings forecasts, whereas stronger and more experienced analysts are more likely to issue bold forecasts. In his paper, Kumar (2010) found that female analysts were significantly more likely to issue positive bold forecasts compared to their male counterparts. However, given the different institutional environments between the U.S. and the European market, the female sell-side analyst characteristics in Europe might differ than those in the U.S. Therefore, the additional analysis tested whether there is gender heterogeneity in analyst earnings forecast characteristics, hence career concerns, in Europe.

Following previous studies (e.g. Clement and Tse, 2005, Kumar, 2010), the analyst's earnings forecasts were categorised as Bold, Bold Positive, Bold Negative, Herding Positive and Herding Negative. Specifically, forecasts that are both above the prevailing consensus for a certain firm during the year, and above the most recent forecast issued by the analyst for the firm were classified as bold positive (Bold_positive). The forecasts that were below the prevailing consensus for a certain firm during the year, and below the most recent forecast issued by the analyst for the firm were classified as bold negative (Bold_negative). Both bold positive and bold negative forecasts were classified as bold (Bold), with the remaining forecasts classified as herding forecasts, which fall into two categories, herding positive and herding negative. Forecasts that were revised above the analyst's most recent forecast, were classified as herding positive, and forecasts that were revised below the analyst's most recent forecasts were classified as herding negative. To test whether female analysts were likely to issue certain types of forecasts than males, logit regressions were estimated, where one of five forecast types is the dependent variable (i.e. bold, bold_positive, bold_negative, herding_positive, herding_negative).

Furthermore, following Clement and Tse (2005) and Kumar (2010), the regression model (7.3) was extended by adding Ddays_elapsed and lag_PMAFE control variables. Ddays_elapsed is defined as the number of days elapsed since the most recent forecast issued for a firm by any analyst, minus the average number of days elapsed of the analysts following the company during the year. The lag_PMAFE variable is the PMAFE error of an analyst over the prior year. Detailed definitions of the remaining variables can be found in Table 24. Industry, year, and country fixed effects were also included.

The empirical specification of the multivariate regressions for the earnings forecast type is:

(7.4) $$\mathit{Forecast\_type} = \beta_0 + \beta_1(\mathrm{GENDER}) + \beta_2(\mathrm{DGeneral\_exp}) + \beta_3(\mathrm{DFirm\_exp}) + \beta_4(\mathrm{DAge\_forec})\ \beta_5(\mathrm{DForec\_frequency}) + \beta_6(\mathrm{Ddays\_elapsed}) + \beta_7(\mathrm{lag\_PMAFE}) + \beta_8(\mathrm{Firm\_coverage}) + \beta_9(\mathrm{DCountry\_coverage}) + \beta_{10}(\mathrm{DSIG2}) + \beta_{11}(\mathrm{DTop10}) + \beta_{12}(\mathrm{Firm\_size}) + \beta_{13}(\mathrm{MB\_ratio}) + \beta_{14}(\mathrm{PRCMOM}) + \beta_{15}(\mathrm{Analysts\_follow}) + \beta_{16}(\mathrm{Fin\_crisis}) + \sum\mathrm{IND} + \sum\mathrm{TIME} + \sum\mathrm{COUNTRY} + \varepsilon$$

Where, Forecast_type is one of the five forecast type measures. Analyst and broker characteristics are firm year mean-adjusted (D stands for cross sectionally-centred) and standard errors are clustered at analyst and firm-level (Petersen, 2009).

Bold forecasts account for the 59% of the total sample, with bold positive and bold negative accounting for 23% and 36% respectively. Herding positive forecasts account for 20% and 21% respectively. Table 31 presents the regression results of equation (7.4). Panel A of Table 31 shows that female analysts were significantly less likely to issue bold forecasts than their male counterparts, at the 10% level of significance. When the bold forecasts were classified as bold positive and bold negative, the results showed that female analysts were significantly less likely to issue bold positive forecasts than males, at the 1% level of significance. These results differ from those of Kumar (2010) who found that female analysts in the U.S. are significantly more likely to issue bold positive forecasts compared to their male counterparts. The present study was conducted in a European setting and differences in the findings can be attributed to the differences between the U.S. and the European markets.

In addition, female analysts were significantly more likely to issue bold negative forecasts than males, at the 5% level of significance, which is in line with Green et al. (2009) who found that female analysts in the U.S. are significantly less optimistic than male analysts in their earnings forecasts. Furthermore, Panel B of Table 31, tested whether female or males have a propensity to herd, documenting that female analysts were more likely to herd positively compared to their male counterparts, at the 1% level of significance.

Overall, the results indicated that female sell-side analysts are less likely to issue bold forecasts but are more likely to herd than their male counterparts, suggesting that females have more reputational and career concerns than males (e.g. Trueman, 1994).

Table 31: *Regression Results of Forecast Types*

Panel A: Regression results for bold forecasts

	(1) Bold	(2) Bold_positive	(3) Bold_negative
GENDER	**-0.028***	**-0.095*****	**0.041****
DGeneral_exp	0.001	0.001	0.000
DFirm_exp	-0.013***	-0.029***	0.011***
DAge_forec	0.001***	0.002***	-0.000***
DForec_frequency	0.031***	0.192***	-0.136***
Ddays_elapsed	0.000	-0.002***	0.001***
lag_PMAFE	0.001	0.011	-0.008
DFirm_coverage	0.001	0.002**	-0.000
DCountry_coverage	-0.009***	0.019***	-0.024***
DSIG2	-0.008*	-0.003	-0.006
DTOP10	0.030*	0.029	0.006
Firm_size	-0.078***	0.212***	-0.239***
MB_ratio	-0.000**	-0.000	-0.000
PRCMOM	-0.005	0.021***	-0.031
Analysts_follow	0.010***	-0.001	0.011***
Fin_crisis	-0.167***	-0.550***	0.278***
Constant	2.097***	-5.881***	4.590***
Observations	155,558	155,558	155,558
Pseudo R^2	0.004	0.064	0.042
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	YES	YES	YES

Panel B: Regression results for herding forecasts

	(1) Herding_positive	(2) Herding_negative
GENDER	**0.064*****	**-0.018**
DGeneral_exp	0.003***	-0.003***
DFirm_exp	-0.009**	0.037***
DAge_forec	0.001***	-0.003***
DForec_frequency	0.159***	-0.265***
Ddays_elapsed	0.001***	-0.002***
lag_PMAFE	0.007	-0.005
DFirm_coverage	0.000	-0.001
DCountry_coverage	-0.006	0.020***
DSIG2	0.026***	-0.015**
DTOP10	-0.032	-0.007
Firm_size	0.121***	-0.001
MB_ratio	0.001***	0.000
PRCMOM	-0.032***	0.018***
Analysts_follow	-0.018***	0.003***
Fin_crisis	-0.451***	0.802***
Constant	-3.975***	-1.730***
Observations	155,558	155,558
Pseudo R^2	0.043	0.055
Industry FE	YES	YES
Year FE	YES	YES
Country FE	YES	YES

Table 31 *(continued)*

Table 31 presents the regression results of equation (7.4). Panel A presents the regression results for bold forecasts. Panel B presents the regression results for herding forecasts. Year, industry, and country fixed effects were used. Standard errors are clustered at the analyst and firm-level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 24.

Dependent Variables
Bold an indicator variable (0, 1) equal to 1 if analyst's *i* forecast is above(below) the prevailing consensus for firm *j* at time *t*, and above(below) the most recent forecast issued by the analyst for the firm *j*.
Bold_positive an indicator variable (0, 1) equal to 1 if analyst's *i* forecast is above the prevailing consensus for firm *j* at time *t*, and above the most recent forecast issued by the analyst for the firm *j*.
Bold_negative an indicator variable (0, 1) equal to 1 if analyst's *i* forecast is below the prevailing consensus for firm *j* at time *t*, and below the most recent forecast issued by the analyst for the firm *j*.
Herding_postive an indicator variable (0, 1) equal to 1 if analyst's *i* forecast is not below or above the prevailing consensus for firm *j* at time *t*, but it is revised above the analyst's most recent forecast for firm *j*.
Herding_negative an indicator variable (0, 1) equal to 1 if analyst's *i* forecast is not below or above the prevailing consensus for firm *j*, but it is revised below the analyst's most recent forecast for firm *j*.

Main Independent Variable
GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

7.6.2 Do Female Analysts Face Discrimination in Hiring Decisions?

In the U.S., studies on analyst gender were particularly interested to test whether female sell-side analysts face discrimination in the hiring decisions. For instance, if gender discrimination affects hiring decisions, women need to be more qualified than men to be chosen to enter the profession. Kumar (2010) concluded that the superior forecasting skills documented in the female sell-side analysts are explained by the gender discrimination in sell-side analyst profession, where only highly skilled women enter the profession. Although the results in section 7.5 do not support the argument of gender discrimination in hiring decisions, following Kumar (2010), a further robustness test was conducted, specifically, limiting the sample to analysts with general experience of less than three years, and testing differences in the forecasting skill of newly employed and relatively less experienced analysts.

Table 32 presents the results of the robustness analysis, showing that gender is not statistically significant in the early years of employment, in the earnings forecast accuracy. Other analyst characteristics that seem to affect the forecast accuracy for the newly employed analysts are the firm experience (i.e. DFimr_exp) and portfolio complexity (i.e., DCountry_coverage and DSIG2) of the analysts. Therefore, the robustness analysis further supports the findings in section 7.5.

Table 32: *Regression Results of Earnings Forecast Accuracy – Limited Sample*

	PMAFE
GENDER	**0.024**
DGeneral_exp	-0.002
DFirm_exp	-0.018**
DAge_forec	0.003***
DForec_frequency	0.011
DFirm_coverage	0.000
DCountry_coverage	0.008**
DSIG2	0.012**
DTOP10	-0.063***
Analysts_follow	-0.004***
Firm_size	0.002
MB_ratio	0.000
PRCMOM	0.003
Fin_crisis	-0.025
Observations	27019
R-squared	0.056
Industry FE	YES
Year FE	YES
Country FE	YES

Table 32 presents the regression results of equation (7.3) for the limited sample of analysts with general experience (General_exp) equal or less than three years. Year, industry, and country fixed effects were used. Standard errors are clustered at the analyst and firm- level. ***, **, * represent significance at the 0.01, 0.05 and 0.1 level, respectively. For brevity, the table provides the definition of the dependent and the main independent variables only, while the definition of the remaining variables can be found in Table 24.

Dependent Variable
PMAFE the proportional mean absolute forecast error defined as the difference between the absolute forecast error (AFE) for analyst *i* on firm *j* and the mean absolute forecast error (MAFE) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*.

Main Independent Variable
GENDER an indicator variable (0, 1) equal to 1 if an analyst is female and 0 otherwise.

7.7 Conclusion

Earnings forecast accuracy is important for the sell-side analyst profession, therefore studies have extensively examined analyst characteristics that are likely to be associated with better earnings forecast accuracy (e.g. Clement, 1999, Bradley et al., 2017). The determinants of earnings forecast accuracy are important for investors as they systematically differentiate between analyst characteristics that proxy for forecast accuracy (e.g. Stickel, 1995, Kumar, 2010, Bradley et al., 2017). Furthermore, greater forecast accuracy might lead to better career outcomes (e.g. Hong and Kubic, 2003) or poor forecasting skills might lead an analyst to exit the profession (e.g. Bolliger, 2004).

Given the importance of earnings forecast accuracy for the sell-side analyst profession, it would be expected that analysts with superior forecasting skills are likely to have a greater representation within the profession compared to those with poor forecasting skills. This raises the question of whether the male dominance within the sell-side analyst profession is justified by the superior forecasting skills that male analysts might have compared to their female counterparts.

In the U.S., Kumar (2010) found that female sell-side analysts issue more accurate earnings forecasts than males, which does not justify their low representation. Kumar explains that female analysts face discrimination in hiring decisions, therefore they need to be more qualified than their male counterparts to enter the profession. The study of Kumar (2010) is limited to the U.S., therefore the results of his research may not generalise to other markets. To date there has been no study examining gender differences in earnings forecast accuracy outside the U.S.

The European market, where the analyst profession is also male dominated, is large enough to bear comparison with Kumar's (2010) U.S. study. Moreover, the distinct incentives to issue accurate earnings forecasts across the two markets hinder the generalisability of the findings in the U.S., hence adds more validity to a European study.

Motivated by the low female representation within the sell-side analyst profession and the importance of earnings forecast accuracy to market participants, this study examined whether there is gender heterogeneity in sell-side analyst forecasting skills in Europe. The findings show that in thirteen out of the fourteen sample European countries, there is no significant gender difference in earnings forecast accuracy, which proxies for differences in forecasting skills. Therefore, low female representation in the sell-side analyst profession is not justified by lower forecasting skills. In the additional analysis, male analysts were found to be significantly more likely to issue bold forecasts, whereas female analysts were more likely to herd, implying that female analysts are more concerned with their career and reputation than males.

The results of the study complement the extant gender studies within the sell-side analyst profession in the U.S. In addition, this study contributes to the stream of literature testing for gender differences in high profile and male dominated professions. Furthermore, the findings have implications for policymakers and investment banks, because the low female representation within the sell-side analyst profession is not justified by gender differences in forecasting skills.

Chapter 8: Conclusion

8.1 Background of the Thesis

While gender studies in the finance industry have received much attention from academics, studies on sell-side analyst gender are limited, mainly due to data restrictions since information regarding analyst gender is not readily available. Furthermore, studies on sell-side analyst gender yield mixed results regarding gender differences and are limited to the U.S. market, therefore, more research is required to complement the extant studies and to extend the findings in other markets. Therefore, this thesis investigated gender differences in sell-side analyst bias, optimism, and performance across Europe and/or the U.S.

Ethical behaviour of analysts is fundamental to fulfilling their role as an intermediary and supplier of useful information to investors. However, there is repeated evidence of bias in analysts' outputs in the U.S. Moreover, where analysts are affiliated, bias is even more pronounced (Kolasinski and Kothari, 2008). There is, however, growing evidence that women exhibit greater moral reasoning than men (i.e. gender socialisation theory), which is associated with an increased quality of financial information (Chen et al., 2017), fewer environmental violations (Liu, 2018) and securities fraud (Cumming et al., 2015). Therefore, the first empirical chapter tested whether gender influenced the way affiliated sell-side analysts respond to their conflicts of interest in the U.S.

Sell-side analyst optimism is an important factor affecting target price forecasts (Bradshaw et al., 2019). However, studies suggest that females exhibit less optimism than males (Barber and Odean, 2001), resulting in improved corporate outcomes (e.g. Francis.et al., 2015). Within the sell-side analyst profession, there are mixed findings on gender differences in risk attitude, and due to data restrictions, the studies on analyst gender are limited to the U.S. For this reason, the second empirical chapter examined whether male sell-side analysts issue more optimistic target prices than females across both Europe and the U.S.

The determinants of earnings forecast accuracy are important for market participants, who systematically differentiate for analyst characteristics that are associated with greater forecast accuracy. In the U.S., Kumar (2010) found that being a female is associated with superior earnings forecast accuracy, but these findings are not generalisable to markets with different institutional environment than the U.S. The European market is a good setting to test for gender differences in earnings forecasts since it is large enough to bear comparison with the U.S. market. Consequently, the third empirical chapter investigated whether there is gender heterogeneity in sell-side analyst forecasting skills in Europe.

8.2 Summary of Findings

8.2.1 Does Gender Influence the Way Affiliated Sell-side Analysts Respond to Their Conflicts of Interest?

The findings of Chapter 5 show that affiliated sell-side analysts are significantly more biased than unaffiliated sell-side analysts in their target prices forecasts, but gender does not play a significant role in the way affiliated sell-side analysts respond to their conflicts of interest. The latter finding is consistent with the occupational socialisation theory whereby employees tend to develop similar moral reasoning as they adapt to the same working environment and organisational culture.

The sell-side analyst profession is male dominated and the proportion of males to females is large enough to influence the organisational culture in which both male and female analysts are adapting to (Kanter, 1977), thus, female analysts are adopting the values of a male dominated culture. However, it was not possible to determine if female analysts were more ethical before adopting the ethical values underpinning the male dominated culture. Nevertheless, it could be tested whether higher female representation can positively affect the values and the culture of the organisation. As expected, affiliated analysts exhibited less bias in their target prices when the percentage of females was higher within the sanctioned banks.

The findings of Chapter 5 contribute to the extant literature in several ways. First, the documented bias on affiliated analysts' target price forecasts complements the extant literature on affiliated sell-side analysts' conflicts of interest. Second, the study examines the 2003–2014 period, which is the most recent period that tests for bias on the analysts' target prices affiliated with an equity issue in the post regulatory period. Third, the paper provides evidence of the gender differences in affiliation bias, thus complements the extant studies on analyst gender. Fourth, using the affiliation setting for examining gender differences in ethical decision-making, these findings provide support for the occupational socialisation theory.

8.2.2 Do Male Sell-side Analysts Issue More Optimistic Target Prices than Females? Evidence from Europe and the United States

The results of Chapter 6 show that female analysts issue more optimistic target price forecast than males across both Europe and the U.S. However, the documented gender differences in optimism do not persist in Europe when the endogenous decision to follow the same stocks was controlled for. Therefore, female analysts in Europe initially appear less optimistic because of reverse causality as they do not follow certain risky stocks covered by their male counterparts due to their risk aversion. In the U.S., the documented gender differences in optimism are robust to the choice of the stock followed. Furthermore, after controlling for the choice of the stock followed, gender differences in optimism, if any, do not affect an analyst's target price performance.

The findings of Chapter 6 contribute to the sell-side analyst literature by providing evidence of the gender effect on target price optimism from the U.S. and the European markets. In addition, the paper complements the stream of literature testing for gender differences in risk attitude and corporate outcomes in high profile professions.

8.2.3 Is There Gender Heterogeneity in Sell-side Analyst Forecasting Skills? Evidence from Europe

Chapter 7 established that there are no gender differences in earnings forecast accuracy in Europe, therefore, low female representation in the sell-side analyst profession, is not justified by lower forecasting skills. Also, the low female representation is not explained by gender discrimination in hiring decisions, since females did not outperform their male counterparts.

Furthermore, in the country regressions, Denmark was the only European sample country where female analysts were more accurate than males following stocks headquartered in Denmark. Although analyst target prices of Danish stocks account for 2% of the final sample, therefore this does not affect the conclusion for the overall European sample.

Despite the documented lack of gender difference in forecast accuracy across the overall sample, there were gender differences in the forecasting characteristics, for instance, male analysts were significantly more likely to issue bold forecasts, whereas female analysts were more likely to herd, implying that females have more reputational and career concerns than their male counterparts.

Chapter 7 contributes to the sell-side analyst literature, by providing evidence of the gender effect on earnings forecast accuracy, within Europe. In addition, the paper contributes to the stream of literature that tests for gender differences in performance within the finance industry.

8.3 Policy Implications

The results of this thesis provide several policy implications. First, the documented bias on affiliated analysts' target prices in Chapter 5 has implications for regulators' efforts to protect investors from biased analyst research. Regulations are primarily aimed to mitigate bias on analyst stock recommendations, therefore, the documented bias on analyst target price forecasts, which like stock recommendations represent a direct investment recommendation, highlights the need for the regulators to address bias on analyst target prices.

Second, the consistent findings with the gender socialisation theory in Chapter 5 have implications for the male dominated sell-side analyst profession, because females are adopting the informal work norms, attitudes, and behaviours of the male dominated organisational culture. Chapter 5 also showed that in sanctioned banks, the organisational culture can benefit from the inclusion of more women, since higher female representation is associated with less affiliation bias. Therefore, regulators should consider increasing female representation within the sell-side analyst profession in the U.S., as a way of improving the ethical culture within investment banks.

Third, the findings of Chapter 6 show that the gender effect in optimism materialises differently in distinct markets, so the European and the U.S. markets should not be treated homogenously when issuing any future potential gender policies. Fourth, the findings of Chapter 7 imply that in Europe, the low female representation is not driven by lower forecasting skill or gender discrimination in hiring decisions. Consequently, policies which regulate the European market should consider increasing the supply of female sell-side analysts by encouraging more females to enter the sell-side analyst profession.

8.4 Limitations and Directions for Further Research

The main limitation of gender studies is that other unobservable factors might drive the association of gender and certain corporate outcomes (e.g. Sila et al., 2016). In this thesis, even though variables expected to explain an analyst bias, optimism, accuracy and the endogenous decision of female analysts to follow certain stocks were controlled for, there is still a possibility that other unobservable factors might be associated with the documented gender effect and certain corporate outcomes.

Furthermore, the findings regarding the gender effect are limited to the U.S. and the European markets, hence are not generalisable in an international context. Therefore, further research should explore gender differences in sell-side analyst profession in an international context.

Lastly, this is a quantitative thesis, which used corporate outcomes to draw conclusions regarding gender biases. Even though the findings of the thesis have several contributions to the literature, qualitative data could add a further dimension in our understanding of the gender biases within the sell-side analyst profession. Future studies might extent the findings of this thesis by providing qualitative data on the sell-side analyst intentions to behave ethically and gender differences in the perception of risk.

Chapter 9: Appendix

Chapter 6 showed that while females issue significantly more optimistic target price forecasts than their male counterparts, there was no significant gender difference in their target price performance. The following examples from the sample data in the U.S. are provided to better understand why this might be the case:

Example 1

Analyst A (female), analyst B (male), and analyst C (male) issue their target price forecast with a 12-month forecast horizon for NASDAQ on 3rd May 2010. The stock price of NASDAQ on 3rd May 2010 is 21.11 USD, and at the end of the 12-month forecast horizon (i.e. 3rd May 2011) the stock price of NASDAQ is 27.14 USD. The table below shows the analyst optimism (TP_t/P_t) and how it materialises ex-post (aTPE).

	Target Price Forecast (USD)	TP_t/P_t	aTPE
Analyst A - Female	24	0.137	0.139
Analyst B - Male	25	0.184	0.097
Analyst C - Male	26	0.231	0.053

TP_t/P_t ratio defined as an analyst's target price forecast divided by the stock price at the target price issue date, minus 1.
aTPE defined as the natural logarithm of the absolute value of $(P_{t+12} - TP_t)/P_{t-3}$, where P_{t+12} is the stock price 12 months following the target release date, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price 3 days before the target price release date.

Ex-ante, all three analysts are optimistic for the NASDAQ stock. However, ex-post they all appear to be pessimistic since NASDAQ stock has exceeded their target price forecasts at the end of the 12-month forecast horizon. Analyst A appears to be the least optimistic ex-ante and ex-post is the least accurate, whereas analyst C is the most optimistic ex-ante and ex-post is the most accurate compared to the other analysts.

Therefore, higher optimism is more favourable over less optimistic forecasts when the optimism materialises ex-post.

Example 2

Analyst A (female) and analyst B (male) issue their target price forecast with a 12-month forecast horizon for PENN VA CORP on 9th May 2009. The stock price of PENN VA CORP on 9th May 2009 is 8.76 USD, and at the end of the 12-month forecast horizon (i.e. 9th May 2010) the stock price of PENN VA CORP is 25.2 USD. The table below shows the analyst optimism (TP_t/P_t) and how it materialises ex-post (aTPE).

	Target Price Forecast (USD)	TP_t/P_t	aTPE
Analyst A - Female	16	0.826	0.718
Analyst B - Male	31	1.692	0.508

TP_t/P_t ratio defined as an analyst's target price forecast divided by the stock price at the target price issue date, minus 1.
aTPE defined as the natural logarithm of the absolute value of $(P_{t+12} - TP_t)/P_{t-3}$, where P_{t+12} is the stock price 12 months following the target release date, TP_t is the target price forecast with a 12-month forecast horizon, and the P_{t-3} is the stock price 3 days before the target price release date.

Ex-ante, both analysts are optimistic, with analyst B being more optimistic than analyst A. The difference in the TP_t/P_t ratio between the two analysts is 0.866, whereas the difference in aTPE measure is 0.21, so there is a large difference in optimism between the two analysts, but a small difference in their error, since the actual stock price at the end of the 12-month forecast horizon lies between analyst A and analyst B target price forecast.

Chapter 10: Bibliography

Abdolmohammadi, M. J., Read, W. J. & Scarbrough, D. P. 2003. Does selection-socialization help to explain accountants' weak ethical reasoning? *Journal of Business Ethics,* 42, 71–81.

Adams, R. B. & Ferreira, D. 2009. Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics,* 94, 291–309.

Adams, R. B. & Funk, P. 2012. Beyond the glass ceiling: Does gender matter? *Management Science,* 58, 219–235.

Adams, R. B. & Ragunathan, V. 2015. Lehman sisters. *SSRN eLibrary*. Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3046451

Agrawal, A., Chadha, S. & Chen, M. A. 2006. Who is afraid of reg FD? The behavior and performance of sell-side analysts following the SEC's fair disclosure rules. *The Journal of Business,* 79, 2811–2834.

Ameen, E. C., Guffey, D. M. & McMillan, J. J. 1996. Gender differences in determining the ethical sensitivity of future accounting professionals. *Journal of Business Ethics,* 15, 591–597.

Atkinson, S. M., Baird, S. B. & Frye, M. B. 2003. Do female mutual fund managers manage differently? *Journal of Financial Research,* 26, 1–18.

Bae, K.-H., Stulz, R. M. & Tan, H. 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics,* 88, 581–606.

Bailey, W., Li, H., Mao, C. X. & Zhong, R. 2003. Regulation fair disclosure and earnings information: Market, analyst, and corporate responses. *The Journal of Finance,* 58, 2487–2514.

Barber, B. M., Lehavy, R., McNichols, M. & Trueman, B. 2006. Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations. *Journal of Accounting and Economics,* 41, 87–117.

Barber, B. M., Lehavy, R. & Trueman, B. 2007. Comparing the stock recommendation performance of investment banks and independent research firms. *Journal of Financial Economics,* 85, 490–517.

Barber, B. M. & Odean, T. 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics,* 116, 261–292.

Barniv, R., Hope, O.-K., Myring, M. J. & Thomas, W. B. 2009. Do analysts practice what they preach and should investors listen? Effects of recent regulations. *The Accounting Review,* 84, 1015–1039.

Barniv, R., Hope, O. K., Myring, M. & Thomas, W. B. 2010. International evidence on analyst stock recommendations, valuations, and returns. *Contemporary Accounting Research,* 27, 1131–1167.

Barua, A., Davidson, L. F., Rama, D. V. & Thiruvadi, S. 2010. CFO gender and accruals quality. *Accounting Horizons,* 24, 25–39.

Berger, A. N., Kick, T. & Schaeck, K. 2014. Executive board composition and bank risk taking. *Journal of Corporate Finance,* 28, 48–65.

Bessler, W. & Stanzel, M. 2009. Conflicts of interest and research quality of affiliated analysts in the German universal banking system: evidence from IPO underwriting. *European Financial Management,* 15, 757–786.

Betz, M., O'Connell, L. & Shepard, J. M. 1989. Gender differences in proclivity for unethical behavior. *Journal of Business Ethics,* 8, 321–324.

Bilinski, P., Cumming, D., Hass, L. H., Stathopoulos, K. & Walker, M. 2019. Strategic distortions in analyst target prices in the presence of short-term institutional investors. *Accounting Business Research,* 49, 305–341.

Bilinski, P., Lyssimachou, D. & Walker, M. 2012. Target price accuracy: International evidence. *The Accounting Review,* 88, 825–851.

Boatright, J. R. 2000. Conflicts of interest in financial services. *Business and Society Review,* 105, 201–219.

Bolliger, G. 2004. The characteristics of individual analysts' forecasts in Europe. *Journal of Banking & Finance,* 28, 2283–2309.

Boni, L. & Womack, K. L. 2003. Wall street research: will new rules change its usefulness? *Financial Analysts Journal*, 59, 25–29.

Bossuyt, S. & Van Kenhove, P. 2016. Assertiveness bias in gender ethics research: Why women deserve the benefit of the doubt. *Journal of Business Ethics*, 150, 1–13.

Bradley, D., Gokkaya, S. & Liu, X. 2017. Before an analyst becomes an analyst: Does industry experience matter? *The Journal of Finance,* 72, 751–792.

Bradley, D. J., Jordan, B. D. & Ritter, J. R. 2008. Analyst behavior following IPOs: the "bubble period" evidence. *Review of Financial Studies,* 21, 101–133.

Bradshaw, M. T. 2002. The use of target prices to justify sell-side analysts' stock recommendations. *Accounting Horizons,* 16, 27–41.

Bradshaw, M. T. 2004. How do analysts use their earnings forecasts in generating stock recommendations? *The Accounting Review,* 79, 25–50.

Bradshaw, M. T., Brown, L. D. & Huang, K. 2013. Do sell-side analysts exhibit differential target price forecasting ability? *Review of Accounting Studies,* 18, 930–955.

Bradshaw, M. T., Huang, A. G. & Tan, H. 2019. The Effects of Analyst-Country Institutions on Biased Research: Evidence from Target Prices. *Journal of Accounting Research,* 57, 85–120.

Bradshaw, M. T., Richardson, S. A. & Sloan, R. G. 2006. The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics,* 42, 53–85.

Brown, L., Call, A., Clement, M. & Sharp, N. 2015. Inside the "Black Box" of Sell-Side Financial Analysts. *Journal of Accounting Research,* 53, 1–47.

Caccese, M. S. 1997. Ethics and the financial analyst. *Financial Analysts Journal*, 53, 9–14.

Capstaff, J., Paudyal, K. & Rees, W. 2001. A comparative analysis of earnings forecasts in Europe. *Journal of Business Finance & Accounting,* 28, 531–562.

Chan, L. K., Karceski, J. & Lakonishok, J. 2007. Analysts' conflicts of interest and biases in earnings forecasts. *Journal of Financial and Quantitative Analysis,* 42, 893–913.

Chen, C.-Y. & Chen, P. F. 2009. NASD Rule 2711 and changes in analysts' independence in making stock recommendations. *The Accounting Review,* 84, 1041–1071.

Chen, J., Leung, W. S. & Goergen, M. 2017. The impact of board gender composition on dividend payouts. *Journal of Corporate Finance*, 43, 86–105.

Chen, P. F., Novoselov, K. E. & Wang, Y. 2018. Regulatory effects on Analysts' conflicts of interest in corporate financing activities: Evidence from NASD Rule 2711. *Journal of Corporate Finance,* 48, 658–679.

Christie, P. M. J., Kwon, I.-W. G., Stoeberl, P. A. & Baumhart, R. 2003. A cross-cultural comparison of ethical attitudes of business managers: India Korea and the United States. *Journal of Business Ethics,* 46, 263–287.

Clarke, J., Khorana, A., Patel, A. & Rau, P. R. 2004. Analyst behavior at independent research firms, brokerage houses, and investment banks: conflicts of interest or better information. *Krannert Graduate School of Management, Purdue University,* Working Paper.

Clement, M. B. 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics,* 27, 285–303.

Clement, M. B. & Tse, S. Y. 2005. Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance,* 60, 307–341.

Cliff, M. T. 2007. Do Affiliated Analysts Mean What They Say? *Financial Management,* 36, 5–29.

Coate, S. & Loury, G. C. 1993. Will affirmative-action policies eliminate negative stereotypes? *The American Economic Review,* 83, 1220–1240.

Cohen, J. R., Pant, L. W. & Sharp, D. J. 2001. An examination of differences in ethical decision-making between Canadian business students and accounting professionals. *Journal of Business Ethics,* 30, 319–336.

Cole, B. C. & Smith, D. L. 1996. Perceptions of business ethics: Students vs. business people. *Journal of Business Ethics,* 15, 889–896.

Corwin, S. A., Larocque, S. A. & Stegemoller, M. A. 2017. Investment Banking Relationships and Analyst Affiliation Bias: The Impact of the Global Settlement on Sanctioned and Non-Sanctioned Banks. *Journal of Financial Economics,* 124, 614–631.

Croson, R. & Gneezy, U. 2009. Gender differences in preferences. *Journal of Economic Literature,* 47, 448–474.

Cumming, D., Leung, T. Y. & Rui, O. 2015. Gender diversity and securities fraud. *Academy of Management Journal,* 58, 1572–1593.

Dalton, D. & Ortegren, M. 2011. Gender differences in ethics research: The importance of controlling for the social desirability response bias. *Journal of Business Ethics*, 103, 73–93.

Das, S., Levine, C. B. & Sivaramakrishnan, K. 1998. Earnings predictability and bias in analysts' earnings forecasts. *Accounting Review*, 73, 277–294.

Dawson, L. M. 1997. Ethical differences between men and women in the sales profession. *Journal of Business Ethics,* 16, 1143–1152.

Deshpande, S. P. 1997. Managers' perception of proper ethical conduct: The effect of sex, age, and level of education. *Journal of Business Ethics,* 16, 79–85.

Di Lorenzo, V. 2007. Business ethics: Law as a determinant of business conduct. *Journal of Business Ethics,* 71, 275–299.

Du, Q., Yu, F. & Yu, X. 2017. Cultural proximity and the processing of financial information. *Journal of Financial and Quantitative Analysis,* 52, 2703–2726.

Dugar, A. & Nathan, S. 1995. The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations. *Contemporary Accounting Research,* 12, 131–160.

Duru, A. & Reeb, D. M. 2002. International diversification and analysts' forecast accuracy and bias. *The Accounting Review,* 77, 415–433.

Egan, M. L., Matvos, G. & Seru, A. 2017. When Harry Fired Sally: The Double Standard in Punishing Misconduct. *The National Bureau of Economic Research,* Working Paper.

Ellis, K., Michaely, R. & O'Hara, M. 2000. When the underwriter is the market maker: An examination of trading in the IPO aftermarket. *The Journal of Finance,* 55, 1039–1074.

Emerson, T. L., Conroy, S. J. & Stanley, C. W. 2007. Ethical attitudes of accountants: Recent evidence from a practitioners' survey. *Journal of Business Ethics,* 71, 73–87.

Epstein, R. A. 1995. *Forbidden grounds: The case against employment discrimination laws*. Harvard University Press.

Eynon, G., Hills, N. T. & Stevens, K. T. 1997. Factors that influence the moral reasoning abilities of accountants: Implications for universities and the profession. *Journal of Business Ethics,* 16, 1297–1309.

Fang, B., Hope, O.-K., Huang, Z. & Moldovan, R. 2019. The Effects of MiFID II on Sell-Side Analysts, Buy-Side Analysts, and Firms. *SSRN eLibrary*. Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3422155

Fang, L. H. & Huang, S. 2017. Gender and connections among Wall Street analysts. *The Review of Financial Studies,* 30, 3305–3335.

Fang, L. & Yasuda, A. 2009. The effectiveness of reputation as a disciplinary mechanism in sell-side research. *Review of Financial Studies,* 22, 3735–3777.

Feldberg, R. L. & Glenn, E. N. 1979. Male and female: Job versus gender models in the sociology of work. *Social Problems,* 26, 524–538.

Florio, C. V. D. 2012. *Conficts of Interest adn Risk Governance. US Securities and Exchange Commission.* [Online]. [Accessed 27 January 2020]. Available from: https://www.sec.gov/news/speech/2012-spch103112cvdhtm

Francis, B., Hasan, I., Park, J. C. & Wu, Q. 2015. Gender differences in financial reporting decision making: Evidence from accounting conservatism. *Contemporary Accounting Research,* 32, 1285–1318.

Francis, B., Hasan, I. & Wu, Q. 2013. The impact of CFO gender on bank loan contracting. *Journal of Accounting, Auditing & Finance,* 28, 53–78.

Francis, B. B., Hasan, I., Wu, Q. & Yan, M. 2014. Are female CFOs less tax aggressive? Evidence from tax aggressiveness. *The Journal of the American Taxation Association,* 36, 171–202.

Francis, J. & Philbrick, D. 1993. Analysts' decisions as products of a multi-task environment. *Journal of Accounting Research,* 31, 216–230.

Frye, M. B. & Pham, D. T. 2018. CEO gender and corporate board structures. *The Quarterly Review of Economics and Finance,* 69, 110–124.

Garcia Lara, J. M., Garcia Osma, B., Mora, A. & Scapin, M. 2017. The monitoring role of female directors over accounting quality. *Journal of Corporate Finance*, 45, 651–668

Ge, W., Matsumoto, D. & Zhang, J. L. 2011. Do CFOs have style? An empirical investigation of the effect of individual CFOs on accounting practices. *Contemporary Accounting Research,* 28, 1141–1179.

Gilligan, C. 1982. *In a different voice: Psychological theory and women's development.* Cambridge: Harvard University Press.

Glazer, N. 1975. *Affirmative discrimination: Ethnic inequality and public policy.* New York: Harvard University Press.

Glover, S. H., M. A. Bumpus, J. E. Logan and J. R. Ciesla: 1997. Re-Examining the Influence of Individual Values on Ethical Decision Making. *Journal of Business Ethics,* 16, 1319–1329.

Glover, S. H., Bumpus, M. A., Sharp, G. F. & Munchus, G. A. 2002. Gender differences in ethical decision making. *Women in Management Review,* 17, 217–227.

Gneezy, U., Niederle, M. & Rustichini, A. 2003. Performance in competitive environments: Gender differences. *The Quarterly Journal of Economics,* 118, 1049–1074.

Green, C., Jame, R., Markov, S. & Subasi, M. 2014. Access to management and the informativeness of analyst research. *Journal of Financial Economics,* 114, 239–255.

Green, C., Jegadeesh, N. & Tang, Y. 2009. Gender and job performance: Evidence from Wall Street. *Financial Analysts Journal,* 65, 65–78.

Guan, Y., Lu, H. & Wong, M. F. 2012. Conflict-of-interest reforms and investment bank analysts' research biases. *Journal of Accounting, Auditing & Finance,* 27, 443–470.

Gul, F. A., Srinidhi, B. & Ng, A. C. 2011. Does board gender diversity improve the informativeness of stock prices? *Journal of Accounting and Economics,* 51, 314–338.

Herrmann, D. R., Hope, O.-K. & Thomas, W. B. 2008. International diversification and forecast optimism: The effects of Reg FD. *Accounting Horizons,* 22, 179–197.

Hirshleifer, D., Levi, Y., Lourie, B. & Teoh, S. H. 2019. Decision fatigue and heuristic analyst forecasts. *Journal of Financial Economics,* 133, 83–98.

Hong, H. & Kubik, J. D. 2003. Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *The Journal of Finance,* 58, 313–351.

Huang, H. J. & Hung, Y. 2013. Gender differences and behavioral integrity: From a social contract perspective. *Journal of Management & Organization,* 19, 86–100.

Huang, J. & Kisgen, D. J. 2013. Gender and corporate finance: Are male executives overconfident relative to female executives? *Journal of Financial Economics,* 108, 822–839.

Irvine, P. J. 2004. Analysts' forecasts and brokerage-firm trading. *The Accounting Review,* 79, 125–149.

Iskoz, S. 2003. Bias in underwriter analyst recommendations: Does it matter? *SSRN eLibrary*. Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=481442

Jacob, J., Lys, T. Z. & Neale, M. A. 1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics,* 28, 51–82.

Jegadeesh, N., Kim, J., Krische, S. D. & Lee, C. M. 2004. Analyzing the analysts: When do recommendations add value? *The Journal of Finance,* 59, 1083–1124.

Jennings, M. M. 2013. Ethics and Financial Markets: The Role of the Analyst. *SSRN eLibrary*. Available from: https://ssrn.com/abstract=2574744

Jones, D. R. & Makepeace, G. H. 1996. Equal worth, equal opportunities: pay and promotion in an internal labour market. *The Economic Journal,* 106, 401–409.

Kadan, O., Madureira, L., Wang, R. & Zach, T. 2009. Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations. *Review of Financial Studies,* 22, 4189–4217.

Kanter, R. M. 1977. Some effects of proportions on group life: Skewed sex ratios and responses to token women. *American Journal of Sociology,* 82, 965–990.

Ke, B. & Yu, Y. 2006. The effect of issuing biased earnings forecasts on analysts' access to management and survival. *Journal of Accounting Research,* 44, 965–999.

Kennedy, P. 2003. *A guide to Econometrics*. 5th ed. Malden:Blackwell Publishing.

Koch, A. S., Lefanowicz, C. E. & Robinson, J. R. 2013. Regulation FD: A review and synthesis of the academic literature. *Accounting Horizons,* 27, 619–646.

Kolasinski, A. C. & Kothari, S. 2008. Investment banking and analyst objectivity: Evidence from analysts affiliated with mergers and acquisitions advisors. *Journal of Financial and Quantitative Analysis,* 43, 817–842.

Krishnan, G. V. & Parsons, L. M. 2008. Getting to the bottom line: An exploration of gender and earnings quality. *Journal of Business Ethics,* 78, 65–76.

Kumar, A. 2010. Self-selection and the Forecasting Abilities of Female Equity Analysts. *Journal of Accounting Research,* 48, 393–435.

Lacy, W. B., Bokemeier, J. L. & Shepard, J. M. 1983. Job attribute preferences and work commitment of men and women in the United States. *Personnel Psychology,* 36, 315–329.

Larkin, J. M. 2000. The ability of internal auditors to identify ethical dilemmas. *Journal of Business Ethics,* 23, 401–409.

Li, X., Sullivan, R. N., Xu, D. & Gao, G. 2013. Sell-side analysts and gender: A comparison of performance, behavior, and career outcomes. *Financial Analysts Journal,* 69, 83–94.

Lim, T. 2001. Rationality and analysts' forecast bias. *The Journal of Finance,* 56, 369–385.

Lin, H.-W. & McNichols, M. F. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics,* 25, 101–127.

Liu, C. 2018. Are women greener? Corporate gender diversity and environmental violations. *Journal of Corporate Finance,* 52, 118–142.

Ljungqvist, A., Marston, F., Starks, L. T., Wei, K. D. & Yan, H. 2007. Conflicts of interest in sell-side research and the moderating role of institutional investors. *Journal of Financial Economics,* 85, 420–456.

Ljungqvist, A., Marston, F. & Wilhelm, W. J. 2006. Competing for securities underwriting mandates: Banking relationships and analyst recommendations. *The Journal of Finance,* 61, 301–340.

Lourie, B. 2018. The Revolving-Door of Sell-Side Analysts. *The Accounting Review,* 94, 249–270.

Lu, R., Hou, W., Oppenheimer, H. & Zhang, T. 2016. The Integrity of Financial Analysts: Evidence from Asymmetric Responses to Earnings Surprises. *Journal of Business Ethics,* 151, 761–783.

Malinowski, C. & Berger, K. A. 1996. Undergraduate student attitudes about hypothetical marketing dilemmas. *Journal of Business Ethics,* 15, 525–535.

Malloy, C. J. 2005. The geography of equity analysis. *The Journal of Finance,* 60, 719–755.

Malmendier, U. & Shanthikumar, D. 2007. Are small investors naive about incentives? *Journal of Financial Economics,* 85, 457–489.

Mason, E. S. & Mudrack, P. E. 1996. Gender and ethical orientation: A test of gender and occupational socialization theories. *Journal of Business Ethics,* 15, 599–604.

Matsa, D. A. & Miller, A. R. 2013. A female style in corporate leadership? Evidence from quotas. *American Economic Journal: Applied Economics,* 5, 136–169.

Merkley, K., Michaely, R. & Pacelli, J., 2017. Does the scope of the sell-side analyst industry matter? An examination of bias, accuracy, and information content of analyst reports. *The Journal of Finance,*72, 1285–334.

McNichols, M. & O'Brien, P. C. 1997. Self-selection and analyst coverage. *Journal of Accounting Research,* 35, 167–199.

Michaely, R. & Womack, K. L. 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies,* 12, 653–686.

Mikhail, M. B., Walther, B. R. & Willis, R. H. 1997. Do security analysts improve their performance with experience? *Journal of Accounting Research,* 35, 131–157.

Milian, J. A., Smith, A. & Alfonso, E. 2016. Does an Analyst's Access to Information Vary with the Favorableness of Their Language when Speaking to Management? *Accounting Horizons,* 31, 13–31.

Mohan, N. J. & Chen, C. R. 2004. Are IPOs priced differently based upon gender? *The Journal of Behavioral Finance,* 5, 57–65.

Moloney, N. 2014. *EU Securities and Financial Markets Regulation.* 3rd ed. Oxford: Oxford University Press.

Nguyen, N. T., Basuray, M. T., Smith, W. P., Kopka, D. & Mcculloh, D. 2008. Moral issues and gender differences in ethical judgment using Reidenbach and Robin's (1990) multidimensional ethics scale: Implications in teaching of business ethics. *Journal of Business Ethics,* 77, 417–430.

Niederle, M. & Vesterlund, L. 2007. Do women shy away from competition? Do men compete too much? *The Quarterly Journal of Economics,* 122, 1067–1101.

O'Brien, P. C., McNichols, M. F. & Hsiou-Wei, L. 2005. Analyst impartiality and investment banking relationships. *Journal of Accounting Research,* 43, 623–650.

O'Brien, P. C. & Tan, H. 2015. Geographic proximity and analyst coverage decisions: Evidence from IPOs. *Journal of Accounting and Economics,* 59, 41–59.

OICV-IOSCO. 2003. *Report on analyst conflicts of interest.* [Online]. [Accessed 27 January 2020]. Available from: https://www.iosco.org/library/pubdocs/pdf/IOSCOPD152.pdf

Okleshen, M. & Hoyt, R. 1996. A cross cultural comparison of ethical perspectives and decision approaches of business students: United States of America versus New Zealand. *Journal of Business Ethics,* 15, 537–549.

Olsen, R. A. & Cox, C. M. 2001. The influence of gender on the perception and response to investment risk: The case of professional investors. *The Journal of Psychology and Financial Markets,* 2, 29–36.

Olson, C. A. & Becker, B. E. 1983. Sex discrimination in the promotion process. *Industrial & Labor Relations Review,* 36, 624–641.

Palazzo, G. & Rethel, L. 2008. Conflicts of interest in financial intermediation. *Journal of Business Ethics,* 81, 193–207.

Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies,* 22, 435–480.

Randall, D. M. & Fernandes, M. F. 1991. The social desirability response bias in ethics research. *Journal of Business Ethics,* 10, 805–817.

Reingold, D. 2007. *Confessions of a Wall Street Analyst.* New York: Collins

Reiss, M. C. & Mitra, K. 1998. The effects of individual difference factors on the acceptability of ethical and unethical workplace behaviors. *Journal of Business Ethics,* 17, 1581–1593.

Rest, J. R. 1986. Moral development: Advances in research and theory. New York: Praeger

Richards, L. 2002. Analysts Conflicts of Interest: Taking steps to Remove Bias. [Online] [Accessed 27 January 2020] Available from: https://www.sec.gov/news/speech/spch559.htm

Roozen, I., De Pelsmacker, P. & Bostyn, F. 2001. The ethical dimensions of decision processes of employees. *Journal of Business Ethics,* 33, 87–99.

Ross, W. T. & Robertson, D. C. 2003. A typology of situational factors: Impact on salesperson decision-making about ethical issues. *Journal of Business Ethics,* 46, 213–234.

Roxas, M. L. & Stoneback, J. Y. 2004. The importance of gender across cultures in ethical decision-making. *Journal of Business Ethics,* 50, 149–165.

Sapienza, P., Zingales, L. & Maestripieri, D. 2009. Gender differences in financial risk aversion and career choices are affected by testosterone. *Proceedings of the National Academy of Sciences,* 106, 15268–15273.

Schipper, K. 1991. Analysts' forecasts. *Accounting horizons,* 5, 105–121.

Shaukat, A., Qiu, Y. & Trojanowski, G. 2016. Board attributes, corporate social responsibility strategy, and corporate environmental and social performance. *Journal of Business Ethics,* 135, 569–585.

Sheeran, P. & Abraham, C. 2003. Mediator of moderators: Temporal stability of intention and the intention-behavior relation. *Personality and Social Psychology Bulletin,* 29, 205–215.

Sila, V., Gonzalez, A. & Hagendorff, J. 2016. Women on board: Does boardroom gender diversity affect firm risk? *Journal of Corporate Finance,* 36, 26–53.

Singhapakdi, A. 1999. Perceived importance of ethics and ethical decisions in marketing. *Journal of Business Research,* 45, 89–99.

Soltes, E. 2014. Private interaction between firm management and sell-side analysts. *Journal of Accounting Research,* 52, 245–272.

Sonney, F. 2007. Financial analysts' performance: Sector versus country specialization. *The Review of Financial Studies,* 22, 2087–2131.

Srinidhi, B., Gul, F. A. & Tsui, J. 2011. Female directors and earnings quality. *Contemporary Accounting Research,* 28, 1610–1644.

Trueman, B. 1994. Analyst forecasts and herding behavior. *The Review of Financial Studies,* 7, 97–124.

Vermeir, I. & Van Kenhove, P. 2008. Gender differences in double standards. *Journal of Business Ethics,* 81, 281–295.

Weber, J. & Gillespie, J. 1998. Differences in Ethical Beliefs, Intentions, and Behaviors The Role of Beliefs and Intentions in Ethics Research Revisited. *Business and Society,* 37, 447–467.

Wimalasiri, J. S., Pavri, F. & Jalil, A. A. 1996. An empirical study of moral reasoning among managers in Singapore. *Journal of Business Ethics,* 15, 1331–1341.

Winter-Ebmer, R. & Zweimüller, J. 1997. Unequal assignment and unequal promotion in job ladders. *Journal of Labor Economics,* 15, 43–71.

Wu, M., Wilson, M. & Wu, Y. 2015. Was the Global Settlement Effective in Mitigating Systematic Bias in Affiliated Analyst Recommendations? *Journal of Business Ethics,* 146, 485–503.