Three essays on gender differences among financial analysts

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Three Essays on Gender Differences among Financial Analysts

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General Introduction

1.1 Overview and Structure of the Dissertation

Security analysts are prominent figures of stock markets. They interpret public information and collect private information useful in determining the fair price of the stocks they cover. Having long been seen as sophisticated processors of financial information, they are presumed to help investors allocate their resources in a more efficient and rewarding way (Ramnath, Rock, and Shane 2008). Prior literature investigates financial analysts in an extensive way. Researchers seek to identify the financial analysts who manage to produce more accurate forecasts (Clement 1999; Jacob, Lys, and Neale 1999; Kini et al. 2009) and influential recommendations (Michaely and Womack 1999; Bradley, Jordan, and Ritter 2008; Sorescu and Subrahmanyam 2006; Loh and Stulz 2011) than their peers. They find that heterogeneity in analysts' performance is partly determined by factors such as analysts' forecasting ability, availability of corporate information and portfolio complexity.

Gender issues, however, have not been fully investigated in the context of financial analysts, due to data limitation. Prior literature on gender issues of financial analysts essentially underlines the under-representation of female analysts and some gender-based difference in analysts' behavioral patterns. Green, Jegadeesh, and Tang (2009) find that earnings forecasts issued by female analysts are less accurate than those of male analysts. However, contrary to the findings of Green, Jegadeesh, and Tang (2009), Kumar (2010) shows that female analysts have a superior forecasting ability. They issue bolder and more accurate earnings forecasts than their male counterparts. Kumar (2010) further provides evidence for investors' perception about forecasts issued by female analysts: abnormal stock returns are stronger for bold earnings forecasts of female analysts. Instead of investigating gender heterogeneity in earnings forecast, Li et al. (2013) focus on recommendations revisions and find that abnormal stock returns associated with stock recommendations of female analysts are similar to those associated with male analysts' recommendations, but with lower idiosyncratic risks. Consistent with Green, Jegadeesh, and Tang (2009), they find that female analysts are more likely to be designated as “All-stars" analysts by Institutional Investor magazine, which confirms job performance of female analysts. Furthermore, stock recommendations of female analysts are less likely to be optimistic, all other things equal (Bosquet, Goeij, and

Smedts 2014). In a recent work, Fang and Huang (2017) extend the gender observation of financial analysts to analysts' connections with corporate boardroom and document a gender-based difference in exploring alumni ties with corporate boards. Analysts' private connection with corporate managers improves analysts' forecast accuracy and recommendation informativeness. However, such an effect is two to three times larger for male analysts than for female analysts.

In light of prior research, my PhD dissertation aims to investigate gender issues relating to financial analysts in the context of European countries. It consists of three studies. The first study investigates the impact of culture on female representation among financial analysts. The second study analyzes gender heterogeneity in issuing innovative stock recommendations. The third study focuses on gender difference in market reactions to innovative stock recommendations. The titles of three papers are presented as follows:

- “The Influence of National Culture on Cross-country Gender Diversity in the European Financial Analyst Industry"
- “Innovation in Financial Analysts' Recommendations: Does Gender Matter?"
- “Analyst Overconfidence and Market Reactions to Innovative Recommendations"

In a first essay, I investigate the relation between national culture and female representation among financial analysts. National culture is characterized by the Hofstede (2001)'s cultural subregions and cultural dimensions. The study first explores the female representation of financial analysts in European countries. Further, it investigates the explanatory power of national culture in explaining the cross-country variation of female representation among financial analysts.

The second essay investigates innovation in analyst's recommendations. Innovative recommendations are important to investors because they are often more informative than less innovative recommendations. The study aims to explore whether there are gender differences in issuing innovative stock recommendations. My conjecture is that female analysts' lower overconfidence (superior ability) leads to less (more) innovative stock recommendations.

The third essay deals with market reactions to innovative recommendations. I investigate whether there is gender difference in abnormal stock returns and abnormal trading volumes associated with innovative recommendations. The primary hypothesis is that investors discount more innovative recommendations of male analysts than those of female analysts due to men's systematically higher overconfidence.

The three essays use quantitative research methods and merge data from different sources. Both commonly available databases and hand-collected data are used to address the research questions discussed in the three studies. This dissertation makes several contributions given the existing research gap in gender issues of financial analysts.

The first study contributes to the literature by shedding light on female representation of financial analysts in Europe and providing evidence of strong variation across countries. By documenting women representation in the financial analyst industry, my research findings complement the growing body of research in finance that addresses the gender issue in different areas such as corporate boardroom directors (Burgess and Tharenou 2002; Farrell and Hersch 2005; Adams and Ferreira 2009). Furthermore, This study also complements the research relating to the economic relevance of culture. The analysis of the impact of national culture on gender diversity among financial analysts adds to prior literature by introducing national culture as an important country-level factor in financial research in an international setting.

The second study contributes to the literature by shedding light on the mechanism behind analysts' innovation in recommendation revisions. My empirical evidence shows that male analysts are more innovative than their female counterparts. This contributes to the gender literature by confirming that women have different behavioral patterns than men in the world of financial analysts. Further, regarding the financial analyst literature, the higher level of innovation in male analysts' recommendations evidenced in this study leads to consider that innovative stock recommendations are more likely to be driven by overconfidence than by forecasting skills. Indeed, prior literature provides evidence suggesting that men are systematically more overconfident than women and that female analysts exhibit superior forecasting ability than their male counterparts.

The last study proposes an analysis of market reactions to innovative recommendations. The main contributions of the third essay to prior literature are threefold. First, it complements prior literature with empirical evidence for the relationship between innovation in recommendation revisions and recommendations' informativeness, by showing that innovative recommendations are more informative than non-innovative recommendations. Second, this study relates to literature on gender-based difference among financial analysts. In line with the findings of Li et al. (2013), it rejects the gender heterogeneity in market reactions to stock recommendations, regardless of recommendations' innovation level. Third, this study contributes to prior research on the impact of overconfidence on innovation in financial market settings. It analyzes investors' perception about innovative recommendations issued by overconfident male analysts, which is an extension of prior studies relating to market reactions to corporate financial decisions of overconfident CEOs (Malmendier and Tate 2008; Huang and Kisgen 2013).

The remaining of this introductory chapter presents the theoretical background of my research in Section 2. I discuss the research motivations of this dissertation in Section 3. In Section 4, I provide a more detailed summaries of the three papers.

Subsequently, the three papers are presented as individual chapters. A final chapter of this dissertation summarizes the main findings, provides a discussion of the limitations of the research and suggests directions of future research.

1.2 Theoretical Background

Traditional finance assumes that individuals are rational. According to the efficient market hypothesis, financial markets are efficient and stock prices immediately incorporate all available information on firm's value (Malkiel and Fama 1970). Market participants are sophisticated and trade only on available information. However, researchers observe numerous anomalies that sharply violate the efficient market theory. In light of the findings in psychology and sociology, behavioral finance, "that is, finance from a broader social science perspective including psychology and sociology", seeks to address some financial phenomena that cannot be understood using the rational expectations advocated by traditional financial theory (Shiller 2003). The theoretical background of this dissertation relates essentially to the implication of culture and gender difference in behavioral finance studies.

Culture is often defined as the collective mental programming that leads to patterned ways of thinking, feeling and acting. National culture influences economic activities both by conditioning formal institutions and by shaping human actors' incentives and subjective perceptions of the external world (Zheng et al. 2012). The cultural dimensions defined by Hofstede (2001) characterize the patterns of national cultures and features prominently in business studies dedicated to the impact of culture on financial activities. The Hofstede classification is based on five cultural dimensions: power distance, individualism *vs* collectivism, masculinity *vs* femininity, uncertainty avoidance and long-term *vs* short-term orientation. Based on these five dimensions, prior literature provides evidence on the economic relevance of national cultures on diverse issues related to accounting and finance decisions (Kanagaretnam, Lim, and Lobo 2011; Han et al. 2010; Shao, Kwok, and Zhang 2013).

Apart from the implication of culture, an emerging literature is dedicated to the role of gender in financial market decisions. Research in psychology finds evidence of gender difference in individual's personal dispositions. Women are more risk-averse and less efficient in competitive environments than men. They also attach more importance to ethic values. In addition, men are systematically more overconfident than women, overconfidence being a behavioral bias that causes individuals to overestimate their knowledge or ability to perform well under uncertainty. Such dispositional differences originated from gender impel individuals to have specific behavioral patterns when they are involved in social activities. Analyses of the common stock investment strategies for men and women, for example, suggest that overconfident men are more engaged in excessive stock trading than women (Barber and Odean 2001). Nonetheless, empirical evidence also suggests that gender stereotypes cannot be applied to a professional environment due to a self-selection process in the entry of labor market. Gender difference in personal dispositions, for instance overconfidence, may disappear when women choose to pursue a career, especially in a male-dominated industry (Kumar 2010).

In this dissertation, I investigate gender issues among financial analysts in light of prior literature on the impact of culture and gender on financial activities.

1.3 Research Motivations

This dissertation is motivated by the current research gap in gender issues of financial analysts. Prior studies dedicated to gender issues mainly cluster in the business field: the presence of women figures in the boardroom (Adams and Ferreira 2009; Krishnan and Parsons 2008; Campbell and Mínguez-Vera 2008), performance of female loan managers (Beck, Behr, and Guettler 2013), audit fees for female auditors (Ittonen and Peni 2012). The current lack of systematic investigation on women financial analysts leaves a research gap to fulfill, especially for countries outside the U.S.

1.3.1 Culture & Female Representation among Financial Analysts

Greater interests should be paid to the European countries. A high-level of standardization has been achieved in institutional settings since the foundation of the European Union in 1993, but a wide variety persists in cultural and social dimension. This is why I gave priority to descriptive statistics on the presence of female financial analysts (the percentage of women financial analysts, percentage of financial institutions having one or more women financial analysts etc) to check whether female analysts' representation was the same in all European countries under study. In the United States, women are constantly underrepresented in the world of financial analysts. Roughly 15% of all American analysts are female (Kumar 2010; Green, Jegadeesh, and Tang 2009). Female representation of financial analysts outside the United States remains unexplored. I, therefore, provide in this dissertation statistics for European female analysts and investigate the impact of culture on female representation of financial analysts. The analysis of the impact of cultural values on female representation in the European financial industry is motivated by prior literature on the economic relevance of national culture. Kanagaretnam, Lim, and Lobo (2011) indicate that cultures that encourage higher risk-taking experienced more bank troubles in the form of larger losses or larger loan loss provisions. Han et al. (2010) find that uncertainty avoidance and individualism explain managers' earnings discretion across countries. Shao, Kwok, and Zhang (2013) show that firms in individualistic countries invest more in long-term (risky) than in short-term (safe) assets.

1.3.2 Gender & Innovation in Stock Recommendations

This dissertation focuses on gender-based differences in analysts' recommendations, more specifically in innovative recommendations. The reason to distinguish innovative recommendations from less innovative recommendations in the study of gender difference among financial analysts is threefold.

First, analysts' recommendation revisions are not all equally useful to investors (Loh and Stulz 2011). The cross-sectional difference in recommendations' informativenss emanates partially from the innovation level of recommendations. Gleason and Lee (2003) find that highly innovative earnings forecasts, *i.e.*, forecasts away from the analysts' consensus and forecasts that significantly diverge from the analyst's own prior estimate for the same stock, trigger larger market reactions. Prior research has not studied innovation in recommendations as comprehensively as innovation in forecasts. Nonetheless, prior empirical findings still confirm that recommendations with the same characteristics as innovative forecasts are more informative to the markets. For example, research relating to the informativeness of recommendation revisions finds that abnormal price returns increase with the distance of stock recommendation to the analysts' consensus (Jegadeesh and Kim 2006) and the change strength in recommendation relative to the analyst's prior revision for the same stock (Sorescu and Subrahmanyam 2006).

Second, innovation is closely associated with one personal attribute: overconfidence, for which there is a well-documented gender difference. Men are expected to be more engaged in innovation than women because of their relatively higher overconfidence. Overconfident individuals tend to under-estimate the probability of failure under uncertainty and, therefore, are more likely to undertake innovative projects. Literature clearly shows that overconfident CEOs are more likely to pursue patent-based innovation (Galasso and Simcoe 2011). The existing gender difference in overconfidence suggests a potential gender difference in the level of innovation in recommendation that is worth being investigated.

Third, conditionning gender effect on innovation in recommendations allows to determine whether innovation resulting from overconfidence is discounted by investors. Prior literature documents that overconfidence is associated with higher propensity to innovate but provides no evidence for whether innovation motivated by overconfidence is rational. Investors are found to be more suspicious about mergers and acquisitions undertaken by overconfident CEOs (Malmendier and Tate 2008; Huang and Kisgen 2013) because they systematically over-estimate their ability and are over-optimistic about the outcome of undertaken M&A. Market reactions at M&A announcements are significantly more negative for overconfident CEOs, suggesting that investors discount projects undertaken by overconfident agents in corporate financial decisions. If the same story holds for analysts, innovation in recommendations of overconfident analysts, *i.e.* male analysts, should be discounted by investors.

The above-mentioned motivations lead me to study gender-based difference among financial analyst by targeting innovation in recommendation more specifically.

Overall, in the next three chapters of the dissertation, I answer the following three research questions:

- Does national culture affect female representation among financial analysts?
- Do female financial analysts issue more or less innovative recommendations compared to their male counterparts?
- Do investors discount innovative recommendations issued by male analysts, due to their relatively higher overconfidence?

1.4 Overview of the Three Empirical Research

In this section I summarize the three empirical studies that compose this PhD dissertation.

1.4.1 First Research

The first study is entitled “The Influence of National Culture on Cross-country Gender Diversity in the European Financial Analyst Industry". In this study, I investigate the impact of culture on female representation among financial analysts. This study uses European recommendation data from *I/B/E/S* to examine the extent to which financial analysts' gender diversity in Europe is affected by the national culture that characterizes each European country. I choose the Hofstede (2001)'s cultural sub-regions and cultural dimensions as a proxy for national cultural because of its dominating position in most cultural frames applied to accounting and finance research.

Consistent with prior research in the United States (Green, Jegadeesh, and Tang 2009; Kumar 2010), I document an under-representation of female financial analysts for European countries. Women account for 16.15% of financial analysts in Europe during the period under study with significant country-level variations. Female financial analysts represent 40% of all financial analysts in Italy, however, in Denmark only 4.17% of them are female. Furthermore, though female analysts are broadly distributed in all economic sectors, I find that they are more inclined to work in specific industries such as "Apparel" and "Restaurant", while keeping distance from "Rubber and Plastic Products" and "Electrical Equipment" market segments. Differences in female representation are also remarkable among the different cultural sub-regions identified by (Hofstede 2001). Descriptive statistics show that Anglo countries, *i.e.* Ireland and United Kingdom, enjoy the highest proportion of female financial analysts. Meanwhile, the highest proportion of recommendations issued by females are found among Latin countries, *i.e.* Belgium, France, Italy, Portugal and Spain. In Nordic countries, *i.e.* Denmark, Finland, Netherlands, Norway and Sweden, the proportion of female analysts and the proportion of recommendations issued by female analysts are significantly lower than in Anglo and Latin countries.

Further, regression models at country level and at analyst level respectively have been conducted to investigate the impact of national culture on female representation among financial analysts. The incremental influence of national culture, proxied by the Hofstede cultural sub-regions and cultural dimensions successively, persists when I control for variables that are likely to be related to gender diversity, such as analysts' workload, the density of analysts' influential stock recommendations, financial market size, *etc*. The multivariate analyses suggest that Nordic countries have, all things equal, the lowest female representation among financial analysts relative to countries in other cultural sub-regions. Furthermore, additional regression results using cultural dimensions rather than cultural sub-regions show that female representation is higher in countries where people have more acceptance for unequal distribution of power. This finding is consistent with the lower female representation observed in Nordic countries, countries that have lower tolerance about unequal power distribution (Hofstede 2001).

1.4.2 Second Research

The second essay is entitled "Innovation in Financial Analysts' Recommendations: Does Gender Matter?". This essay analyzes gender difference in innovation of recommendation revisions. Based on previous literature on gender difference showing that men are more overconfident than women and male analysts less skill than female analysts, my primary hypotheses are that female financial analysts issue less (more) innovative stock recommendations due to lower overconfidence (superior forecasting ability). To test my hypotheses, I examine the innovation level in stock recommendations issued by female and male analysts by creating an innovation index.

Investment recommendations are usually reported along with the last revision date, the recent analyst consensus and analyst's own prior recommendation on the same stock. Therefore, divergence from analyst consensus, revision from prior recommendation, and recommendation timing are three benchmarks that I use to determine innovation in stock recommendations. I refer stock recommendations that diverge from the analyst consensus, that are much revised relative to the analyst's own prior recommendation and that are ahead in time of other recommendations, as innovative recommendations. Using these three criteria, I define an innovation index for recommendation revisions. Based on this index, a recommendation is innovative if it falls in the first quartile of at least two out of the three above-mentioned criteria sorted by descending order.

My final sample contains $89,312$ recommendations issued by European analysts from 2006 to 2013. According to the innovation index, innovative recommendations represent about 16.6% of stock recommendations issued during the sample period. The statistics at analyst level suggest that female analysts are less likely to issue innovative recommendations, compared to male analysts. More precisely, I find that female analysts issue stock recommendations that diverge less from their prior investment advice and from the analyst consensus. Stock recommendations issued by women also are less ahead in time. Empirical results from multivariate tests confirm that gender heterogeneity in analysts' recommendations cannot be attributed to differences in analysts' characteristics and covered stocks' characteristics.

I conclude from these findings that overconfidence exerts larger marginal effect on equity analyst decision of issuing innovative stock recommendations than forecasting ability, which leads to higher (lower) innovative recommendation issued by overconfident male (skillful female) analysts.

1.4.3 Third Research

The third essay is entitled "Analyst Overconfidence and Market Reactions to Innovative Recommendations". This study analyzes gender difference in market reactions to innovative recommendations. Overconfidence leads to more engagement in innovation because overconfident individuals under-estimate the probability of failure. Empirical evidences for corporate financial decisions suggest that investors are skeptic about projects undertaken by male CEOs, due to their relative overconfidence (Huang and Kisgen 2013; Malmendier and Tate 2008). I posit that investors should discount innovative recommendations issued by male analysts, compared to innovative recommendations issued by female analysts.

Using a comprehensive sample of sell-side analyst investment recommendations, I find that abnormal stock returns around innovative recommendations are significantly higher, holding other factors constant. This finding is consistent with prior literature that shows that innovative outputs of financial analysts are more informative to investors (Gleason and Lee 2003). Further, I investigate the potential gender difference in market reactions to innovative recommendations. I consider a battery of analyst, recommendation, and firm variables. The multivariate results show that investors do not discount the innovative recommendations issued by overconfident male analysts. The cumulative abnormal returns associated with innovative recommendations of female analysts are similar to those of male analysts, suggesting that male analysts are not unduly overconfident to the detriment of investors who follow their stock recommendations. I find similar results for abnormal trading volume around recommendation dates.

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Chapter 2

The Influence of National Culture on Cross-country Gender Diversity in the European Financial Analyst Industry

Abstract: I explore the relation between national culture and female representation among financial analysts. National culture is characterized by the Hofstede (2001)'s cultural sub-regions and cultural dimensions. The main analyses, based on a sample of 3579 financial analysts from 2006 to 2013 for 28 European countries, indicate that women only account for 16.15% of financial analysts with strong cross-country variations. The proportion of female analysts ranges from 4% in Denmark as the lowest to 40% in Italy as the highest. With regard to the Hofstede's cultural sub-regions, multivariate tests show that Nordic and Germanic countries have the lowest proportion of female analysts. In contrast, Latin countries exhibit the highest proportion of female analysts. Further, the exploratory analyses of the effects of national culture on analyst gender diversity indicate that cultures with more tolerance toward unequal power distribution experience higher female representation among financial analysts.

Keywords: financial analysts, gender, Europe, national culture

2.1 Introduction

Financial analysts are important intermediaries in financial markets, because of their efforts to information dissemination and their expertise in investment decision. However, gender issues are barely discussed in the context of financial analysts. Studies dedicated to gender issues mainly cluster in the business field: the presence of women figures in the boardroom (Adams and Ferreira 2009; Krishnan and Parsons 2008; Campbell and Mínguez-Vera 2008), performance of female loan managers (Beck, Behr, and Guettler 2013), audit fees for female auditors (Ittonen and Peni 2012). The studies of Kumar (2010) and Green, Jegadeesh, and Tang (2009) are, nonetheless, two remarkable exceptions. Using a sample from the United States, they show that women are constantly underrepresented in the world of financial analysts and that female analysts issue bolder and more influential recommendations than their male counterparts. Taking advantage of the cultural diversity that characterizes European countries, I extend these studies by investigating the role of national culture in explaining cross-country differences in gender diversity among financial analysts.

The analysis of the influence of national culture is motivated mainly by Aggarwal and Goodell (2014), who emphasize the economic relevance of national culture and summarize the sparse use of cultural dimensions in accounting and finance. Extant arguments in the literature suggest that national culture, which is very stable over time, is an important factor influencing financial activities as it shapes both the institutional environment within a country and the way human actors react to the institutions around them.

This study uses European recommendation data from *I/B/E/S* to examine the extent to which financial analysts' gender diversity in Europe is affected by the national culture that characterizes each European country. I choose the Hofstede (2001)'s cultural sub-regions and cultural dimensions as a proxy for national culture because of its dominating position in most cultural frames applied to accounting and finance research.

The research sample consists of 125 908 recommendations issued by 3 579 European analysts over the 2006-2013 period. Consistent with prior research in the United States (Green, Jegadeesh, and Tang 2009; Kumar 2010), I document an under-representation of female financial analysts for European countries. Women account for 16.15% of financial analysts in Europe during the period under study with significant country-level variations. Female financial analysts represent 40% of all financial analysts in Italy, however, in Denmark only 4.17% of them are female. Furthermore, though female analysts are broadly distributed in all economic sectors, I find that they are more inclined to work in specific industries such as “Apparel" and “Restaurant", while keeping distance from “Rubber and Plastic Products" and “Electrical Equipment" market segments. Differences in female representation are also remarkable among the different cultural sub-regions identified by Hofstede (2001). Descriptive statistics show that Anglo countries, *i.e.* Ireland and United Kingdom, enjoy the highest proportion of female financial analysts. Meanwhile, the highest proportion of recommendations issued by females are found among Latin countries, *i.e.* Belgium, France, Italy, Portugal and Spain. In Nordic countries, *i.e.* Denmark, Finland, Netherlands, Norway and Sweden, the proportion of female analysts and the proportion of recommendations issued by female analysts are significantly lower than in Anglo and Latin countries.

Further, regression models at country level and at analyst level respectively have been conducted to investigate the impact of national culture on female representation among financial analysts. The incremental influence of national culture, proxied by the Hofstede cultural sub-regions and cultural dimensions successively, persists when I control for variables that are likely to be related to gender diversity, such as analysts' workload, the density of analysts' influential stock recommendations, financial market size, *etc*. The multivariate analyses suggest that Nordic countries have, all things equal, the lowest female representation among financial analysts relative to countries in other cultural sub-regions. Furthermore, additional regression results using cultural dimensions rather than cultural sub-regions show that female representation is higher in countries where people have more acceptance for unequal distribution of power. This finding is consistent with the lower female representation observed in Nordic countries, countries that have lower tolerance about unequal power distribution (Hofstede 2001).

By shedding light on gender observations for financial analysts working in Europe, I expand the existing literature about gender concerns in the business area into the world of financial analysts in countries other than the United States. My research findings contribute to the growing body of research in finance that addresses the gender issue in different areas such as corporate boardroom directors (Burgess and Tharenou 2002; Farrell and Hersch 2005; Adams and Ferreira 2009). Furthermore, I also complement the research about female financial analysts by focusing on European countries and their cultural specific features. The analysis of the impact of national culture on gender diversity adds to the culture and business literatures by introducing national culture as an important country-level factor in financial research in an international setting.

The remainder of the paper is organized as follows: Section 2 reviews the existing literature about gender issues and the implication of national culture in the finance field. The data and research methodology are discussed in Section 3. Section 4 provides descriptive statistics for female European financial analysts at both country and industry levels. Section 5 displays the main results about the impacts of national culture on gender diversity in the European financial analysis industry. The final section contains conclusions and discussions.

2.2 Prior Literature

Only a few studies examine gender concerns among financial analysts. Notable exceptions are Green, Jegadeesh, and Tang (2009), Kumar (2010), Li et al. (2013), and Bosquet, Goeij, and Smedts (2014) which investigate the gender difference among financial analysts in the U.S. context. Our main research question aims to determine whether and how national culture influences gender diversity among financial analysts in an international setting. In this section I present a synthesis of the extant literature on the influence of national culture on finance and accounting systems.

Hofstede (2001) defines culture as the collective mental programming that leads to patterned ways of thinking, feeling and acting and that "distinguishes the members of one category of people from those of another". National culture influences economic activities both by conditioning formal institutions and by shaping human actors' incentives and subjective perceptions of the external world (Zheng et al. 2012). In addition, national culture also shapes the way human actors react to the institutions that are in place or are being shaped around them (Aggarwal and Goodell 2014). The economic relevance of national culture has been highlighted by researchers in business and corporate management. In the field of accounting and finance, several studies investigate the role and impacts of cultural dimensions, given that national cultural dimensions can provide additional perspectives on financial and accounting research concerns (Aggarwal and Goodell 2014).

Hofstede (2001) defines five key dimensions to characterize national culture, namely power distance, uncertainty avoidance, individualism *v.s.* collectivism, masculinity *v.s.* femininity, and long-term *v.s.* short-term orientation. These dimensions capture different attributes of national culture. Each of these cultural dimensions is defined extensively in Appendix A. Power distance refers to the extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally. Uncertainty avoidance pertains to the stress perceived by people who are in uncertain or unknown situation. Individualism/Collectivism refers to the patterns of inter-personal links shared by the members of a society. Masculinity/Femininity refers to the extent to which the emotional gender roles are distinct. Long-term/Short-term orientation stands for the preference of fostering virtues oriented towards future or towards past. Long-term/short-term orientation accounts mainly for the difference between oriental and occidental countries. Asian countries have the highest scores for long-term orientation.

Using these cultural dimensions, Hofstede (2001) divides nations into sub-regions based on similarities in national cultural profiles. He defines five country clusters in Europe labeled Anglo, Germanic, Latin, Near Eastern and Nordic. *Anglo* includes Ireland, United Kingdom; *Germanic* refers to Austria, Germany, and Switzerland; *Latin* stands for Belgium, France, Italy, Portugal, and Spain; *Near Eastern* includes Greece; *Nordic* represents Denmark, Finland, Netherlands, Norway, and Sweden. Nordic countries tend to have a lower power distance than other countries. Anglo and Nordic nations have a stronger attachment to individualism. Latin countries express a greater intolerance towards changes and uncertainty. Nordic countries have the most feminist cultures.

Recent studies provide evidence on the impact of national cultural on diverse issues in the accounting and finance field. Kanagaretnam, Lim, and Lobo (2011) indicate that cultures that encourage higher risk-taking experienced more bank troubles in the form of larger losses or larger loan loss provisions. Han et al. (2010) find that uncertainty avoidance and individualism explain managers' earnings discretion across countries. Shao, Kwok, and Zhang (2013) show that firms in individualistic countries invest more in long-term (risky) than in short-term (safe) assets. In this paper, I investigate whether national culture can explain the cross-country variation in female representation among financial analysts.

2.3 Data and Research Design

This study is based on recommendations issued by European analysts, *i.e.* analysts located in the 28 European countries under study; namely, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom. Countries outside the European Union, such as Switzerland, Norway and Russia, have been included in the research sample because, first, they belong to the same economic region, second, their inclusion in the sample increases the cultural variety at country level.

Analysts' stock recommendations are collected from the *I/B/E/S* database of *Thomson Financial*. Useful data are composed of 1) the International Securities Identification Number (hereafter, *ISIN*) code of targeted firms, 2) the date when the recommendations were issued (Recommendation date), 3) the level of recommendations[1], 4) the identification code of the analyst who issued the stock recommendation and 5) the identification code of the broker for which the analyst works.

The data cover a eight-year period from January 2006 to December 2013. The beginning of the sample period is coincident with the date when the European Union countries finished transposing the Market Abuse Directive (generally referred to as *MAD*) into their local legislation (Dubois, Fresard, and Dumontier 2014). The Market Abuse Directive (Directive 2003/6/EC), hereafter MAD, adopted in 2003 by the European Commission to curb insider dealing and market manipulation states that

[1] A five-level recommendation scale is adopted by *I/B/E/S*: namely, Strong Buy, Buy, Hold, Underperform, and Sell.

> "The identity of the producer of investment recommendations, his conduct of business rules and the identity of his competent authority should be disclosed, since it may be a valuable piece of information for investors to consider in relation to their investment decisions."

Since the implementation of MAD, analysts are therefore required to disclose their identification, *i.e.* first name and last name, when publishing their reports, which makes our study feasible.

Since *I/B/E/S* does not provide information about the analyst's gender, gender is identified by the analyst's first name. However the *I/B/E/S* database only provides a brief identity code for each analyst, which is composed of the analyst's last name and the initial letter of his/her first name. For example, an analyst named "Joe Black" is coded as "J Black" in the *I/B/E/S* database. Thus, complementary information about analysts' complete first name and their workplace (at the country level) is obtained from the official website of *Thomson One*[2]. *Thomson One* provides more detailed and thorougher information about analysts from whom it collects financial data. Analyst first name, last name, employer, workplace, contact coordinates can all be found in the website. After merging the recommendation data from *I/B/E/S* with data about analyst identities, I determine the gender of each analyst in the database using a list of 22,345 unique first names[3]. Thus according to the outcome of gender identification, analysts are separated into three categories: male, female and undefined. Some analyst's gender is undefinable due to the following facts: 1) unisex first name, some first names, such as "Alex", could be used as a first name for both male and female; 2) duplicate last name and first initial, there are more than one analyst identification that could be matched with an analyst identity code, for example, "Julia Smith" and "John Smith" could both be abbreviated as "J Smith"; or 3) undisclosed analyst code: some analyst identity codes are deliberately veiled by the data provider and thus turn out to be "Undisclosed" during the data collection.

The final sample consists of 3 579 analysts from 28 European countries. They have issued

[2] www.thomsonone.com

[3] The data mainly come from in the following sites: www.behindthename.com/, www.babynameindex.com/, en.wikipedia.org/wiki/Category:Masculine_given_names, and en.wikipedia.org/wiki/Category:Feminine_given_names

a total of 125 908 recommendations for 10 676 companies around the world over the eight-year period under study (2006-2013).

Following prior research on the economic relevance of national culture, I use two approaches to investigate how national culture affects gender observation among financial analysts in European countries. First, I test whether the percentages of female financial analysts per country are different across different cultural sub-regions defined by Hofstede (2001). Second, I test whether national culture affect female representation at both the analyst level and recommendation level. To investigate whether the proportion of female analysts differs across cultural sub-regions, I estimate the following model at country level:

$$\begin{aligned} GenderObservation_{i,t} = \alpha_0 + \sum_{i=1}^{5} \beta_i SubRegions_i + \alpha_2 dFemaleInf_i \\ + \alpha_3 (\frac{Rec}{Firm})_{i,t} + \alpha_4 InfluRec_{i,t} + \alpha_5 FemaleInflu_{i,t} \\ + \alpha_6 (\frac{MarketCap}{GDP})_{i,t} + \alpha_7 IndustryM_{i,t} + \alpha_8 IndustryF_{i,t} \\ + \alpha_9 UndfAnalyst + \alpha_{10} LocalBroker_{i,t} \\ + \text{Year Fixed Effects} + \varepsilon_{i,t} \end{aligned} \tag{2.1}$$

Dependent variable: The measurement for gender diversity is successively the proportion of female analysts in a given country *i* for year *t* ($FemAnalyst\%_{i,t}$) and the proportion of recommendations issued by female analysts in a given country *i* for year *t* ($FemRec\%_{i,t}$).

Independent variables of interest: I identify sources of differences in gender observations among financial analysts across European countries that are related to national culture. They are captured by the five cultural sub-regions of Hofstede (2001), *i.e.*, *Anglo*, *Germanic*, *Latin*, *Near Eastern*, *Nordic*. *Anglo* includes Ireland, United Kingdom; *Germanic* refers to Austria, Germany, and Switzerland; *Latin* stands for Belgium, France, Italy, Portugal, and Spain; *Near Eastern* includes Greece; *Nordic* represents Denmark, Finland, Netherlands, Norway, and Sweden. I create a dummy for each of the five subregions. The dummy variable *Anglo* is set to one for a country labelled as anglo countries, *idem* for dummy variables of other cultural sub-regions.

Independent control variables: Gender diversity in the financial analysis industry may also be affected by factors other than national cultures. Hereafter are discussed three factors that are considered to be influential to female representations among financial analysts, namely, the importance of capital markets, the importance of financial analysts, and the industrial preferences of financial analysts.

First, the activity of financial analysts is closely linked to stock markets. Therefore, the size of capital markets may affect the demand for financial analysis. The proxy used for the importance of capital markets, $MarketCap/GDP_{i,t}$, is calculated as the ratio of total market capitalization of all listed firms over GDP for country i in year t.

Besides, the characteristics of the financial analysis industry in a given country may also affect the gender diversity among financial analysts in this country. The importance of financial analysts in the financial market is measured by two proxies. First, I assume that the usefulness and therefore importance of financial analysts increases with the number of recommendations they issue. The quantity of recommendations issued by financial analysts, $Rec/Firm_{i,t}$, is the number of recommendations issued by analysts in country i divided by the number of listed firms in country i during year t. Next, I assume that the usefulness of analysts depends on how influential to stock markets they are. The quality of recommendations is used to capture the analysts' importance. $InfluRec_{i,t}$ measures the percentage of influential recommendations issued by financial analysts of country i in year t. $femaleInflui,t$ measures the percentage of influential recommendations issued by female analysts of country i in year t. Following Loh and Stulz (2011), I use a standard event-study methodology to identify influential recommendations. Daily stock prices are collected from *Thomson One*. The event window includes the day an analyst issues a recommendation, as reported by *I/B/E/S*, and the day that follows. A recommendation is classified as influential if it triggers a two-day cumulative abnormal return (CAR) in the event window that is in the correct direction of recommendation change, and statistically significant. Following the existing literature, I define $CAR_i = \prod_{t=-1}^{0}(1+AR_{it})-1$, where AR_{it} is the daily abnormal return estimated by the market model. The estimation period for the market model parameters covers the three months prior to the recommendation announcement date. I check whether the CAR accords with the direction of the associated recommendation change, *i.e.* a positive (negative) CAR is associated with an upgrade (downgrade) in recommendation levels. I also check whether the CAR is statistically significant. According to the central limit theorem, the mean value of a random sample follows the normal distribution $N \sim (\mu, \sigma/\sqrt{n})$, where μ is the population mean, σ is the population standard deviation and n is the number of observations in the random sample. Therefore, the mean abnormal returns in the two-day time window around the recommendation date, $\overline{AR}$, follows the normal distribution with μ that equals the population mean of daily abnormal returns and σ that equals the standard deviation of daily abnormal returns. I use the idiosyncratic volatility, σ_ε, to calculate the standard deviation of daily abnormal return. This is the standard deviation of the residuals from a daily time-series regression of firm returns against market returns for the estimation period. The critical value at the 0.95 confidence level is 1.96 for the standard normal distribution. Under the null hypothesis that $\mu = 0$, the hypothesis is rejected at the 0.95 confidence level if

$$|\overline{AR}| > 1.96 \times \sigma_\varepsilon \div \sqrt{2}$$

The $\sqrt{2}$ accounts for the fact that $\overline{AR}$ is a two-day mean abnormal return. Therefore, the two-day CAR is statistically significant if

$$|CAR| > 1.96 \times \sigma_\varepsilon \div \sqrt{2} \times 2$$

which can be simplified as follows,

$$|CAR| > 1.96 \times \sigma_\varepsilon \times \sqrt{2}$$

The industrial preferences of financial analysts affect their choice of covered firms. Constrained by information availability, financial analysts tend to cover firms that share certain commonalities. Thus they tend to be sector specialized (Kini et al. 2009; Salva and Sonney 2010). Kumar (2010) suggests that female analysts concentrate in certain industries while keeping distance from others. Thus, countries with more industries favored by female analysts should exhibit a higher female representation among financial analysts. The proxy $IndustryF_{i,t}$ measures the percentage of firms in the five industries where female representation in financial analysts is the highest for country i in year t. $IndustryM_{i,t}$ refers to the percentage of firms in the five industries where male representation in financial analysts is the highest for country i in year t.

I control for year fixed effects and for the percentage of undefined analysts, $UndAnalyst_{i,t}$, which refers to the percentage of analysts whose gender cannot be determined for country i in year t. I also control for the internationalization of brokerage houses. $LocalBroker_{i,t}$ refers to the percentage of recommendations issued by analysts working in a local brokerage house in country i and year t. I exclude observations for countries with less than 1% of the financial analysts in the sample.

To test whether national culture affect female representation among financial analysts at individual level and recommendation level respectively, I use the following probit model:

$$\begin{aligned} Female_i/FemRec_i = \gamma_0 + \sum_{i=1}^{5} \delta_i SubRegion_i + \gamma_2 NbRec_{i,t} \\ + \gamma_3(BrokerSize)_{i,t} + \gamma_4 NbFirmFol_{i,t} \\ + \gamma_5(\frac{MarketCap}{GDP})_{i,t} + \gamma_6 NbCountry_{i,t} + \gamma_7 InflCARp_{i,t} \\ + \gamma_8 AnalystExpG_{i,t} + \text{Year Fixed Effects} + \varepsilon_{i,t} \end{aligned} \tag{2.2}$$

where the dependent variable is either *Female* or *FemRec*. *Female* is a dummy variable equal to one if an analyst is identified to be female, zero otherwise. *FemRec* is a dummy variable equal to one if a stock recommendation is issued by a female analyst, zero otherwise. The variables of interests are the five dummy variables characterizing the cultural sub-regions, *i.e.*, *Anglo*, *Germanic*, *Latin*, *Near Eastern*, and *Nordic*.

I include several analyst-specific variables as control variables in Equation (2), but I do not offer directional prediction on their coefficients. First, I control for the number of recommendations issued by an analyst (*NbRec*), which is a proxy for the analyst's workload. I use the number of companies covered by an analyst (*NbFirmFol*) as another proxy for the analyst's workload. Prior literature documents an association between analyst job performance and geographic distance between analysts and covered companies. Following this stream of research, I control for the number of countries in which followed firms are located (*NbCountry*). The potential gender difference in terms of analyst credibility is also taken into account. I include the percentage of influential recommendations issued by an analyst (*InflCARp*) into the regression model as an additional variable. Analyst's general experience (*AnalystExpG*) is another important personal attribute of financial analysts, which is measured by the number of years between the recommendation announcement date and the date when the analyst issues his/her first recommendation recorded by *I/B/E/S*. Green, Jegadeesh, and Tang (2009) find that female analysts are more likely than men to work at large brokerages. Therefore, I control for the size of brokerage house where the analyst works (*BrokerSize*), which is measured by the number of analysts working in a given brokerage house in a given year. The size of capital market at country level ($\frac{MarketCap}{GDP}$) may also affect female representation among financial analysts. Finally, I control for the year fixed effects when estimating the probit model at stock recommendations level and at analyst level at well.

A common approach in empirical research is to model dichotomous variables ($y \in [0,1]$) using a generalized linear model (*GLM)* with a binomial distribution, either a logistic (logit) distribution or a standard normal cumulative (probit) distribution. The advantage of this approach is that it restricts the predicted dependent variable to range between zero and one, unlike ordinary least squares regression (OLS). Here, I estimate coefficients using the probit model. A major difference between the *GLM* approach and the ordinary least square approach is that the estimated coefficients do not provide marginal effects, as in OLS, but multiplicative effects. Fortunately, transforming these coefficients into marginal effects is a reasonably straightforward procedure. I use the average of the sample marginal effects to proxy for marginal effects from our binary dependent variable models. The average of the sample marginal effects is calculated as follows:

$$\frac{\partial y}{\partial x_k} = \beta_k \times \frac{\sum_{i=0}^{n} g\left(X^T \hat{\beta}\right)}{n} \tag{2.3}$$

where n is the number of observations in the dataset and g is the probability density function for the normal distribution. The marginal effect for continuous (dummy) explanatory variables represents the change in the predicted probability when the independent variable changes by one standard deviation (changes from zero to one).

The residuals from the regression models may be serially correlated. I therefore use OLS/probit regressions with clustered robust errors to account for serial correlations. For all tests, I report the clustered standard errors after correcting for serial correlation in the residuals at country level. To mitigate the influence of extreme values, I winsorize all the variables at 0.01 level. For the multivariate tests, I eliminate the observations if 1) they are issued by analysts who issue less than ten recommendations in a given year, 2) they are for firms covered by less than ten analysts in a given year.

2.4 Breakdown of Female Representation in Europe

Based on the above-mentioned sample, discussion about gender composition and recommendation style for European analysts is presented in detail in this section. The statistics based on stock recommendations indicate that female financial analysts are much less represented than their male counterparts. 78.35% of the 3 579 European analysts included in the sample period (2006-2013) are male analysts. On average, for the eight years under consideration, 16.15% of all the identified European analysts are female, which is comparable to the proportion documented in the United States: 15.6% for Green, Jegadeesh, and Tang (2009) from 1995 to 2005 and 16.03% for Kumar (2010) from 1983 to 2005. Between 2006 and 2013, 125 908 recommendations have been issued by European analysts for 10 676 firms. However, among the 10 676 firms, only 2 501 of them have been covered by both male and female European analysts, representing roughly 23% of all firms.

⟨ Insert Table 2.1 about here ⟩

Table 2.1 suggests[4] that the 2 804 male analysts from the European countries issued 101 442 recommendations for 9 217 firms, which reflects an average of 36.46 recommendations per male analyst. In contrast, the 578 female financial analysts issued 18 386 recommendations on 3 282 firms. On average, female analysts produced each 31.98 recommendations only. A closer look at

[4] All tables are presented at the end of the chapter to allow for easier reading.

the stocks for which analysts provide recommendations indicates that, on average, female analysts issued 3.40 recommendations per firm, which is roughly the same as the number of recommendations per firm recorded for their male counterparts: 3.45 recommendations per firm. Finally, at the individual level, female analysts followed less firms than male analysts: on average, nine firms were covered by each female analyst, compared to ten firms per male analyst.

2.4.1 Variations across Countries

In order to clarify the country-level comparisons, all countries with less than 1% of all financial analysts are grouped into one category labeled as “others". These countries include Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Ireland, Lithuania, Luxembourg, Portugal, Romania, and Slovenia. Table 2.1 provides summary statistics for analysts and analysts' recommendations across European countries. In terms of gender composition, an average of 16.15% is observed for women financial analysts across the 28 European countries with a remarkable country-level variation. The proportion of female analysts reaches 40.00% for Italy, which is the highest record among the European countries under study. In contrast, the lowest proportion of women figures is recorded in Denmark, 4.14%. Countries in Northern Europe do not report a high proportion of women analysts: Denmark, Norway and Switzerland all have a proportion of female financial analysts lower than the average one, with the exception of Finland, where women financial analysts occupy more than one-fifth of the positions. Regarding stock recommendations, women analysts issued only 14.6% of all recommendations, which is relatively low compared to their representation among European financial analysts (16.15%). This suggests that each female analyst issued on average fewer recommendations relative to each male analyst. However, France is an interesting exception, since French female analysts have on average issued more recommendations than male analysts. The standard deviation for both the proportion of female analysts and the proportion of recommendations issued by female analysts are high, 9.39% and 10.11% respectively, which suggests a high volatility in gender observation across countries.

Further, I investigate the difference between the two genders with regard to the financial analyst's workload, *i.e.*, the number of stocks followed per capita, the number of recommendations issued per capita, and the number of recommendations issued for each covered company. Table 2.2 shows that the difference between genders is the largest in Belgium, where, on average, one male analyst followed 4 more companies than a female analyst. The largest difference in the number of recommendations per capita is also observed in Belgium: each male analyst in Belgium issued twice more recommendations than each female. In contrast, in France, each female analysts issued significantly more recommendations compared to their male counterparts, consistent with the findings of Table 2.2 which show that the proportion of recommendations issued by French female analysts is higher that that of French male analysts. The findings also suggest that in countries such as Austria, Belgium, Denmark, Finland, Greece, Netherlands, Switzerland, and United Kingdom, female analysts issued less recommendations per stock than male analysts. According to the t-tests, the differences are all significant at the 0.01 level. Nonetheless, in Germany, male analysts issued significantly less recommendations per stock than women. Furthermore, in Italy, female analysts are those who have issued the highest number of recommendations for the companies they followed compared to female analysts from other European countries. In Finland, male analysts had the highest recommendations per stock ratio.

⟨ Insert Table 2.2 about here ⟩

2.4.2 Evolution across Years

Table 2.3 describes the evolution of gender observations among European financial analysts over the sample period. First, from the full sample, I find that despite a remarkable decline in the number of analysts after the peak observed in 2011, women representation reaps a steady increase from 14.66% in 2007 to 16.26% in 2012. Regarding stock recommendations, after a steady increase recorded from 2006 to 2008, I notice a dramatic decline of more than 13% in the number of stock recommendations in 2009. This is probably due to the 2008 financial crisis. Accordingly, the proportion of recommendations issued by female also declined from 14.54% in 2008 to 13.53% in 2009. However, in the subsequent year, the proportion of their recommendations enjoyed a promising increase. In 2013, 15.47% of all the recommendations were issued by women, slightly lower than the proportion recorded in 2012 (15.71%).

⟨ Insert Table 2.3 about here ⟩

Data from the restricted sample with only active analysts and firms are given in Panel B of Table 2.3. The percentage of female analysts peaked in 2008 (16.15%) before a three-year decrease. Despite the recent rebound observed in 2011-2012, women representation declined again in 2013. In terms of percentage of recommendations issued by female analysts, a remarkable decline can be observed in 2013 subsequent to a peak in 2011 and 2012, when female analysts issued more than eighteen percent of all the recommendations.

2.4.3 Industrial Preference

Because of the complexity in getting information and understanding benchmarks for firms in different economic sectors, financial analysts are often specialized in specific economic sectors. In accordance with analysts' industrial specialization, extant literature confirms a negative relationship between the number of industries followed by an analyst and the analyst's performance as captured by earning forecast accuracy or recommendation profitability, *e.g.* Clement (1999) and Salva and Sonney (2010). With regard to gender differences in industrial specialization, Kumar (2010) documents that the distribution of female analysts in different market segments is not random. Female analysts in the U.S. are concentrated in economic sectors such as retail and clothing. I analyze the gender composition of financial analysts working for each market segment to examine whether female analysts in Europe have a preference for certain economic sectors. The classification is based on two-digit *SIC*s and I categorize companies according to the 48 Fama and French industry list (Fama and French 1997). The p-values from chi-square tests suggest that neither male nor female analysts are equally distributed in the listed industries.

⟨ Insert Table 2.4 about here ⟩

Results in Table 2.4 suggest that despite the fact that women analysts cover all industries, they are concentrated in specific sectors categorized as “Apparel", “Restaurants, Hotels, Motels", “Food Products". In these industries, female financial analysts represent more than one-fifth of all the analysts covering the industry. In contrast, for “Rubber and Plastic Products" and “Electrical Equipment"industry, women figures are relatively under-represented: less than 10% of analysts working in these market segments are female.

2.4.4 Statistics for Cultural Sub-regions

Sub-regions that differ in their cultural profiles also differ systematically in gender diversity among financial analysts. After grouping European countries into homogeneous cultural sub-regions using the Hofstede cultural model (see Table 2.5), I find that Latin countries, which include Belgium, France, Italy, Portugal and Spain, record the highest proportion of female analysts (24.31%), whereas Germanic countries (i.e. Austria, Germany, and Switzerland) have the lowest. Contrary to the common sense of highly achieved gender equality in Nordic countries, these nations have the second lowest percentage of female analysts. Regarding statistics for stock recommendations, although most recommendations are issued by analysts working in Anglo countries (i.e. Ireland and United Kingdom), the highest proportion of recommendations issued by female analysts is recorded in Latin countries (26.27%), consistent with the results for the proportion of female analysts.

⟨ Insert Table 2.5 about here ⟩

The statistics for the comparisons among different cultural sub-regions suggest that the differences in female representation among financial analysts across sub-regions are statistically significant. With regard to the proportion of female financial analysts, the results of the Pearson’s chi-squared tests (See Panel A of Table 2.6) reveal that Latin countries have significantly more female financial analysts than Anglo, Germanic and Nordic countries. Regarding the recommendations issued by female financial analysts (See Panel B in Table 2.6), the proportion of stock recommendations issued by female analysts in Latin countries is significantly higher than in countries classified in the other four cultural sub-regions: Anglo, Germanic, Near Eastern and Nordic countries, consistent with the results observed for the proportion of female analysts in each sub-region. The Pearson’s chi-squared tests suggest that the differences among the five cultural sub-regions are highly significant.

⟨ Insert Table 2.6 about here ⟩

Finally, I compare the situation of 2006 with that of 2013 in order to shed light on the variation over time. The comparison for analysts in the Hofstede's cultural sub-regions between 2006 and 2013 is presented in the Panel A of Table 2.8. I observe an increase in the number of financial analysts from 2006 to 2013 in Anglo and Nordic countries only. Regarding the proportion of female financial analysts, Anglo and Germanic countries show an increase while the proportion of female analysts has dramatically declined in Near Eastern countries and Nordic countries, from 26.92% to 4.76% and from 13.36% to 7.92%, respectively.

⟨ Insert Table 2.8 about here ⟩

In addition, by comparing the recommendations issued by financial analysts between 2006 and 2013 (See Panel B in Table 2.8), I find that all cultural sub-regions, especially Germanic countries, have suffered from a decline in the number of stock recommendations made by financial analysts, except Nordic countries where the number of recommendations increased dramatically from 1 771 analysts in 2006 to 2 066 analysts in 2013. As for the proportion of recommendations issued by female financial analysts, Germanic and Latin countries enjoyed a remarkable increase over the sample period. Anglo countries did not benefit from their increase in the proportion of female analysts from 2006 to 2013: the proportion of recommendations issued by female has declined from 12.87% to 10.84% in 2013. For the other countries, a shrink in the proportion of recommendations issued by female analysts is also documented for both Near Eastern and Nordic countries, which is probably due to the sharp decline in female representation among financial analysts.

2.5 Impacts of Culture on Female Representation among Financial Analysts

2.5.1 Summary Statistics of the Variables in the Regressions

Table 2.10 presents descriptive statistics for the dependent and independent variables for the regression model. The average proportion of female analysts is 17.6% and female analysts issued 16.3% of all recommendations in the regression sample. This observation is similar to the results obtained by Green, Jegadeesh, and Tang (2009) and Kumar (2010) in the United States. The percentage of analysts for whom I did not manage to identify his/her gender remains modest for all the country-year observations: the average percentage of analysts with undefined gender is 2.7%. In all, 5.3% of firms belongs to industries favored by female analysts, while firms in masculine industries account for 3.4% of all firms in our sample. On average, only 7.3% of all stock recommendations are influential because of a statistically significant two-day cumulative abnormal return around the recommendation issue date. About 42.3% of brokerage houses employ only local financial analysts. Financial analysts issue on average three recommendations per year for the publicly-listed companies. The size of capital markets in European countries on average represents 64.7% of the GDP value.

⟨ Insert Table 2.10 about here ⟩

2.5.2 Regression Results of Cultural Sub-regions

In this section, I discuss the regression results for the Hofstede cultural sub-regions.

Regression results at country level: Table 2.11 provides the regression results for the difference in gender diversity among financial analysts across cultural sub-regions. In the first specification, the dependent variable is the percentage of female analysts (FemAnalyst%) (columns 1 and 2). The percentage of recommendations issued by female analysts (FemRec%) is used as dependent variable for the second specification (columns 3 and 4). To study the incremental effect of cultural sub-regions on female representation, I include the five dummy variables for five cultural sub-regions in column 2 and 4, in addition to the variables presented in the partial models. The effect related to countries not categorized into either of the five Hofstede sub-regions (labeled as "unclassified") is captured in the intercept. It is worth noticing that the adjusted R^2 is higher for regression models with the sub-region variables (in columns 2 and 4), suggesting that the Hofstede sub-regions have a strong explanatory power for the proportion of female analysts and for the proportion of recommendations issued by female analysts as well. The adjusted R^2s for regressions of female analysts increase from 0.225 to 0.416 depending on whether the dummy variables for sub-regions are included in the regression models or not. In the same vein, the adjusted R^2s for regressions of recommendations issued by female analysts increase from 0.165 (when the dummy variables for sub-regions are omitted) to 0.363 (when I include the sub-region dummies into the regression model).

Regarding the dummy variables for cultural sub-regions, the model specification of column 2 shows that the coefficients for *Germanic* and *Nordic* are significantly negative. This indicates that countries in *Germanic* and *Nordic* have less female representation among financial analysts. The comparison of coefficients presented in Panel B confirms the difference across sub-regions. *Nordic* and *Germanic* countries have the least percentage of female analysts. Other factors hold constant, the percentages of female equity analysts in *Nordic* countries are 9% less than *Anglo* countries, 15% less than *Latin* countries, and 12% less than *Near Eastern* countries.

⟨ Insert Table 2.11 about here ⟩

Column 3 and 4 present the regression results using an alternative measurement of gender diversity, *i.e.* the percentage of recommendations issued by female analysts (*FemRec%*). The results for cultural sub-regions are consistent with those from regressions for *FemAnalyst%*. The comparison of coefficients suggest that the percentage of stock recommendations issued by female analysts are significantly lower in *Nordic* and *Germanic* countries (See Panel C of Table 2.11 for detail). The proportion of recommendations issued by female analysts in Latin countries is 0.17 higher than that of Nordic countries. In the same vein, I find that the proportion of recommendations issued by female analysts in Near Eastern countries is 0.11 higher than that of Nordic countries. The F-tests suggest that the difference between the coefficients are statistically significant.

The coefficient estimates of the percentage of influential recommendations (*InfluRec*) is significantly negative. The cumulative abnormal returns around the recommendation issue date is commonly used to proxy for the influence of financial analysts. Given the fact that the variable *InfluRec* measures the proportion of recommendations that triggered a statistically significant two-day cumulative abnormal return, this result suggests that there are more female analysts in countries where investors attach less importance to the analysts' opinion. Countries where financial analysts exert less influence on capital market have more female figures among financial analysts. In contrast, the coefficients for the variable that measures the influence of female analysts are significantly positive across the four model specifications, indicating that there are more female analysts in countries where female analysts are more influential to the market.

The coefficient on the percentage of recommendations issued by analysts working in a local brokerage house *LocalBroker* is insignificant at conventional levels, suggesting that the internationalization of brokerage houses exerts no influence on the female representation among financial analysts. In contrast, analysts' workload is an important characteristic. The coefficients on the numbers of recommendations issued per listed firms (*Rec/Firm*) are constantly positive at conventional levels of significance. This suggests that female representation among financial analysts is higher in countries where financial analysts are more active in issuing stock recommendations.

Regression results at analyst level: I report the probit regression results for female analysts at analyst level in Table 2.12. The probit model is estimated with a dummy variable *Female* as dependent variable, which is equal to one if the analyst is a woman, zero otherwise. The regression results are presented in the first two columns for partial models. The estimated coefficients and the marginal effects for full models are reported in Column (3) and (4). The coefficient for *Germanic* is significantly negative. In contrast, the estimated coefficient for *Latin* is significantly positive.

⟨ Insert Table 2.12 about here ⟩

Panel B of Table 2.12 presents the comparison of coefficients for the five cultural dimensions.

The results suggest that in *Germanic* countries the probability of being a female financial analysts is the lowest, although the difference between *Nordic* countries and *Germanic* countries is weak.

Regression results at recommendation level: The results for probit model with *FemRec* as the dependent variable confirm the findings obtained from probit model at analyst level (See Table 2.13 for detail). The probability of a recommendation issued by a woman is significantly lower in *Nordic* and *Germanic* countries. Further, the marginal effects of the independent variable *NbRec* is significantly positive, suggesting that female analysts issue more recommendations for covered firms, compared to their male counterparts. Also, *BrokerSize* has a significant positive marginal effect on the likelihood of a recommendation issued by a female analyst, indicating that stock recommendations from larger brokerage houses are more likely to be issued by female analysts.

⟨ Insert Table 2.13 about here ⟩

The comparison of coefficients for cultural sub-regions are reported in Panel B of Table 2.13. The F-tests confirm that the coefficients for *Germanic* and *Nordic* countries are significantly lower than other countries, suggesting that stock recommendations are less likely to be issued by female analysts in *Germanic* and *Nordic* countries.

Taken together, the analyses in Tables 2.11, 2.12, 2.13 suggest that gender diversity among financial analysts are heterogeneous across cultural sub-regions. I observe the least female representation among financial analysts in *Germanic* and *Nordic* countries, where national culture is characterized by lower power distance (Hofstede 2001), after controlling for other related factors.

2.6 Additional Tests with Cultural Dimensions

To clarify the impact of cultural sub-regions on gender diversity among financial analysts, I perform a number of additional analyses to complement the results obtained from regressions with the cultural sub-regions defined by Hofstede (2001). I replace the cultural sub-regions by the scores of the four cultural dimensions used by Hofstede (2001) to form the cultural sub-regions, *i.e*, power distance, individualism, masculinity, and uncertainty avoidance. These dimensions capture different attributes of national culture. Each of these cultural dimensions is defined extensively in appendix A. Power distance refers to the extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally. Uncertainty avoidance pertains to the stress perceived by people who are in uncertain or unknown situation. Individualism *v.s.* Collectivism refers to the patterns of inter-personal links shared by the members of a society. Masculinity *v.s.* Femininity refers to the extent to which the emotional gender roles are distinct. Long-term *v.s.* Short-term orientation stands for the preference of fostering virtues oriented towards future or towards past. Long-term *v.s.* short-term orientation accounts mainly for the difference between oriental and occidental countries. Therefore, I omit the long-term orientation dimension because this dimension is mainly used to capture national culture differences between oriental and occidental countries. The countries under study are all European countries. They are, therefore, all short-term oriented.

First, I perform OLS regressions at country level to examine the impact of each cultural dimension on the percentage of female analysts and percentage of stock recommendations issued by female analysts per country.

$$\begin{aligned} GenderObservation_{i,t} = {} & \alpha_0 + \sum_{i=1}^{4} \beta_i CDs_i + \alpha_2 dFemaleInf_i \\ & + \alpha_3 (\frac{Rec}{Firm})_{i,t} + \alpha_4 InfluRec_{i,t} + \alpha_5 FemaleInflu_{i,t} \\ & + \alpha_6 (\frac{MarketCap}{GDP})_{i,t} + \alpha_7 IndustryM_{i,t} + \alpha_8 IndustryF_{i,t} \\ & + \alpha_9 UndfAnalyst + \alpha_{10} LocalBroker_{i,t} \\ & + \text{Year Fixed Effects} + \varepsilon_{i,t} \end{aligned} \tag{2.4}$$

where CDs_i includes the scores of the four cultural dimensions (*PDIs* for power distance, *IDVs* for individualism, *MASs* for masculinity, and *UAIs* for uncertainty avoidance).

Regressions results of cultural dimensions at country level are presented in Table 2.14. The regression results with the scores of the four cultural dimensions are reported in column 2 and column 4. The adjusted R^2 of the regression models with cultural dimensions highly increases compared to the adjusted R^2 of the partial models. The estimated coefficients for power distance score (*PDIs*) is 0.2%. The regression results at country level suggest that female representations among financial analysts increase with the score of power distance. Power distance measures culture's tolerance toward unequal power distribution. The findings suggests that female analysts are more represented in countries where social members accept more the inequalities between individuals.

The results from cultural dimensions are also consistent with the previous regression results obtained from cultural sub-regions. Hofstede (2001) characterizes Nordic countries as those with lower scores of power distance. Therefore, the lower female representations of financial analysts in countries with lower scores of power distance is consistent with the previous findings which suggest that Nordic countries have a significantly lower female representation among financial analysts, all things being equal.

⟨ Insert Table 2.14 about here ⟩

Next, I investigate the impact of the Hofstede cultural dimensions on gender diversity among financial analysts at stock recommendation level and analyst level as well using the probit model.

$$\begin{aligned} Female_i/FemRec_i = \gamma_0 &+ \sum_{i=1}^{4} \delta_i CD_i + \gamma_2 NbRec_{i,t} \\ &+ \gamma_3 (BrokerSize)_{i,t} + \gamma_4 NbFirmFol_{i,t} \\ &+ \gamma_5 (\frac{MarketCap}{GDP})_{i,t} + \gamma_6 NbCountry_{i,t} + \gamma_7 InflCARp_{i,t} \\ &+ \gamma_8 AnalystExpG_{i,t} + \text{Year Fixed Effects} + \varepsilon_{i,t} \end{aligned} \tag{2.5}$$

In the first model specification, the dependent variable is a dummy variable that equals one if the stock recommendation is issued by a female analyst (*FemRec*). In the second specification, I use as dependent variable a dummy variable that is equal to one if the analyst is identified as a woman. The results of probit models at both levels are presented in Table 2.15. The power distance dimension has a positive marginal effect that remains significant at 0.05 level. The results indicate that in countries with higher power distance, stock recommendations are more likely to be issued by a female analyst and the probability of financial analysts being women is also higher. Other cultural dimensions *i.e.*, individualism, masculinity and uncertainty avoidance do not exert significant marginal effect on the likelihood of a stock recommendation being issued by female analysts or on the likelihood of a financial analyst being female. The findings from probit regressions confirm the results from OLS regressions at country level.

⟨ Insert Table 2.15 about here ⟩

The full models at individual levels (column 2 and 4 of Table 2.15) also suggest that female financial analysts issue more stock recommendations. Meanwhile, women analysts cover less companies compared to their male counterparts, consistent with the findings provided by Green, Jegadeesh, and Tang (2009).

Overall, regression results with the Hofstede cultural dimensions are largely consistent with regression results of Hofstede cultural sub-regions, which suggest that Nordic countries have lower female representation among financial analysts because of their lower tolerance toward unequal power distribution.

2.7 Conclusions and Discussions

The primary goal of this study is to assess whether and how national culture influences female representations among financial analysts. As such, this study sheds light on gender diversity among financial analysts. It also complements the literature on the effect of national culture on financial characteristics (Kanagaretnam, Lim, and Lobo 2011; Han et al. 2010). The empirical studies about female financial analysts are limited to the U.S. context. Green, Jegadeesh, and Tang (2009) document female representation among financial analysts of 15.6% in the United States. Kumar (2010) and Li et al. (2013) confirm such female under-representation among American financial analysts. However, the gender issue for financial analysts outside United States remains unexplored. Motivated by the work of Aggarwal and Goodell (2014), I investigate the influence of national culture on female representation among financial analysts in European countries.

I conduct main analyses using a sample of financial analysts working in European countries over the period 2006-2013. I first provide descriptive statistics for female financial analysts working in European countries. I provide evidence suggesting that female analysts are constantly under-represented across Europe during the sample period. Female representation only enjoyed a moderate increase over the period under study. My findings confirms a across-country variation in female representation among financial analysts. Besides, female financial analysts are more likely to cover companies in specific economic sectors such as “Apparel", “Restaurants, Hotels, Motels", “Food Products". In these feminine industries, women enjoy a higher representation among financial analysts.

Second, I examine how national culture influences female representation among financial analysts by comparing the proportions of female analysts in different cultural sub-regions defined by Hofstede (2001), *i.e.*, Anglo, Germanic, Latin, Near Eastern and Nordic countries. The univariate tests suggest that Germanic and Nordic countries are those with the lowest proportions of female analysts. In contrast, in Latin countries, female representation among financial analysts is the highest. The regression analyses at the country level show that the proportions of female analysts and proportions of recommendations issued by female analysts are significantly lower in Nordic countries, other factors being constant. The probit models at both analyst level and recommendation level confirm the same findings. For analysts located in Nordic countries, the likelihood of being a female analyst is significantly lower, all things being equal. The same conclusion can be reached using stock recommendations issued by female analysts. In Nordic countries, the likelihood of stock recommendation issued by a woman is significantly lower.

Further, I replace the sub-region dummy variables by the cultural dimensions defined by Hofstede (2001) and rerun the regressions at country level and at individual levels respectively. The results suggest that power distance is positively associated with female representation while other cultural dimensions do not exert significant marginal effects. This findings is consistent with those for sub-regions because Nordic countries have a lower power distance than any other countries. Therefore, the results show that there are more women working as financial analysts in countries where people are likely to accept inequality in power distribution.

To my knowledge, it is the first research to document observations for gender diversity among financial analysts in the European setting. Furthermore, in addition to confirming the results of concurrent studies that have been performed in the U.S., I find that national culture has a significant impact on female representation among financial analysts. As such, my findings contribute to the finance and culture literature by adding new evidence of the economic relevance of national culture, especially when research is conducted at the international scale.

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Appendices

2.A Hofstede Cultural Dimensions

Definitions for Five Cultural Dimensions of Hofstede (2001)

Culture dimension	Definition
Power distance	The extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally.
Individualism/Collectivism	Individualism stands for a society in which the ties between individuals are loose: everyone is expected to look after himself/herself and his/her immediate family only. Collectivism, stands for a society in which people are integrated into strong, cohesive in-groups, which throughout people's lifetime continue to protect them in exchange for unquestioning loyalty.
Masculinity/Femininity	Masculinity stands for a society in which emotional gender roles are clearly distinct: men are supposed to be assertive, tough, and focused on material success; women are supposed to be more modest, tender, and concerned with the quality of life. Its opposite, femininity, stands for a society in which emotional gender roles overlap: both men and women are supposed to be modest, tender, and concerned with the quality of life.
Uncertainty avoidance	The extent to which the members of a culture feel threatened by uncertain or unknown situations.
Long-term/Short-term orientation	Long-term orientation stands for the fostering of virtues oriented towards future rewards and adapting to changing circumstances. Short-term orientation, stands for the fostering of virtues related to the past and present, in particular respect for tradition, preservation of 'face', and fulfilling social obligations.

Scores of the Five Cultural Dimensions defined by Hofstede for European Countries

This table reports the scores of the five cultural dimensions defined by (Hofstede 2001) for European countries. *pdi* stands for power distance; *idv* refers to the individualism/collectivism; *mas* is the masculinity/femininity dimension; *uai* refers to the uncertainty avoidance; *lto* stands for long-term/short-term orientation.

Country	**PDI**	**IDV**	**MAS**	**UAI**	**LTO**
Austria	11	55	79	70	60
Belgium	65	75	54	94	82
Bulgaria	70	30	40	85	69
Croatia	73	33	40	80	58
Cyprus	NA	NA	NA	NA	NA
Czech Republic	57	58	57	74	70
Denmark	18	74	16	23	35
Estonia	40	60	30	60	82
Finland	33	63	26	59	38
France	68	71	43	86	63
Germany	35	67	66	65	83
Greece	60	35	57	100	45
Hungary	46	80	88	82	58
Ireland	28	70	68	35	24
Italy	50	76	70	75	61
Lithuania	42	60	19	65	82
Luxembourg	40	60	50	70	64
Netherlands	38	80	14	53	67
Norway	31	69	8	50	35
Poland	68	60	64	93	38
Portugal	63	27	31	99	28
Romania	90	30	42	90	52
Russia	93	39	36	95	81
Slovenia	71	27	19	88	49
Spain	57	51	42	86	48
Sweden	31	71	5	29	53
Switzerland	34	68	70	58	74
United Kingdom	35	89	66	35	51

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2.B Variable Measurements

Definition of Variables

The table presents the definitions for all the variables used in this study.

Variable	Definition	Source
Dependent variables:		
FemAnalyst%	percentage of female analysts for a given country	I/B/E/S
FemRec%	percentage of recommendations issued by female analysts for a given country	I/B/E/S
Female	dummy variable equal to one if an analyst is identified to be women, zero otherwise	I/B/E/S
FemRec	dummy variable equal to one if a recommendation is issued by female analyst, zero otherwise	I/B/E/S
Cultural variables:		
PDIs	the scores of power distance for a given country	Hofstede (2001)
IDVs	the scores of Individualism for a given country	Hofstede (2001)
MASs	the scores of masculinity/femininity for a given country	Hofstede (2001)
UAIs	the scores of uncertainty avoidance for a given country	Hofstede (2001)
Anglo	dummy variable that is equal to one for countries belonging to cultural sub-regions labeled as *Anglo*	Hofstede (2001)
Germanic	dummy variable that is equal to one for countries belonging to cultural sub-regions labeled as *Germanic*	Hofstede (2001)
Latin	dummy variable that is equal to one for countries belonging to cultural sub-regions labeled as *Latin*	Hofstede (2001)
Near Eastern	dummy variable that is equal to one for countries belonging to cultural sub-regions labeled as *Near Eastern*	Hofstede (2001)
Nordic	dummy variable that is equal to one for countries belonging to cultural sub-regions labeled as *Nordic*	Hofstede (2001)
Country-level variables:		
FemaleInf	percentage of influential recommendations issued by female analysts in a given year	I/B/E/S, Compustat
Rec/Firm	number of recommendations issued per firm in a given year	I/B/E/S
InfluRec	percentage of influential recommendations issued by financial analysts in a given year	I/B/E/S, Compustat

Continued on next page

Table Definition of Variables – *Continued from previous page*

Variable	**Definition**	**Source**
MarketCap/GDP	the sum of market capitalization of all listed firms divided by GDP	Compustat
IndustryM	percentage of firms in sectors favored by male analysts	Compustat
IndustryF	percentage of firms in sectors favored by female analysts	Compustat
UndAnalyst	percentage of analysts with undefined gender	I/B/E/S
LocalBroker	percentage of recommendations issued by analysts working for local brokerage houses	I/B/E/S
Individual-level variables:		
NbRec	number of recommendations issued by an analyst in a given year	I/B/E/S
NbFirmFol	number of firms followed by an analyst in a given year	I/B/E/S
BrokerSize	number of analysts working in the brokerage house in a given year	I/B/E/S
NbCountry	number of countries in which followed firms are located	I/B/E/S, Compustat
pInfluRec	percentage of influential recommendations issued by an analyst in a given year	I/B/E/S, Compustat
GenAnalystExp	number of years since analyst's first recommendation recorded in the database	I/B/E/S

2.C Tables

Table 2.1: Stock Coverage and Recommendations by Analyst Gender

The table summarizes gender difference in stock coverage and stock recommendations. Panel A summarizes gender difference for the whole sample. *Analysts* refers to the number of analysts; *Stocks* stands for the number of stocks followed by analysts; *Rec* is the number of recommendations issued by analysts; the number of stocks followed per analyst is labeled as *Stocks/Analyst*; the number of recommendations issued per analyst is labeled as *Rec/Analyst*; *Rec/Stock/Analyst* refers to recommendations made by each analyst per firm. I test the significance of the difference between male and female at country level by using the t-statistics: ***, **, * means that the difference is significant at the 0.01 level, at the 0.05 level and at the 0.10 level, respectively. Panel B reports the number of analysts working in each country (*Analysts*), the proportion of analysts who are female (*FemAnalysts*), or male (*MalAnalysts*), the number of recommendations issued by all analysts (*Rec*), the proportion of recommendations issued by female analysts (*FemRec*) and by male analysts (*MalRec*). *Others* refers to the countries with less than 1% of all financial analysts under study: namely Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Ireland, Lithuania, Luxembourg,, Portugal, Romania, and Slovenia.

Panel A: Whole Sample

	Analysts	**Stocks**	**Rec**	**Stocks /Analyst**	**Rec /Analyst**	**Rec/Stock /Analyst**
Male	2804	9217	101442	10.56	36.46	3.45
Female	578	3282	18386	9.39	31.98	3.40
Diff	2226	5935	83056	1.17***	4.49**	0.05

Panel B: Country Level

Country	**Analysts**	**FemAnalysts**	**MalAnalysts**	**Rec**	**FemRec**	**MalRec**
Austria	52	19.23%	73.08%	1538	10.99%	84.01%
Belgium	46	8.70%	84.78%	2075	4.00%	90.31%
Denmark	48	4.17%	89.58%	1512	1.06%	97.35%
Finland	78	21.79%	76.92%	4752	18.41%	80.81%
France	298	18.79%	74.50%	12546	24.54%	69.36%
Germany	389	9.51%	84.06%	16507	8.63%	87.11%
Greece	48	20.83%	79.17%	1132	17.58%	82.42%
Italy	110	40.00%	60.00%	5714	35.65%	64.35%
Netherlands	90	7.78%	85.56%	2986	3.25%	94.61%
Norway	143	10.49%	88.81%	4888	9.62%	88.52%
Poland	86	26.74%	73.26%	3283	23.58%	76.42%
Russia	163	23.93%	75.46%	2134	21.42%	77.88%
Spain	94	31.91%	63.83%	2945	34.57%	64.48%
Sweden	132	12.12%	87.88%	5146	9.50%	90.50%
Switzerland	121	11.57%	85.95%	3431	10.14%	89.22%
United Kingdom	1543	14.78%	77.32%	51760	12.29%	79.77%
Others	138	18.84%	78.26%	3559	13.71%	85.53%

Table 2.2: Country-level Comparisons of Recommendations Issued and Stocks Followed by European Analysts

The table reports gender comparison at individual level for European countries. I compare for the two genders the number of stocks followed by an analyst, the number of recommendations issued by an analyst, as well as the number of recommendations per stock issued by an analyst. *Others* refers to countries with less than 1% of all financial analysts under study: namely Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Ireland, Lithuania, Luxembourg, Portugal, Romania, Slovenia. I test the difference between male and female for each country using the *t*-statistics: *** if difference is significant at the 0.01 level, ** if difference is significant at the 0.05 level, * if difference is significant at the 0.10 level.

Country	**Stocks**			**Recommendations**			**Rec per Stock**		
	Female	Male	Difference	Female	Male	Difference	Female	Male	Difference
Austria	8.00	10.58	2.58	18.78	35.89	17.11**	2.35	3.39	1.04***
Belgium	7.75	12.08	4.33**	20.75	52.06	31.31***	2.68	4.31	1.63***
Denmark	3.50	9.10	5.60	8.00	35.90	27.90*	2.29	3.95	1.66***
Finland	11.82	12.03	0.21	51.47	65.08	13.61	4.35	5.41	1.06***
France	15.04	11.15	−3.89	57.02	40.47	−16.54*	3.79	3.63	−0.16
Germany	9.38	11.89	2.51**	38.51	44.24	5.73	4.11	3.72	−0.39*
Greece	7.80	7.32	−0.48	19.90	24.55	4.65	2.55	3.36	0.8***
Italy	10.25	12.53	2.28*	46.30	55.71	9.42	4.52	4.45	−0.07
Netherlands	7.14	11.65	4.51*	13.86	36.69	22.83***	1.94	3.15	1.21***
Norway	9.73	9.41	−0.32	31.33	34.07	2.74	3.22	3.62	0.40
Poland	8.65	10.78	2.13*	33.65	39.83	6.17	3.89	3.70	−0.19
Russia	5.82	7.20	1.37	11.72	13.51	1.79	2.01	1.88	−0.14
Spain	9.00	9.40	0.40	33.93	31.65	−2.28	3.77	3.37	−0.4*
Sweden	8.62	9.29	0.67	30.56	40.15	9.58	3.54	4.32	0.78***
Switzerland	7.71	9.39	1.67	24.86	29.72	4.86	3.22	3.17	−0.06
United Kingdom	9.33	10.92	1.58**	27.90	34.73	6.82**	2.99	3.18	0.19***
Others	5.19	7.95	2.76***	18.77	28.19	9.42*	3.61	3.54	−0.07

Table 2.3: Descriptive Statistics about the Evolution of Gender Observations for Analysts over Time

The table reports statistics for analysts data from 2006 to 2013. All recommendations for stocks with available information in the *I/B/E/S* database are included in the *Full sample*. The *Restricted sample* consists only of stock recommendations issued by analysts who have issued at least 10 recommendations in a given year. *NbStocks* refers to the total number of stocks followed by European analysts. *NbAnalysts* is the total number of analysts in office during the given time period, and *NbRec* stands for the total number of recommendations issued by these analysts. Finally, the proportion of all analysts that are female (*FemAnalysts*) and the proportion of stock recommendations of female analysts (*FemRec*) are also reported in the table.

(a) Full Sample

Year	NbRec	NbStocks	NbAnalysts	FemAnalysts	FemRec
2006	13,307	4,041	1,634	14.99%	13.66%
2007	17,553	4,626	1,733	14.66%	14.56%
2008	20,083	4,641	1,727	14.88%	14.51%
2009	17,408	4,723	1,742	14.93%	13.38%
2010	14,332	4,657	1,861	15.26%	14.50%
2011	15,542	4,675	1,893	15.74%	15.27%
2012	14,441	4,532	1,753	16.26%	15.71%
2013	13,242	4,440	1,700	15.65%	15.47%

(b) Restricted Sample

Year	NbRec	NbStocks	NbAnalysts	FemAnalysts	FemRec
2006	8,088	2,757	497	13.28%	13.48%
2007	12,543	3,604	710	15.21%	14.85%
2008	15,161	3,714	794	14.11%	14.36%
2009	12,126	3,642	674	13.06%	12.61%
2010	8,339	3,146	513	12.67%	12.74%
2011	9,818	3,314	575	13.91%	14.73%
2012	9,116	3,035	532	14.10%	15.29%
2013	7,678	2,949	475	12.42%	15.15%

Table 2.4: Industry Segments for European Analysts

The table reports European analysts' industrial preferences during the sample period. *NbAnalysts* is the number of analysts for each market segment, *FemAnalysts* refers to the proportion of female analysts in the given industry. *PerTotRec* is the percentage of all recommendations issued for the related industry, and *FemRec* refers to the proportion of recommendations issued by female analysts within a given industry. The industrial segments are based on the Fama and French industry classification (Fama and French 1997).

Industry	**NbAnalysts**	**FemAnalysts**	**PerTotRec**	**FemRec**
Agriculture	188	16.489	0.726	21.335
Aircraft	113	15.044	0.596	16.511
Almost Nothing	82	15.854	0.230	24.138
Apparel	235	30.638	1.223	30.844
Automobiles and Trucks	383	12.533	2.591	9.565
Banking	468	17.735	5.226	17.660
Beer and Liquor	143	20.979	0.916	21.162
Business Services	1,261	13.957	9.470	12.311
Business Supplies	202	17.327	1.141	15.449
Candy and Soda	151	14.570	0.486	16.013
Chemicals	494	13.563	2.717	14.060
Coal	103	13.592	0.415	13.193
Communication	536	14.552	4.449	14.959
Computers	391	13.299	1.940	11.789
Construction	557	12.926	3.229	14.736
Construction Materials	483	14.907	2.375	11.371
Consumer Goods	382	20.157	1.568	23.860
Defense	19	15.789	0.044	12.500
Electrical Equipment	279	9.319	0.907	9.632
Electronic Equipment	578	12.457	3.907	8.498
Entertainment	249	17.269	0.961	18.760
Fabricated Products	78	12.821	0.218	12.774
Food Products	333	21.622	1.848	22.475
Healthcare	146	13.699	0.672	9.693
Insurance	247	17.409	2.422	11.016
Machinery	693	13.276	4.463	11.621
Measuring and Control Equipment	229	10.044	0.709	12.878
Medical Equipment	222	18.468	1.355	15.123
Non-Metallic and Industrial Metal Mining	326	12.883	1.933	10.435
Personal Services	117	13.675	0.406	15.068
Petroleum and Natural Gas	542	16.790	5.751	13.714
Pharmaceutical Products	355	20	2.321	17.248
Precious Metals	134	12.687	1.276	8.899
Printing and Publishing	256	17.188	1.642	26.367

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Table 2.4 – *Continued from previous page*

Industry	**NbAnalysts**	**FemAnalysts**	**PerTotRec**	**FemRec**
Real Estate	407	16.462	4.059	13.129
Recreation	132	20.455	0.621	23.018
Restaurants, Hotels, Motels	206	22.816	1.399	19.478
Retail	653	19.449	5.218	19.452
Rubber and Plastic Products	147	8.844	0.518	7.209
Shipbuilding, Railroad Equipment	98	11.224	0.298	8.800
Shipping Containers	69	20.290	0.191	23.237
Steel Works Etc	448	12.277	2.454	15.210
Textiles	62	12.903	0.181	14.035
Tobacco Products	58	17.241	0.195	17.551
Trading	587	13.969	3.460	10.629
Transportation	545	14.679	4.529	9.644
Unclassified	80	11.250	0.206	11.583
Utilities	440	16.136	3.736	20.153
Wholesale	691	14.906	2.800	14.351

Table 2.5: Statistics for the Hofstede (2001) Cultural Sub-Regions

The table reports differences between cultural sub-regions based on the Hofstede's cultural model. *NbAnalysts* (*NbRec*) is the total number of analysts (recommendations issued by analysts) working in the given cultural sub-regions during the sample period. *FemAnalysts%* (*FemRec%*) refers to the proportion of all analysts (recommendations issued by analysts) that are female. According to the Hofstede's culture model, *Anglo* includes Ireland, United Kingdom; *Germanic* refers to Austria, Germany, and Switzerland; *Latin* stands for Belgium, France, Italy, Portugal, and Spain; *Near Eastern* includes Greece; *Nordic* represents Denmark, Finland, Netherlands, Norway, and Sweden. All the remaining countries (Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Lithuania, Luxembourg, Poland, Romania, Russia, and Slovenia) are not classified by Hofstede (2001) and thus grouped into *Unclassified*.

Sub-Regions	**NbAnalysts**	**FemAnalysts%**	**NbRec**	**FemRec%**
Anglo	1577	14.77%	52538	12.29%
Germanic	562	10.85%	21476	9.04%
Latin	576	24.31%	24195	26.27%
Near Eastern	48	20.83%	1132	17.58%
Nordic	491	11.61%	19284	10.1%
Unclassified	325	23.69%	7283	20.42%

Table 2.6: Comparison of Analyst Gender Representation Between the Hofstede (2001) Cultural Sub-regions

The table reports differences on the proportion of female analysts and the proportion of recommendations issued by women between cultural sub-regions based on the Hofstede's cultural model. I conduct Pearson's chi-squared test to compare the proportions of female financial analysts and the proportions of stock recommendations issued by female analysts recorded in different cultural sub-regions. Panel A of the table reports the comparison of the percentage of female analysts. The comparison for the percentage of female analysts' stock recommendation is reported in Panel B. Values in the first line and first column stands for the difference between the proportion of female analysts in Anglo countries and in Germanic countries (the former minus the latter). χ^2 values of the chi-squared test are in parentheses. The *,**,*** means that the differences are significant at the 0.10, 0.05, 0.01 level respectively using a two-tailed test.

(a) Proportion of female financial analysts

	Germanic	Latin	Near Eastern	Nordic
Anglo	3.92%**	−9.53%***	−6.06%	3.17%*
	(5.05)	(26.09)	(0.91)	(2.86)
Germanic		−13.45%***	−9.98%*	−0.75%
		(34.47)	(3.37)	(0.08)
Latin			3.47%	12.70%***
			(0.13)	(27.55)
Near Eastern				9.22%
				(2.62)

(b) Proportion of stock recommendations issued by female financial analysts

	Germanic	Latin	Near Eastern	Nordic
Anglo	3.25%***	−13.98%***	−5.29%***	2.19%***
	(159.32)	(2326.05)	(28.08)	(65.38)
Germanic		−17.22%***	−8.54%***	−1.05%***
		(2268.98)	(90.42)	(12.95)
Latin			8.69%***	16.17%***
			(42.09)	(1815.07)
Near Eastern				7.48%***
				(62.86)

Table 2.8: Comparison of Analyst Gender Representation for the Hofstede (2001) Cultural Sub-Regions between 2006 and 2013

The table reports the comparison for European analysts in Hofstede's cultural sub-regions between 2006 and 2013. *NbAnalysts* is the total number of analysts in office during the given time period. *FemAnalysts* refers to the proportion of female analysts. *NbRec* is the total number of recommendations issued by European analysts during the sample period. *FemRec* refers to the proportion of recommendations issued by female analysts. Δ *Fem* stands for the difference between 2006 and 2013, the latter minus the former. *,**,*** means that the differences are significant at the 0.10, 0.05, 0.01 level respectively using Pearson's chi-squared test.

(a) Comparison for analysts

Sub-Regions	**2006**		**2013**		**Δ Fem**
	NbAnalysts	FemAnalysts	NbAnalysts	FemAnalysts	
Anglo	663	12.52%	723	14.11%	1.59%
Germanic	346	9.54%	246	12.20%	2.66%
Latin	321	24.61%	271	24.35%	−0.26%
Near Eastern	26	26.92%	21	4.76%	−22.16%
Nordic	232	13.36%	265	7.92%	−5.44%*

(b) Comparison for stock recommendations

Sub-Regions	**2006**		**2013**		**Δ Fem**
	NbRec	FemRec	NbRec	FemRec	
Anglo	5430	12.87%	5229	10.84%	−2.03%***
Germanic	3029	7.10%	2023	11.07%	3.97%***
Latin	2576	23.64%	2538	30.34%	6.70%***
Near Eastern	157	17.20%	68	5.88%	−11.32%**
Nordic	1771	12.54%	2066	9.05%	−3.48%***

Table 2.10: Descriptive Statistics for the Variables in the Regression Model

The table reports descriptive statistics for the variables in the regression model. I use data for European countries with more than 1% of the financial analysts recorded in the sample. $FemAnalyst_{i,t}$ refers to the proportion of female analysts. $FemRec_{i,t}$the proportion of recommendations issued by female analysts. $UndAnalyst_{i,t}$ refers to the percentage of analysts whose gender cannot be determined. $IndustryF_{i,t}$ measures the percentage of firms in the five industries where female representation is the highest. $IndustryM_{i,t}$ measures the percentage of firms in the five industries where male representation is the highest. $InfluRec_{i,t}$ is the percentage of influential stock recommendations that trigger a significant two-day cumulative abnormal returns around the announcement date of stock recommendation. $LocalBroker_{i,t}$ refers to the percentage of recommendations issued by analysts working in a local brokerage house. $Rec/Firm_{i,t}$ is the number of all the recommendations issued by analysts in a given country divided by the number of listed firms in that country during a given year. $MarketCap/GDP_{i,t}$, stands for the ratio of total market capitalization of all the listed firms in a country over the country's GDP.

Variable	Mean	StdDev	1^{st} Quantile	Median	3^{rd} Quantile
FemAnalyst	0.176	0.101	0.100	0.151	0.226
FemRec	0.163	0.106	0.085	0.130	0.229
UndAnalyst	0.027	0.031	0	0.018	0.045
industryF	0.053	0.021	0.034	0.045	0.069
industryM	0.034	0.017	0.020	0.028	0.052
InfluRec	0.073	0.081	0	0.067	0.104
LocalBroker	0.423	0.233	0.258	0.410	0.571
Rec/Firm	3.128	1.203	2.272	2.920	3.595
MarketCap/GDP	0.647	0.452	0.368	0.516	0.807

Table 2.11: Regressions for Cultural Sub-regions at Country Level

Panel A of the table reports the results of regression models for cultural sub-regions at country level. The dependent variable is either the proportion of female analysts ($FemAnalyst_{i,t}$) (column 1 and 2) or the proportion of recommendations issued by female analysts ($FemRec_{i,t}$)(column 3 and 4). I use data from European countries with more than 1% of all financial analysts in the sample from 2006 to 2013. $FemAnalyst_{i,t}$ refers to the proportion of female analysts. $FemRec_{i,t}$ the proportion of recommendations issued by female analysts. $UndAnalyst_{i,t}$ refers to the percentage of analysts whose gender cannot be determined. $IndustryF_{i,t}$ measures the percentage of firms in the five industries where female representation is the highest. $IndustryM_{i,t}$ measures the percentage of firms in the five industries where the male representation is the highest. $InfluRec_{i,t}$ is the percentage of recommendations that trigger a significant two-day cumulative abnormal returns. $femaleInflu_{i,t}$ is the percentage of recommendations issued by female analysts that trigger a significant two-day cumulative abnormal returns. $LocalBroker_{i,t}$ refers to the percentage of recommendations issued by analysts working in a local brokerage house. $Rec/Firm_{i,t}$ is the number of recommendations issued by analysts in a given country divided by the number of listed firms in that country during a given year. $MarketCap/GDP_{i,t}$, stands for the ratio of total market capitalization of all the listed firms in a country over the country's GDP. According to the Hofstede's culture model, *Anglo* includes Ireland, United Kingdom; *Germanic* refers to Austria, Germany, and Switzerland; *Latin* stands for Belgium, France, Italy, Portugal, and Spain; *Near Eastern* includes Greece; *Nordic* represents Denmark, Finland, Netherlands, Norway, and Sweden. All the remaining countries (Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Lithuania, Luxembourg, Poland, Romania, Russia, and Slovenia) are not classified by Hofstede (2001) and thus grouped into *Unclassified*. I control for the year fixed effect. The standard errors are clustered at country level. ***, **, * stand for p-value less than 0.01, 0.05, and 0.1 respectively. In Panel B, I compare the coefficients of the dummy variables for the five cultural sub-regions. ***, **, * mean that the differences between coefficients are significant at the 0.01, 0.05, and 0.1 level, respectively, using a F-test.

Panel A: Regression Results at Sub-region Level

	Dependent variable:			
	FemAnalyst%		FemRec%	
	Partial model	Full model	Partial model	Full model
	(1)	(2)	(3)	(4)
IndustryF	0.399	−1.171	0.539	−1.185
	(1.295)	(0.798)	(1.310)	(0.911)
IndustryM	−1.079*	−1.892***	−1.087*	−1.952**
	(0.642)	(0.695)	(0.646)	(0.784)
InfluRec	−0.806*	−0.997**	−0.879*	−1.072**
	(0.416)	(0.430)	(0.476)	(0.484)
FemaleInflu	0.724**	0.750***	0.696**	0.726***
	(0.293)	(0.185)	(0.338)	(0.215)
Rec/Firm	0.009***	0.008**	0.009**	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
UndAnalyst	−0.409	−0.414**	−0.359	−0.333*
	(0.253)	(0.199)	(0.268)	(0.186)
MarketCap/GDP	−0.003	0.048**	0.010	0.066**
	(0.020)	(0.024)	(0.022)	(0.027)

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Table 2.11 – *Continued from previous page*

	Dependent variable:			
	FemAnalyst%		FemRec%	
	Partial model	Full model	Partial model	Full model
	(1)	(2)	(3)	(4)
LocalBroker	0.086*	−0.011	0.082	−0.016
	(0.047)	(0.040)	(0.052)	(0.044)
Anglo		−0.006		−0.024
		(0.055)		(0.065)
Germanic		−0.119**		−0.134**
		(0.049)		(0.057)
Latin		0.059		0.058
		(0.061)		(0.072)
NearEastern		0.025		0.006
		(0.036)		(0.042)
Nordic		−0.095*		−0.107
		(0.056)		(0.066)
Constant	0.108	0.274***	0.095	0.276***
	(0.092)	(0.081)	(0.097)	(0.090)
Observations	127	127	127	127
R^2	0.318	0.508	0.265	0.464
Adjusted R^2	0.225	0.416	0.165	0.363
Fixed effect	Year	Year	Year	Year

Panel B: Comparison of coefficients for the percentage of female analysts at sub-region level

	Germanic	Latin	Near Eastern	Nordic
Anglo	0.11**	−0.07	−0.03	0.09*
Germanic		−0.18***	−0.14**	−0.02
Latin			0.03	0.15***
Near Eastern				0.12**

Panel C: Comparison of coefficients for the percentage of recommendations by female analysts at sub-region level

	Germanic	Latin	Near Eastern	Nordic
Anglo	0.11*	−0.08	−0.03	0.08
Germanic		−0.19***	−0.14**	−0.03
Latin			0.05	0.17***
Near Eastern				0.11*

Table 2.12: Regressions for Cultural Sub-regions at Analyst Level

The table reports the results of probit models. The dependent variable is a dummy variable that is set to one if analyst is identified as female analyst ($Female_{i,t}$). I use data from European countries with more than 1% of all analysts in the sample. $NbRec_{i,t}$ refers to number of stock recommendations issued by a given analyst during the year under consideration. $BrokerSize_{i,t}$ measures the number of analysts working in the same brokerage house. $NbFirmFol_{i,t}$ measures the number of firms covered by a given analyst. $MarketCap/GDP_{i,t}$, stands for the ratio of total market capitalization of all listed firms in a country over the country's GDP. $pInfluRec_{i,t}$ is the percentage of recommendations that trigger a significant two-day cumulative abnormal returns issued by a given analyst during the year under consideration. $GenAnalystExp_{i,t}$ is general experience for an analyst, which is measured by the number of years since analyst's first recommendations recorded in *I/B/E/S*. The standard errors are clustered at country level. ***, **, * stand for p-value less than 0.01, 0.05, and 0.1 respectively. In Panel B, I compare the coefficients of the dummy variables for the five cultural sub-regions. ***, **, * mean that the differences between coefficients are significant at the 0.01, 0.05, and 0.1 level, respectively, using a F-test.

Panel A: Regressions with Cultural Sub-regions

	Dependent variable:			
	Female			
	Partial model	Marginal effects	Full model	Marginal effects
	(1)	(2)	(3)	(4)
NbRec	0.002	0.039	0.002	0.036
	(0.007)		(0.006)	
BrokerSize	0.001*	0.027	0.001**	0.020
	(0.001)		(0.0005)	
NbFirmFol	0.006	0.129	0.001	0.032
	(0.014)		(0.016)	
MarketCap/GDP	−0.260	−5.849	−0.081	−1.766
	(0.171)		(0.099)	
NbCountry	−0.011	−0.248	−0.004	−0.092
	(0.015)		(0.010)	
pInfluRec	0.441	9.931	0.237	5.174
	(0.420)		(0.339)	
GenAnalystExp	0.017	0.394	0.017	0.368
	(0.015)		(0.014)	
Anglo			−0.138	−3.002
			(0.169)	
Germanic			−0.396***	−8.634
			(0.148)	
Latin			0.343*	7.467
			(0.176)	
NearEastern			0.078	1.700
			(0.148)	

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Table 2.12 – *Continued from previous page*

	Dependent variable:			
	dFemale			
	Partial model	Marginal effects	Full model	Marginal effects
	(1)	(2)	(3)	(4)
Nordic			−0.317	−6.912
			(0.201)	
Observations	4,529	4,529	4,529	4,529
Akaike Inf. Crit.	3,734.579	3,734.579	3,627.581	3,627.581
Pseudo-R^2	0.008		0.040	
Fixed effect	Year		Year	
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B: Comparison of coefficients for female analysts at sub-region level

	Germanic	Latin	Near Eastern	Nordic
Anglo	0.26∗∗∗	−0.48∗∗∗	−0.22	0.18∗∗
Germanic		−0.74∗∗∗	−0.47	−0.08
Latin			0.26	0.66∗∗∗
Near Eastern				0.40

Table 2.13: Regressions for Cultural Sub-regions at Recommendation Level

The table reports the results of probit models. The dependent variable is either a dummy variable that is set to one if a stock recommendation is issued by female analyst ($dfemaleRec_{i,t}$). I use data from European countries with more than 1% of all financial analysts recorded in our sample from 2006 to 2013. $NbRec_{i,t}$ refers to number of stock recommendations issued by a given analyst during the current year. $BrokerSize_{i,t}$ measures the number of analysts working in the same brokerage house. $NbFirmFol_{i,t}$ measures the number of firms covered by a given analyst. $MarketCap/GDP_{i,t}$, stands for the ratio of total market capitalization of all the listed firms in a country over the country's GDP. $pInfluRec_{i,t}$ is the percentage of recommendations that trigger a significant two-day cumulative abnormal returns issued by a given analyst during the year under consideration. $GenAnalystExp_{i,t}$ is general experience for an analyst. The standard errors are clustered at country level. ***, **, * stand for p-value less than 0.01, 0.05, and 0.1 respectively. In Panel B, I compare the coefficients of the dummy variables for the five cultural sub-regions. ***, **, * mean that the differences between coefficients are significant at the 0.01, 0.05, and 0.1 level, respectively, using a F-test.

Panel A: Regressions with Cultural Sub-regions

	Dependent variable:			
	FemRec			
	Partial model	Marginal effects	Full model	Marginal effects
	(1)	(2)	(3)	(4)
NbRec	0.007***	0.162	0.007***	0.146
	(0.002)		(0.002)	
BrokerSize	0.002**	0.035	0.001**	0.029
	(0.001)		(0.001)	
NbFirmFol	−0.007	−0.161	−0.010	−0.214
	(0.010)		(0.010)	
MarketCap/GDP	−0.249	−5.719	0.004	0.082
	(0.169)		(0.088)	
NbCountry	−0.014	−0.324	−0.009	−0.189
	(0.019)		(0.017)	
pInfluRec	0.493	11.341	0.234	5.184
	(0.522)		(0.369)	
GenAnalystExp	0.008	0.191	0.009	0.199
	(0.015)		(0.015)	
Anglo			−0.260	−5.758
			(0.167)	
Germanic			−0.457***	−10.117
			(0.153)	
Latin			0.313*	6.928
			(0.173)	
Near Eastern			−0.099	−2.187
			(0.155)	
Nordic			−0.433**	−9.601

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Table 2.13 – *Continued from previous page*

	Dependent variable:			
	dFemRec			
	Partial model	Marginal effects	Full model	Marginal effects
	(1)	(2)	(3)	(4)
			(0.198)	
Observations	78,657		78,657	
Akaike Inf. Crit.	65,604.150		63,248.760	
Pseudo-R^2	0.010		0.045	
Fixed effect	Year		Year	
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B: Comparison of coefficients for stock recommendations issued by female analysts at sub-region level

	Germanic	Latin	Near Eastern	Nordic
Anglo	0.26***	−0.36***	−0.06	0.20***
Germanic		−0.62***	−0.32***	−0.06
Latin			0.29***	0.56***
Near Eastern				0.26**

Table 2.14: Regressions for Cultural Dimensions at Country Level

The table reports the results of regression models for the cultural dimensions defined by Hofstede (2001). The dependent variable is either the proportion of female analysts ($FemAnalyst\%_{i,t}$) (column 1, 2) or the proportion of recommendations issued by female analysts ($FemRec\%_{i,t}$) (column 3, 4) in each of the countries under study for each year under consideration. $PDIs_i$, $IDVs_i$, $MASs_i$, $UAIs_i$ refer to the scores of power distance, individualism, masculinity and uncertainty avoidance, respectively. The measurement of control variables is the same as presented in Table 2.11. I control for the year fixed effects. The standard errors are clustered at country level. ***, **, * stand for p-value less than 0.01, 0.05, and 0.1 respectively.

	Dependent variable:			
	FemAnalyst%		FemRec%	
	Partial Model	Full Model	Partial Model	Full Model
	(1)	(2)	(3)	(4)
PDIs		0.002*		0.003*
		(0.001)		(0.002)
IDVs		−0.002		−0.001
		(0.003)		(0.003)
MASs		0.001*		0.001
		(0.001)		(0.001)
UAIs		−0.001		−0.001
		(0.002)		(0.002)
industryF	0.399	1.347	0.450	0.918
	(1.295)	(1.348)	(1.329)	(1.348)
industryM	−1.079*	−0.823	−1.104*	−1.191**
	(0.642)	(0.558)	(0.650)	(0.593)
InfluRec	−0.806*	−0.230	−0.915*	−0.447
	(0.416)	(0.509)	(0.473)	(0.557)
femaleInflu	0.724**	0.827***	0.674**	0.781***
	(0.293)	(0.174)	(0.337)	(0.214)
Rec/Firm	0.009***	0.014***	0.008**	0.013***
	(0.004)	(0.005)	(0.004)	(0.005)
UndAnalyst	−0.409	−0.312	−0.364	−0.251
	(0.253)	(0.193)	(0.271)	(0.194)
MarketCap/GDP	−0.003	0.026	0.009	0.041
	(0.020)	(0.029)	(0.022)	(0.032)
LocalBroker	0.086*	0.017	0.089*	0.005
	(0.047)	(0.036)	(0.052)	(0.042)
Constant	0.108	0.041	0.102	0.0002
	(0.092)	(0.124)	(0.098)	(0.133)
Observations	127	127	127	127
R^2	0.318	0.455	0.251	0.392

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Table 2.14 – *Continued from previous page*

	Dependent variable:			
	FemAnalyst%		FemRec%	
	Partial Model	Full Model	Partial Model	Full Model
	(1)	(2)	(3)	(4)
Adjusted R^2	0.225	0.358	0.150	0.285
Fixed effect	Year	Year	Year	Year

Table 2.15: Regressions for Cultural Dimensions at Individual Level

The table reports the results of probit regression models of stock recommendations issued by female financial analysts (*dFemRec* and of female analysts (*dFemale*. $PDIs_i$, $IDVs_i$, $MASs_i$, $UAIs_i$ refer to the scores of power distance, individualism, masculinity and uncertainty avoidance, respectively. *NbRec* refers to the number of recommendations issued by analyst *i* in year *t*. *BrokerSize* is the number of analysts working for the given brokerage house in a given year. *NbFirmFol* refers to the number of firms followed by analyst *i* in year *t*. *NbCountry* is the number of countries in which followed firms are located. *InflCARp* refers to the percentage of influential recommendations issued by an analyst. *AnalystExpG* refers to analyst's general experience. $\frac{MarketCap}{GDP}$ is the value of market capitalization divided by the GDP. I control for the fixed effect at year levels. The standard errors are clustered at country level. The *,**,*** means the difference is significant at the 0.10, 0.05, 0.01 level respectively, using a two-tailed test.

	Dependent variable:			
	FemRec		Female	
	Partial Model	Full Model	Partial Model	Full Model
	(1)	(2)	(3)	(4)
PDIs		0.012**		0.010**
		(0.006)		(0.005)
IDVs		0.004		−0.001
		(0.008)		(0.007)
MASs		0.002		0.003
		(0.003)		(0.003)
UAIs		0.002		−0.001
		(0.006)		(0.005)
NbRec	0.088	0.120*	0.073*	0.103**
	(0.067)	(0.071)	(0.043)	(0.051)
BrokerSize	−0.001	0.006	−0.014	0.002
	(0.061)	(0.075)	(0.032)	(0.035)
NbFirmFol	−0.122	−0.181*	−0.155***	−0.186***
	(0.085)	(0.101)	(0.052)	(0.060)
MarketCap/GDP	−0.203	−0.034	−0.195	−0.092
	(0.150)	(0.185)	(0.144)	(0.193)
NbCountry	−0.028	−0.021	−0.023	−0.023
	(0.055)	(0.062)	(0.042)	(0.041)
pInfluRec	−0.089	−0.134	−0.194	−0.188*
	(0.334)	(0.248)	(0.124)	(0.107)
GenAnalystExp	−0.006	−0.0001	−0.014	−0.008
	(0.012)	(0.009)	(0.011)	(0.008)
Constant	−0.800***	−2.056***	−0.636***	−1.306**
	(0.269)	(0.624)	(0.220)	(0.570)
Observations	78,657	78,657	4,529	4,529
Akaike Inf. Crit.	100,055.700	98,097.470	11,701.500	11,574.940

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Table 2.15 – *Continued from previous page*

	Dependent variable:			
	FemRec		Female	
	Partial Model	Full Model	Partial Model	Full Model
	(1)	(2)	(3)	(4)
Pseudo-R^2	0.006	0.034	0.009	0.020
Fixed effect	Year	Year	Year	Year

Chapter 3

Innovation in Financial Analysts' Recommendations: Does Gender Matter?

Abstract: This paper investigates innovation in analyst's recommendations. It aims to determine whether there are gender differences in issuing innovative stock recommendations. My conjecture is that female analysts' lower overconfidence (superior ability) leads to less (more) innovative stock recommendations. The empirical evidence shows that female analysts are less likely to issue innovative recommendations. Stock recommendations issued by female analysts diverge less from the analyst consensus, or from their own prior recommendation for the same stock. They are also less ahead in time than those of male analysts. The observed gender differences in issuing innovative stock recommendation are not attributable to other analyst characteristics or characteristics of covered stock, and they are robust to different estimation methods. The lower innovation in female analysts' recommendations suggests that analysts' recommendations are overall more driven by overconfidence, which is characteristic of men and eventually leads to innovations, than by superior forecasting ability, which also leads to innovation in recommendations but is mostly characteristic of female analysts.

Keywords: financial analysts, gender, stock recommendations, overconfidence

3.1 Introduction

Traditional accounting and finance research largely ignores the influence of personal attributes on decision making, mainly focusing on patterns at firm, industry or country levels. Nevertheless, in the light of the behavioral differences in gender documented in psychology, an emerging literature examines the impact of personal attributes on decision making and job performance in accounting and finance by focusing on an important characteristic: gender. Prior studies on corporate boardroom suggest that female directors are less power oriented (Adams and Funk 2012) and have better attendance records than their male counterparts (Adams and Ferreira 2009). Huang and Kisgen (2013) show that firms with female executives are less likely to make acquisitions and that acquisitions made by female executives trigger higher stock returns on the announcement date. Beck, Behr, and Guettler (2013) examine the job performance of loan managers and find that loans screened and monitored by female loan officers have a lower likelihood to turn problematic than loans handled by male officers. In this paper, I examine whether the gender of financial analysts has a material impact on stock recommendation characteristics. Specifically, assuming that analysts' innovation in recommendation revisions result from higher overconfidence or from superior forecasting ability, I explore the idea that gender difference in overconfidence and forecasting ability leads to gender heterogeneity in issuing innovative recommendations, *i.e.*, recommendations that diverge from the analyst consensus or from their own prior recommendations, and leading recommendations significantly ahead of those of other analysts.

The existing literature that focuses on the impact of gender on financial analysts' decisions making have not examined the role of gender on innovation of stock recommendation revisions. Examining this problem is important not only because it provides more insights into analysts' behavior, but also because the representation of female equity analysts continues to be relatively small. Female financial analysts are constantly under-represented. In the United States, roughly 15% of equity analysts are women, despite an increase in female representation in the recent years (Green, Jegadeesh, and Tang 2009). I investigate whether female financial analysts are different from male analysts in terms of recommendation innovation, which is a fascinating setting to study gender difference among financial analysts for at least three reasons.

First, prior literature on analysts' outputs suggests that analysts' stock recommendations or earnings forecast revisions are not all informative to market investors. Innovation is an important attribute of the informativeness of financial analysts' outputs. Gleason and Lee (2003) argue that forecast revisions are innovative when they diverge away from the analyst's own prior estimate and the current analyst consensus. Based on these criteria, they show that innovative revisions incorporate more analysts' private information and therefore, provide new and useful information to investors. In the same vein, Cooper, Day, and Lewis (2001) suggest that stock recommendations that are leader in time also convey more information to stock markets. Consistent with the idea that innovative recommendations are more informative, Loh and Stulz (2011) find that market abnormal returns associated with innovative stock recommendation that are away from the analyst consensus are significantly higher.

Second, several personal attributes are associated with innovation. Psychological studies provide evidence that agents appear to constantly overestimate their personal ability. A growing literature studies the impact of overconfidence and suggests that overconfidence results in a higher propensity to innovate and more engagement in innovative activities (Galasso and Simcoe 2011; Hirshleifer, Low, and Teoh 2012). In the context of corporate arena, Galasso and Simcoe (2011) find that firms with overconfident CEO are more engaged in innovative investments because they routinely underestimate the probability of failure. Overconfidence helps CEOs to be more effective at exploiting growth opportunity. On the other hand, innovative recommendations are associated with superior forecasting ability (Clement and Tse 2005). The likelihood of issuing innovative forecasts increases with analysts prior forecast accuracy.

Third, prior works confirm a gender difference in two personal attributes related to innovation: overconfidence and forecasting ability. Men are different from female in terms of overconfidence. Men are systematically more overconfident than women (Dahlbom et al. 2011; Bengtsson, Persson, and Willenhag 2005). With respect to gender difference in forecasting ability, Kumar (2010) argues that only female security analysts with superior ability enter into the profession of equity analysts, hence, they demonstrate more accuracy in forecasting than their male counterparts.

Based on previous literature on gender difference in business, my primary hypotheses to test are that female financial analysts issue less (more) innovative stock recommendations due to lower overconfidence (superior forecasting ability). Prior literature finds evidence of gender difference in overconfidence and forecasting ability, two personal attributes that results in innovation. If recommendation revisions of male analysts are more innovative than those of female analysts, innovation is more driven by overconfidence than ability. In case that female analysts issue more innovative recommendations than male analysts, forecasting ability exerts larger marginal effects than overconfidence when analysts issue stock recommendations.

I test the above-mentioned two opposite hypotheses using a comprehensive sample of stock recommendations issued by sell-side equity analysts. I investigate whether innovation in stock recommendations vary with European analyst personal attributes, and specially with gender. To directly test my hypotheses, I examine the innovation level in stock recommendations issued by female and male analysts. If overconfidence (superior ability) has a larger impact on the analyst's decision of issuing innovative recommendation, female analysts would issue less (more) innovative recommendations. Investment recommendations are usually reported along with the last revision date, the recent analyst consensus and analyst's own prior recommendation on the same stock. Therefore, divergence from analyst consensus, revision from prior recommendation, and recommendation timing are three benchmarks that I use to determine innovation in stock recommendations. I refer stock recommendations that diverge from recent analyst consensus, that are much revised relative to the analyst's own prior recommendation and that are ahead in time of other recommendations, as innovative recommendations. Using these three criteria, I define an innovation index for recommendation revisions. Based on this index, a recommendation is innovative if if falls in the first quartile of at least two out of the three above-mentioned criteria sorted by descending order.

According to the innovation index, innovative recommendations represent about 16.6% of stock recommendations issued during the sample period (from 2006 to 2013). My empirical findings suggest that female analysts are less likely to issue innovative recommendations, compared to male analysts. More precisely, I find that female analysts issue stock recommendations that diverge less from their prior investment advice and from the analyst consensus. Stock recommendations issued by women also are less ahead in time. Empirical results from multivariate tests confirm that gender heterogeneity in analysts' recommendations can not be attributed to differences in analysts' characteristics and covered stocks' characteristics. I conclude from these findings that for equity analysts, overconfidence exerts larger marginal effect on analyst decision of issuing innovative stock recommendations than forecasting ability, which leads to lower innovative recommendation issued by female analysts.

This study is not the first to examine the impact of gender on financial analysts' decision making and job performance. Gender heterogeneity among financial analysts has been scrutinized from different aspects in previous literature. For instance, Li et al. (2013) find that investment recommendations issued by female financial analysts trigger similar market abnormal returns as those issued by male analysts but they are associated with lower idiosyncratic risks. Furthermore, gender does not have a negative impact on either female analysts likelihood to be ranked as "All-star analysts" or their promotion to larger brokerage houses. Bosquet, Goeij, and Smedts (2014) focus on differences between male and female analysts in terms of optimistic investment recommendations. They find that the odds that female analysts issue optimistic recommendations are lower than male analysts. Analysts also produce earnings forecasts. However, prior work on gender differences in analysts' forecast revisions provided mixed conclusions. Green, Jegadeesh, and Tang (2009) show reduced coverage and lower forecast accuracy from women financial analysts, indicating that they are less competent compared to male analysts in terms of forecasting ability, but the authors still allege that women outperform male analysts in other aspects such as client service, given that female analysts are more likely to be designated as "All-stars" analysts. A related paper, Kumar (2010), reports evidence that only female analysts with superior ability self-select into the profession. He finds that due to the self-selection bias, female financial analysts issue more accurate earnings forecasts than male analysts. Further, forecast revisions issued by women diverge farther away from the analyst consensus. A key distinguishing feature of my approach from this literature is that I control for the potential endogeneity problem caused by stock coverage. Some authors find a significant gender effect on analysts' decision making and job performance, others do not find the same empirical evidence. The mixture in the empirical results might result from the fact that female financial analysts cover stocks that differ from those covered by male analysts.

I control this selection bias using a battery of robustness tests including fixed effects, Heckman selection model and propensity score matching.

This study is related to prior research on analyst behavioral pattern when they issue stock recommendations (Bradley, Jordan, and Ritter 2008; Sorescu and Subrahmanyam 2006; Loh and Stulz 2011). Extant literature confirms that analyst forecasting ability, brokerage size, information environment of covered stocks lead analysts to different behavior in issuing investment recommendations. My empirical findings complement the existing literature by exploring the previously unexplored gender effects, controlling for various analyst and covered stock characteristics. This study also relates to the literature on gender differences in general. Researchers have found that across various settings, women differ from men regarding risk aversion (Eckel and Grossman 2008), effectiveness under competition (Gneezy, Niederle, and Rustichini 2003), ethnic values (Alice H. Eagly 1990; Eagly, Johannesen-Schmidt, and Van Engen 2003) and overconfidence (Dahlbom et al. 2011; Bengtsson, Persson, and Willenhag 2005). This study complements and extends prior research by investigating the existence of any gender effect on analysts' innovation with respect to stock recommendations while controlling for other key analyst characteristics.

The remainder of the paper is organized as follows: Section 2 briefly outlines the prior literature on gender difference in finance and develop the hypotheses. The data and research methodology are discussed in Section 3. Section 4 discusses the results. Section 5 presents the results of additional tests. Robustness checks are discussed in Section 6. The final section contains conclusions and discussions.

3.2 Literature Review and Hypothesis Development

This study is related to the literature that examines gender difference among financial analysts. In the context of financial analysts, prior research about gender heterogeneity in financial analysts' milieu focuses uniquely on financial analysts in the United States and yields mixed empirical results about gender heterogeneity among financial analysts. Green, Jegadeesh, and Tang (2009) document that female equity analysts make less accurate EPS forecasts but outperform men in all other aspects of job performance. Consistent with the self-selection hypothesis that female analysts who are able to survive in the competitive world of financial analysts are more “men-like" and share more similarities than differences with their male counterparts, Kumar (2010) shows that female analysts are more likely to issue bold forecasts. He also shows that investors are aware of this self-selection bias: market responds strongly to the bold forecasts issued by female. In contrast, Bosquet, Goeij, and Smedts (2014) finds that female analysts are less likely to issue optimistic recommendations than their male colleagues. Li et al. (2013) analyse the abnormal stock returns associated with stock recommendations of female analysts and find that female analysts underperform with respect to their upgrade recommendation revisions. Different from the extant research, I focus only on innovative recommendations and investigate gender difference in issuing innovative recommendations.

3.2.1 Innovation in Recommendations

Financial analysts are key pillars of financial markets. The activities of analysts, in particular, analysts' earnings forecasts and stock recommendations, provide a natural settings for behavioral research of individuals' decision process. Extant literature confirms that the value of financial analysts' stock recommendations is of great interests to investors (Womack 1996; Gleason and Lee 2003). Francis and Soffer (1997) find that recommendation revisions explain the variation of excess stock returns around recommendation announcement dates. Not surprisingly, all stock recommendations or forecast revisions are not equally informative to market investors. Loh and Stulz (2011) document that only a subset (roughly 12%) of investment recommendations issued by financial analysts are valuable to the market and trigger significant abnormal price returns. Innovative recommendations are shown to be more informative because investors place emphasis on the strength of the signal (Sorescu and Subrahmanyam 2006).

Gleason and Lee (2003) refer earnings estimates that diverge away from analyst own prior estimate and the current analyst consensus as innovative earnings forecasts. Based on this criteria, they show that innovative forecast revisions incorporate more analysts' private information and, therefore, provide new information to investors. In the same vein, Cooper, Day, and Lewis (2001) suggest that stock recommendations that are leader in time also convey more information to the market. Consistent with the theory that innovative recommendations are more informative, Loh and Stulz (2011) find that market abnormal returns associated with innovative stock recommendation that are away from analyst consensus are significantly higher.

The recommendation attribute examined in this paper is the level of innovation in the recommendations issued by sell-side analysts. Analyst recommendations are usually compared to both the analyst's prior recommendation for the same firm and the most recent analyst consensus as well. Therefore, both the analyst's own prior recommendation and the prior recommendation consensus are potentially important benchmarks in assessing the information content of recommendation revisions. Following Gleason and Lee (2003), I use both benchmarks in distinguishing between innovative and non-innovative recommendations. The timing of a recommendation is also an important factor. Cooper, Day, and Lewis (2001) formulate a leader-follower ratio for recommendation timeliness and contend that analysts with superior ability issue more leader recommendations that are followed by other analysts. The leader-follower ratio is the gap sum of the prior forecasts divided by the gap sum of later forecasts issued by other analysts. A ratio larger than one shows that other analysts issue new forecasts quickly in response to the analyst's current forecasts. Following their paper, I define lead recommendations as those issued ahead of other analysts. Stock recommendations issued ahead of other recommendations are innovative because they are the first to convey new information to the market. Different from Cooper, Day, and Lewis (2001)'s leader-follower ratio, I do not take into consideration recommendations subsequent to the recommendation announcement. My interest is on the analyst's intention to innovate. Therefore, whether other analysts react or not to the current recommendation announcement does not matter.

In sum, an innovative recommendation is defined as a recommendation that diverges from the analyst consensus (*Divergent*), that is revised compared to the analyst own prior recommendation (*Bold*), and that is issued ahead of other recommendations (*Lead*). I will refer to any recommendation that falls in the first quartile of at least two of the three above-mentioned criteria sorted in decreasing order, as an innovative recommendation (*InnoRec*).

Prior studies on analyst forecasts of corporate earnings per share (EPS) find evidence that innovative forecasts are more accurate, suggesting that analyst superior ability leads to more innovative outputs (Clement and Tse 2005). High-innovative forecast revisions likely contain more information than low-innovative forecast revisions, and therefore generate higher return responses in stock markets (Gleason and Lee 2003). Analysts with inferior forecasting ability are more likely to herd so as to preserve their reputation. Stickel (1990) finds that members of on the Institutional Investor annual “All-American Research Team", who represent analysts with superior forecasting ability, are less likely to herd than other analysts when they issue forecast revisions.

Apart from that, personal dispositions such as overconfidence also influence the level of innovation. In psychology, overconfidence is a well-established behavioral bias that leads individuals to overestimate their ability to perform well. Shefrin (2007) explains that overconfidence “pertains to how well people understand their own abilities and the limits of their knowledge". Griffin and Tversky (1992) point out that overconfidence is the greatest when people estimate their performance on difficult tasks. A particular variant of overconfidence applies to the use of private information. In this setting, overconfident agents believe that their private information is more accurate than it actually is and, therefore, emphasize on their private information in an irrational way (Hilary and Menzly 2006). The existence of overconfidence in form of overestimation on private signal value impulses individuals to be engaged in aggressive decision-makings.

Consistent with the psychological theories related to individual behavior, prior literature in the field of accounting and finance finds evidence that overconfidence is associated with an increased propensity to innovation. Galasso and Simcoe (2011) find that overconfident CEOs, who underestimate the probability of failure are more likely to pursue corporate innovation. In the same vein, Hirshleifer, Low, and Teoh 2012 find that overconfident CEOs invest more in innovation and achieve more innovative success. In the context of financial analysts, Hilary and Menzly (2006) provide evidence that overconfidence, as a cognitive bias, affects the analyst's decision making process. Analysts with higher prior forecast accuracy become overconfident in their forecasting ability, which leads them to issue less accurate earnings forecasts subsequently.

3.2.2 Gender Difference in Overconfidence

Prior studies show that women are different from men in many aspects, physically and psychologically. Such dispositional differences originated from gender impel them to have specific behavioral patterns when they are involved in social activities. Empirical findings in the domain of behavioral finance identify gender differences in the following dispositional factors: 1) Risk aversion. Women are more risk averse than men at least in field studies (Eckel and Grossman 2008). Once they enter the financial world, stronger risk-aversion makes them reluctant to invest (Charness and Gneezy 2012), unless sufficiently qualified information is available. 2) Competitiveness. Women may be less effective than men in competitive environments, even if they are capable of the same performance as men within non-competitive environments. Furthermore, the situation worsens when women have to compete with men instead of other women (Gneezy, Niederle, and Rustichini 2003). Although competition has a positive influence on performance, such influence is stronger on men than on women. This might account for the rarity of women in the financial world, because financial activities are commonly considered as full of competition. 3) Ethic values. The psychological and sociological literature reveals that women usually attach more importance to ethic values. More ethical, women executives are less intended to trade on insider information and exhibit more participative spirit in their leadership compared to male leaders (Alice H. Eagly 1990). Overall, they appear to have more sense of cooperation and care more about others' self-worth (Eagly, Johannesen-Schmidt, and Van Engen 2003). 4) Overconfidence. Overconfidence is a well-established behavioral bias that lead individuals to overestimate their ability to perform well.

In this study, I focus on gender difference in overconfidence. Research on psychology provides evidence that while men and women exhibit both overconfidence, men are more overconfident than women, particularly in male-dominated realms such as finance (Dahlbom et al. 2011; Bengtsson, Persson, and Willenhag 2005). Consistent with the findings in psychology, Barber and Odean (2001) document that stock trading reduces men's net returns by 2.65 percentage points a year as opposed to 1.72 percentage points for women. They attribute the difference to men's overconfidence in their ability to trade.

Under the conjecture that overconfidence leads to more innovation and that men are systematically more overconfident than women, I hypothesize that

Hypothesis 1. *All others things being equal, female analysts issue less innovative recommendations than male analysts because they are less overconfident than their male counterparts.*

3.2.3 Gender Difference in Forecasting Ability

Prior research confirms a systematic gender difference in analyst job performance. Female analysts exhibit superior forecasting ability by issuing more accurate earnings forecasts than male analysts possibly due to a self-selection bias for female financial analysts. Kumar (2010) argues that only female analysts with superior forecasting abilities enter the profession due to a perception of discrimination in the analyst labor market. He shows that their earnings forecasts are bolder and more accurate than those of male analysts. Female analysts' superior forecasting ability is also recognized by investors. Kumar (2010) finds that market reactions to earnings forecasts of female analysts are stronger despite the limited media coverage for female analysts.

With regard to stock recommendations, Li et al. (2013) find evidence that recommendation revisions of female analysts generate excess stock returns similar to those of male analysts, but with less idiosyncratic risks. Because superior ability is likely to result in higher innovation, the well-documented superior forecasting ability of female analysts provides us with an alternative hypothesis to test.

Hypothesis 2. *All others things being equal, female analysts issue more innovative recommendations than male analysts because of their superior forecasting ability.*

3.3 Research Design

3.3.1 Model Specification

When investigating analyst forecast revisions, Gleason and Lee (2003) distinguish between high-innovation and low-innovation revisions using two benchmarks: the analyst's own prior forecast and the prior day's consensus forecast. Following Gleason and Lee (2003), I characterize innovative recommendations as recommendations that diverge from analyst consensus, that differ from the analyst's own prior opinion and that are issued ahead in time of other recommendations. I compare male and female analysts in terms of innovation in three aspects: (1) recommendation divergence, measured by the distance from analyst consensus, (2) recommendation revision, measured as the absolute value of recommendation change relative to the analyst's own prior estimation on the same stock, (3) recommendation gap, measured as the number of days between the current recommendation and the latest previous recommendation by other analysts for the same stock. I sort recommendations for the sample firms in decreasing order of innovation for each of the above-mentioned criteria. Recommendations are expected to be innovative if they fall in the first quartile of a given criteria sorted by descending order in order to obtain an innovation index. Based on this index, a recommendation is considered as innovative if it is innovative for two out of the three criteria.

I examine the relation between the likelihood of an innovative recommendation and several characteristics of recommendations, analysts and recommended firms in both univariate and probit settings. My baseline model allows to estimate the incremental contribution of each characteristics on innovative recommendations and its economic significance.

$$\begin{aligned}\text{InnoRec}_{i,j,t} = \beta_0 + \beta_1\text{Female}_i + \beta_4\text{BrokerSize}_{i,j,t} + \beta_5\text{Favorable}_{i,j,t} + \beta_6\text{Unfavorable}_{i,j,t} \\ + \beta_7\text{Affiliation}_{i,j,t} + \beta_8\text{EPS support}_{i,j,t} + \beta_9\text{NbFirm}_{i,j,t} + \beta_{10}\text{FirstRec}_{i,j,t} \\ + \beta_{11}\text{FirmExper}_{i,j,t} + \beta_{12}\text{AnalystFol}_{i,j,t} + \beta_{13}\text{SameCountry}_{i,j,t} + \varepsilon_{i,j,t} \qquad (3.1)\end{aligned}$$

where, the dependent variables *InnoRec* is a binary variable that equals one if a recommendation falls in the first quartile of at least two of the following three criteria ranked by descending order:

$Bold_{i,j,t}$ = change in recommendation by analyst i for firm j at time t relative to the previous recommendation made by the analyst i for firm j. The calculation of recommendation changes is based on a five-point scale, *i.e.* 1 = Strong Sell, 2 = Underperform, 3 = Hold, 4 = Buy, 5 = Strong Buy. If the current recommendation is the first recommendation issued by analyst i for firm j, the recommendation change is set to be zero.

$Divergent_{i,j,t}$ = absolute value of the difference between recommendation by analyst i for firm j at time t and the six-month consensus. The consensus for the six months preceding the recommendation date is based on the five-point scale of recommendation, *i.e.* 1 = Strong Sell, 2 = Underperform, 3 = Hold, 4 = Buy, 5 = Strong Buy.

$Lead_{i,j,t}$ = analyst i's recommendation timeliness for firm j at time t. It is measured by the number of days between the current recommendation and the previous recommendation for the same firm. If the current recommendation is the first recommendation for firm j, *Lead* is not available.

The variable of interest in the probit model is the gender of the analyst issuing a recommendation (*Female*). Analyst's gender is determined by the first name.

$Female_{i,j,t}$ = analyst's gender, which is a dummy variable that equals 1 if the analyst is a female, zero otherwise;

According to hypotheses H1 and H2, the coefficient of *Female* should be negative (positive) if overconfidence (superior forecasting ability) has a greater marginal effect on issuing innovative recommendations.

I control for several other analyst, firm, and recommendation characteristics in the estimation model. The measurement of these control variables are as follows:

(a) Analyst coverage: The overall level of information available for a firm affects the analyst's recommendations (Hong, Lim, and Stein 2000). Prior studies find evidence that analyst coverage (*i.e.*, number of analysts that follow a stock) influences the market ability to process information. Gleason and Lee (2003) suggest that in case of innovative forecast revisions, additional analyst coverage facilitates market price discovery by amplifying the market reaction to the information conveyed in the revision innovation level. Therefore, I argue that the likelihood to issue innovative recommendations increases with the number of financial analysts who cover the firm. $AnalystFol_{i,j,t}$ is the number of analysts covering the firm j recommended by analyst i during the year of the recommendation.

(b) Broker affiliation: Prior studies indicate that underwriting relations between brokerage houses and covered firms bias analyst recommendations. Due to conflicts of interests, affiliated analysts are more reluctant to issue unfavorable recommendations for underwritten firms (Clarke et al. 2011), and investors systematically discount favorable recommendations issued by affiliated analyst (Barber, Lehavy, and Trueman 2007). Therefore, affiliated analysts are less likely to issue innovative recommendations. I characterize analyst affiliation ($Affiliation_{i,j,t}$) by a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation.

(c) Broker size: Equity analysts in large brokerage houses issue more accurate earnings forecast because they have easier access to corporate information (Jacob, Lys, and Neale 1999). Such superior forecasting ability may lead to higher innovation in stock recommendations. $BrokerSize_{i,j,t}$ which refers to the analyst's broker size, is calculated as the number of analysts working for the brokerage house employing the analyst i during the year of the recommendation under study.

(d) Forecast support: $EPSsupport_{i,j,t}$ is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of an earnings forecast for the same firm by the same analyst, zero otherwise. Recommendation revisions supported by forecast revisions have a greater price impact than those without forecast revisions (Kecskés, Michaely, and Womack 2016). Earnings-based recommendations contain more verifiable information because earnings estimates are sooner or later exposed to actual earnings. Hence, issuing recommendations supported by earnings forecasts requires higher forecasting ability. Therefore, earnings-based recommendations are more likely to be innovative.

(e) Analyst firm-specific experience: Sorescu and Subrahmanyam (2006) show that recommendation revisions of more experienced analysts outperform those of less experienced analysts, under the conjecture that only analysts with superior forecasting skills can survive. Hence, analyst experience may be related to the innovation in stock recommendations. Analyst's firm-specific experience ($FirmExper_{i,j,t}$) is measured as the number of year between the analyst's first recommendation recorded by *I/B/E/S* and the current recommendation.

(f) Initial recommendation: Financial analysts tend to cover firms for which they intuitively have optimistic views (McNichols and O'Brien 1997). Investors are aware of their behavioral pattern and tend to react more strongly to initial stock recommendations. Therefore, I conjecture that initial recommendations are less likely to be innovative because the initiation of stock coverage already conveys a strong information signal to the stock market. $FirstRec_{i,j,t}$ is an indicator variable that equals 1 if a recommendation is the first recommendation made by the analyst for the recommended firm *j*, zero otherwise.

(g) Recommendation level: $Favorable_{i,j,t}$ is an indicator variable that equals 1 if the recommendation is either labeled as "Strong Buy" or "Buy", zero otherwise. $Unfavorable_{i,j,t}$ is an indicator variable that equals 1 if the recommendation is either labeled as "Under-perform" or "Sell", zero otherwise. The distribution of analysts' recommendations is skewed to favorable recommendations because analysts stop covering stocks for which they do not have an optimistic view instead of issuing unfavorable recommendations. Market reactions to unfavorable recommendations are therefore always systematically stronger. Hence, I argue that unfavorable recommendations are more innovative than favorable recommendations.

(h) Analyst workload: Stock coverage is one of the financial analysts' job performance metrics. Jacob, Lys, and Neale (1999) argue that as their workload increases, analysts spare less effort for each of the firms they cover. Analysts covering numerous firms simultaneously are therefore less likely to issue innovative recommendations. I measure analyst's workload by the number of firms covered by the analyst during the year of the recommendation ($NbFirms_{i,j,t}$).

(i) Analyst geographic location: Analysts that are geographically close to the firms they cover have an information advantage over the other analysts covering the same firms and, therefore, issue more accurate analyses (Malloy 2005; Sonney 2007). Bae, Stulz, and Tan (2008) find that analyst domiciled in the same country as the covered firms issue more precise earnings forecasts than non-resident analysts. Local analyst's advantage on information may therefore lead to more innovative recommendations. $SameCountry_{i,j,t}$ is a binary variable that equals 1 if the recommendation is issued by an analyst located in the same country as the recommended firm, zero otherwise.

I use a probit regression to model the binary response variable *InnoRec*. Subscripts i, j, t refer to the analyst, firm and recommendation date, respectively. To make the scale of the regressors irrelevant, all the variables (except the dummy variables) are standardized. The explanatory variables are put on equal footing because they have a mean of zero and a variance (and therefore a standard deviation) equal to one. To ensure that extreme values do not affect the estimates, all variables are winsorized at their 0.5 and 99.5 percentile levels.

Prior literature suggests that the residuals of panel data may be correlated, resulting in biased standard errors (Petersen 2009). Following Loh and Stulz (2011), I adopt a two-way clustering method in the probit models to correct the potential biases. I adjust the standard errors for firm-specific and analyst-specific dependence by clustering standard errors at firm and analyst level in order to control for the correlation problem. Dummy variables are not added to the probit regressions as additional variables to control for fixed effects because of the incidental parameters problems (Neyman and Scott 1948) that will be discussed in detail in section 6.

3.3.2 Data and Sample Selection

To study the impact of gender difference on innovative recommendations, I merge several data sets. The most important one is *I/B/E/S* detailed recommendation database. The recommendations under scrutiny are those issued by European analysts, i.e. analysts located in the 28 European countries; namely, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom. Countries outside the European Union, such as Switzerland, Norway and Russia, are included in this research given that they belong to the same economic region as EU countries.

I/B/E/S database provides information about analysts' stock recommendation consisting of 1) company identifier, *i.e.*, *ISIN* code of recommended firms, 2) the announcement date of recommendation (Recommendation date), 3) the level of each recommendation[1], 4) the identification code of each analyst and 5) the broker for which the analyst works. Our data cover a eight-year period from January 2006 to December 2013. The beginning of the sample period is coincident with the date when European countries finished transposing the Market Abuse Directive (generally referred to as *MAD*) into their local legislation (Dubois and Dumontier 2008). The Market Abuse Directive (Directive 2003/6/EC), hereafter MAD, was adopted in 2003 by the European Commission to curb the insider dealing and market manipulation. The Directive 2003/6/EC states that

> "The identity of the producer of investment recommendations, his conduct of business rules and the identity of his competent authority should be disclosed, since it may be a valuable piece of information for investors to consider in relation to their investment decisions."

Since the implementation of MAD, analysts are therefore required to disclose their names and informations about their previous research reports when publishing their outputs, which makes our study much more feasible since I can determine each analyst's gender by the first name.

[1]For the whole sample period under study, *I/B/E/S* database use a five-level recommendation scale: namely, Strong Buy, Buy, Hold, Underperform, and Sell.

Since the *I/B/E/S* database does not mention the analyst's gender, the gender is identified by the analyst's first name. However *I/B/E/S* only provides a brief identity code for each analyst, which is composed of the analyst's last name and the initial letter of his/her first name. For example, an analyst named "Joe Black" is coded as "J Black" in the *I/B/E/S* database. Thus, complementary information about analysts' complete first name and their workplace (at the country level) is obtained from the official website of *Thomson One*[2]. *Thomson One* provides more detailed and thorougher information about the analysts from whom it collects data. The analyst's first name, last name, employer, workplace, contact coordinates can all be found in the website. After merging the recommendation data from *I/B/E/S* with data of analyst identities, I determine the gender of associated analysts by using a list of 22,345 unique first names[3]. Thus according to the outcome of gender identification, analysts are separated into three categories: male, female and undefined. Some analyst's gender is undefinable due to the following facts: 1) unisex first name, some first names, such as "Alex", could be used as a first name for both male and female; 2) duplicate last name and first initial, there are more than one analyst identification that could be matched with an analyst identity code, for example, "Julia Smith" and "John Smith" could both be abbreviated as "J Smith"; or 3) undisclosed analyst code: some analyst identity codes are deliberately veiled by the data provider and thus turn out to be "Undisclosed".

⟨ Insert Table 3.1 about here ⟩

I identify 125,908 recommendations issued by 3,554 European analysts from 2006 to 2013 (See Table 3.1 [4]). Almost half of the recommendations are favorable. The statistics show that among the 3,554 European analysts, 575 analysts are women. The proportion of female analysts in Europe, 16.18%, is comparable to the statistics obtained from the United States (Kumar 2010). Further, 18,386 recommendations were issued by female analysts. They account for 14.6% of all the recommendations. Female analysts, on average, issued less recommendations that their male counterparts. I use a five-point scale (1 = Strong Sell, 2 = Underperform, 3 = Hold, 4 =

[2] www.thomsonone.com

[3] The data mainly come from in the following sites: www.behindthename.com/, www.babynameindex.com/, en.wikipedia.org/wiki/Category:Masculine_given_names, and en.wikipedia.org/wiki/Category:Feminine_given_names

[4] All the tables are presented in the end of chapter for easier reading purposes.

Buy, 5 = Strong Buy) for analysts' investment recommendations. I label "Strong Buy" and "Buy" recommendations as "favorable" recommendations, "Hold" recommendations as "neutral" recommendations, and "Underform" and "Sell" recommendations as "unfavorable" recommendations. The descriptive statistics for each of the three levels of recommendations indicate that female analysts issue less neutral recommendations than their male counterparts. 13.6% of all the neutral recommendations are issued by female financial analysts, lower than the percentage of favorable (unfavorable) recommendations issued by female analysts.

I eliminate recommendations from the sample if they fall in one of the following criteria. First, recommendations are dropped from the sample if they are issued by an analyst for whom I cannot define the gender. Second, *I/B/E/S* sometimes records twice the same recommendation revision. In case of duplicate recommendations, the earliest date observation is chosen. Third, I eliminate recommendations that occur within the three-day window around a firm-specific news release date. This is to remove recommendations that merely repeat the information contained in firm-specific news releases. Not removing observations contaminated by contemporaneous firm-specific news releases leads to falsely giving credit to analyst performance. Finally, if different analysts issue recommendations for the same company on the same date, all the recommendations issued at this date are removed from the sample. This requirement is necessary because it is not possible to determine which recommendation triggers the abnormal stock returns when more than one recommendations are issued simultaneously (see Table 3.2 for details). The final sample contains $89,312$ recommendations issued by European analysts from 2006 to 2013.

⟨ Insert Table 3.2 about here ⟩

In order to control for brokerage house affiliation, I collect data for equity offering for years 2001 to 2013 from the Securities Data Company (*SDC*) databases. Using *SDC*, I obtain information on initial public offerings (*IPO*s) and secondary equity offerings (*SEO*s) conducted during the sample period, including the date of the offering and the name of underwriters and bookrunners. I, then, merge information on these *IPO*s and *SEO*s with the stock recommendation sample, so that I can categorize for each recommended firm whether the analyst's brokerage house had an underwriting relationship with the covered firm over the five proceeding year.

3.4 Main Results

3.4.1 Descriptive Statistics

Table 3.3 reports the univariate analyses for gender difference in recommendation characteristics. 16.6% of all stock recommendations are innovative according to my innovation index. Among all stock recommendations issued by male (female) analysts, 17.0% (14.5%) of them are innovative. T-statistics confirm that the gender difference in terms of recommendation innovation is significant at 0.01 level for univariate tests.

I also observe statistically significant gender difference in the boldness of stock recommendations. Female analysts issue recommendations closer to the recommendation consensus than their male counterparts. On average, recommendations issued by female analysts diverge from the consensus by 0.895 while male analysts issue recommendations more away from the consensus, with an average divergence of 0.925. The change in the recommendation level relative to the analyst's prior recommendations is also smaller for recommendations issued by women. The average revision degree from the previous recommendation is 0.798 for female analysts, less than that for male analysts (0.849). The descriptive statistics also show that female analysts issue stock recommendations 30 days after the previous recommendation available for the same stock, which is more than the average recommendation gap of male analysts, *i.e.*, 26 calender days.

⟨ Insert Table 3.3 about here ⟩

The distribution of innovative recommendations is reported in Table 3.4. The statistics show that most of stock recommendations are not innovative according to our criteria. 45.6% of all the stock recommendations are neither *Bold*, *Divergent*, nor *Lead* recommendations. 37.5% of them are innovative in only one dimension. For stock recommendations that are innovative in two dimensions, most of them are innovative in terms of boldness and divergence from the consensus (8%). Less recommendations are both *bold* and *lead* (2.8%). Among all the stock recommendations in our sample, only 2.6% are innovative in all of the three criteria, *i.e.*, they are simultaneously bold, divergent from analyst consensus and lead in time.

⟨ Insert Table 3.4 about here ⟩

Table 3.5 reports the Pearson correlation coefficients for all the explanatory variables in the baseline model. The coefficients are all trivial in absolute value, indicating none of the variables are highly correlated one to the other. T-tests for the Pearson correlation coefficients confirm a low probability of collinearity or multicollinearity among the regressors.

⟨ Insert Table 3.5 about here ⟩

3.4.2 Regression Results

Next, I turn to regression analyses to provide more direct evidence on whether there exists a gender effect on issuing innovative recommendations. Analysts characteristics as well as firm characteristics are incorporated as control variables in the probit regressions. Table 3.6 presents the estimation results from Equation (1) for the whole sample. Standard errors of estimated coefficients are clustered at firm and analyst levels. The marginal effects of the independent variables are reported beside the coefficient estimates. The marginal effects for dummy (continuous) explanatory variables represents the change in the predicted probability when the independent variable changes from zero to one (by one standard deviation).

The empirical evidence shows significant gender heterogeneity among analysts' stock recommendations. Compared to male analysts, female analysts issue less innovative recommendations, all other things being equal. The magnitude of the marginal effect at the mean value of *Female* is 3.4%, which suggests that on average, the predicted probability of innovative recommendations is 3.4% less for female analysts than for male analysts. Given that the unconditional probability of a recommendation being innovative is 16.6%, such a gender effect on innovation is large. This means that for a male analyst, the probability that his current recommendation is innovative increases by 3.4%.

⟨ Insert Table 3.6 about here ⟩

The coefficient of *FirstRec* is negative and significant at 0.01 level, suggesting that initial investment recommendations on a newly-covered firm are less likely to be innovative. Prior literature finds evidence suggesting that security analysts selectively provide coverage for firms for which their expectations are favorable (Das, GUO, and Zhang 2006). Market reactions to analyst's initiations are also significantly higher than those to other recommendations. Therefore, initial recommendations already convey strong information to investors and are less likely to be innovative. *Affiliation* has a negative coefficient that is significant at conventional level. This indicates that affiliated analysts are less likely to issue innovative recommendations. This finding is consistent with prior research that suggests affiliated analysts publish more optimistic and favorable recommendations than non-affiliated analysts (Lin and McNichols 1998) because recommendations are less likely to be innovative if they are always favorable.

Innovation in recommendations is also driven by the recommendation levels. The marginal effect of *Unfavorable* is significantly negative and larger than that of *Favorable*, suggesting that unfavorable recommendations (*i.e.* Underperform and Sell) leads to more innovative recommendations relative to favorable and neutral recommendations. Furthermore, the coefficient of *Brokersize* is negative and statistically significant at 0.01 level, indicating that analysts working in large brokerage houses are less likely to issue innovative recommendations.

The coefficient of *AnalystFol* is significantly negative, which indicates that recommendations for firms followed by numerous analysts are less likely to be innovative. The marginal effect of *AnalystFol* is 1.1%. Firms with low analyst coverage are therefore more likely to receive innovative recommendations, consistent with the idea that security analysts are more innovative when they speak in a smaller crowd. The coefficient of *SameCountry* is both positive and significant at 0.01 level, suggesting that analysts working in the same country as the recommended firm issue more innovative recommendations. The similar advantage of local analysts is also documented by Malloy (2005) and Sonney (2007), who find evidence that local analysts issue more accurate forecasts and have stronger impact on security prices than other analysts.

Not surprisingly, the estimated coefficient on *EPS support* is strongly positive, indicating that stock recommendations are more likely to be innovative if supported by a forecast on ESP. I also find that the analyst's firm specific experience (*FirmExper*) as well as the analyst's workload (*NbFirms*) do no provide incremental predictability in identifying recommendation innovation.

To summarize, I show evidence of gender difference in issuing innovative stock recommendations. Female analysts issue less innovative recommendations than their male counterparts, all other things being equal. Based on the hypotheses H1 and H2, this evidence suggests analysts' overconfidence exerts a larger marginal effect on recommendation revisions than their forecasting ability.

3.5 Additional Tests

3.5.1 Three Criteria of Innovation

In the previous section, I examined the relation between the likelihood of an innovative recommendation and several characteristics at the recommendation, analyst and firm levels. If the effect documented for the dummy variable *InnoRec* is robust, I should observe similar patterns for each of the three criteria (*Bold*, *Divergent*, *Lead*). To test this, I examine the incremental effect of gender on each of these three criteria respectively.

$$\begin{aligned}
\text{Criteria}_{i,j,t} = \beta_0 + \beta_1 \text{Female}_i + \beta_2 \text{Bold}_{i,j,t} + \beta_3 \text{Divergent}_{i,j,t} + \beta_4 \text{Lead}_{i,j,t} \\
\beta_5 \text{BrokerSize}_{i,j,t} + \beta_6 \text{Favorable}_{i,j,t} + \beta_7 \text{Unfavorable}_{i,j,t} \\
+ \beta_8 \text{Affiliation}_{i,j,t} + \beta_9 \text{EPS support}_{i,j,t} + \beta_1 0\text{NbFirms}_{i,j,t} + \beta_{11} \text{FirstRec}_{i,j,t} \\
+ \beta_{12} \text{FirmExper}_{i,j,t} + \beta_{13} \text{AnalystFol}_{i,j,t} + \beta_{14} \text{SameCountry}_{i,j,t} \\
+ \text{Firm fixed effects} + \varepsilon_{i,j,t} \qquad (3.2)
\end{aligned}$$

where, *Criteria* is either *Bold*, *Divergent*, or *Lead*. I use *OLS* model to estimate the coefficients. I include firm dummies to control for firm fixed effects. Standard errors are clustered at analyst level.

Table 3.7 reports the coefficient estimates for the three criteria as the response variable respectively. I find that the coefficients of the indicator variable *Female* are significantly negative across all of the three model specifications. Results in Table 3.7 based on the three criteria of innovation lead to similar qualitative conclusions as the baseline model of *InnoRec*. Female analysts issue less innovative recommendations. Recommendation revisions of female analysts diverge less from the analyst consensus. They are less revised relative to the analyst's own prior recommendation for the same firm. They are also less ahead in time of other recommendations for the same firm.

⟨ Insert Table 3.7 about here ⟩

In the model specification with *Divergent* as dependent variable, the results suggest that *Bold* and *Lead* both have positive marginal effects, all other things being equal. Analyst's initial recommendations (*FirstRec*) diverge more from the analyst consensus. Affiliated analysts are not significantly different from non-affiliated analysts with regard to divergence from the analyst consensus. Unfavorable recommendations are more divergent, because the distribution of recommendation revisions are skewed to favorable recommendations, *i.e.*, recommendations labeled as Strong Buy and Buy. Recommendations issued by analysts in larger brokerage houses (*BrokerSize*) are less divergent. For firms with larger analyst coverage (*AnalystFol*), recommendation revisions diverge less from the consensus. Analysts domiciled in the same country as the recommended firms (*SameCountry*) issue more divergent recommendations. Earning forecasts support (*EPS support*), analyst firm-specific experience (*FirmExper*) and analyst workload (*NbFirms*) do not exert statistically significant effect on the divergence of recommendation revisions from the analyst consensus.

With regard to regression results with *Bold* as dependent variable, I find that recommendation revisions that diverge more from the analyst consensus (*Divergent*) are bolder recommendations. Nonetheless, recommendations that are more ahead in time than other recommendations (*Lead*) are less revised relative to analyst's own prior revision for the same firm. In the research design, I set that if the current recommendation is the first recommendation, the recommendation change is set to be zero. Therefore, the coefficient of the initial recommendations (*FirstRec*) is significantly negative. The findings also suggest that affiliated analysts (*Affiliation*) issue less bold recommendations than non-affiliated analysts. The coefficients of *Favorable* and *Unfavorable* are both negative at conventional level, which indicates that neutral recommendations are bolder than favorable and unfavorable recommendations. Revisions to neutral recommendations, *i.e.*, recommendations labeled as Hold are the largest revisions. Similar to the results of *Divergent*, analysts working in large brokerage houses (*BrokerSize*) publish less revised recommendations. Recommendations are more revised if they are related to firms with large analyst coverage (*AnalystFol*). Analysts domiciled in the same country as recommended firms (*SameCountry*) issue bolder recommendations. Recommendation revisions are bolder when they are supported by an earnings forecast (*EPS support*). I find no significant marginal effects for analyst firm-specific experience (*FirmExper*) and analyst workload (*NbFirms*).

As for the model specification of *Lead* presented in Column 4 of Table 3.7, the findings indicate that strongly revised recommendations (*Bold*) are less ahead in time. However, recommendations that diverge more from the analyst consensus (*Divergent*) lead more in the timeliness. In addition, analysts' initial recommendations (*FirstRec*) are more ahead in time. Similar to the regression findings of *Bold*, recommendations issued by affiliated analysts (*Affiliation*) lead less in time relative to other recommendations for the same firm. The coefficient of *Favorable* is not significant while that of *Unfavorable* is negative at the conventional level, suggesting that analysts issue unfavorable recommendation in a less timely way, later than other recommendations. Analysts working in large brokerage houses (*BrokerSize*) issue more recommendations ahead of others. Recommendations issued for firms with larger analyst coverage (*AnalystFol*) are less ahead in time because the time gap between recommendation revisions reduces as the number of analysts following the firm increases.

The coefficient of *SameCountry* is negative, suggesting that recommendations issued by analysts domiciled in the same country as the recommended firms are less ahead in time just like recommendations supported by an earnings forecast (*EPS support*). Earnings forecasts are more sophisticated and more complicated to produce than stock recommendations. Therefore, it may take more time to issue recommendations supported by such forecasts. I also find that analysts with more firm-specific experience (*FirmExper*) issue recommendations that are more ahead of others. More surprisingly, recommendations issued by analysts who cover numerous firms (*NbFirms*), *i.e.*, those with a larger workload, issue recommendations that are more ahead in time.

3.5.2 Recommendation Levels

Using the pooled sample of all recommendations, I have shown that female analysts are less likely to issue innovative recommendations than male analysts. I now examine the association between innovation in recommendations and gender for recommendations with different tones. Table 3.8 reports sub-sample regression results on favorable, neutral and unfavorable recommendations respectively. The marginal effect of the variable *Female* is -3.5% for favorable recommendations, which indicates that, on average, the predicted probability of favorable innovative recommendations is 3.5% less for female analysts than for male analysts. The same negative marginal effects for the *Female* variable are documented for neutral and unfavorable stock recommendations as well: -2.2% (-4.7%) for neutral (unfavorable) stock recommendations. I find that the marginal effects of *Female* are not homogeneous across the three recommendation levels. Female analysts are more unlikely to issue innovative stock recommendations when they issue unfavorable stock recommendations.

Results in Table 3.8 are consistent with the baseline results presented in Table 3.6. The dummy variable *Female* is consistently negative across the three specifications: favorable recommendations, neutral recommendations, and unfavorable recommendations. In sum, results in Table 3.8 using stock recommendations with different tones lead to similar qualitative conclusions. Female financial analysts are less likely to issue innovative recommendations than male analysts. Prior research shows that men are systematically more overconfident than women and that female analysts have higher predicting skills than male analysts. In the light of prior literature, I conclude that innovation in recommendations is more driven by overconfidence than by analyst's predicting skills.

⟨ Insert Table 3.8 about here ⟩

3.6 Robustness Tests

3.6.1 Endogeneity Corrections

The main concern is that analysts' recommended firms are not randomly distributed to financial analysts. Gender difference in innovative recommendations might therefore result from gender heterogeneity in stock coverage. This is why the following robustness tests are mainly focused on mitigating the endogeneity resulting from selection biases in firm coverage.

The first approach I use is based on fixed effects by adding firm dummies in the baseline equation, using standard estimation procedures. However, prior literature suggests that fixed effect estimators of non-linear models such as binary response models suffer from incidental parameters problems (Neyman and Scott 1948). The maximum likelihood estimators (*MLE*) are asymptotically unbiased and consistent only if the number of observations (N) and time periods (T) tend to infinity. When T is small, fixed effects are biased and poorly estimated, which contaminates the rest of the coefficients estimated by MLE procedure. A quick yet efficient remedy is to use linear probability model (*LPM*) with fixed effects (Aeberhardt and Davezies 2012). Although the issue of fitted values being outside the unit interval is a obvious weakness, the LPM is often considered to provide "good estimates of the partial effects on the response probability near the center of the distribution of X" (Wooldridge 2002). Therefore, I estimate the following *LPM* with firm fixed effects:

$$P(InnoRec = 1 \mid X) = \beta^T X + FE\gamma \tag{3.3}$$

As in the baseline model, X is the set of recommendation, analyst, firm characteristics, including the binary explanatory variable *Female*. The coefficient estimate of *Female* is just the difference in the probability of success when $InnoRec = 1$ and $InnoRec = 0$, holding the other independent variables fixed. FE is the set of firm dummies used as additional variables to control for firm fixed effects.

Table 3.9 reports the OLS estimators for the linear probability model. The firm fixed effects are included in the model. Standard errors are clustered at the analyst level. The OLS estimates are comparable to the marginal effects calculated from the probit model presented in Table 3.6. Consistent with the results from the baseline probit model, I find that female analysts are less likely to issue innovative recommendations. The difference in the probability of issuing innovative recommendation is 3.2% between male and female analysts. The results of other control variables are similar to those reported in Table 3.6 for the baseline model. The coefficients for the control variables are with the same scale as those of the marginal effects estimated using the baseline probit model.

⟨ Insert Table 3.9 about here ⟩

As a robustness check, I also use the Heckman's two-stage technique to address the concern that female analysts cover stocks that differ from those covered by their male counterparts. The first approach uses linear probability regression that includes firm fixed effects. Nevertheless, I use the two-stage Heckman selection model (Heckman 1979) to directly account for this type of endogeneity problem. The treatment effect model is the baseline model presented in Equation (1), which can be written as follows:

$$InnoRec = \beta_1 \text{Female} + \beta^T X + \varepsilon \tag{3.4}$$

where X is a vector of exogenous variables (including an intercept) that affect the dependent variable, *InnoRec*. The dummy variable of interest, *Female*, is estimated using a binary choice model:

$$\text{Female}^* = \alpha_0 Z + \alpha^T X + \upsilon \tag{3.5}$$

where Female $= 1$ if Female$^* > 0$ and Female $= 0$ if Female$^* < 0$. Z refers to the instrumental variable. To implement the Heckman procedure, I first regress the dummy variable *Female* on an exogenous factor that could affect the likelihood of a recommendation to be issued by a female analyst (Z). The key instrumental variable is the percentage of analysts with undefined gender in each country (*Undefined*). While this variable *Undefined* is likely to affect the likelihood of recommendations issued by female analysts, it is unlikely to affect individual analysts' innovation in stock recommendations, *i.e.*, the variable *InnoRec*. The first-stage Heckman model is usually estimated using probit model (Lennox, Francis, and Wang 2011).

In Panel A of Table 3.10, the probit regression results suggest that the proportion of undefined analysts (*Undefined*) significantly predicts the likelihood of stock recommendation to be issued by female analysts. I then estimate the inverse Mill's ratio (*IMR*) from the first stage Heckman regression.

$$\text{IMR} = \begin{cases} \frac{\varphi(\widehat{\alpha_0}\text{Undefined}+\widehat{\alpha}^T X)}{\Phi(\widehat{\alpha_0}\text{Undefined}+\widehat{\alpha}^T X)}, & \text{if Female} = 1 \\ \frac{-\varphi(\widehat{\alpha_0}\text{Undefined}+\widehat{\alpha}^T X)}{1-\Phi(\widehat{\alpha_0}\text{Undefined}+\widehat{\alpha}^T X)}, & \text{if Female} = 0 \end{cases} \tag{3.6}$$

where $\varphi(.)$ and $\Phi(.)$ are the normal density and cumulative distribution functions, respectively. I include the estimated *IMR* as an additional variable in the second-stage Heckman regression.

In Panel B of Table 3.10, I report the results for the second-stage Heckman model for *InnoRec*. Consistent with findings for the baseline probit model, the coefficient of *Female* is significantly negative, with a marginal effect of -3.4%. I then replicate the same two-stage Heckman procedure for each of the three criteria (See Panel C of Table 3.10). The coefficients for *Female* are constantly negative across three model specifications.Therefore, after the Heckman correction for endogeneity, the main results remain valid, *i.e.*, female financial analysts issue less innovative recommendations than male analysts.

⟨ Insert Table 3.10 about here ⟩

The final alternative model specification refers to a propensity score matching used as robustness check. To isolate the effect of gender heterogeneity in firm coverage, I compare female recommendations against a benchmark sample with similar characteristics but issued by male analysts. I use a propensity-score matching to select the control sample. The matching begins with a probit regression of a female dummy variable on control variables presented below.

$$\begin{aligned}\text{Female}_{i,j,t} = \beta_0 &+ \beta_1\text{FirstRec}_i + \beta_4\text{BrokerSize}_{i,j,t} + \beta_5\text{Favorable}_{i,j,t}\\ &+ \beta_6\text{Unfavorable}_{i,j,t} + \beta_7\text{Affiliation}_{i,j,t} + \beta_8\text{EPS support}_{i,j,t} + \beta_9\text{NbFirm}_{i,j,t}\\ &+ \beta_{10}\text{FirmExper}_{i,j,t} + \beta_{11}\text{AnalystFol}_{i,j,t} + \beta_{12}\text{SameCountry}_{i,j,t} + \varepsilon_{i,j,t} \qquad (3.7)\end{aligned}$$

Panel A of Table 3.11 reports the pooled probit regressions before and after matching for two-way (by firm and analyst) cluster-robust standard errors. All of the determinants that significantly predict the probability of innovative recommendation before matching become insignificant after matching, which suggests that the matching effectively reduces the differences in the observable recommendation characteristics between female and male analysts and, therefore, mitigates the endogeneity issues.

I then use the propensity scores from this probit estimation and perform a nearest neighbor match with replacement. This procedure ensures that a female recommendation is paired with a male recommendation with statistically the same characteristics. During the sample period, the propensity-score matching generates $11,506$ female-male recommendation pairs I then run a univariate regression, and a multivariate regression with control variables on the matched sample to examine the gender differences in innovative recommendations (See Panel B of Table 3.11). In the regression with *Innorec* as the dependent variable, the marginal effect of *Female* is -3.9%, consistent with the results from the baseline model.

Results for each of the three innovative criteria (*Bold*, *Divergent*, and *Lead*) are reported in Table 3.11. The negative and significant coefficients on *Female* for three model specifications indicate that female analysts issue less recommendations that diverge less from the analyst's own prior recommendation, from the current analyst consensus. They also issue recommendations that are less ahead in time.

⟨ Insert Table 3.11 about here ⟩

3.6.2 Bias in Sample Selections

This study shows that female analysts are, all things equal, less innovative than their male counterparts. To strengthen this conclusion, I replicate the baseline model [Equation (1)] on different sub-samples. First, I eliminate all recommendations issued by inactive analysts, who issued less than five recommendations in a given year. Second, the recommendations issued from United Kingdom are withdrawn from the sample. Almost one third of the recommendations in the sample are issued by analysts in United Kingdom. By eliminating these recommendations, I can determine the extent to which the observed gender difference in recommendation innovation is driven by UK observations. Third, I exclude all recommendations issued during the financial crisis, *i.e.*, stock recommendations from 2008 to 2009, in order to eliminate the abnormality in the stock market returns during the crisis period. Fourth, I exclude recommendations for the less covered firms, which are followed by less than five analysts in a given year.

The results from these additional tests are presented in Table 3.12. In all instances, the results are qualitatively similar to the baseline results obtained using the full sample. The coefficient estimates of *Female* remain significantly negative across the four model specifications. The regressions with different sub-samples confirm that female analysts issue, all things equal, less innovative stock recommendations. In sum, my results are robust to alternative methods of endogeneity corrections and different samples.

⟨ Insert Table 3.12 about here ⟩

3.7 Conclusion and Discussion

Prior research shows that innovative recommendations are associated with higher abnormal stock returns because they incorporate more private information. The existing literature focuses on the attributes of financial analysts who issue the most innovative stock recommendations or earnings forecasts and finds evidence that overconfidence and superior skills lead to innovation. In the same vein, this study investigates whether female financial analysts issue less/more innovative recommendations than their male counterparts. The research question is motivated by two behavioral principles. First, extensive literature confirms that men are more overconfident than women in general circumstances. Second, with regard to financial analysts, prior research provides evidence that female analysts have superior forecasting ability than male analysts. Hence, investigating whether female analysts issue more innovative recommendations than their male counterparts helps to determine whether innovation in recommendation revisions, which accounts for most of the excess stock returns associated with recommendations, is driven by analysts' overconfidence or by analysts' superior predicting skills.

I use three criteria to detect innovative recommendations. A recommendation is likely to be innovative if it is bold because it is much revised relative to the analyst's own prior revision, if it is divergent because it diverges from the analyst consensus, and finally, if it is lead because it is issued ahead of other recommendations for the same firm. Based on the three criteria, I construct an innovation index "InnoRec" equal to one if a recommendation falls in the first quartile of at least two out of the three criteria ranked by decreasing order.

I show that the gender of financial analysts exerts an incremental effect on the likelihood of issuing innovative recommendations. I find that 16.6% of the investment recommendations are innovative after eliminating recommendation revisions contaminated by confounding corporate news. Nearly half of the sample recommendations are not innovative regardless of the criterion under consideration. I find that female financial analysts are less likely to issue innovative recommendations. Considering that prior research shows that women are less overconfident than men and that female analysts have higher forecasting abilities than male analysts, this findings suggest that innovation in stock recommendations is more driven by analyst's overconfidence than analyst's superior forecasting skills. I also find that a) unfavorable recommendations are more innovative relative to favorable and neutral recommendations, b) affiliated analysts, analysts working in large brokerage houses are less expected issue innovative recommendations, c) analysts close to the headquarter of covered firms issue more innovative recommendations, giving credit to the view that geographic proximity is an important determinant of information availability, d) stock recommendations supported by earnings forecasts are more likely to be innovative.

Stock recommendations are a direct outcome of the analysts' decision process. They are, therefore, often used to investigate gender heterogeneity among financial analysts (Green, Jegadeesh, and Tang 2009; Li et al. 2013). This study contributes to the literature by shedding light on the mechanism behind analysts' innovation in recommendation revisions. The empirical evidence provided here clearly shows that male analysts are more innovative than their female counterparts. This contributes to the gender literature by confirming that women have different behavioral patterns than men in the world of financial analysts. More interestingly, regarding the financial analyst literature, the higher level of innovation in male analysts' recommendations evidenced in this study leads to consider that innovative stock recommendations are likely more driven by overconfidence than by forecasting skills. However, this needs to be confirmed notably by investigating whether investors react differently to innovative recommendations depending on whether they are issued by male or by female analysts.

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Appendices

3.A Tables

Table 3.1: Summary Statistics of Stock Recommendations

This table provides descriptive statistics for recommendations issued by European financial analysts during the 2006-2013 period.

	Full sample	Female	Male	Undefined	%female
Nb recommendations	125,908	18,386	101,442	6,080	0.146
Nb favorable recommendations	61,600	9,322	49,364	2,914	0.151
Nb neutral recommendations	43,583	5,943	35,229	2,411	0.136
Nb unfavorable recommendations	20,725	3,121	16,849	755	0.151
Nb analysts	3,554	575	2,782	197	0.162

Table 3.2: Sample Selection Criteria

The table presents the sample selection procedure. *Criteria* refers to the selection criteria imposed to the recommendation sample. *NumObservations* is the number of remaining recommendations after the application of the criteria.

Criteria	Number of Observations
Recommendations issued by European analysts	125,908
After deleting:	
- recommendations with undefined gender	119,828
- duplicated recommendations	111,782
- rec by different analysts at the same date for the same firm	96,523
- recommendations around the firm news release dates	89,312

Table 3.3: Univariate Tests for Gender Differences in Recommendation Characteristics

The table reports the gender difference in behavioral patterns of financial analysts. *Diverge* is the divergence from the consensus. *Lead* is the number of days between the current recommendation and previous recommendations issued for the same firm. *Bold* is the absolute value of recommendation change relative to the previous recommendation by the same analyst for the same firm. The values in the column *Full sample*, *Female rec*, and *Male rec* are mean values. *Difference (Male-Female)* reports the difference between the statistics for male analysts and those for female analysts. *** , ** , and * denote two-tailed significance of t-test at the 0.01, 0.05, and 0.10 levels, respectively

	Full Sample	Female Rec	Male Rec	Difference (Male-Female)
InnoRec	0.166	0.145	0.170	0.024***
Diverge	0.921	0.895	0.925	0.030***
Lead	27.170	30.134	26.624	-3.509***
Bold	0.841	0.798	0.849	0.051***

Table 3.4: Distribution of Innovative Stock Recommendations

The table reports the distributions of stock recommendations in terms of innovation. *Bold* refers to the change in recommendation by analyst i for firm j at time t relative to the previous recommendation made by the analyst i for firm j. *Divergent* is the absolute value of the difference between recommendation by analyst i for firm j at time t and the six-month consensus. *Lead* is the number of days between the current recommendation and previous recommendation for the same firm.

	Number of rec	% rec
Not innovative recommendations	47,369	0.456
Innovative recommendations at one dimension	37,641	0.375
Bold	11,444	0.106
Divergent	10,910	0.106
Lead	15,287	0.162
Innovative recommendations at two dimensions	14,520	0.143
Bold+Diverge	8,571	0.080
Bold+Lead	2,741	0.028
Diverge+Lead	3,208	0.034
Innovative recommendations at three dimensions	2,517	0.026

Table 3.5: Pearson Correlations

This table reports the Pearson product-moment correlation coefficients between the independent variables of the baseline regression model. *FirstRec* is an indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for recommended firm *j*, zero otherwise. *Affiliation* is a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation. *SupportEPS* is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of the EPS forecast for the same firm, zero otherwise. *Favorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Strong Buy" or "Buy", zero otherwise. *Unfavorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Under-perform" or "Sell", zero otherwise. *SameCountry* is an binary variable that equals 1 if recommendation is issued by analyst located in the same country as the firm covered by analyst, zero otherwise. *BrokerSize* refers to analyst's broker size, which is calculated as the number of analysts working for the brokerage house employing the analyst *i* during the year of recommendation. *AnalystFol* is the number of analysts covering the firm *i* during the year of the recommendation. *FirmExper* is measured as the number of year between analyst's first recommendation recorded by *I/B/E/S* and the current recommendation. *NbFirms* the number of firms covered by the analyst during the year of the recommendation revisions. *** , ** , and * denote two-tailed significance of t-test at the 0.01, 0.05, and 0.10 levels, respectively

	Female	*FirstRec*	*Affiliation*	*supportEPS*	*Favorable*	*Unfavorable*	*SameCountry*	*BrokerSize*	*AnalystFol*	*FirmExper*
FirstRec	0.00	0.02***	−0.04***	0.01***	0.00	0.02***	−0.02***	−0.01***	0.00	−0.01***
Affiliation		−0.01**	0.05***	0.08***	−0.05***	−0.09***	0.04***	−0.05***	−0.47***	−0.05***
SupportEPS			−0.02***	0.00	−0.01***	0.01***	0.05***	0.02***	0.00	−0.04***
Favorable				0.01***	0.00	−0.03***	0.08***	0.05***	0.03***	0.01***
Unfavorable					−0.44***	0.02***	−0.05***	−0.04***	−0.06***	−0.01***
SameCountry						0.02***	0.03***	0.06***	0.03***	0.00
BrokerSize							−0.24***	−0.12***	0.12***	−0.06***
AnalystFol								0.09***	−0.03***	−0.07***
FirmExper									0.09***	−0.08***
NbFirms										0.04***

Table 3.6: Regressions for Innovative Recommendations

This table reports the results for the probit regressions conducted for innovative recommendations. The dependent variables are *InnoRec* for both restraint and extended models. *FirstRec* is an indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for recommended firm *j*, zero otherwise. *Affiliation* is a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation. *SupportEPS* is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of the EPS forecast for the same firm, zero otherwise. *Favorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Strong Buy" or "Buy", zero otherwise. *Unfavorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Under-perform" or "Sell", zero otherwise. *SameCountry* is an binary variable that equals 1 if recommendation is issued by analyst located in the same country as the firm covered by analyst, zero otherwise. *BrokerSize* refers to analyst's broker size, which is calculated as the number of analysts working for the brokerage house employing the analyst *i* during the year of recommendation. *AnalystFol* is the number of analysts covering the firm *i* during the year of the recommendation. *FirmExper* is measured as the number of year between analyst's first recommendation recorded by *I/B/E/S* and the current recommendation. *NbFirms* the number of firms covered by the analyst during the year of the recommendation revisions. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized.

	Dependent variable:		
	InnoRec		
	Restricted model	Full model	Marginal effects
	Probit	*Probit*	
	(1)	(2)	(3)
Female	-0.118^{***}	-0.151^{***}	-0.034
	(0.036)	(0.039)	
FirstRec		-0.803^{***}	-0.179
		(0.022)	
Affiliation		-0.157^{**}	-0.035
		(0.073)	
Favorable		0.479^{***}	0.107
		(0.020)	
Unfavorable		1.029^{***}	0.229
		(0.024)	
BrokerSize		-0.099^{***}	-0.022
		(0.015)	
AnalystFol		-0.050^{***}	-0.011
		(0.011)	
SameCountry		0.057^{**}	0.013
		(0.027)	
EPS support		0.050^{***}	0.011
		(0.018)	
FirmExper		-0.005	-0.001
		(0.012)	

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Table 3.6 – *Continued from previous page*

	Dependent variable:		
	InnoRec		
	Restricted model	Full model	marginal effects
	Probit	*Probit*	
	(1)	(2)	(3)
NbFirms		-0.014	-0.003
		(0.013)	
Constant	-0.947^{***}	-1.298^{***}	
	(0.015)	(0.031)	
Observations	79,418	79,418	
Pseudo-R^2	-0.092	0.014	
SE cluster	Firm+Analyst	Firm+Analyst	
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 3.7: Regressions for the Three Criteria of Innovation

This table reports the results for the OLS regressions conducted for the three criteria used to determine innovative recommendations. The dependent variables are *Divergent*, *Bold*, and *Lead*, respectively. *Bold* refers to the change in recommendation by analyst *i* for firm *j* at time *t* relative to the previous recommendation made by the analyst *i* for firm *j*. *Divergent* is the absolute value of the difference between recommendation by analyst *i* for firm *j* at time *t* and the six-month consensus. *Lead* is the number of days between the current recommendation and previous recommendation for the same firm. *FirstRec* is an indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for recommended firm *j*, zero otherwise. *Affiliation* is a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation. *SupportEPS* is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of the EPS forecast for the same firm, zero otherwise. *Favorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Strong Buy" or "Buy", zero otherwise. *Unfavorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Under-perform" or "Sell", zero otherwise. *SameCountry* is an binary variable that equals 1 if recommendation is issued by analyst located in the same country as the firm covered by analyst, zero otherwise. *BrokerSize* refers to analyst's broker size, which is calculated as the number of analysts working for the brokerage house employing the analyst *i* during the year of recommendation. *AnalystFol* is the number of analysts covering the firm *i* during the year of the recommendation. *FirmExper* is measured as the number of year between analyst's first recommendation recorded by *I/B/E/S* and the current recommendation. *NbFirms* the number of firms covered by the analyst during the year of the recommendation revisions. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized.

	Dependent variable:		
	Divergent	Bold	Lead
	OLS	*OLS*	*OLS*
	(1)	(2)	(3)
Female	-0.053^{***}	-0.046^{**}	-0.024^{*}
	(0.015)	(0.019)	(0.014)
Bold	0.362^{***}		-0.013^{**}
	(0.007)		(0.006)
Diverge		0.349^{***}	0.031^{***}
		(0.011)	(0.007)
Lead	0.055^{***}	-0.024^{**}	
	(0.012)	(0.010)	
FirstRec	0.410^{***}	-1.373^{***}	0.074^{***}
	(0.012)	(0.013)	(0.013)
Affiliation	-0.018	-0.145^{***}	-0.083^{***}
	(0.025)	(0.035)	(0.024)
Favorable	0.537^{***}	-0.141^{***}	0.008
	(0.015)	(0.009)	(0.009)
Unfavorable	1.280^{***}	-0.068^{***}	-0.060^{***}
	(0.020)	(0.015)	(0.013)
BrokerSize	-0.049^{***}	-0.053^{***}	0.020^{***}
	(0.006)	(0.008)	(0.006)

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Table 3.7 – *Continued from previous page*

	Dependent variable:		
	Divergent	Bold	Lead
	OLS	*OLS*	*OLS*
	(1)	(2)	(3)
AnalystFol	-0.023^{***}	0.048^{***}	-0.214^{***}
	(0.005)	(0.006)	(0.005)
SameCountry	0.053^{***}	0.079^{***}	-0.245^{***}
	(0.010)	(0.013)	(0.013)
supportEPS	-0.004	0.103^{***}	-0.126^{***}
	(0.008)	(0.009)	(0.009)
FirmExper	-0.003	0.004	0.008^{*}
	(0.004)	(0.008)	(0.005)
NbFirms	0.0002	-0.005	0.017^{**}
	(0.005)	(0.006)	(0.008)
Constant	-0.951^{***}	0.071^{***}	0.179^{***}
	(0.013)	(0.019)	(0.016)
Observations	80,690	80,690	80,690
R^2	0.286	0.473	0.064
Adjusted R^2	0.285	0.473	0.064
Fixed effects	Firm	Firm	Firm
SE cluster	Analyst	Analyst	Analyst
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3.8: Regression for Innovative Recommendations: Conditional on Recommendation Levels

The table reports the results for the probit regressions conducted for innovative recommendations. The dependent variable is *InnoRec*. Stock recommendations are categorized into favorable, neutral and unfavorable recommendations. *FirstRec* is an indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for recommended firm *j*, zero otherwise. *Affiliation* is a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation. *SupportEPS* is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of the EPS forecast for the same firm, zero otherwise. *Favorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Strong Buy" or "Buy", zero otherwise. *Unfavorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Under-perform" or "Sell", zero otherwise. *SameCountry* is an binary variable that equals 1 if recommendation is issued by analyst located in the same country as the firm covered by analyst, zero otherwise. *BrokerSize* refers to analyst's broker size, which is calculated as the number of analysts working for the brokerage house employing the analyst *i* during the year of recommendation. *AnalystFol* is the number of analysts covering the firm *i* during the year of the recommendation. *FirmExper* is measured as the number of year between analyst's first recommendation recorded by *I/B/E/S* and the current recommendation. *NbFirms* the number of firms covered by the analyst during the year of the recommendation revisions. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized.

	Dependent variable:					
	InnoRec					
	Favorable		Neutral		Unfavorable	
	Probit		*Probit*		*Probit*	
	Coeff	Marg. eff	Coeff	Marg. eff	Coeff	Marg. eff
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.147^{***}	-0.035	-0.160^{***}	-0.022	-0.138^{**}	-0.047
	(0.044)		(0.051)		(0.055)	
FirstRec	-0.768^{***}	-0.181	-0.794^{***}	-0.110	-0.861^{***}	-0.295
	(0.028)		(0.044)		(0.037)	
Affiliation	-0.156^{*}	-0.037	-0.065	-0.009	-0.258^{**}	-0.088
	(0.083)		(0.096)		(0.124)	
BrokerSize	-0.081^{***}	-0.019	-0.111^{***}	-0.015	-0.122^{***}	-0.042
	(0.016)		(0.019)		(0.022)	
AnalystFol	0.036^{***}	0.008	-0.282^{***}	-0.039	0.012	0.004
	(0.013)		(0.016)		(0.017)	
SameCountry	0.102^{***}	0.024	0.0002	0.00002	0.023	0.008
	(0.031)		(0.039)		(0.038)	
supportEPS	0.059^{**}	0.014	-0.014	-0.002	0.100^{***}	0.034
	(0.023)		(0.028)		(0.029)	
FirmExper	0.024^{*}	0.006	-0.049^{***}	-0.007	-0.022	-0.007
	(0.014)		(0.016)		(0.019)	
NbFirms	-0.039^{***}	-0.009	0.0004	0.0001	0.029	0.010
	(0.015)		(0.017)		(0.018)	

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Table 3.8 – *Continued from previous page*

	Dependent variable:					
	InnoRec					
	Favorable		Neutral		Unfavorable	
	Probit		*Probit*		*Probit*	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.854^{***}		-1.290^{***}		-0.278^{***}	
	(0.032)		(0.039)		(0.037)	
Observations	38,446		27,377		13,595	
Pseudo R^2	0.060		0.093		0.064	
SE cluster	Firm+Analyst		Firm+Analyst		Firm+Analyst	
Note:					*p<0.1; **p<0.05; ***p<0.01	

Table 3.9: Linear Probability Model for Innovative Recommendations

This table reports the results for linear probability models conducted for innovative recommendations. The dependent variables are *InnoRec*. *FirstRec* is an indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for recommended firm *j*, zero otherwise. *Affiliation* is a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation. *SupportEPS* is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of the EPS forecast for the same firm, zero otherwise. *Favorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Strong Buy" or "Buy", zero otherwise. *Unfavorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Under-perform" or "Sell", zero otherwise. *SameCountry* is an binary variable that equals 1 if recommendation is issued by analyst located in the same country as the firm covered by analyst, zero otherwise. *BrokerSize* refers to analyst's broker size, which is calculated as the number of analysts working for the brokerage house employing the analyst *i* during the year of recommendation. *AnalystFol* is the number of analysts covering the firm *i* during the year of the recommendation. *FirmExper* is measured as the number of year between analyst's first recommendation recorded by *I/B/E/S* and the current recommendation. *NbFirms* the number of firms covered by the analyst during the year of the recommendation revisions. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized.

	Dependent variable:	
	InnoRec	
	Restricted model	Full model
	OLS	*OLS*
	(1)	(2)
Female	-0.028^{***}	-0.032^{***}
	(0.008)	(0.004)
FirstRec		-0.153^{***}
		(0.003)
Affiliation		-0.027^{***}
		(0.009)
Favorable		0.099^{***}
		(0.003)
Unfavorable		0.265^{***}
		(0.005)
BrokerSize		-0.026^{***}
		(0.002)
AnalystFol		-0.045^{***}
		(0.004)
SameCountry		0.018^{***}
		(0.005)
EPS support		0.013^{***}
		(0.003)
FirmExper		0.002
		(0.002)

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Table 3.9 – *Continued from previous page*

	Dependent variable:	
	InnoRec	
	Restricted model	Full model
	OLS	*OLS*
	(1)	(2)
NbFirms		-0.003^{*}
		(0.002)
Constant	0.172^{***}	
	(0.004)	
Observations	79,418	79,418
R^2	0.001	0.102
Adjusted R^2	0.001	0.014
Fixed effects	None	Firm
SE cluster	Analyst	Analyst
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3.10: Analysis of Innovative Recommendations Using the Heckman Model

The table reports the regression results using the Heckman two-stage model to account for endogeneity in analyst coverage. Panel A reports the first-stage Heckman model, where I regress *Female* on the percentage of analysts with undefined gender in the country where an analyst is located. Other analyst-level characteristics and firm-level characteristics are added to the regression model as control variables. Panel B reports the main coefficients for the second-stage Heckman model, where the inverse Mill's ratio(*IMR*) is calculated from the first-stage model. *Undefined* is the percentage of analysts for whom I can not determine the gender in a given country for a given year. All the other independent variables are defined in the same way as presented in Table 3.6. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are all standardized.

Panel A. First-stage Heckman

	Dependent variable:
	Female
	Probit
Undefined	-0.046^{*}
	(0.027)
FirstRec	0.018
	(0.023)
Affiliation	0.201^{**}
	(0.091)
BrokerSize	-0.050^{*}
	(0.028)
AnalystFol	-0.003
	(0.016)
SameCountry	0.049^{**}
	(0.020)
supportEPS	0.050^{*}
	(0.027)
FirmExper	0.016
	(0.045)
NbFirms	-0.106^{***}
	(0.026)
AEF	-0.002
	(0.016)
lognbFirms	-0.032
	(0.026)
Constant	-1.017^{***}
	(0.039)
Observations	81,874
Akaike Inf. Crit.	69,998.090
SE cluster	Analyst

Panel B. Second-stage Heckman of InnoRec

	Dependent variable:		
	InnoRec		
	Restricted model	Full model	
	Probit	*Probit*	
	Coefficients	Coefficients	Marginal effects
	(1)	(2)	(3)
Female	−0.138***	−0.151***	−0.034
	(0.036)	(0.039)	
IMR	−0.091***	0.029	0.006
	(0.011)	(0.038)	
Observations	80,678	80,678	
Control variables	None	Yes	
Pseudo R^2	0.005	0.111	
SE cluster	Firm+Analyst	Firm+Analyst	
Note:			*p<0.1; **p<0.05; ***p<0.01

Panel C. Second-stage Heckman of Three Criteria

	Dependent variable:		
	Divergent	Bold	Lead
	OLS	*OLS*	*OLS*
	(1)	(2)	(3)
Female	−0.052***	−0.048**	−0.023
	(0.015)	(0.019)	(0.014)
IMR	0.036**	−0.043**	0.052***
	(0.015)	(0.018)	(0.015)
Control variables	Yes	Yes	Yes
Observations	80,678	80,678	80,678
R^2	0.286	0.473	0.064
Adjusted R^2	0.286	0.473	0.064
SE cluster	Firm+Analyst	Firm+Analyst	Firm+Analyst
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3.11: Analysis of Innovative Recommendations Using Propensity Score Matching

The table reports results from a propensity score matching approach. I first run a probit regression to pair each female recommendation with a male recommendation with statistically the same recommendation characteristics. I then run a univariate regression and a multivariate regression of financial analyst gender on the dummy dependent variable *InnoRec*. All the independent variables are defined in the same way as presented in Table 3.6. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are all standardized.

Panel A

	Dependent variable:	
	Female	
	Before matching	After matching
	Probit	*Probit*
	(1)	(2)
FirstRec	0.022	−0.006
	(0.039)	(0.039)
Affiliation	0.192	0.080
	(0.124)	(0.142)
BrokerSize	0.053*	0.015
	(0.032)	(0.036)
AnalystFol	0.054	−0.0001
	(0.043)	(0.050)
SameCountry	−0.015	0.008
	(0.040)	(0.041)
supportEPS	−0.012	0.005
	(0.027)	(0.030)
FirmExper	0.060	0.013
	(0.068)	(0.079)
NbFirms	−0.115***	−0.039
	(0.041)	(0.044)
AEF	−0.005	−0.010
	(0.026)	(0.030)
nbFirms	−0.008	0.060
	(0.060)	(0.057)
Constant	−1.037***	0.104
	(0.059)	(0.068)
Observations	81,886	23,012
Akaike Inf. Crit.	70,263.730	31,723.110
SE cluster	Firm+Analyst	Firm+Analyst
Note:		*p<0.1; **p<0.05; ***p<0.01

Panel B. Propensity Score Matching Model of InnoRec

	Dependent variable:		
	InnoRec		
	Restricted model	Full model	
	Probit	*Probit*	
	Coefficients	Coefficients	Marginal effects
	(1)	(2)	(3)
Female	-0.160^{***}	-0.177^{***}	-0.039
	(0.038)	(0.040)	
Control variables	None	Yes	
Observations	23,012	23,012	
Akaike Inf. Crit.	20,107.430	17,940.390	
SE cluster	Firm+Analyst	Firm+Analyst	
Note:			*p<0.1; **p<0.05; ***p<0.01

Panel C. Propensity Score Matching Model of Three Criteria

	Dependent variable:		
	Divergent	Bold	Lead
	OLS	*OLS*	*OLS*
	(1)	(2)	(3)
Female	-0.053^{***}	-0.062^{***}	-0.036^{**}
	(0.016)	(0.021)	(0.017)
Control variables	Yes	Yes	Yes
Observations	23,012	23,012	23,012
R^2	0.275	0.473	0.071
Adjusted R^2	0.275	0.472	0.071
SE cluster	Firm+Analyst	Firm+Analyst	Firm+Analyst
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3.12: Regressions Results for Restricted Samples

This table reports results from different the restricted samples. I run the baseline model for 1) recommendations issued by active analysts who issued at least five recommendations in a given year (Active analysts); 2) recommendations issued by analysts not located in the United Kingdom (UK excluded); 3) recommendations issued out of the financial crisis period in the year 2008-2009 (Out of Crisis); 4) recommendations issued for firms followed by at least five analysts (Firms well followed). The dependent variable is *InnoRec*. *FirstRec* is an indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for recommended firm *j*, zero otherwise. *Affiliation* is a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation. *SupportEPS* is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of the EPS forecast for the same firm, zero otherwise. *Favorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Strong Buy" or "Buy", zero otherwise. *Unfavorable* is an indicator variable that equals 1 if the recommendation is either labeled as "Under-perform" or "Sell", zero otherwise. *SameCountry* is an binary variable that equals 1 if recommendation is issued by analyst located in the same country as the firm covered by analyst, zero otherwise. *BrokerSize* refers to analyst's broker size, which is calculated as the number of analysts working for the brokerage house employing the analyst *i* during the year of recommendation. *AnalystFol* is the number of analysts covering the firm *i* during the year of the recommendation. *FirmExper* is measured as the number of year between analyst's first recommendation recorded by *I/B/E/S* and the current recommendation. *NbFirms* the number of firms covered by the analyst during the year of the recommendation revisions. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized.

	Dependent variable:			
	InnoRec			
	Active analysts	UK excluded	Out of Financial Crisis	Firms well followed
	Probit	*Probit*	*Probit*	*Probit*
	(1)	(2)	(3)	(4)
Female	-0.168^{***}	-0.197^{***}	-0.156^{***}	-0.172^{***}
	(0.042)	(0.043)	(0.039)	(0.041)
FirstRec	-0.809^{***}	-0.883^{***}	-0.789^{***}	-0.805^{***}
	(0.024)	(0.027)	(0.024)	(0.023)
Affiliation	-0.165^{**}	-0.028	-0.218^{***}	-0.183^{**}
	(0.076)	(0.080)	(0.075)	(0.081)
Favorable	0.462^{***}	0.515^{***}	0.449^{***}	0.595^{***}
	(0.021)	(0.026)	(0.021)	(0.021)
Unfavorable	1.020^{***}	1.064^{***}	1.032^{***}	1.128^{***}
	(0.025)	(0.031)	(0.026)	(0.025)
BrokerSize	-0.092^{***}	-0.090^{***}	-0.093^{***}	-0.108^{***}
	(0.016)	(0.018)	(0.016)	(0.015)
AnalystFol	-0.052^{***}	-0.036^{***}	-0.063^{***}	-0.026^{**}
	(0.012)	(0.014)	(0.012)	(0.012)
SameCountry	0.061^{**}	-0.013	0.029	0.046^{*}
	(0.029)	(0.033)	(0.028)	(0.028)
supportEPS	0.045^{**}	0.066^{***}	0.016	0.045^{**}

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Table 3.12 – *Continued from previous page*

	Dependent variable:			
	InnoRec			
	Active analysts	UK excluded	Out of Financial Crisis	Firms well followed
	Probit	*Probit*	*Probit*	*Probit*
	(1)	(2)	(3)	(4)
	(0.020)	(0.023)	(0.021)	(0.020)
FirmExper	−0.012	0.015	0.004	0.002
	(0.013)	(0.015)	(0.013)	(0.013)
NbFirms	−0.006	−0.016	-0.021^{*}	−0.009
	(0.014)	(0.015)	(0.013)	(0.014)
Constant	-1.286^{***}	-1.232^{***}	-1.238^{***}	-1.393^{***}
	(0.033)	(0.041)	(0.033)	(0.033)
Observations	69,335	48,374	57,468	69,563
Pseudo R^2	0.108	0.118	0.112	0.123
SE cluster	Firm+Analyst	Firm+Analyst	Firm+Analyst	Firm+Analyst
Note:				*p<0.1; **p<0.05; ***p<0.01

Chapter 4

Analyst Overconfidence and Market Reactions to Innovative Recommendations

Abstract: This study analyses the role that analysts' overconfidence plays in the investors' perception of innovative recommendations. I investigate whether investors discount innovative recommendations of overconfident analysts. The underlying conjecture is that if investors consider analysts' overconfidence to be detrimental to their job performance, stock markets should discount the innovative recommendations issued by male analysts, who are more overconfident than female analysts. The empirical findings suggest that market reactions to innovative recommendations are stronger than those to non-innovative recommendations. Nonetheless, I document no empirical evidence for gender differences in market reactions to innovative recommendations. The findings contrast to the empirical evidence in corporate financial decisions (Huang and Kisgen 2013; Malmendier and Tate 2008), which suggests that investors are more skeptical about projects undertaken by overconfident CEOs. My findings indicate that innovation of overconfident male analysts is not less credible than that of female analysts, suggesting that investors do not find analysts' overconfidence to be detrimental.

Keywords: financial analysts, gender, stock recommendations

4.1 Introduction

Sell-side equity analysts are important figures in the financial investment arena. Extensive prior research aims to identify the characteristics of financial analysts who produce more accurate forecasts (Clement 1999; Jacob, Lys, and Neale 1999; Kini et al. 2009) and more influential recommendations (Bradley, Jordan, and Ritter 2008; Sorescu and Subrahmanyam 2006; Loh and Stulz 2011) than their peers. Difference in analysts' performance is partly determined by factors such as analysts' forecasting ability, available resources and portfolio complexity. Past research also documents the existence of an upward bias in the outputs of financial analysts and attributes its possible origin to analysts' temptation to favor company managers or to attract investment banking business (Agrawal and Chen 2008; Cowen, Groysberg, and Healy 2006; Michaely and Womack 1999). In this paper, I investigate investors' perception of the cross-sectional difference in stock recommendations by focusing on one potentially important personal attribute of financial analysts: overconfidence. More specifically, I examine whether the well-documented gender differences in overconfidence lead to different market reactions to innovative recommendation revisions issued by male and female analysts.

Psychologists define overconfidence as an individual's over-estimation of his knowledge or ability under uncertainty. Research in psychology provides evidence for gender difference in this particular personal disposition. Men are more overconfident than women when they are involved in social activities, especially in male-dominated fields such as finance (Dahlbom et al. 2011; Bengtsson, Persson, and Willenhag 2005). In corporate decisions, overconfidence causes CEOs to be more engaged in innovations because they tend to under-estimate the probability of failure associated with innovative projects (Hirshleifer, Low, and Teoh 2012; Galasso and Simcoe 2011). From shareholders' perspective, CEOs' overconfidence leads to increased engagement in projects with negative net values, which is detrimental to shareholder value. This is why Huang and Kisgen (2013) and Malmendier and Tate (2008) find evidence that investors discount projects undertaken by overconfident male CEOs.

In the light of prior research, I argue that male analysts are more overconfident than female analysts when issuing stock recommendations. Overconfidence in this setting implies that analysts overestimate their forecasting ability, notably because they rely too much on their private information. Similar to market distrust on corporate projects undertaken by overconfident CEOs, I posit that investors discount innovative recommendations issued by male analysts if their innovation is motivated essentially by the over-estimation of their forecasting ability, *i.e*, male analysts' overconfidence.

I test the hypothesis using a comprehensive sample of sell-side analyst investment recommendations from $I/B/E/S$. I find that abnormal stock returns around innovative recommendations are significantly higher, holding other factors constant. This finding is consistent with prior literature that shows that innovative output of financial analysts are more informative to investors (Gleason and Lee 2003). Further, I investigate the potential gender difference in market reactions to innovative recommendations. The underlying conjecture is that investors should be skeptical about innovation in recommendations of male analysts, due to their relative overconfidence. I consider a battery of analyst, recommendation, and firm variables. The multivariate results show that investors do not discount innovative recommendations issued by overconfident male analysts. The cumulative abnormal returns associated with innovative recommendations of female analysts are similar to those of male analysts. The hypothesis which states that investors should discount innovative recommendations of male analysts is, therefore, rejected, suggesting that male analysts are not unduly more overconfident than female analysts to the detriment of investors who follow their stock recommendations. I find similar results using abnormal trading volume around recommendation dates as a proxy for market reactions. Additionally, I use the Heckman approach and propensity-matching scores to mitigate potential endogeneity concerns relating to the distribution of recommended firms. The results remain robust to alternative empirical approaches.

To my knowledge, this study is the first to investigate gender differences in overconfidence for financial analysts and, more specifically, in the European context. Prior research on gender heterogeneity in the financial analysts' milieu focuses uniquely on financial analysts in the United States and does not address the overconfidence issue. Green, Jegadeesh, and Tang (2009) document that female equity analysts make less accurate EPS forecasts but outperform men in all other aspects of job performance. In contrast, Kumar (2010) shows that female analysts are more likely to issue bolder and more accurate earnings forecasts than their male counterparts. He classifies forecasts that are both above (below) the prevailing analyst consensus and above (below) the analyst's most recent forecast as bold forecasts. He also shows that investors are aware of female analysts' superior forecasting abilities. Market responds more strongly to the bold earnings forecasts of female analysts. In contrast, Bosquet, Goeij, and Smedts (2014) find that female analysts are less likely to issue optimistic recommendations than their male colleagues. Li et al. (2013) analyze the abnormal stock returns associated with stock recommendations issued by female analysts and find that female analysts underperform with respect to their upgraded recommendation revisions. However, they do not find statistically significant gender difference in stock abnormal returns around recommendation announcements. This study differs from previous literature as I focus on gender difference in market reactions to innovative recommendations rather than those to all confounded recommendations.

This study's main contribution to prior literature is threefold. First, my empirical findings complement the literature on overconfidence by showing that innovation resulting from overconfidence is not detrimental to investors in the context of financial analysts. Hence, investors do not discount innovation in recommendations issued by overconfident male analysts, contrary to the empirical evidence documented for corporate financial decisions made by overconfident CEOs. Second, this study complements prior research on determinants of recommendation informativeness. Past research shows that recommendations are not equally informative to stock markets and that informativeness of recommendations can be attributed to analysts' experience, reputation, geographic proximity, brokerage size, availability of corporate information for the recommended firms, *etc* (Bradley, Jordan, and Ritter 2008; Sorescu and Subrahmanyam 2006; Loh and Stulz 2011; Sonney 2007). Consistent with Gleason and Lee (2003), I confirm that recommendation informativeness also depends on innovation in recommendation revisions. Third, this study contributes to the literature on gender heterogeneity among financial analysts by providing evidence for the impact of gender on market reactions to stock recommendations. My findings are generally consistent with those of Li et al. (2013), which, without taking into consideration the innovation level of recommendations, also confirm no gender-based difference in market reactions to recommendations revisions.

The rest of the paper is organized as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the research design. Section 4 reports the results about gender differences in market reactions to innovative recommendations. Section 5 presents robustness tests using different sub-samples. Section 6 offers a concluding discussion.

4.2 Review of Prior Literature

Extensive prior literature investigates the analyst's personal attributes that influence market reactions to stock recommendations. Heterogeneity among financial analysts may influence the investors' perception of the informativeness of earnings forecasts and investment recommendations, if investors are aware that analysts' characteristics affect forecast accuracy and recommendation profitability (Sorescu and Subrahmanyam 2006). One important analyst attribute that I study is the analyst gender. Li et al. (2013) investigate the impact of gender on market reactions to recommendation revisions and find that investment recommendations of female analysts, on average, produce abnormal stock returns comparable to those of male analysts. In this study, I investigate, whether innovative recommendations of female financial analysts are more informative to investors than those of male analysts. To develop the hypothesis under study, I rely on recent research that explicitly addresses gender difference in personal dispositions *i.e.*, overconfidence and the association between overconfidence and innovation.

4.2.1 Significance of Innovative Recommendations

This study builds on previous literature that examines the effect of analyst personal attributes on the informativeness of stock recommendations. Investment recommendations issued by sell-side equity analysts aim to provide investors with profitable investment advice. Nonetheless, only a subset of recommendation revisions are price informative and associated with visible impacts on stock prices and trading volume (Loh and Stulz 2011). Previous literature that analyses the impact of analysts' outputs on capital markets provide evidence for price informativeness of innovative recommendations and forecasts. Stickel (1990) implies that earnings forecasts revisions are more informative to investors when they are of high innovation. In the same vein, Gleason and Lee (2003) find that a forecast of high-innovation triggers larger short-term market reactions. They define as forecasts of high innovation those significantly revised from the analyst's prior advice, and far away from the analyst consensus. Furthermore, Cooper, Day, and Lewis (2001) find evidence that timeliness is also an important dimension of innovation. Analysts who issue earnings forecasts or stock recommendations ahead of other analysts are more likely to issue influential recommendations that triggers larger market reactions. This study contributes to this literature by examining the influence of a primary analyst characteristics, gender, on market reactions to innovative recommendations.

4.2.2 Overconfidence and Innovation in Stock Recommendations

The recent financial analyst research examines how analysts' psychological biases or characteristics affect their outputs such as investment recommendations and earnings forecasts (see, for example, Kumar (2010), Friesen and Weller (2006)). My focus is on overconfidence. In psychology, overconfidence is a well-established behavioral bias that causes individuals to overestimate their knowledge and their ability to perform well in decision making under uncertainty. Shefrin (2007) explains that overconfidence "pertains to how well people understand their own abilities and the limits of their knowledge". Griffin and Tversky (1992) point out that overconfidence is at its greatest when people estimate their performance on difficult tasks. An important variant of overconfidence applies to the use of private *versus* public signal value. In this setting, overconfident subjects systematically believe that their private information is more accurate than it actually is and, therefore, excessively value private over public information (Kraemer, Nöth, and Weber 2006).

Researchers in finance often refer to findings in psychology related to overconfidence to explain various puzzling anomalies in financial markets and corporate finance that can not be explained by traditional theory assuming rational behaviors and expectations. Prior behavioral research in capital markets shows that overconfidence may explain excessive trading volumes. Odean (1998) shows that overconfident investors, who believe that the precision of their private information about the value of a security is greater than it actually is, trade more than rational investors and, therefore, lower their expected utilities. He develops a model in which overconfident investors overestimate the probability that their personal assessments of the security's value are more accurate than the assessments of others, which intensifies differences of opinion. The overconfident investor overestimates the precision of his information and, thereby, the expected gains of trading.

Recent studies also prove the existence of overconfidence in corporate environment. These studies mainly investigate the relation between overconfidence and decisions on mergers and acquisitions, internal corporate financing and investment. Overconfident CEOs are found to be more prone to make acquisitions and market reactions to acquisition announcements by overconfident CEOs are more negative (Malmendier and Tate 2008; Huang and Kisgen 2013). However, the negative impact of overconfident CEOs on merger and acquisition decisions may be compensated by their increased propensity to innovate. Hirshleifer, Low, and Teoh (2012) find that overconfident CEOs are better innovators. Firms with overconfident managers accept greater risk and invest more heavily in innovative projects. Overconfident CEOs are more likely to pursue innovation because they underestimate the probability of failure and they innovate to provide evidence of their ability (Galasso and Simcoe 2011).

Prior literature points out that selecting stocks that will outperform the market is the type of task for which people are subject to overconfidence (Barber and Odean 2001). This obviously applies to stock recommendations issued by financial analysts who are therefore subject to overconfidence. Consistent with this argument, Hilary and Menzly (2006) find that, due to overconfidence resulting from past successes, analysts tend to put excessive weight on their private information and to discount public signals. They also point out that overconfident analysts do not necessarily underperform relative to other analysts, but rather they underperform compared to their own expectations.

If investors are overconfident in their assessment of private information, I would expect to observe similar biases in the way security analysts process information to produce investment recommendations. I further argue that analyst's overconfidence, similar to overconfidence exhibited by CEOs in the corporate arena, is associated with an increased propensity to innovate in their stock recommendations. Successful innovation in recommendations should be recognized and rewarded by the market because it reveals new information about the recommended firm's value. Failure causes investors to infer analyst's lack of ability. Overconfident analysts underestimate the likelihood of failure, and are therefore more likely to pursue innovation when they issue stock recommendations.

Innovative recommendations issued by overconfident analysts are more likely to be driven by overconfidence in the precision of their own information (Friesen and Weller 2006). Investors should hence discount the innovative recommendations of overconfident analysts. Nonetheless, Hilary and Menzly (2006) argue that overconfident analysts do not necessarily underperform relative to other analysts. Their under-performance is rather relative to their own estimation. Overconfident analysts perform worse than what they expected but not systematically worse than non-overconfident analysts. As a consequence, stock markets do not necessarily discount innovative recommendations issued by overconfident analysts. Accordingly, the effect of overconfidence on market reactions to innovative recommendations remains ambiguous. Therefore, a negative relationship between innovation in recommendations of overconfident analysts and abnormal market reactions at the recommendation announcement would indicate that analysts are excessively overconfident to the detriment of investors who follow their stock recommendations. In contrast, a positive relationship would indicate that analysts issue innovative recommendations that are beneficial to investors, even when they are driven by overconfidence.

4.2.3 Overconfidence and Gender

In this part, I discuss the hypothesis that male analysts exhibit more overconfidence compared to female analysts when issuing investment recommendations. Prior literature in finance and in psychology provides evidence that while both men and women exhibit overconfidence, men are more overconfident than women, particularly in male-dominated domains such as finance (Dahlbom et al. 2011; Bengtsson, Persson, and Willenhag 2005). Overconfidence implies that women generally make fewer significant decisions than men, all other things held constant (Huang and Kisgen

2013). Because overconfident men overestimate their ability, they undertake more transactions and expand the spectrum of acceptable transactions to include some deals with negative net present value. Barber and Odean (2001) document that male investors trade more than female investors but trading reduces men's net returns by 2.65 percentage points a year as opposed to 1.72 percentage points for women. They attribute the difference to men's overconfidence in their ability to trade. In the same vein, Huang and Kisgen (2013) confirm men's overconfidence in corporate financial and investment decision making. Male executives undertake more mergers and acquisitions and issue more debts relative to female analysts. However, market returns associated with *M&A* and debt issuance undertaken by male executives are systematically lower, which supports the interpretation that male executives are overconfident relative to their female counterparts.

In the context of financial analysts, men's overconfidence implies that, holding other factors constant, male analysts issue more innovative recommendations than female analysts. I test this implication by examining innovation in recommendations for male versus female analysts. If male analysts are systematically overconfident to the detriment of investors who follow their recommendations, markets should discount their innovative recommendations. In contrast, if female analysts are less excessively overconfident than male analysts, market reactions to their recommendations should be stronger than reactions to those issued by male analysts for a given level of innovation in recommendations.

In summary, overconfidence leads to more innovation in stock recommendations. Since men are systematically more overconfident than women in their ability to predict firm's value and that overconfidence leads to inaccurate decisions, I posit the following testable hypothesis:

Hypothesis *Ceteris paribus, stock markets give less credit to innovative recommendations issued by male analysts than to those issued by female analysts.*

4.3 Research Design

4.3.1 Model Specification

In a study of analyst forecast revisions, Gleason and Lee (2003) distinguish between high-innovation and low-innovation revisions by using two benchmarks: the analyst's own prior forecast and the prior day's consensus forecast. Following Gleason and Lee (2003), I characterize innovative recommendations as recommendations that diverge from the analyst consensus and from the analyst's own prior opinion. I also consider as recommendations of high-innovation, recommendations ahead of other recommendations for the same stock in time. Using these three criteria, I build an innovation index. According to this index, a recommendation revision is classified as innovative (*InnoRec*) if it falls in the last quartile of at least two of the following three criteria sorted by increasing order:

$Bold_{i,j,t}$ = change in recommendation level at time t relative to the previous recommendation made by analyst i for firm j. Recommendation changes are based on the *I/B/E/S* five-point scale fors recommendation, *i.e.* $1 =$ Strong Sell, $2 =$ Underperform, $3 =$ Hold, $4 =$ Buy, $5 =$ Strong Buy. If the current recommendation is the first recommendation issued by analyst i for firm j, the recommendation change is set to zero.

$Diverge_{i,j,t}$ = analyst i's recommendation divergence from the analyst consensus for firm j at time t, which is the absolute value of the recommendation grade minus the six-month consensus. Recommendation consensus is based on the *I/B/E/S* five-point scale of recommendation described above.

$Lead_{i,j,t}$ = analyst i's recommendation timeliness for firm j at time t, which is the number of days between the current recommendation and the previous recommendation for the same firm. If the current recommendation is the first recommendation for firm j, the *Lead* is not available.

Dependent Variables: I examine the relation between the market reaction to each stock recommendation announcement and the recommendations' characteristics, especially the level of innovation in the recommendation and the analyst gender. I measure market reactions using both absolute abnormal returns and abnormal trading volume. To calculate abnormal returns, I use the classic three-factor model developed by Fama and French (1993).

$$\mathrm{R}_{j,t} = \beta_0 + \beta_1(\mathrm{Rm}_t - \mathrm{Rf}_t) + \beta_2\mathrm{SMB}_t + \beta_3\mathrm{HML}_t + \varepsilon_{j,t} \tag{4.1}$$

where,

$\mathrm{Rm}_t =$	the daily t return on the market index;
$\mathrm{R}_{j,t} =$	the daily t return of firm j;
$\mathrm{Rf}_t =$	the daily t return on risk-free bonds;
$\mathrm{SMB}_t =$	the difference between the daily returns of a value-weighted portfolio of small stocks and one of large stocks;
$\mathrm{HML}_t =$	the difference between the daily returns of a value-weighted portfolio of high book-to-market stocks and one of low book-to-market stocks.

The estimation period is three month before the recommendation announcement date t. The regression yields parameter estimates that are used to estimate expected daily returns. The daily abnormal return of stock j at time t ($AR_{j,t}$) is the difference between the observed daily return and the expected daily return. I calculate the cumulative abnormal return over a three-day window around the recommendation announcement date as follows:

$$\mathrm{CAR}_{j,t} = \Pi_{t-1}^{t+1}(\mathrm{AR}_{j,t} + 1) - 1 \tag{4.2}$$

Apart from cumulative abnormal stock returns, I also capture market reaction using cumulative abnormal trading volume. Following Loh and Stulz (2011), I calculate the daily abnormal turnover of stock j on the date t, $ATV_{j,t}$ as follows,

$$\mathrm{ATV}_{j,t} = \mathrm{lturnover}_{j,t} - \overline{\mathrm{lturnover}_{j,t}} \tag{4.3}$$

where,

$\text{turnover}_{j,t} =$ the number of shares j traded at time t divided by the number of outstanding shares j;

$\text{lturnover}_{j,t} =$ $\log(\text{turnover}_{j,t} + 0.00000255)$;

$\overline{\text{lturnover}_{j,t}} =$ the average of daily turnover in log form, $\text{lturnover}_{j,t}$, over the past three months.

The cumulative abnormal trading volume is the sum of daily abnormal trading volumes over the three-day window around the event date.

$$\text{CAV}_{j,t} = \sum_{t-1}^{t+1} \text{ATV}_j \tag{4.4}$$

Control Variables: The selection of control variables is motivated by prior literature. Previous research has extensively investigated the stock market impacts of recommendations issued by sell-side financial analysts. Market reactions to stock recommendations are closely linked to various characteristics of the recommendation, financial analyst, financial institution and followed company under study.

Recommendation characteristics: Stock recommendations are conventionally labeled as “Strong buy", “Buy", “Hold", “Underperform" or “Sell". Market reactions to recommendations differ across recommendation levels. The distribution of analysts' recommendations is skewed to favorable recommendations because analysts tend to stop covering stocks for which they do not have an optimistic view instead of issuing unfavorable recommendations. Market reactions to unfavorable recommendations are therefore always systematically stronger. Therefore, I add to the regression model two dummy variables as control variables to capture the level of stock recommendations. $Favorable$ is an indicator variable that equals 1 if the recommendation is either labeled as “Strong Buy" or “Buy", zero otherwise. $Unfavorable$ is an indicator variable that equals 1 if the recommendation is either labeled as “Under-perform" or “Sell", zero otherwise.

Extant literature also shows that recommendations are more informative to the market if they are simultaneously accompanied by an analyst's earnings forecast for the recommended company (Jegadeesh and Kim 2010; Loh and Stulz 2011). Kecskés, Michaely, and Womack (2016) find that stock price reaction is greater for stock recommendation changes accompanied by earnings forecast revisions in the same direction as the change of recommendations. The greater informativeness of earnings-based recommendations stems from the fact that earnings-based recommendations contain detailed quantitative information, which can be eventually verified by investors at the firm's earnings announcement date. *EPSsupport* is used in the regression model to capture the effect of earnings forecasts supports. This is an indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement of an earnings forecast for the same firm by the same analyst, zero otherwise.

Prior studies also document a stronger market reactions to initial recommendations than to other recommendations made by analysts who already cover the firm (Irvine 2003; Li and You 2015). McNichols and O'Brien (1997) suggest that financial analysts tend to cover firms for which they intuitively have optimistic views. Hence, *FirstRec* is used in the model to control for the effect of initial recommendations. This is an indicator variable that equals 1 if a recommendation is the first recommendation made by the analyst for the recommended firm, zero otherwise.

Analyst characteristics: Market reactions to recommendation revisions are closely related to analyst' experience and reputation (Sorescu and Subrahmanyam 2006; Stickel 1995). Analysts with more firm-specific experience tend to issue more informative recommendations than other analysts. Sorescu and Subrahmanyam (2006) show that recommendation revisions of more experienced analysts outperform those of less experienced analysts, under the conjecture that only analysts with superior forecasting skills can survive. I capture the impact of analyst's firm-specific experience using a variable *FirmExper*, which is measured as the number of years between the analyst's first recommendation recorded by *I/B/E/S* and the current recommendation.

Further, sell-side analysts are subject to conflicts of interest because they face pressure to inflate stock recommendations when their employer has major business relations with the recommended firm. Financial institutions, undertaking IPO, SEO and M&A for current or potential clients, would like their sell-side analysts to disseminate favorable information to the market so as to facilitate the operations. Analysts with affiliation to the covered firm are, hence, more reluctant to issue unfavorable recommendations (Kadan et al. 2009). Agrawal and Chen (2008), Michaely and Womack (1999) find that investors are aware of this upward bias and therefore discount recommendation upgrades of affiliated analysts. Barber, Lehavy, and Trueman (2007) show that the average daily abnormal returns to favorable recommendations issued by independent research firms exceed those to favorable recommendations issued by analysts working for investment banks, whose opinions are potentially biased. Therefore, analyst's affiliation is controlled in the regression model. I characterize analyst affiliation ($Affiliation$) by a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house that worked for the recommended firm as a book-runner or lead-manager for an IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation.

The geographic proximity of financial analysts to followed companies is also shown to be relevant to the analysts' performance and the informativeness of their outputs. Prior literature documents a local analyst advantage that leads to better performance (Bae, Stulz, and Tan 2008; Malloy 2005). Forecast revisions made by local analysts have a larger impact on stock prices than those by other analysts because local analysts benefit from superior knowledge of country-specific factors (Sonney 2007). To control for the effect of analysts' geographic proximity, *SameCountry* is used in the model. This is a binary variable that equals 1 if the recommendation is issued by an analyst located in the same country as the recommended firm, zero otherwise.

Broker characteristics: Analysts work for brokerage houses of different sizes. Prior literature suggests that marketing ability of brokerage houses differs, which affects the visibility of analysts' investment advices (Stickel 1995; Jegadeesh and Kim 2006). Stock recommendations issued by analysts working for large brokerage houses exert stronger influence on stock markets than those issued by analysts working for small brokers. In addition, equity analysts in large brokerage houses have easier access to corporate information (Jacob, Lys, and Neale 1999), which enables them to issue more informative recommendations. To control for the effect of the brokerage house size, I add to the regression model the variable *BrokerSize* which is calculated as the number of analysts working for the brokerage house employing the analyst.

Firm characteristics: The information environment of recommended companies affects the value of recommendations. Analysts' opinions are more influential to investors in case of higher information asymmetry (Stickel 1995). Prior literature use analyst coverage or market capitalization of the recommended company as a proxy for information environment. Moreover, Gleason and Lee (2003) suggest that in case of innovative forecast revisions, additional analyst coverage facilitates market price discovery by amplifying the market reaction to the information conveyed by the innovation. Therefore, I add *AnalystFol* to the regression model as a control variable. *AnalystFol* refers to the number of analysts covering the recommended firm.

In sum, the empirical model used to investigate whether the informativeness of a stock recommendation is related to the level of innovation in recommendation and analyst's gender is as follows:

$$\begin{aligned}\text{absCAR}_{i,j,t}/\text{CAV}_{i,j,t} = {} & \beta_0 + \beta_1\text{Female}_i + \beta_2\text{InnoRec}_{i,j,t} + \beta_3\text{Female} \times \text{InnoRec}_{i,j,t} \\ & + \beta_4\text{BrokerSize}_{i,j,t} + \beta_5\text{Favorable}_{i,j,t} + \beta_6\text{Unfavorable}_{i,j,t} \\ & + \beta_7\text{Affiliation}_{i,j,t} + \beta_8\text{EPS support}_{i,j,t} + \beta_9\text{NbFirm}_{i,j,t} \\ & + \beta_{10}\text{FirstRec}_{i,j,t} + \beta_{11}\text{FirmExper}_{i,j,t} + \beta_{12}\text{AnalystFol}_{i,j,t} \\ & + \beta_{13}\text{SameCountry}_{i,j,t} + \sum_{1}^{m}\text{Firm}_j + \varepsilon_{i,j,t} \end{aligned} \tag{4.5}$$

where,

$absCAR_{i,j,t} =$ absolute value of the cumulative abnormal returns over a three-day window centered around the recommendation announcement day. I use the three-factor model developed by Fama and French (1993) to estimate expected daily returns;

$CAV_{i,j,t} =$ cumulative abnormal trading volume over a three-day window centered by around the recommendation announcement day;

$Female_{i,j,t} =$ analyst's gender, which is a dummy variable that equals 1 if the analyst is a female, zero otherwise;

$InnoRec_{i,j,t} =$ an indicator variable that equals 1 if the recommendation is classified as "innovative", zero otherwise;

$AnalystFol_{i,j,t} =$ number of analysts covering firm i during the year of the recommendation;

$Affiliation_{i,j,t} =$ a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house who worked for the recommended firm as a book-runner or lead-manager for an IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation., zero otherwise;

$BrokerSize_{i,j,t} =$ analyst's broker size, which is calculated as the number of analysts working for the brokerage house employing the analyst i during the year of recommendation;

$EPSsupport_{i,j,t} =$ indicator variable equal to one if the analyst's recommendation occurred within ten days around the announcement date of an EPS forecast by the same analyst for the same firm, zero otherwise;

$FirmExper_{i,j,t} =$ analyst's firm-specific experience, which is the number of years between analyst's first recommendation recorded by *I/B/E/S* and the current recommendation;

$FirstRec_{i,j,t} =$ indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for the recommended firm j, zero otherwise;

$Favorable_{i,j,t} =$ indicator variable that equals 1 if the recommendation is labelled as "Strong Buy" or "Buy", zero otherwise;

$Unfavorable_{i,j,t} =$ indicator variable that equals 1 if the recommendation is labeled as "Under-perform" or "Sell", zero otherwise;

$NbFirm_{i,j,t} =$ number of firms covered by the analyst during the year of the recommendation;

$SameCountry_{i,j,t} =$ binary variable that equals 1 if the recommendation is issued by an analyst located in the same country as the recommended firm, zero otherwise.

Subscripts i, j, t refer to the analyst, firm and recommendation date, respectively. All the variables (except the dummy variables) are standardized so that each variable has a mean of zero and a standard deviation of one. To ensure that extreme values do not affect the estimates, all variables are winsorized at their 0.5 and 99.5 percentile levels. I control for firm fixed effects by including dummy variables for each companies in the regression model. Standard errors are adjusted for cross-section and time-series dependence by clustering on each financial analyst to control for potential heteroscedasticity.

4.3.2 Data and Selection Method

To study the market reactions to analysts' recommendations, I merge several data sets. The most crucial one is the *I/B/E/S* database with stock recommendation data. The recommendations under scrutiny are those issued by European analysts, i.e. analysts located in the 28 European countries; namely, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom. Countries outside the European Union, such as Switzerland, Norway and Russia, are included in the research given that they belong to the same economic region.

The *I/B/E/S* database provides information on stock recommendations consisting of 1) company identifier, *i.e.*, *ISIN* code of recommended firms, 2) the date when the recommendation was issued (Recommendation date), 3) the level of each recommendation[1], 4) the identification code of each analyst and 5) the broker for which the analyst works. My data cover an eight-year period from January 2006 to December 2013. The sample period begins with the date when Euro-

[1]A five-level recommendation scale is adopted by the *I/B/E/S* database: namely, Strong Buy, Buy, Hold, Underperform, and Sell.

pean countries finished transposing the Market Abuse Directive (generally referred to as *MAD*) into their local legislation (Dubois and Dumontier 2008). The Market Abuse Directive (Directive 2003/6/EC), hereafter MAD, was adopted in 2003 by the European Commission to curb the insider dealing and market manipulation. The Directive 2003/6/EC states that

> "The identity of the producer of investment recommendations, his conduct of business rules and the identity of his competent authority should be disclosed, since it may be a valuable piece of information for investors to consider in relation to their investment decisions."

Since the implementation of MAD, analysts are therefore required to disclose their names and provide information about their previous research reports when publishing their outputs. This makes my study much more feasible since I can determine each analyst's gender by the first name.

Since the *I/B/E/S* database does not mention the analyst's gender, the gender is identified by the analyst's first name. However *I/B/E/S* only provides a brief identity code for each analyst, which is composed of the analyst's last name and the initial letter of his/her first name. For example, an analyst named "Joe Black" is coded as "J Black" in the *I/B/E/S* database. Thus, complementary information about analysts' complete first name and their workplace (at the country level) is obtained from the official website of *Thomson One*[2]. *Thomson One* provides more detailed and thorougher information about the analysts from whom it collects data. The analyst's first name, last name, employer, workplace, contact coordinates can all be found in the website. After merging the recommendation data from *I/B/E/S* with data of analyst identities, I determine the gender of associated analysts basing on a list of 22,345 unique first names[3]. Thus according to the outcome of gender identification, analysts are separated into three categories: male, female and undefined. Some analyst's gender is undefinable due to the following facts: 1) unisex first name, some first names, such as "Alex", could be used as a first name for both male and female; 2) duplicate last name and first initial, there are more than one analyst identification that could be matched with an

[2] www.thomsonone.com

[3] The data mainly come from in the following sites: www.behindthename.com/, www.babynameindex.com/, en.wikipedia.org/wiki/Category:Masculine_given_names, and en.wikipedia.org/wiki/Category:Feminine_given_names

analyst identity code, for example, “Julia Smith" and “John Smith" could both be abbreviated as “J Smith”; or 3) undisclosed analyst code: some analyst identity codes are deliberately veiled by the data provider and thus turn out to be “Undisclosed" during the data collection.

I identify 125,908 recommendations issued by 3,554 European analysts from 2006 to 2013. Almost half of the recommendations are classified as favorable recommendations. The statistics in Table 4.1 show that among all the 3,554 European analysts, 575 analysts are women. The proportion of female analysts in Europe, 16.18%, is comparable to the one observed in the United States (Kumar 2010). Further, 18,386 recommendations were issued by female analysts. They account for 14.6% of all the recommendations. Female analysts, on average, issued less recommendations that their male counterparts. Using the $I/B/E/S$ five-point scale for analysts' investment recommendations (1 = Strong Sell, 2 = Underperform, 3 = Hold, 4 = Buy, 5 = Strong Buy), I label “Strong Buy" and “Buy" recommendations as “favorable" recommendations, “Hold" recommendations as “neutral" recommendations, and “Underform" and “Sell" recommendations as “unfavorable" recommendations. The descriptive statistics suggest that analysts issue more favorable recommendations. Unfavorable recommendations are the least numerous, consistent with prior studies. This suggests that analysts' recommendation distribution is upward-biased. Female analysts issue less frequently neutral recommendations. Only 13.6% of all neutral recommendations are issued by female analysts, lower than the proportions for favorable and unfavorable recommendations, *i.e.* , 15.1%.

⟨ Insert Table 4.1 about here ⟩

I eliminate recommendations from the sample if 1) they are issued by an analyst with an undefined gender; 2) they are duplicated in *I/B/E/S*; 3) they occur within the three-day window around a firm-specific news release; 4) they are contemporaneous with other recommendations (see Table 3.2 for details in data selection). Starting from 125,908 recommendations, the final sample consists of 89,312 recommendations issued by European analysts from 2006 to 2013.

⟨ Insert Table 4.2 about here ⟩

I obtain daily stock prices and daily stock trading volume from *Compustat*. My data source for initial public and follow-on equity offering is the Securities Data Company (*SDC*) database. The index for the Fama-French three factor model are obtained from the website of Fama and French [4].

4.4 Main Results

4.4.1 Descriptive Statistics

Table 4.3 reports univariate statistics for gender difference in recommendation characteristics and market reactions to recommendation revisions. 16.9% of the recommendations under study are innovative according to my innovation index. Among the recommendations issued by male (female) analysts, 17.3% (14.5%) of them are innovative. T-statistics confirm a significant gender difference in terms of innovation in recommendations. I also observe statistically significant gender difference in market reactions to stock recommendations. On average, recommendation revisions issued by male (female) analysts trigger a three-day cumulative abnormal return that equals 3.5% (3.3%). The three-day cumulative abnormal trading volumes for stock recommendations issued by male (female) analysts is 0.423 (0.397). Recommendation revisions issued by male analysts are associated with higher *absCAR* and *CAV* than those issued by women. T-statistics suggest that the gender difference in terms of *absCAR* is significant at 0.01 level. The same statistics suggest that gender does not impact the abnormal trading volume to analysts' recommendations.

⟨ Insert Table 4.3 about here ⟩

4.4.2 Regression Results

I conduct multivariate analyses to investigate a potential gender heterogeneity in terms of market reactions to innovative recommendation revisions. Analysts characteristics as well as firm characteristics are incorporated as control variables in the estimated regressions. Table 4.4 presents

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

the estimation results from Equation (1) for the whole sample. Standard errors of estimated coefficients are clustered at the analyst level. Regression results with *absCAR* as dependent variable are presented in columns (1) and (2), while in columns (3) and (4) are presented regression results with *CAV* as dependent variable. Results for the partial model, without any control variable, are reported in columns (1) and (3). Results for the full model, described by Equation (1), are reported in columns (2) and (4), respectively.

⟨ Insert Table 4.4 about here ⟩

The empirical results show that the estimated coefficients for *InnoRec* are significantly positive across all model specifications, suggesting that innovative recommendations lead to higher market reactions. The coefficient for *Female* is significantly negative only for the partial model. The coefficients remain negative but loss statistical significance once the control variables are included in the regression model. This implies that the significant impact of the analyst gender on the market reactions to recommendation revisions comes from the omitted factors that are captured by analyst gender.

More interesting, the coefficients for the interaction between *Female* and *InnoRec* are constantly not significant at conventional level, which suggests that investors do not make a difference between innovative recommendations based on gender of the analyst who issues the innovative recommendations. This rejects the hypothesis that investors should give less credit to innovation in recommendations issued by male analysts, due to their higher overconfidence. Contrary to empirical evidence in corporate financial decisions, which indicates that markets are skeptic about projects undertaken by overconfident CEOs, I document no evidence that investors discount innovation in recommendations issued by overconfident analysts. I argue that overconfident male analysts do not necessarily underperform to female analysts but rather, as suggested by Hilary and Menzly (2006), they underperform relative to their own expectations. Hence, investors do not find less credible innovative recommendations issued by male analysts, despite their overconfidence.

Overall, the empirical findings of the baseline model document no evidence for gender difference in market reactions to recommendations, regardless of the innovation level. This is consistent with the findings of Li et al. (2013), which confirm, without taking into consideration the level of recommendation innovation, that on average, recommendations of female analysts produce similar abnormal stock returns as those of male analysts. However, my findings are, to some extent, contrary to those of Kumar (2010) relating to earnings forecasts. Kumar (2010) shows that short-term market reactions to bold forecasts are stronger when they are issued by female analysts.

The regression results also suggest that analyst's initial investment recommendations on newly-covered firms (*FirstRec*) trigger significantly less *absCAR* and less *CAV* as well, contrary to the prior evidence which shows that analysts' initial recommendations are more informative to investors. This finding suggests that investors find analysts' recommendations for a newly-covered firm less credible. The incremental impact of the analyst's affiliation (*Affiliation*) is not significant. This may result from the effectiveness of the Market Abuse Direction. Subsequent to the adoption of this directive, analysts have to disclose any potential conflict of interest resulting from business relations with the recommended firms over the twelve-month period preceding the recommendation announcement. This effectively curbs analysts' propensity to issue over-optimistic recommendations for stocks of affiliated clients.

Favorable recommendations (*Favorable*) trigger higher abnormal trading volume but no significant abnormal returns. In contrast, unfavorable recommendations (*Unfavorable*) are associated with significantly higher abnormal stock returns but no significant abnormal trading volume. The findings are consistent with prior literature which provides evidence that investors weight more unfavorable recommendations than favorable ones due to analysts' incentive to issue upward-biased recommendations (Francis and Soffer 1997). The broker size (*BrokerSize*) also affects market reactions. Recommendations issued by analysts working in larger brokerage houses are associated with larger *absCAR* and *CAV*. This finding confirms the superior marketing ability of large brokerage houses and the superior forecasting ability of analysts working in larger brokerage houses documented in prior literature. The coefficients for *AnalystFol* are significantly negative, implying that recommendations are less influential when analysts coverage is large for the recommended firm.

In addition, I find that recommendation revisions issued by financial analysts located in the same country as the covered firm (*SameCountry*) are more useful to investors, consistent with the information advantage related to analysts with geographic proximity to the recommended firm (Sonney 2007). Further, recommendations supported by an ESP forecast are associated with larger market reactions. Earnings forecasts are more sophisticated outputs and can eventually be verified at the earnings announcement. Therefore, investors find recommendations more credible if they are supported by an EPS forecast. The coefficients for the analyst firm-specific experience (*FirmExper*) yield conflicting results. I find that recommendations issued by more experienced analysts are associated with less abnormal stock returns but with more abnormal trading volume. The workload of the financial analyst, proxied by the number of firms covered by financial analysts, does not exert a significant incremental impact on market reactions.

The final discussion on the regression results of baseline models focuses on the negative values of adjusted R^2 observed for all model specifications in Table 4.4. The adjusted R^2 is derived from R^2 which measures the explanatory power of the set of X predictors on the variation of dependent variable y. R^2 is inflated as more X independent variables are added to the regressions models, which results in a faked goodness of fit. The use of adjusted R^2 corrects this bias by taking into account the number of predictors included in the model.

$$R^2_{adj} = 1 - (1 - R^2)\frac{n-1}{n-k-1} \tag{4.6}$$

where, n is the number of observations in the research sample and k is the number of independent variables X (not including the intercept). As suggested in the equation above, a small R^2 and a high variable-to-sample size ratio $\frac{n-1}{n-k-1}$ can lead to a negative adjusted R^2. This is the case for the baseline model specification because numerous dummy variables at firm level are added to the regression models to control for the firm fixed effects. The inclusion of firm dummy variables amplifies the variable-to-sample size ratio, which accounts for the negative values of adjusted R^2.

In sum, my regression results confirm that investors give more credit to innovative recommendations. I find no evidence of gender difference in market reactions to innovative recommendations. This suggests that innovation in recommendations accounts for the informativeness of recommendation revisions. However, analyst's gender, a proxy for the magnitude of overconfidence, does not exert a material impact on investors perception of innovative recommendations.

4.4.3 Additional Tests Using Recommendation Levels

Using a pooled sample of all recommendations, I have shown that innovative recommendations lead to larger market reactions but there is no evidence of gender difference in investors' reactions to innovative recommendations. I now test whether the same conclusion holds for recommendations with different tones. Table 4.5 reports sub-sample regression results of market reactions on favorable, neutral and unfavorable recommendations, respectively.

Panel A of Table 4.5 reports the regression results with three-day cumulative abnormal returns as dependent variable. Given that recommendation revisions are already categorized into three levels, I do not use the absolute value of *CAR* in this model specification. Results for the signed value of *CAR* are consistent with the baseline results presented in Table 4.4. The dummy variable *InnoRec* is significantly positive (negative) for favorable (unfavorable) recommendations. Innovative favorable (unfavorable) recommendations are associated with more positive (negative) stock returns. With regard to gender difference in market reactions to innovative recommendations, there is no evidence of a gender impact for favorable and neutral recommendations classified as innovative. Nonetheless, the regression results for unfavorable recommendations suggest that larger negative *CAR*s are associated with innovative unfavorable recommendations issued by female analysts. This finding implies that investors find that innovative unfavorable recommendations issued by female analysts are more informative. Extant literature documents that market reactions are stronger to unfavorable recommendations than favorable recommendations because of the analysts' incentive to issue upward-biased recommendations. Instead of issuing favorable recommendations, analysts tend to stop issuing recommendations for firms on which they do not have a positive investment opinion. Hence, innovative unfavorable recommendations send a strong signal to investors about the analyst's pessimistic view on the recommended firm. Investors seek for other information in the recommendation report when the report leads to an unfavorable recommendation since analysts are more intended to issue favorable recommendations (Hirst, Koonce, and Simko 1995). In such a case, investors may rely more on analysts' personal attributes such as gender.

⟨ Insert Table 4.5 about here ⟩

Results for regressions with *CAV* as dependent variable are reported in Panel B of Table 4.5. The findings are similar to those from *CAR*. The coefficients of *InnoRec* are significantly positive for both favorable and unfavorable recommendations. I find no evidence of gender difference in market reactions to innovative recommendations.

Results in Table 4.5 based on the tone of stock recommendations lead to similar qualitative conclusions. Regardless of the recommendation tone, investors find innovative recommendations more informative. In general, market reactions to innovative recommendations issued by female analysts are not different from those by male analysts except for innovative unfavorable recommendations. Innovative unfavorable recommendations issued by female analysts result in more stock trades than those by male analysts.

4.4.4 Additional Tests for Each of the Three Criteria of Innovation

The previous results focus on the relation between analyst gender and market reactions to innovative recommendations using an innovation index. The findings show that innovative recommendations are associated with larger market reactions but there is no gender difference in market reactions to innovative recommendations, except when recommendations are unfavorable. If the documented effect is robust, I should observe similar patterns for each of the three criteria used to characterize innovation in recommendations: (1) recommendation boldness, measured by the absolute distance from analyst consensus (*Bold*), (2) magnitude of the recommendation revision, measured as the absolute value of recommendation change relative to the analyst's own prior recommendation on the same stock (*Diverge*), (3) recommendation gap, measured as the number of days between the current recommendation and the last recommendation by any other analyst available for the same stock (*Lead*). To test this, I rerun the baseline model using each of the three innovation variables respectively, instead of the innovation index.

⟨ Insert Table 4.6 about here ⟩

Table 4.6 reports the coefficient estimates for each of the three criteria as the response variable respectively. The coefficients of variables *Bold* and *Diverge* are significantly positive across all of the four model specifications. The findings confirm that recommendation revisions that are away from the analyst consensus and those that diverge much from the analyst's own prior revision trigger larger abnormal stock returns and trading volumes. However, *Bold* and *Diverge* recommendations issued by female analysts do not differ from those issued by male analysts in terms of market reactions. In contrast, and to some extent surprisingly, *Lead* recommendations are associated with significantly less market reactions. It implies that investors find recommendations ahead of other recommendations less credible.

4.5 Robustness Tests

The main concern is that recommended firms are not randomly distributed to financial analysts. The lack of gender difference in innovative recommendations may therefore result from gender heterogeneity in stock coverage. The following robustness tests are mainly aimed at mitigating endogeneity resulting from potential biases in firm coverage. In this section, I discuss the three methods used to address the endogeneity concerns.

4.5.1 Heckman model

First, I use the two-stage procedure of Heckman (1979). In a first stage, consistent estimates of the αs are obtained from a probit regression of the dummy variable, *female*, on a set of independent variables Z_i. These estimates are used to compute the inverse Mills ratios (IMR). In a second stage, the market reaction equation is estimated with an OLS estimation, the inverse Mills ratio being included as an additional explanatory variable. The probit regression for the Heckman first stage model is as follows:

$$\begin{aligned}\text{Female}_i = {} & \alpha_0 + \alpha_1 \text{Favorable}_{i,j,t} + \alpha_2 \text{Unfavorable}_{i,j,t} \\ & + \alpha_3 \text{BrokerSize}_{i,j,t} + \alpha_4 \text{InnoRec}_{i,j,t} + \alpha_5 \text{Affiliation}_{i,j,t} \\ & + \alpha_6 \text{SameCountry}_{i,j,t} + \alpha_7 \text{EPS support}_{i,j,t} + \alpha_8 \text{NbFirm}_{i,j,t} + \alpha_9 \text{FirstRec}_{i,j,t} \\ & + \alpha_{10} \text{FirmExper}_{i,j,t} + \alpha_{11} \text{AnalystFol}_{i,j,t} + \alpha_{12} \text{UndAnalysts}_{i,j,t} + \varepsilon_{i,j,t} \qquad (4.7)\end{aligned}$$

My key instrumental variable is the percentage of analysts with undefined gender in the country where the analyst is located (*UndAnalysts*). While this variable *UndAnalysts* is likely to affect the likelihood of recommendations issued by female analysts, it is unlikely to affect market reactions to analysts' recommendations. The Heckman first-stage model is usually estimated using a probit model (Lennox, Francis, and Wang 2011).

Table 4.7 reports the results for the second stage of the Heckman model using *InnoRec* as a proxy for the level of innovation in recommendations. Consistent with the findings for the baseline OLS model, the coefficients of *InnoRec* are significantly positive. Further, the interaction between *Female* and *InnoRec* is not significant for either abnormal returns or abnormal turnovers. The regression results of the Heckman model confirm that innovative recommendations are more informative to investors. However, there is no evidence of any gender difference in market reactions to innovative recommendations. The coefficient of the inverse Mill's ratio (*IMR*) is marginally significant, suggesting the existence of endogeneity in the model.

⟨ Insert Table 4.7 about here ⟩

4.5.2 Propensity-score matching

The alternative specification to address endogeneity concerns is the propensity score matching method. To isolate the effect of gender heterogeneity in firm coverage, I compare female recommendations against a benchmark sample of similar recommendations issued by male analysts. I use propensity-score matching to select the benchmark sample. Matching begins with a probit regression of a female dummy variable on control variables presented as follows.

$$\begin{aligned}\text{Female}_{i,j,t} = {} & \beta_0 + \beta_1\text{InnoRec}_i + \beta_2\text{FirstRec}_i + \beta_3\text{BrokerSize}_{i,j,t} + \beta_4\text{Favorable}_{i,j,t} \\ & + \beta_5\text{Unfavorable}_{i,j,t} + \beta_6\text{Affiliation}_{i,j,t} + \beta_7\text{EPS support}_{i,j,t} + \beta_8\text{NbFirm}_{i,j,t} \\ & + \beta_9\text{FirmExper}_{i,j,t} + \beta_{10}\text{AnalystFol}_{i,j,t} + \beta_{11}\text{SameCountry}_{i,j,t} + \varepsilon_{i,j,t} \qquad (4.8)\end{aligned}$$

Panel A of Table 4.8 reports the pooled probit regressions before and after matching for two-way (by firm and analyst) cluster-robust standard errors. All of the determinants that significantly predict the probability of innovative recommendations before matching become insignificant after matching. This suggests that matching effectively reduces the differences in the observable recommendation characteristics between female and male analysts and, therefore, mitigates endogeneity issues.

I then use the propensity scores from this probit estimation and perform a nearest neighbor match with replacement to other recommendations. This procedure ensures that a female recommendation is paired with a male recommendation with statistically the same characteristics. I impose that the benchmark recommendation is within a distance (*i.e.*, a caliper) of 0.01 of the female recommendation's propensity score. This constraint aims to guarantee similarity between the female and male samples for the observable variables.

⟨ Insert Table 4.8 about here ⟩

During the sample period, the propensity-score matching generates $18,513$ female-male recommendation pairs I then run a univariate regression, and a multivariate regression with control variables on the matched sample to examine the gender differences in market reactions to innovative recommendations (See Panel B of Table 4.8). In the regression with *absCAR* as dependent variable, the coefficients of *InnoRec* are significantly positive for both partial and full models. Moreover, the interaction between *Female* and *InnoRec* is negative but of no statistical significance with regards to stock abnormal returns. Results for regressions with *CAV* yield similar conclusions. This suggests that, consistent with the findings of my baseline model, investors find more credible innovative recommendations but they react identically to innovative recommendations issued by analysts of different gender.

4.5.3 Restricted Samples

In a last step, to check the robustness of the results described above, I rerun the baseline model on different sub-samples. First, I eliminate all stock recommendations issued by inactive analysts, who issued less than five recommendations in a given year. Second, recommendation revisions issued from United Kingdom are withdrawn from the sample. Almost one third of the recommendations in the sample are issued by analysts in United Kingdom. By eliminating these recommendations, I can determine the extent to which the observed lack of gender difference in the market impacts of innovative recommendations is driven by UK observations. Third, I exclude all recommendations issued during the financial crisis from 2008 to 2009, in order to eliminate the impact of the abnormality in stock market returns during the period. Fourth, I rerun the regression models after excluding recommendations for the less covered firms, which are followed by less than five analysts in a given year.

The results for these additional tests are presented in Table 4.9. Panel A of Table 4.9 reports the regression results with *absCAR* as dependent variable. In all instances, the results are qualitatively similar to the baseline results obtained with the full sample. The coefficient estimates of *Female* remain insignificant across the four model specifications. The coefficients of *InnoRec* are significantly positive, confirming that innovative recommendations are more informative to market investors. The interaction between analyst gender and innovative recommendations have systematically no significant impact on stock returns.

Further, I replicate the same regressions with *CAV* as dependent variable. Results are reported in Panel B of Table 4.9. The coefficients of *InnoRec* are significantly positive for all the four sub-samples and the interaction between *Female* and *InnoRec* are systematically insignificant for all sub-samples.

⟨ Insert Table 4.9 about here ⟩

Consistent with the findings of the main regressions, regressions with different sub-samples confirm that innovative recommendations are more informative and that investors do not treat with difference innovative recommendations issued by male/female analysts. In sum, my results are robust to alternative methods of endogeneity corrections and different samples.

4.6 Conclusion and Discussion

Motivated by behavioral patterns caused by overconfidence, I investigate in this study whether investors discount innovation in recommendations of overconfident analysts. I posit that innovation driven by overconfidence is detrimental to investors because overconfidence causes analysts to over-estimate their forecasting ability. Therefore, innovation achieved by overconfident analysts results in recommendations that are less credible to investors. Psychology finds evidence that men are more overconfident than women when they are involved in social activities. Following prior studies on corporate financial decisions (Huang and Kisgen 2013) and investment decisions (Barber and Odean 2001), I use the analyst's gender as a proxy for overconfidence to investigate market reactions to innovative recommendations issued by overconfident analysts.

The research sample consists of recommendation revisions issued by European analysts between January 1, 2006 and December 31, 2013. I find that abnormal returns and abnormal trading volumes at recommendation announcements are larger for innovative recommendations, which is consistent with the extant literature on the informativeness of recommendation changes. Furthermore, the empirical findings indicate that there is no gender difference in market reactions to stock recommendations, regardless of the recommendations' innovation level. This is contrary to the findings of Kumar (2010) relating to earnings forecasts, who finds that bold forecasts issued by female analysts trigger stronger abnormal returns than those by male analysts.

The lack of gender difference in market reactions to innovative recommendations also rejects the hypothesis which states that markets should be skeptic about innovative recommendations of overconfident analysts. The findings suggest that innovation driven by analyst's overconfidence is not detrimental to investors. The fact that my results are opposite to Huang and Kisgen (2013)'s findings (*i.e.* they find that M&As conducted by overconfident male CEOs are associated with more negative market reactions) suggests that overconfident male analysts do not necessarily underperform relative to other analysts, even though they underperform compared to their own expectations (Hilary and Menzly 2006). An alternative explanation is that the interaction between analyst's gender and innovation in recommendations is more complicated than the one captured in the baseline model. In fact, the additional tests for the unfavorable recommendations find evidence of more negative abnormal stock returns associated with innovative unfavorable recommendations issued by female analysts. This implies that investors' reference to analyst's personal attributes, such as the analyst's gender, is conditional on the recommendation level. In case of unfavorable recommendations, investors rely more on analysts' personal attributes such as the gender.

Further analysis indicates that the informativeness of stock recommendations derives from a battery of factors including recommendation levels, information environment of recommended firms, size of brokerage house, analysts' geographic location *etc*. I find that market reactions to analyst's initial recommendations are generally weaker than to other recommendations. Recommendations revisions supported by earnings forecasts are also more informative.

This study contributes to the literature on equity analysts in several ways. First, by documenting that market reactions to analysts' recommendations are significantly related to innovation in recommendations, my analysis confirms that innovative recommendations are more informative and useful to investors. This finding complements previous research on the determinants of recommendation informativeness. Second, this study contributes to the literature on gender issues of financial analysts by providing evidence for the impact of gender on market reactions to stock recommendations. Consistent with Li et al. (2013), I document no gender difference in terms of market reactions associated with recommendations. Third, the similar market reactions to innovative recommendations issued by male and by female analysts suggest that investors do not find innovative recommendations issued by male analysts detrimental to recommendation profitability, even if male analysts have a higher propensity to issue innovative recommendation due to higher overconfidence. This finding complements the literature relating to overconfidence by showing that innovation resulting from overconfidence is not systematically detrimental.

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Appendices

4.A Tables

Table 4.1: Summary Statistics for Recommendations and Analysts under Study

This table provides descriptive statistics for recommendations issued by European financial analysts during the sample period.

	Full sample	Female	Male	%Female
Number Rec	125,908	18,386	101,442	0.146
Favorable Rec	61,600	9,322	49,364	0.151
Neutral Rec	43,583	5,943	35,229	0.136
Unfavorable Rec	20,725	3,121	16,849	0.151
Number analysts	3,554	575	2,782	0.162

Table 4.2: Sample Selection Criteria

The table presents the sample selection procedure. *Criteria* refers to the selection criteria imposed to the recommendation sample. *NumObservations* is the number of remaining recommendations after application of the criteria.

Criteria	NumObservations
recommendations issued by European analysts	125,908
- recommendations with undefined gender	119,828
- duplicated recommendations	111,782
- rec by different analysts at the same date for the same firm	96,523
- recommendations around the firm news release dates	89,312

Table 4.3: Univariate Tests for Gender Differences in Recommendation Characteristics

The table reports gender differences in terms of innovative recommendations and market reactions associated with recommendation revisions. *InnoRec* is a binary variable that is equal to one if stock recommendation is labeled as “innovative". *absCAR* refers to the absolute value of the three-day cumulative abnormal returns around the recommendation announcement date. *CAV* is the three-day cumulative abnormal trading volume around the recommendation announcement date. *Difference (Male-Female)* reports the difference between the statistics for male analysts and those for female analysts. *** , ** , and * denote two-tailed significance of t-test at the 0.01, 0.05, and 0.10 levels, respectively

	Full Sample	Female Rec	Male Rec	Difference (Male-Female)
InnoRec	0.169	0.145	0.173	0.028***
absCAR	0.035	0.033	0.035	0.002***
CAV	0.419	0.397	0.423	0.026

Table 4.4: Market Reactions to Innovative Recommendations

The table reports the results for the OLS regressions conducted for market reactions to innovative stock recommendations. The dependent variables are the absolute value of three day cumulative abnormal returns (*absCAR*) and three-day cumulative abnormal trading volume (*CAV*), respectively. *Female* is a binary variable that equals one if the recommendation is issued by a female analyst, zero otherwise. *InnoRec* is an indicator variable that equals one if the recommendation is classified as “innovative", zero otherwise. *FirstRec* is an indicator variable that equals 1 if the recommendation is the first recommendation made by the analyst for recommended firm *j*, zero otherwise. *Affiliation* is a binary variable that equals one if the recommendation is issued by an analyst employed by a brokerage house that worked for the recommended firm as a book-runner or lead-manager for an IPO (initial public offering) or SEO (second equity offering) during the five-year preceding the recommendation. *SupportEPS* is an indicator variable equal to one if the analyst’s recommendation occurred within ten days around the announcement date of the EPS forecast for the same firm, zero otherwise. *Favorable* is an indicator variable that equals 1 if the recommendation is either labeled as “Strong Buy" or “Buy", zero otherwise. *Unfavorable* is an indicator variable that equals 1 if the recommendation is either labeled as “Under-perform" or “Sell", zero otherwise. *SameCountry* is a binary variable that equals 1 if the recommendation is issued by an analyst located in the same country as the recommended firm, zero otherwise. *BrokerSize* is the number of analysts working for the brokerage house employing the analyst *i* during the year of the recommendation. *AnalystFol* is the number of analysts covering the recommended firm during the year of the recommendation. *FirmExper* is measured as the number of years between the analyst’s first recommendation recorded by *I/B/E/S* and the current recommendation. *NbFirms* is the number of firms covered by the analyst during the year of the recommendation revisions. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized. The standard errors for the coefficient estimates are shown in parentheses below the estimates.

	Dependent variable:			
	absCAR		CAV	
	Partial Model	*Full Model*	*Partial Model*	*Full Model*
	OLS	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
Female	−0.024**	−0.016	−0.028**	−0.017
	(0.012)	(0.012)	(0.013)	(0.013)
InnoRec	0.093***	0.055***	0.064***	0.046***
	(0.012)	(0.013)	(0.012)	(0.013)
Female*InnoRec	0.021	0.015	0.028	0.022
	(0.033)	(0.033)	(0.032)	(0.032)
FirstRec		−0.120***		−0.068***
		(0.010)		(0.010)
Affiliation		−0.007		−0.025
		(0.027)		(0.029)
Favorable		−0.001		0.026***
		(0.009)		(0.009)
Unfavorable		0.068***		−0.014
		(0.013)		(0.012)
BrokerSize		0.036***		0.026***
		(0.004)		(0.004)
AnalystFol		−0.050***		−0.043***

Continued on next page

Table 4.4 – *Continued from previous page*

	Dependent variable:			
	absCAR		CAV	
	Partial Model	*Full Model*	*Partial Model*	*Full Model*
	OLS	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
		(0.013)		(0.013)
SameCountry		0.081***		0.054***
		(0.011)		(0.011)
EPS support		0.033***		0.075***
		(0.008)		(0.008)
FirmExper		−0.018***		0.021***
		(0.005)		(0.005)
NbFirms		0.007		−0.005
		(0.005)		(0.005)
Observations	65,196	65,196	64,007	64,007
R^2	0.001	0.007	0.001	0.005
Adjusted R^2	-0.079	-0.073	-0.080	-0.075
SE cluster	Analyst	Analyst	Analyst	Analyst
Fixed effects	Firm	Firm	Firm	Firm
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.5: Market Reactions to Innovative Recommendations: Conditional on Recommendation Levels

The table reports the results for the regressions conducted for innovative recommendations of three different categories: favorable, neutral, unfavorable recommendations. The dependent variables are *CAR* in Panel A and *CAV* in Panel B. Definitions of all independent variables are the same as those defined in Table 4.4. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized. The standard errors for the coefficient estimates are shown in parentheses below the estimates.

Panel A of Table 4.5

	Dependent variable:		
	CAR		
	OLS	OLS	OLS
	Favorable Rec	Neutral Rec	Unfavorable Rec
	(1)	(2)	(3)
Female	−0.023	−0.004	0.016
	(0.019)	(0.024)	(0.038)
InnoRec	0.139***	−0.074**	−0.097***
	(0.020)	(0.034)	(0.027)
Female*InnoRec	0.031	−0.030	−0.131**
	(0.050)	(0.088)	(0.064)
Affiliation	0.034	−0.038	−0.062
	(0.039)	(0.049)	(0.080)
FirstRec	−0.038**	0.004	0.009
	(0.015)	(0.020)	(0.027)
BrokerSize	0.045***	−0.015*	−0.055***
	(0.007)	(0.009)	(0.013)
NbAnalyst	−0.048***	−0.004	0.047
	(0.019)	(0.022)	(0.034)
SameCountry	0.027	−0.009	−0.052*
	(0.017)	(0.022)	(0.030)
EPS support	0.037***	−0.035**	−0.065***
	(0.013)	(0.016)	(0.023)
FirmExper	0.024***	−0.016**	−0.034***
	(0.007)	(0.008)	(0.012)
NbFirm	−0.012	−0.006	0.015
	(0.007)	(0.009)	(0.012)
Observations	31,323	22,007	11,866
R^2	0.007	0.001	0.009
Adjusted R^2	-0.149	-0.211	-0.267
SE cluster	Analyst	Analyst	Analyst

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Table 4.5 – *Continued from previous page*

	Dependent variable:		
	CAR		
	OLS	OLS	OLS
	Favorable Rec	Neutral Rec	Unfavorable Rec
	(1)	(2)	(3)
Fixed effects	Firm	Firm	Firm
Note:			*p<0.1; **p<0.05; ***p<0.01

Panel B of Table 4.5

	Dependent variable:		
	CAV		
	OLS	OLS	OLS
	Favorable Rec	Neutral Rec	Unfavorable Rec
	(1)	(2)	(3)
Female	−0.030	−0.024	−0.001
	(0.018)	(0.023)	(0.041)
InnoRec	0.043**	−0.045	0.060**
	(0.018)	(0.036)	(0.025)
Female*InnoRec	0.053	0.071	0.034
	(0.049)	(0.111)	(0.063)
Affiliation	−0.035	−0.023	−0.051
	(0.045)	(0.049)	(0.075)
FirstRec	−0.068***	−0.052***	−0.064**
	(0.015)	(0.019)	(0.028)
BrokerSize	0.030***	0.020**	0.028**
	(0.007)	(0.009)	(0.012)
NbAnalyst	−0.008	−0.094***	−0.056
	(0.020)	(0.024)	(0.036)
SameCountry	0.042***	0.054***	0.064**
	(0.015)	(0.021)	(0.027)
EPS support	0.088***	0.060***	0.069***
	(0.013)	(0.015)	(0.022)
FirmExper	0.022***	0.022**	0.008
	(0.007)	(0.009)	(0.012)
NbFirm	−0.004	−0.010	−0.026**
	(0.007)	(0.009)	(0.012)
Observations	30,714	21,643	11,650
R^2	0.006	0.005	0.006
Adjusted R^2	-0.152	-0.206	-0.275
SE cluster	Analyst	Analyst	Analyst
Fixed effects	Firm	Firm	Firm
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.6: Market Reactions for Each of the Three Criteria of Innovation

The table reports the results for the OLS regressions of market reactions to stock recommendations characterized as *Bold*, *Diverge*, and *Lead*. The dependent variables are *absCAR* and *CAV*, respectively. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized.

	Dependent variable:			
	absCAR		CAV	
	Partial Model	*Full Model*	*Partial Model*	*Full Model*
	OLS	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
Female	−0.021*	−0.016	−0.023*	−0.014
	(0.012)	(0.012)	(0.012)	(0.012)
Diverge	0.018***	0.015***	0.012***	0.019***
	(0.004)	(0.005)	(0.005)	(0.005)
Lead	−0.014***	−0.018***	−0.045***	−0.050***
	(0.005)	(0.005)	(0.005)	(0.005)
Bold	0.064***	0.051***	0.064***	0.063***
	(0.004)	(0.006)	(0.004)	(0.006)
Female*Diverge	0.002	0.001	−0.004	−0.006
	(0.012)	(0.012)	(0.012)	(0.012)
Female*Lead	−0.021**	−0.021**	−0.018	−0.020
	(0.010)	(0.010)	(0.012)	(0.012)
Female*Bold	−0.011	−0.017	0.011	0.006
	(0.012)	(0.012)	(0.012)	(0.012)
FirstRec		−0.058***		0.016
		(0.012)		(0.012)
Affiliation		−0.001		−0.019
		(0.026)		(0.028)
Favorable		−0.002		0.023**
		(0.009)		(0.009)
Unfavorable		0.051***		−0.039***
		(0.014)		(0.014)
BrokerSize		0.040***		0.031***
		(0.005)		(0.005)
NbAnalyst		−0.071***		−0.084***
		(0.013)		(0.014)
SameCountry		0.076***		0.047***
		(0.010)		(0.010)
EPS support		0.025***		0.058***
		(0.009)		(0.008)
FirmExper		−0.018***		0.021***

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Table 4.6 – *Continued from previous page*

	Dependent variable:			
	absCAR		CAV	
	Partial Model	*Full Model*	*Partial Model*	*Full Model*
	OLS	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
		(0.005)		(0.005)
NbFirm		0.007		−0.004
		(0.005)		(0.005)
Observations	66,245	66,245	64,992	64,992
R^2	0.006	0.009	0.007	0.011
Adjusted R^2	-0.075	-0.071	-0.074	-0.070
Fixed effects	Firm	Firm	Firm	Firm
SE cluster	Analyst	Analyst	Analyst	Analyst

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.7: Market Reactions to Innovative Recommendations: Heckman Model

The table reports regression results using the Heckman two-stage model to account for endogeneity in analyst coverage. The dependent variables are *absCAR* and *CAV*, respectively. *IMR* refers to the inverse Mill's ratio. Definitions of other independent variables are the same as those defined in Table 4.4. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized. The standard errors for the coefficient estimates are shown in parentheses below the estimates.

	Dependent variable:			
	absCAR		CAV	
	Partial Model	*Full Model*	*Partial Model*	*Full Model*
	OLS	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
Female	−0.018	−0.016	−0.020	−0.017
	(0.012)	(0.012)	(0.013)	(0.013)
InnoRec	0.096***	0.054***	0.069***	0.046***
	(0.012)	(0.013)	(0.012)	(0.013)
Female*InnoRec	0.018	0.015	0.024	0.022
	(0.033)	(0.033)	(0.032)	(0.032)
IMR	0.029***	−0.027*	0.041***	0.012
	(0.005)	(0.016)	(0.005)	(0.016)
FirstRec		−0.124***		−0.066***
		(0.010)		(0.011)
Affiliation		−0.053		−0.004
		(0.038)		(0.039)
Favorable		−0.014		0.032***
		(0.012)		(0.012)
Unfavorable		0.056***		−0.008
		(0.014)		(0.014)
BrokerSize		0.050***		0.020**
		(0.010)		(0.010)
AnalystFol		−0.049***		−0.044***
		(0.013)		(0.013)
SameCountry		0.071***		0.058***
		(0.012)		(0.012)
EPS support		0.059***		0.063***
		(0.017)		(0.018)
FirmExper		−0.017***		0.020***
		(0.005)		(0.005)
NbFirms		0.015**		−0.009
		(0.007)		(0.007)
Observations	65,196	65,196	64,007	64,007

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Table 4.7 – *Continued from previous page*

	Dependent variable:			
	absCAR		CAV	
	Partial Model	*Full Model*	*Partial Model*	*Full Model*
	OLS	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
R^2	0.002	0.007	0.002	0.005
Adjusted R^2	-0.078	-0.073	-0.078	-0.075

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4.8: Market Reactions to Innovative Recommendations: Propensity Score Matching

The table reports the results for OLS regressions of the market reactions to innovative stock recommendations using propensity score matching. The dependent variables are *absCAR* and *CAV*, respectively. All variables are winsorized at their 0.5 and 99.5 percentile levels. The independent variables (except the dummy variables) are standardized. I first run a probit regression to pair each female recommendation with male recommendations with statistically the same recommendation characteristics. I report in Panel A the regression results before and after I match stock recommendations based on the propensity scores. I then run a univariate regression and a multivariate regression for market reactions to stock recommendations (results in Panel B).

Panel A of Table 4.8

	Dependent variable:	
	Female	
	Before matching	After matching
	Probit	*Probit*
	(1)	(2)
InnoRec	-0.134^{***}	-0.013
	(0.040)	(0.048)
FirstRec	-0.006	-0.022
	(0.046)	(0.043)
Affiliation	0.195	0.042
	(0.126)	(0.144)
Favorable	0.050	0.027
	(0.037)	(0.040)
Unfavorable	0.096^{**}	0.037
	(0.049)	(0.054)
BrokerSize	-0.046	-0.0001
	(0.039)	(0.001)
AnalystFol	-0.007	0.002
	(0.029)	(0.004)
SameCountry	0.050	0.010
	(0.072)	(0.083)
supportEPS	-0.122^{***}	-0.027
	(0.045)	(0.048)
FirmExper	-0.006	-0.007
	(0.028)	(0.016)
NbFirms	-0.023	0.005
	(0.069)	(0.005)
Constant	-1.004^{***}	0.016
	(0.070)	(0.114)
Observations	63,914	18,531

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Table 4.8 – *Continued from previous page*

	Dependent variable:	
	Female	
	Before matching	After matching
	Probit	*Probit*
	(1)	(2)
Akaike Inf. Crit.	55,027.120	25,555.130
SE cluster	Firm+Analyst	Firm+Analyst
Note:		*p<0.1; **p<0.05; ***p<0.01

Panel B of Table 4.8

	Dependent variable:			
	absCAR		CAV	
	Partial Model	*Full Model*	*Partial Model*	*Full Model*
	OLS	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)
Female	−0.023	−0.011	−0.034*	−0.018
	(0.018)	(0.018)	(0.019)	(0.019)
InnoRec	0.142***	0.108***	0.055*	0.051
	(0.035)	(0.035)	(0.033)	(0.034)
Female*InnoRec	−0.031	−0.039	0.023	0.011
	(0.048)	(0.047)	(0.045)	(0.045)
FirstRec		−0.101***		−0.065***
		(0.020)		(0.020)
Affiliation		−0.019		−0.030
		(0.046)		(0.052)
Favorable		−0.004		0.011
		(0.016)		(0.018)
Unfavorable		0.092***		−0.048*
		(0.025)		(0.025)
BrokerSize		0.049***		0.046***
		(0.009)		(0.008)
AnalystFol		−0.015		−0.042*
		(0.024)		(0.025)
SameCountry		0.081***		0.037*
		(0.022)		(0.022)
EPS support		0.040**		0.075***
		(0.016)		(0.018)
FirmExper		−0.016		0.021**
		(0.010)		(0.010)
NbFirms		0.027***		−0.001
		(0.009)		(0.010)
Observations	18,531	18,531	18,531	18,531
R^2	0.002	0.009	0.001	0.007
Adjusted R^2	-0.217	-0.210	-0.219	-0.212
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.9: Market Reactions to Innovative Recommendations: Restricted Samples

The table reports results from different restricted samples. I run the baseline model for 1) recommendations issued by active analysts; 2) recommendations issued by analysts not located in the United Kingdom; 3) recommendations issued out of the financial crises period; 4) recommendations issued for well covered firms. In Panel A, I report the results with *absCAR* as dependent variable. The results for *CAV* are presented in Panel B. To make the table easier to read, coefficients and standard errors for control variables are not given in this table.

Panel A of Table 4.9

	Dependent variable:			
	absCAR			
	Active	noUK	noCrise	Followed
	(1)	(2)	(3)	(4)
Female	−0.008	−0.018	0.002	−0.017
	(0.013)	(0.015)	(0.014)	(0.013)
InnoRec	0.057***	0.045***	0.064***	0.056***
	(0.013)	(0.016)	(0.016)	(0.014)
Female*InnoRec	0.022	0.051	0.007	0.027
	(0.036)	(0.039)	(0.041)	(0.035)
Observations	54,842	41,879	45,443	56,183
Control variables	Yes	Yes	Yes	Yes
R^2	0.007	0.008	0.006	0.007
Adjusted R^2	-0.083	-0.071	-0.101	-0.059
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B of Table 4.9

	Dependent variable:			
	CAV			
	Active	noUK	noCrise	Followed
	(1)	(2)	(3)	(4)
Female	−0.017	-0.030^{**}	−0.010	-0.023^{*}
	(0.014)	(0.015)	(0.015)	(0.014)
InnoRec	0.047^{***}	0.045^{***}	0.040^{***}	0.041^{***}
	(0.014)	(0.015)	(0.015)	(0.013)
Female*InnoRec	0.027	0.016	0.027	0.025
	(0.036)	(0.039)	(0.039)	(0.035)
Observations	54,842	41,879	45,443	56,183
Control variables	Yes	Yes	Yes	Yes
R^2	0.006	0.006	0.005	0.006
Adjusted R^2	-0.084	-0.073	-0.102	-0.061

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Chapter 5

General Conclusion

5.1 Main Findings and Contributions

Based on a panel of stock recommendations drawn from the $I/B/E/S$ database, this dissertation concentrates on examining gender issues for financial analysts. The empirical findings bring implications to both academics and practitioners from three novel perspectives.

The first essay investigates whether and how differences in national cultures affect female representation among financial analysts. I find that women represent on average 16.15% of all financial analysts, which suggests an under-representation of female financial analysts for European countries, comparable to what was documented in the United States by prior studies (Green, Jegadeesh, and Tang 2009; Kumar 2010). Furthermore, and maybe more importantly, female representation varies significantly across the countries under study. I find that national culture is a strong determinant of female representation among financial analysts in Europe. All other things equal, the lowest female representation is observed in Nordic countries, countries that have the lowest tolerance for unequal power distribution (Hofstede 2001).

The contribution of the first study is twofold. First, prior literature about female financial analysts, which is limited, is exclusively based on data collected in the United States. By providing gender observations for European financial analysts, this essay extends the scope of studies related to gender concerns in the financial analyst industry to countries outside the United States. Second, to my knowledge, the impact of culture on gender diversity among financial analysts has never been explicitly investigated. I contribute to the literature on the economic relevance of cultural values by highlighting how national cultures impact female representation of financial analysts in European countries.

In the second study, I turn my attention to innovative recommendations issued by financial analysts. The second essay examines gender difference in innovation of investment recommendations. This study finds that male analysts are more likely to issue innovative recommendations than female analysts. Recommendation revisions of male analysts are more away from the analyst consensus, more significantly revised relative to their own prior recommendation and more ahead in time of other recommendations for the same stock. The lower innovation in female analysts' recommendations suggests that analysts' innovation in recommendations is overall more driven by overconfidence, which is characteristic of men, than by superior forecasting ability, which also leads to innovation in recommendations but is mostly characteristic of female analysts.

The contribution of the second study is both methodological and practical. First, I provide a comprehensive measurement of innovation in stock recommendations by creating an innovation index. This study, therefore, contributes to the literature by a new research methodology to identify innovative recommendations. Second, by providing evidence for gender difference in issuing innovative recommendations, this study helps enhance the understanding of gender-based behavioral patterns in analysts' recommendations. The empirical findings shed light on the mechanisms behind analysts' innovation in recommendations by showing that innovation in recommendations is more led by analysts' overconfidence rather than superior forecasting ability.

In the third study, I attach importance to market reactions to innovative recommendations. I find that market reactions to innovative recommendations are stronger than those to non-innovative recommendations. Furthermore, recommendations of female analysts produce similar abnormal stock returns and trading volumes as those of male analysts, regardless of the innovation level in recommendations. Therefore, there is no evidence of gender difference in market reactions to innovative recommendations, suggesting that investors do not discount innovation of overconfident analysts because they do not see overconfidence as being detrimental to analysts' job performance.

This study is an extension of the second essay which documents evidence for male analysts' higher propensity to issue innovative recommendations. This study contributes to the literature on equity analysts in several ways. First, by documenting that market reactions to analysts' recommendations are significantly related to innovation in recommendations, my analysis confirms that innovative recommendations are more informative and credible to investors. This finding complements previous research on the determinants of recommendations' informativeness. Second, market reactions to innovative recommendations of the same magnitude for both male and female analysts suggest that investors do not find that innovative recommendation issued by male analysts are less credible, despite male analysts' relative overconfidence. This empirical finding complements the literature related to overconfidence by showing that, even though driven by overconfidence, innovation is not detrimental, notably to investors regarding financial analysts.

Taken together, this dissertation provides a novel picture of gender issues among financial analysts by 1) shedding light on the impacts of culture on female representations of financial analysts; 2) providing empirical evidence for gender difference in innovation in the settings of stock recommendations; 3) investigating investors' perception of innovative recommendations by overconfident analysts.

5.2 Limits and Future Research

This dissertation complements prior literature on the role of financial analysts in capital markets and the impact of gender on financial analysts. However, some limitations could be overcome in future research. I conclude this dissertation with a final discussion about several limits of my research and possible directions for future research.

First, my empirical analyses rely on the analysts' gender. Lacking of reliable information sources, I determined gender using each analyst's first name. This methodology suffers from one limit: I cannot determine the gender of analysts with unisex first name, such as "Alex", "Leslie". This may result in a selection bias in the research sample because all analysts with unisex first names are excluded from the study.

Second, I find, in the second study, that male analysts issue more innovative recommendations due to their relative overconfidence. In this research, overconfidence is proxied by a fixed characteristic: the analyst's gender. However, prior literature suggests a short-term dynamic in analysts' overconfidence. An analyst becomes overconfident in his ability after a series of good predictions (Hilary and Menzly 2006). Overconfidence leads him to perform poorly and the subsequent poor performance reduces his overconfidence. Therefore, future research should take this dynamic cycle into consideration by exploring the relationship between analyst's past performance, gender and innovation in recommendations.

Third, empirical findings of the third essay suggest that market does not discount innovative recommendations issued by overconfident analysts. I use the analyst's gender as a proxy for overconfidence. An important direction for future research is to measure analysts' overconfidence directly. In the study on the relationship between investors' overconfidence and portfolio diversification, Goetzmann and Kumar (2008) propose an index to measure overconfidence by capturing investors who trade the most but attain the worst performance. The index is set to one for an investor if she belongs to the highest portfolio turnover quintile and the lowest risk-adjusted performance quintile. A similar measurement of overconfidence for financial analysts may deserve further investigation.

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Résumé:
Cette thèse de doctorat comprend trois essais relatifs au genre des analystes financiers. Les résultats empiriques de la première étude attestent d'une sous-représentation des femmes analystes et confirment que la culture nationale exerce un impact important sur la représentation des femmes chez les analystes financiers dans les pays européens étudiés. La deuxième étude montre que les analystes hommes sont plus susceptibles de formuler des recommandations innovantes que les analystes femmes, du fait d'une plus forte confiance en leur jugement. Enfin, les conclusions de la troisième étude montrent que les recommandations innovantes déclenchent des réactions plus fortes de la part des investisseurs, mais on ne note aucune différence de genre dans les réactions du marché à ces recommandations innovantes. Les conclusions empiriques de cette thèse complètent la littérature sur les analystes financiers, et plus particulièrement sur l'impact du genre dans la prise de décisions financières.
Mots-clés: culture, genre, analystes financiers, recommandations des actions

Abstract:
This PhD dissertation consists of three essays relating to gender concerns among financial analysts. The empirical results of the first study provide evidence for under-representation of female analysts and confirm that national culture exerts a material impact on female representation among financial analysts across European countries under study. In the second study, I document evidence that male analysts are more likely to issue innovative recommendations than female analysts, due to their relative overconfidence. Finally, the findings of third study suggest that innovative recommendations trigger larger market reactions but there is no gender difference in market reactions to innovative recommendations. The empirical findings of my dissertation complement prior literature on financial analysts, more specifically, gender-based difference in financial market decision making.
Keywords: culture, gender, financial analysts, stock recommendations