Essays on Gender and Investment Decisions

A thesis presented in fulfilment of the requirements for the degree of

Doctor of Philosophy

in

Finance

at Massey University, Albany,

New Zealand

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2020

ABSTRACT

The puzzle is yet to be solved whether gender differences exist in behavioral biases and investment preferences of highly skilled and experienced professionals. Subsequently, this thesis consists of three related essays on investment decisions by gender of professionals in the field of finance. The first essay shows that prospect theory value influences insider trading decisions, and the impact is stronger among female executives' trades. Female insiders tend to carry more biased trades and suffer significantly higher resultant losses, as compared to their male counterparts. Female insiders who buy (sell) when their company's prospect theory value is above (below) other firms' prospect theory values, lose 47 basis points over the next month. While the findings contradict the overconfidence hypothesis that predicts poor trading decisions by male insiders, the results are consistent with the male insiders' superior information access hypothesis, suggesting that informational disadvantage serves as a possible channel of higher behavioral biases in female insiders' trading. The second essay demonstrates that the gender of mutual fund managers affects the liquidity of a portfolio. Female managers prefer higher portfolio liquidity than their male counterparts. Funds managed by single female managers are 8-25% more liquid than single male managed funds. Contrary to the excessive trading hypothesis that expects a higher liquidity preference by overconfident male fund managers, the findings support inclination of female fund managers for the price efficiency hypothesis. Funds experience an increased liquidity when they transition to a female manager. The third essay documents that collective self-construal of female fund managers explains their tendency to invest less actively as compared to their male counterparts. Funds with a higher proportion of female managers in management team closely track multifactor benchmark. For the funds managed by more female managers than males, the economic benefits of diversification are 1.86% lower than other funds. Consistent with the literature, female fund managers herd more, take less risk, and are less overconfident than males. These investment behaviors are likely to be the possible explanations of less active investing strategy of female fund managers.

DEDICATION

I dedicate this thesis to my family for their unconditional love, prayers, and support. To my wonderful parents, Muhammad Arif and Shahnaz Arif, who have believed in me and given me confidence to achieve every milestone. To my thoughtful brother, Muhmmad Adeel Arif, who has always been cooperative through my peaks and valleys. To my affectionate sister, Amna Adeel, whose encouragement has given me strength. Lastly, to my adorable niece, Zymal bint-e-Adeel, whose smile suppresses all the worries. My love for them is unquantifiable.

ACKNOWLEDGEMENTS

"Read! In the Name of your Lord, Who has created (all that exists)"

First and foremost, I am highly grateful to ALLAH (God) Almighty who has given me the opportunity and strength to accomplish this task. Without His countless blessings, I would have never been able to achieve my goals. I would take this opportunity to say thanks to the people who have played an important role in the successful completion of my thesis.

I would like to express the deepest gratitude to my supervisors Prof David K. Ding and Prof Nuttawat Visaltanachoti for their valuable support, dedication, and expert advice at every stage of my Ph.D. journey. Over the last few years, both of my supervisors have made honest efforts to make me gain more knowledge and learn new skills that are necessary for research. I express my heartfelt appreciation to Prof Nuttawat Visaltanachoti for patiently listening to all my queries and promptly addressing the concerns with his commendable knowledge and professionalism, round-the-clock. I will always be grateful to him for his effective guidance that has kept me on the track.

I highly appreciate the valuable comments of the discussants and participants of the conferences that I have attended, they have improved the quality of my thesis. I wish to thank Assoc Prof Liping Zou for putting trust in me and regularly providing tutoring opportunities. I express a special thanks to Assoc Prof Russell Gregory-Allen for helping me to learn Morningstar and Bloomberg databases, and providing a great opportunity of conducting weekly workshops for Bloomberg Champions Program. I owe a humble thanks to Mr. Mark Woods for being a great help in solving all IT issues. I extend my appreciation to Prof Martin Berka, the Head of School; and Prof Sasha Molchanov and Prof Anne de Bruin, the current and previous Associate Heads of School for providing all necessary administrative support for timely completion of the thesis.

For Ms. Sharon Henderson, Ms. Muharram Azizova, Ms. Myrah Corrales, and Ms. Simone Hey I have nothing but enormous respect. They have always gone above and beyond to support and keep my morale high. Additionally, all the academic staff of School of Economics and Finance, and the friends in Massey's External Relations Team and PACE are praiseworthy. I have always enjoyed their company.

I have surely been very lucky to find extremely supportive and sincere friends, particularly, Yasmine Farazami, Hui Zeng, Shamalka Perera, Qinghe Zhao (Link), Anum Malik, Dr Tiffany Tang, and Dr Fatima Junaid. They have been on my side through all the ups and downs, I truly owe them a lot. Thanks to all my dear Ph.D. fellows, their company has gotten me through the rough times. Last, but not the least, a special thanks to all my teachers, relatives, cousins, and friends for their sincere prayers and encouragement throughout my Ph.D. journey. They are all so valuable to me.

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CHAPTER 1

INTRODUCTION

This chapter provides a brief introduction of the thesis. Section 1.1 outlines the motivation, aim, and contribution to the literature to explore gender differences in investment decisions of professionals in the field of finance. Section 1.2 presents a brief overview of the findings of three empirical studies. Section 1.3 lists research outputs from the thesis. Finally, Section 1.4 provides the structure of the remainder of the thesis.

1.1 Motivation, Objective, and Contribution to the Literature

In the past few years, there has been a rise in the number of women holding top positions in companies. However, women continue to be underrepresented in top leadership roles. In the U.S., in companies' executive-level positions, 1 in 5 executives are female (Huang et al., 2019). Within S&P 500 indexed companies, which are the largest and most well-known companies in the U.S., only 5.8% of the Chief Executive Officers (CEOs) are female (Catalyst, 2020a). Globally, women account for less than 29% of senior positions and nearly 20% of board of director positions (Catalyst, 2020b). Men also outnumber women managers in the fund industry. Across 56 countries, about 1 in 5 funds has at least one female manager, and this trend is unchanged since the 2008 financial crisis (Sargis & Lutton, 2016). A detailed study of fund managers by gender shows that only 9.4% of fund managers in the U.S. fund industry are women (Lutton & Davis, 2015). Moreover, from 1990 to 2017, the U.S. active equity and fixed income funds have grown in number from 1,900 to 8,500, indicating more jobs for portfolio managers. However, men have obtained 85 to 90% of these new roles, and women have failed to take significant advantage of the growth in positions (Sargis & Wing, 2018).

Even though the number of females with the autonomy for strategic decision making is small, their attitudes and behaviors are important predictors of investment outcomes. Hence, this thesis explores the personality attributes, investment behaviors, and preferences of female professionals in decision making roles, and their impact on investment choices. When women climb to the top of the corporate ladder, are their investment decisions similar to those of their male counterparts? Do behavioral disparities among gender affect the investment style of professional females? Furthermore, are there some channels that contribute to the investment choices of females? We answer these questions with the help of three research studies. Considering gender, our one study examines insider trading decisions of top executives, while two of the studies investigate the investment preferences of mutual fund managers. The essays of this thesis provide empirical evidence that differences in investment decisions exist between male and female professionals. In addition to personality attributes, some situational factors also play a crucial role in shaping the trading behaviors of females.

Although a gender gap exists within leadership positions, there is a continuous emphasis on the need to improve female participation in corporate decision making. Various studies have shown that firms with gender diverse top management teams perform better than firms with less diversity (Dezsö & Ross, 2012; Hoobler et al., 2018). Nevertheless, in psychology, management, and various other fields of study, the findings are mixed regarding fundamental differences among males and females in top positions. One strand of literature argues that females are passive, sensitive, and do not possess the required skills to lead, whereas evidence also exists which indicates that females' unique cognitive skills help them to excel in leadership roles (Carli & Eagly, 2016; Eagly, 2016).

Similarly, in the field of finance, there has been a continuous debate focused on solving the puzzle of gender differences in investment decisions. Numerous studies have described that female investors are conservative in their investments (Sunden & Surette, 1998), and female executives opt for less risky corporate policies compared to male executives (Faccio, Marchica, & Mura, 2016). Ho et al. (2015) demonstrate a positive association between female executives and accounting conservatism. Contrary to this view, Doan and Iskandar-Datta (2020) provide evidence that female chief financial officers are more ethical in their decisions, but not more risk averse, than their male counterparts. Female directors are highly likely to take more risks than male directors (Adams & Funk, 2012). The literature documents that male investors trade more aggressively and earn smaller net returns than female investors (Barber & Odean, 2001). Huang and Kisgen (2013) conclude that female executives are less overconfident, inclined to make less significant acquisitions, and reduce the debt level of firms. However, Atkinson, Baird, and Frye (2003) find no disparity among male and female fund managers in terms of fund performance, risk taking, and other fund characteristics. Liu, Wei, and Xie (2014) show a positive association between a higher proportion of female executives and firm performance in China. On the other hand, Adams and Ferreira (2009) document that while female directors are more effective monitors than male directors, their impact on firm performance and value is negative.

We contribute to this contradictory issue by analyzing risk preferences of female executives, and investment preferences of female mutual fund managers. To the best of our knowledge, these personality attributes of women have not been studied in detail in the existing literature. Moreover, we find limited literature exploring gender differences in investment decisions, as opposed to corporate decisions, of professionals. Essay one (Chapter 2) shows that trading decisions of insiders are subject to risk preferences. The literature on insider trading reports that insiders earn abnormal profits on their trades because they are well informed about their firm's fundamentals (Lakonishok & Lee, 2001; Rozeff & Zaman, 1998). In contrast, our study provides empirical evidence that insiders earn losses from the trades induced by the prospect theory value and that the prospect theory value bias is stronger among female executives' trades. We measure bias according to the cumulative prospect theory. The motivation of the study relates to the findings of Inci, Narayanan, and Seyhun (2017) that access to information for female insiders is limited in comparison to their male counterparts. The results suggest that the availability of asymmetric information possibly explains the tendency of less-informed female insiders to carry more prospect theory value induces trades. Kumar (2009b) argues that investors exhibit stronger behavioral biases in valuing stocks for which information is scarce and uncertainty is high.

We show that situational attributes, as opposed to personality traits, influence biased trade losses of female executives. Male dominance at top corporate levels remains a barrier that presents a "glass ceiling", hindering females' progress to the top echelons of power (Athey, Avery, & Zemsky, 2000). Even after achieving an elite corporate position, females remain excluded from the informal networks with male peers where critical information is shared (Davies-Netzley, 1998; Lyness & Thompson, 2000). Hence, to provide support to the argument that female insiders face limited access to information which might be one of the determinants of their higher biased trade losses, we test our main results in two settings. First, we run analysis for the trades where information is expected to be equally dispersed among all executives. Examining gender differences in losses from prospect theory value trades within executives' formal titles, trade size, routine trades, and macro-level market uncertainty, the findings indicate higher biased trade losses among female insiders, compared to males. It indicates unequal access to information for female insiders, which possibly contributes to higher biased trade losses. Second, we explore the settings where insider trades are carried only when superior information is available. Buy insider trades possess valuable private information and strongly predict future returns (Lakonishok & Lee, 2001). Considering buy transactions and firms with higher proportion of female trades, our results report a decrease in female insiders' losses from biased trades.

To the best of our knowledge, this study provides the first empirical evidence of gender differences in prospect theory value bias, specifically, for insider trading. Our findings support the argument that female insiders' disadvantage in access to information (Inci, Narayanan, & Seyhun, 2017) is one of the contributors to the association between female insiders and losses from biased trades. The existing literature argues that lack of knowledge and higher uncertainty lead to behavioral biases (e.g., Feng & Seasholes, 2005; Kumar, 2009b). The analysis of insiders' gender disparity in behavioral bias is a contribution to the existing literature on decision making by professional males and females (e.g., Hibbert, Lawrence, & Prakash, 2016; Huang & Kisgen, 2013; Niessen-Ruenzi & Ruenzi, 2019). Our results are consistent with the line of literature describing that insider trades are prone to behavioral biases (e.g., Hillier, Korczak, & Korczak, 2015; Kallunki, Nilsson, & Hellström, 2009).

Essay two (Chapter 3) focuses on fund managers' preference for liquidity and examines the role of gender in selecting liquidity-preferred portfolios. The importance of holding a liquid portfolio motivates this study because holding liquid securities provides a safety cushion to mutual funds to manage liquidity risk in the event of crisis (e.g., Huang, 2015; Scholes, 2000). The study documents that liquidity preference differs among male and female fund managers. Consistent with the literature, we find that male fund managers are involved in aggressive trading. However, female fund managers significantly prefer portfolio liquidity as compared to their male counterparts. We examine why female managed funds hold more liquid stocks. The findings indicate that female fund managers prefer to hold liquid stocks for which prices adjust to information in a timely manner. Subsequently, female fund managers' inclination towards price efficient stocks is a potential channel to a higher portfolio liquidity. To measure the price efficiency of stocks, we use the price delay measure introduced by Hou and Moskowitz (2005).

We investigate the validity of the association between female fund managers and portfolio liquidity by considering fund and manager level controls, along with fund and time fixed effects, in the models. However, it is important to address the endogeneity concern in more detail. We use different techniques to deal with the issues of omitted variables, reverse causality, and selection bias. We apply the propensity score matching approach on the full sample as well as on a subsample of funds which experience a transition from one manager to another. We compare the liquidity preference of funds managed by female managers to a matched sample of peers run by male managers that are indistinguishable in terms of investment objective, time, fund, and manager level characteristics. Second, we compare the portfolio liquidity preference of the same funds managed by managers of a different gender. In addition to panel regressions with fund and time fixed effects, we use the difference-in-differences approach on transition funds to compare fund liquidity before and after transitions from male to female managers with a control sample of male to male transition funds. We conduct an additional test to rule out any endogeneity concerns. The test relies on an instrumental variable approach. Our findings are consistent and significant for all the tests.

The main contribution of the second essay is to examine the difference in preference for portfolio liquidity among male and female mutual fund managers. Our study further contributes to the existing literature that reports liquidity as one of the important characteristics of stockholdings preferred by institutional investors (e.g., Falkenstein, 1996; Gompers & Metrick, 2001). The results are consistent with the notion that behavioral disparities among gender exist even in professional settings (e.g., Faccio, Marchica, & Mura, 2016; Ho et al., 2015; Huang & Kisgen, 2013; Niessen-Ruenzi & Ruenzi, 2019). Our findings also contribute to the literature on females' inclination towards informationally transparent stocks, and the positive association between stock price efficiency and liquidity (e.g., Abad et al., 2017; Gul, Srinidhi, & Ng, 2011; Lang, Lins, & Maffett, 2012).

The third essay (Chapter 4) aims to examine whether female fund managers invest less or more actively. Highly active fund managers utilize their skills and abilities to outperform their fund's benchmark. We document that the returns of funds managed by a high proportion of female managers closely track the benchmark, thereby showing that females manage funds less actively. These results are robust to control variables such as team size, fund size, expense ratio, fund net flow, and manager demographics like age, education, and tenure. The psychology literature on self-construal of gender motivates our study. It describes that collective self-construal is one of the important female self-attributes, which makes women to be more social and interdependent than men (Cross & Madson, 1997; Kashima et al., 1995). Compared to men, women are less likely to make unique decisions which are against the common beliefs of the group. Hence, the results of our study provide evidence that the tendency of funds to deviate from the multifactor benchmark decreases when a high proportion of females are present in the fund management team.

Additionally, we test the impact of a high proportion of female fund managers in management team on the fund's economic benefit of diversification. Using the mean-variance spanning test, the findings show that collective self-construal of female fund managers reduces the benefits of diversification. This indicates that investors are less likely to enjoy diversification gains by investing in funds managed by more female managers than males. In this study, we analyze the impact of investment behaviors related to a manager's gender, i.e., herding, risk taking, and overconfidence, on the co-movement of fund returns with market returns. Considering the interdependent self-construal of female fund managers, we expect that they herd the common and acceptable investment strategies of the market, instead of making bold decisions. The literature suggests that herding behavior leads to an increase in co-movement with the market (Eun, Wang, & Xiao, 2015). Considering females to be more risk averse (Faccio, Marchica, & Mura, 2016) and less overconfident (Barber & Odean, 2001) than males, we indicate a positive impact of these behaviors on the co-movement between fund and benchmark returns. Finally, we test the investment style of female fund managers and its impact on fund activity.

The findings of study three indicate that, in addition to self-construal, investment behaviors of female fund managers are highly likely to explain less active fund management by female managers. Our findings contribute to the psychology literature of collective self-construal of women (e.g., Kashima et al., 1995; Markus & Kitayama, 1991). To the best of our knowledge, this is the first study which explores the role of gender of fund managers in funds' co-movement with the index, by using the activity measure of R^2. Moreover, this research study is an addition to the mutual fund literature on gender diversity of fund managers and team managed funds (e.g. Atkinson, Baird, & Frye, 2003; Bär, Kempf, & Ruenzi, 2010; Bär, Niessen-Ruenzi, & Ruenzi, 2009; Niessen & Ruenzi, 2006). The finding of reduced economic benefits of diversification contributes to the literature, which suggests lower performance of female professionals as compared to males (e.g., Adams & Ferreira, 2009).

1.2 Main Findings

This section highlights the main findings of the three studies. In the first study, we develop a measure of behavioral bias according to the measure of prospect theory value introduced by Barberis, Mukherjee, and Wang (2016). We find that 14.01% of our sample trades are behaviorally biased insider transactions, induced by prospect theory value. Considering all the control variables and the firm fixed effect, our regression results describe that risk preferences of insiders affect their trading decisions. The trading decisions tempted by prospect theory value make insider stocks overvalued (undervalued) and the subsequent future returns of such trades are negatively impacted. The findings indicate that 20.02% (13.86%) of the trades made by female (male) insiders are biased. Furthermore, the losses from these biased trades of female insiders are 47 basis points higher than that of their male counterparts. The coefficient of a higher loss from biased trades by female insiders is economically and statistically significant at the 1% level. Hence, we provide empirical evidence that gender differences exist in insider trading decisions and that female insiders show a stronger tendency to carry out biased trades and suffer higher losses compared to male insiders.

To propose a possible channel contributing to the main findings, we run some additional tests. Considering underrepresentation of females at top positions, and the fact that male professionals gain more benefits from information channels (social connections) than do females (Fang & Huang, 2017), we analyze settings where information is expected to be equally spread among all insiders, irrespective of the gender. Higher trade biases in these settings might be explained by the unequal availability of information. Inci, Narayanan, and Seyhun (2017) conclude that female insiders face an informational disadvantage even within the same executive position. Hence, we examine gender differences in losses from prospect theory value biased trades within similar executive titles (i.e., chairperson, chief officer, and director). Consistent with the literature that uncertainty leads to higher biases, it is evident that in all executive positions female insiders suffer more losses from prospect theory value biased trades, than males. Informed traders carry trades of large size and earn more profits (Easley & O'hara, 1987). In a given trade size, we expect the availability of information to be the same for all traders. However, we find positive association between female insiders and losses from the biased trades. We find similar results under the setting of routine trades and market-level uncertainty, which indicates limited availability or existence of noisy information for all investors (Kumar, 2009b). In these settings, higher losses of female insider trading depict that tendency of females to be influenced by their heuristics is higher than males.

As highlighted in the literature that male dominance and lack of connections become a hurdle for females to collect material information (Lyness & Thompson, 2000). Subsequently, we run a test for a sub-sample of firms where female representation is high. The regression results show that when we limit our sample to the firms in which the proportion of female insider trading is at the 95th percentile and above, no significant positive relation exists between female insider trades and the biases losses. Considering that buy transactions carry superior material information coupled with strict monitoring risk, the results describe that when female insiders buy, the prospect theory value bias does not influence their decisions and, consequently, losses diminish. Hence, access to information factor potentially explains our results.

In the second study, we use a sample of 1,932 U.S. domestic open-end single managed active equity funds from January 2000 to December 2017. The study concludes that the gender of mutual fund managers does affect the choice of portfolio liquidity, and female fund managers prefer liquidity more than male managers. We use three proxies to measure portfolio liquidity; (i) the Portfolio liquidity measure developed by Pastor, Stambaugh, and Taylor (2020), (ii) Amihud (2002) portfolio liquidity, and (iii) Bid-Ask spread portfolio liquidity. The results indicate that funds managed by single female managers are 8% to 25% more liquid than single male managed funds. The coefficients of all three measures of portfolio liquidity exhibit a significantly positive relationship with female managed funds, even after controlling for fund and manager-specific characteristics, and including year and fund fixed effects. The results also demonstrate that funds with more liquid portfolios are larger and cheaper. Moreover, the study suggests that the investment styles of funds play a significant role in either strengthening or weakening the association between portfolio liquidity and female managed funds. The literature shows that female representation at top level positions improves stock price informativeness and reduces information asymmetry in the market (Gul, Srinidhi, & Ng, 2011). We test the conjecture and provide empirical evidence that females' preference for information transparency serves as a potential explanation of the higher portfolio liquidity preference of female fund managers.

By applying propensity scores, the results show that the average portfolio liquidity of funds managed by female managers is higher than the portfolio liquidity of male managed funds, even when other relevant characteristics between the fund pairs are virtually equal. The findings of univariate regressions on the matched sample of transition funds indicate the higher liquidity preference of female managers. Following Huang and Kisgen (2013), we apply a difference-in-differences approach for comparing portfolio liquidity before and after transitions from a male to female fund manager with a control sample of male to male transition funds. The outcome documents that a fund's portfolio liquidity increases after a transition from a male to female fund manager, as compared to a male to male transition. Finally, using the U.S. state's level gender equality index (Di Noia, 2002) as an instrumental variable, we find consistent results that female fund managers prefer higher portfolio liquidity in comparison to male fund managers.

Amihud and Goyenko (2013) present R^2 as a measure of a fund's strategy or selectivity, which is the proportion of fund return variance that is explained by the variation in multifactor benchmark factors. Higher R^2 indicates that fund tracks the benchmark closely. Using a sample of 1,565 U.S. domestic open-end actively managed equity funds (including single as well as team managed funds) from January 2004 to December 2014, the results of the third study show that R^2 increases significantly with a higher fraction of female managers in the fund management team. This indicates that female fund managers tend to make decisions in accordance with market opinions, and the trends of benchmark indexes influence their portfolio management. The study reports that the diversification gains of funds managed by a higher fraction of female fund managers are 1.86% lower than other funds. Hence, we conclude that less actively managed funds pay a price in the form of reduced diversification benefits. Our results show that funds herd more with a higher female proportion in the management team and there exists a positive relation between herding and fund returns' tracking of the benchmark returns. The findings also show that female fund managers manage a portfolio of less risky stocks and have a long-term perspective to investment with a buy and hold strategy. Hence, more risk averse and less overconfidence behaviors may explain the tendency of females to invest less actively.

1.3 Research Output

Essay one, titled "Gender and Prospect Theory Value Bias: Evidence from Insider Trading," has been presented at the following forums:

- PhD symposium of Massey Business School (Albany) on November 28th, 2017.
- Main session of 22nd Annual New Zealand Finance Colloquium (NZFC) at Massey University, Palmerston North, New Zealand on 8th – 9th February 2018.
- Main session of 30th Asian Finance Association (Asian FA) Annual Meeting at Hitotshubashi Hall, Tokyo, Japan on 25th – 27th June 2018.
- Main session of 2018 New Zealand Finance Meeting (NZFM) at Crowne Plaza, Queenstown, New Zealand on 17th – 19th December 2018.

Essay three, titled "Female Fund Managers and Collectivism," has been presented at the following forums:

- PhD symposium of Massey Business School (Albany) on November 24th, 2016.

- PhD symposium of 21st Annual New Zealand Finance Colloquium (NZFC) at University of Auckland, Auckland, New Zealand on 8th – 9th February 2017.
- PhD symposium of 9th Financial Markets and Corporate Governance (FMCG) Conference at La Trobe University, Melbourne, Australia on 4th – 7th April 2018.
- Main session of 2018 Accounting and Finance Association of Australia and New Zealand (AFAANZ) at Cordis, Auckland, New Zealand on 2nd – 3rd July 2018.

1.4 Structure of the Thesis

The remainder of the thesis is structured as follows: Chapter 2 comprises of the first essay which examines bias in insider trading according to the gender of top executives. Chapter 3 includes the second empirical study which analyzes liquidity preference of male and female mutual fund managers. The third research study which tests the effect of collectivism of female fund managers on fund activity is presented in Chapter 4. Chapter 5 provides the conclusions of the three essays.[1]

[1] The studies presented in Chapter 2, 3, and 4 will be submitted to journals as co-authored work with my two supervisors. Therefore, instead of "I" and "my", the terms "we" and "our" are used throughout the thesis.

CHAPTER 2

GENDER AND PROSPECT THEORY VALUE BIAS: EVIDENCE FROM INSIDER TRADING

This chapter documents the first essay of the thesis, which tests insider trading decisions by male and female top executives. We obtain insider trading data of U.S. firms from the comprehensive source of 2iQ Research - Global Insider Transaction Data. We use the FactSet database to identify the gender of the executives, from 2000 to 2016. Our findings show that insider trades are subject to behavioral biases. Biased trade losses of female insiders are higher than the losses of male insiders. The study argues that an informational disadvantage of female insiders possibly explains their higher biased trade losses.

Section 2.1 presents the research question and motivation of the study. Section 2.2 provides the literature review while Section 2.3 establishes the research methodology and specifies the details of our data. Section 2.4 discusses the applications of diagnostic tests, analysis, and discussion of results, along with several additional tests. Section 2.5 concludes. An appendix to this chapter and the relevant reference list are provided at the end of the thesis.

Gender and Prospect Theory Value Bias: Evidence from Insider Trading

Abstract

This study shows that prospect theory value influences insider trading decisions, and that the impact is stronger among female, rather than male, executives' trades. Insiders who buy (sell) when their company's prospect theory value is above (below) other firms' prospect theory values, lose 34 (12) basis points over the next month. Female insiders, compared to their male counterparts, make higher number of prospect theory value biased trades and suffer significantly higher resultant losses (i.e. 47 basis points). While the findings contradict the overconfidence hypothesis that predicts poor trading decisions by male insiders, the results are consistent with the male insiders' superior information access hypothesis, suggesting that scarcity of information possibly explains higher biases in female insider trading.

Keywords: Executive gender, insider trading, prospect theory value, biased trade loss, access to information.

2.1 Introduction

Corporate insiders possess superior private information about their firm's fundamentals; thus, insider trades are generally profitable.[2] However, this study shows that trading decisions of insiders are subject to biases. We investigate whether gender difference exists in biased insider trades of the executives. Our study examines behavioral bias according to the cumulative prospect theory, which defines risk preferences as a function of "decision weights" that tend to overweight small probabilities and underweight high probabilities of gains and losses (Tversky & Kahneman, 1992). Additionally, we explore possible explanations of biased trading decisions of male and female insiders. Insider trading provides a perfect setting to explore the existence of behavioral biases in the environment where trading decisions are based on the company's material information. The extant literature highlights the contribution of insiders' behavioral biases and motives to their trading decisions (Kallunki, Nilsson, & Hellstrom, 2009; Lee & Piqueira, 2019). Nevertheless, these studies do not separately examine biases and resultant losses in the trading decisions of male and female executives.

The issue of behavioral disparities among gender, specifically in a professional setting, is controversial. Based on the existing literature, we develop two competing hypotheses: the *overconfidence hypothesis* and the *information access hypothesis*. The *overconfidence hypothesis* expects that male insiders make more biased trades than their female counterparts. The overconfidence of male insiders may offset their advantage of access to superior information. The overconfident male insiders trade more aggressively (Kallunki, Nilsson, & Hellstrom, 2009), and earn lower returns than females (Barber & Odean, 2001). Therefore, aggressive and frequent trading may explain higher biased trading by male insiders than their female counterparts.

In contrast to the above conjecture, the *information access hypothesis* expects that female insiders make higher biased trading decisions, compared to the ones made by male insiders. Male dominance at top corporate levels remains a barrier that presents a "glass ceiling", hindering females'

[2] See for example, Seyhun (1986); Rozeff and Zaman (1998); Lakonishok and Lee (2001); Jeng, Metrick, and Zeckhauser (2003); Agrawal and Cooper (2015).

progress to the top echelons of power (Athey, Avery, & Zemsky, 2000). Even after achieving an elite corporate position, females remain excluded from the informal networks with male peers where critical information is shared (Davies-Netzley, 1998; Lyness & Thompson, 2000). These information channels (social connections) improve the job performance of both genders but men gain more benefits from the connections than do women (Fang & Huang, 2017). Particularly, Inci, Narayanan, and Seyhun (2017) provide empirical evidence that female insiders are disadvantaged in accessing the informal channels of information and their insider trades' profitability is lower than their male counterparts. There exists a line of literature which suggests the uncertainty and poor information availability are positively associated with behavioral biases (Kumar, 2009b; Zhang, 2006). Furthermore, the literature indicates that market experience and knowledge tend to diminish the impact of behavioral biases on trading decisions (Feng & Seasholes, 2005; List, 2003). Following this stance of the literature, we expect that female insiders may have limited access to information, which possibly explains their tendency to carry higher biased trades.

We develop the measure of bias by using the prospect theory value measure of Barberis, Mukherjee, and Wang (2016). They indicate that, in the cross-section, subsequent returns are low for stocks whose past return distributions have a high prospect theory value because investors overvalue stocks with a positively skewed distribution of past returns. This measure shows the risk preferences of investors who involve in narrow framing and consider that past return distribution is representative of stock's riskiness. Subsequently, we consider that an insider trade is biased if insider stock's prospect theory value is greater (lower) than prospect theory value of the benchmark, the insider times a buy (sell) trade, and earns lower (greater) return over the next month. The resultant return from this trade is referred to a *loss* from the biased trade. To select a benchmark for comparison, we measure cross-sectional average prospect theory value of other stocks in the market (benchmark) at a particular time.

We obtain insider trading data for the United States (U.S.) firms from the comprehensive source of 2iQ Research - Global Insider Transaction Data. We include transactions of only top insiders who are classified "A" in the insider-level category by 2iQ Research. "A" insiders include those with membership on the executive board, chairpersons, and the top 5% beneficial owners of the company's stock. The findings show that insider trading decisions induced by the prospect theory value of their stocks negatively affect future returns. Hence, the results are consistent with the literature that prospect theory value explains future returns of a stock (Barberis, Mukherjee, & Wang, 2016). Considering male and female insider trades, we notice that number of male insider transactions is higher than female ones. However, overconfident male insiders are less likely to make behaviorally biased trades as compared to females. We find that female insiders carry a higher number of biased trades and suffer with higher losses, compared to their male counterparts, even after controlling for firm and insider level characteristics. Subsequently, we rule out the hypothesis that the overconfidence behavior of male insiders contributes to their higher biased trades than females.

We conduct additional tests to explore whether informational disadvantage to female insiders possibly explains their higher biased trading decisions and resultant losses. We run the analyses in two settings; first, where level of information is expected to be equal among all the executives, irrespective of their gender, second, where trades are made when superior or high-quality information is available. We expect that in the first setting, if information is equally dispersed, there ought to be no gender difference in losses from biased insider trades. For the second setting, higher losses from female insiders' biased trades are expected to diminish because the trades are influenced by superior information. For the first setting, we examine the association between female insiders and losses from biased trades under executives' similar formal titles, trade size, routine trades, and macro-level market uncertainty. Whereas, sub-sample of buy trades and firms with high proportion of female insider transactions is used for the second setting.

One may argue that the difference in informational quality between insiders' gender might be driven by their executive positions or formal titles. The extant literature documents that chief financial officers (CFO) incorporate better quality information about their future earnings and make more profitable trades than chief executive officers (CEO) (Wang, Shin, & Francis, 2012). Knewtson and Nofsinger (2014) explain that CEOs refrain from exploiting private information because of the higher scrutiny risk of their insider trades, compared to CFOs' trades. The access to information ought to be equal within each formal title; therefore, we assume that the difference in losses from biased trades among male and female insiders is likely to attenuate within a similar executive position. We group insiders into three executive positions, i.e., chairperson, chief officer, and director. The results show that, within each title category, female insiders earn higher biased trade losses than male insiders. These findings are in line with the argument that female insiders may struggle to access better information even within formal channels of information (Inci, Narayanan, & Seyhun, 2017).

Trade size is a proxy for level of information of the traders. It is evident in the literature that highly informed investors choose to trade in large size to earn greater trading profits (Dufour & Engle, 2000; Easley & O'hara, 1987). Literature provides theoretical argument that trade size is associated with higher confidence of traders with high precision of information quality, and they earn abnormal profits (Grossman & Stiglitz, 1980). Subsequently, we run our analysis conditioned on trade size. We divide our sample in trade terciles and examine the association between female insiders and prospect theory value biased trade losses. We expect that gender difference in losses may reduce in a given trade size, if all executives possess the same access to information. The findings exhibit that, even controlling for trade size, females suffer with higher biased trade losses than male insiders. Hence, females' limited access to private information may serve as a channel for their higher losses.

We categorize insider trading into (i) routine, (ii) opportunistic, and (iii) non-classified trades, following the methodology of Cohen, Malloy, and Pomorski (2012). Opportunistic trades exploit superior non-public information and result in abnormal returns. Whereas, routine trades are unlikely to incorporate better quality information about their future earnings. These trades are made on the same dates and in a regular pattern, demonstrating no information superiority. Hence, we expect to observe no gender difference in biased trade losses in routine trades' category. Similarly, we run our analysis under uncertain market situation. Following Kumar (2009b), our study considers four proxies to measure macro-level market uncertainty: (i) market volatility; (ii) the Chicago Board Options Exchange (CBOE) Volatility Index (VIX); (iii) the American Association of Individual Investors (AAII) Investor

Sentiment Data; and (iv) the U.S. national unemployment rate. There are various macro-level uncertainty variables, however, we focus on the factors which influence investment behaviors of investors and market participants. When uncertainty is high for investors, the signals conveyed from insider trading might be received differently from market participants. Hence, we expect that under uncertain market situation, insiders ought to trade on equal informational level and convey similar signals. In these settings, our outcomes of higher losses of female insiders' biased trading, compared to males, indicate that tendency of females to be influenced by their heuristics is higher than males and poor information availability potentially contribute to this association.

It is evident in the literature that insiders may sell due to reasons other than profit maximization, such as diversification or rebalancing of portfolio, liquidity, wealth, income, or tax-loss selling (Huddart & Ke, 2007). Buy trades, on the other hand, possess private information and insiders earn abnormal returns (Lakonishok & Lee, 2001). We argue that if access to information explains our results, then a reduction in losses of female insiders biased trades is expected for superior information-based buy trades. Our results are consistent with this argument. Furthermore, we follow the argument of Inci, Narayanan, and Seyhun (2017) that informational advantage from informal networks is reduced for male insiders in firms where the number of males is lesser than females. We use the proportion of female trading as a proxy for the proportion of female executives in a firm. We analyze a setting where the proportion of female trading is higher than male trading (95th percentile and above) and find that the results of higher losses from biased female trades do not persist.[3] These findings provide evidence that biased insider trades and the resultant losses of female insiders are highly likely to diminish for the trades induced by superior material information.

To the best of our knowledge, this study provides the first empirical evidence of gender differences in prospect theory value bias, specifically for insider trading. Our results are consistent with the line of literature describing that insider trades are prone to behavioral biases (e.g., Hillier, Korczak,

[3] This result supports the findings of Mobbs, Tan, and Zhang (2018) that in firms with only one female director, female outside directors earn lower abnormal returns than males when buying their company stocks. The gender difference in trading profits is statistically insignificant in firms with more than one female directors.

& Korczak, 2015; Kallunki, Nilsson, & Hellstrom, 2009; Lee & Piqueira, 2019). The analysis of insiders' gender disparity in behavioral bias is a contribution to the existing literature on decision making by professional male and female executives (e.g., Hibbert, Lawrence, & Prakash, 2016; Huang & Kisgen, 2013; Niessen-Ruenzi & Ruenzi, 2019). Our findings are in line with the argument that females, at corporate positions, are excluded from formal and informal channels of information and these networks are more beneficial for males (e.g., Davies-Netzley, 1998; Fang & Huang, 2017; Inci, Narayanan, & Seyhun, 2017; Lyness & Thompson, 2000; Mobbs, Tan, & Zhang, 2018). These findings support the literature that limited availability of information may explain behavioral biases (e.g., Kumar, 2009b; Zhang, 2006). Moreover, this study provides an insight to the limited literature of gender differences in loss aversion and probability-weighting preferences under prospect theory (e.g., Fehr-Duda, De Gennaro, & Schubert, 2006; Hibbert, Lawrence, & Prakash, 2016; Schmidt & Traub, 2002).

The rest of the paper is structured as follows. Section 2.2 provides the literature review while Section 2.3 establishes the research methodology and specifies the details of our data. Section 2.4 presents the applications of diagnostic tests, analysis, and discussion of results, along with several additional tests. Section 2.5 provides the conclusions.

2.2 Literature Review and Hypotheses Development

2.2.1 Insider Trading, Information Advantage, and Behavioral Biases

The literature on insider trading highlights several firm and market-related components that may affect buying and selling decisions and profitability of insider trading. The purchase of stock by insiders is based on superior information and insiders possess predictive ability to forecast cross-sectional stock returns (Jiang & Zaman, 2010; Lakonishok & Lee, 2001). Access to information about a firm's prospects motivates insiders to earn abnormal profits (Rozeff & Zaman, 1998; Seyhun, 1986). Market participants also believe that insiders possess superior information about cash-flow realization and future earnings (Piotroski & Roulstone, 2005); hence, an average investor can possibly make profitable trading decisions by following the trade behaviors of certain insiders. Nonetheless, insiders' sales possess weak information. It is evident in the literature that insiders may sell due to reasons other than profit maximization, such as diversification or rebalancing of portfolio, liquidity, wealth, income, or tax-loss selling (Huddart & Ke, 2007; Lakonishok & Lee, 2001).

The literature sheds light on the existence of information differences among various categories of inside executives and their trades. Cohen, Malloy, and Pomorski (2012) categorize insiders into routine and opportunistic groups based on the information content and abnormal returns earned by their trading patterns. Ali and Hirshleifer (2017) introduce another methodology to identify routine and opportunistic trades, finding that opportunistic trades earn abnormal profits by exploiting private information. By examining the information hierarchy hypothesis, it is reported that executives at the top level of the formal hierarchy (e.g., CEO and executive chairperson) have higher predictive power and earn greater abnormal returns than other executive officers do (Seyhun, 1986; Tavakoli, McMillan, & McKnight, 2012). Similarly, it is found that insider purchases by independent directors and CFOs incorporate better information about future earnings and earn positive abnormal returns, compared with officers and CEOs (Ravina & Sapienza, 2009; Wang, Shin, & Francis, 2012).

The existing literature describes the effects of behavioral biases and personality traits on insider trading. Terpstra, Rozell, and Robinson (1993) highlight that, in addition to personality and demographic variables, a trader's gender may influence the ethical decisions related to insider trading, where men are more likely to be involved in insider trading than women. Using Swedish market data, Kallunki, Nilsson, and Hellstrom (2009) examine behavioral biases, along with situational motives, and conclude that portfolio rebalancing, tax strategies, and disposition effect play the most important roles in insider trades. Moreover, male insiders trade more aggressively than females (overconfidence). Hillier, Korczak, and Korczak (2015) provide evidence that personal attributes such as year of birth, education, and gender explain up to a third of the variability in insider trading performance. Using a stock's 52-week high, Lee and Piqueira (2019) show that insider trading is affected by behavioral biases such as anchoring and disposition effect. However, no study examines gender difference in biased insider trading.

2.2.2 Prospect Theory, Probability Weighting, and Behavior Toward Prior Gains and Losses

Kahneman and Tversky (1979) and Tversky and Kahneman (1992) develop and use prospect theory to describe investors' attitude toward risky choices. According to the theory, in uncertain situations, individuals underweight uncertain outcomes compared to those that can be obtained with certainty. Thus, they become risk averse when facing potential gains and risk seeking when facing possible losses. When probability weights are applied to the value function, given the concavity across gains and convexity across losses, results show that the weighting function generally places more weight on the tails of the distribution. Thus, it reveals a common preference for lottery-like gains and a dis-preference for low probability extreme losses.

Barberis and Huang (2008) test the asset-pricing implication of the cumulative prospect theory by focusing on the probability-weighting component. Their results shed light on the theory's novel prediction that a security's own skewness can be priced. To the extent that preferences for stocks with a positively skewed return distribution are strong, assets tend to be overpriced and subsequently underperform. Barberis and Xiong (2009) argue that differences in evaluation period, expected level of return, and shape of the value function are most likely to cause variation in the prediction of subsequent risk-taking attitudes. They assume that prospect theory predicts a disposition effect only when investors derive utility from realizing gains and losses on some assets. Without this assumption, the change in the value function's curvature might contribute to risk-taking after prior gains instead of losses.

Barberis, Mukherjee, and Wang (2016) indicate that in the cross section, subsequent returns are low for stocks whose past return distributions have a high prospect theory value. Investors overvalue stocks with a high positively skewed distribution of past returns, resulting in the overvalued stock having low subsequent returns. Their study shows that the probability-weighting component of the cumulative prospect theory enhances the prospect theory value (PTV)'s predictive power for returns.

The literature on return skewness highlights the importance of the probability-weighting function. Kumar (2009a) classifies lottery stocks as those with the highest idiosyncratic skewness, the highest idiosyncratic volatility, and the lowest share prices. He shows that lottery stocks typically underperform non-lottery stocks. Using a four-factor asset-pricing model, he demonstrates that lottery stocks generate negative alpha that is both statistically significant and economically meaningful. Boyer, Mitton, and Vorkink (2010) estimate the expected idiosyncratic skewness and show that stocks with the highest expected idiosyncratic skewness underperform other stocks. The relationship between lagged extreme positive returns and future returns is reported to be significant by Bali, Cakici, and Whitelaw (2011). They show that the expected returns on stocks that exhibit extreme positive returns are low; however, controlling for this effect, the expected returns on stocks with high idiosyncratic risk are high.

Advances in the literature have been made to understand how risk attitudes of professional investors are affected based on prior gains and losses. O'Connell and Teo (2009) analyze the effect of trading gains and losses on the risk-taking attitude of institutional managers. Using a proprietary currency trades' database, their study reports that institutional investors are not prone to disposition effects; rather, they aggressively reduce risk following losses and mildly increase risk following gains. Haigh and List (2005) compare behavioral differences among undergraduate students, and professional options and futures traders from the CBOT. They conclude that professional traders, despite having vast trading experience, tend to show greater myopic loss aversion than students.

2.2.3 Gender Differences in Behavioral Biases and Access to Information

The literature on gender differences suggests that systematic dispositional disparities exist between males and females. Investigating a preference condition for loss aversion in the framework of cumulative prospect theory, Schmidt and Traub (2002) show that female subjects contribute over-proportionally to the set of strictly loss-averse choices. They demonstrate a higher degree of loss aversion than their male counterparts do. In experiments on binary choices among lotteries involving small-scale real gains and losses, Brooks and Zank (2005) describe that relatively more women are loss-averse than men. Exploring the sensitivity of women in assessing probabilities, Fehr-Duda, De Gennaro, and Schubert (2006) find women to be more risk-averse than men when facing investment choices. This laboratory experiment reveals that women tend to underweight larger probabilities than do men, and this is more pronounced in the domain of gains.

With an experimental betting game, Lam and Ozorio (2013) examine gender differences in the effect of prior gains or losses on risk-taking behavior. The study finds that women are more likely to take greater risks after a loss, whereas men tend to take greater risks after a gain. In a survey on finance professors, Hibbert, Lawrence, and Prakash (2016) report that women are more loss-averse and more likely to expect unfavorable market conditions than men, irrespective of whether they have made gains or incurred losses in their recent past investments.

The dissimilarities in risk-related behavior between the genders have been tested in multiple settings. Croson and Gneezy (2009) review the economics literature on gender differences in risk preferences, social preferences, and reaction to competition. The evidence provides substantial support that women are more risk-averse than men are. Beckmann and Menkhoff (2008) conduct a survey among professional fund managers and conclude: “fund-managing women will be women in their profession;” they are more risk-averse, shy from competition, and are less over-confident than men are. Huang and Kisgen (2013) provide evidence that female executives are more risk-averse in investment and capital structure decisions as they are more likely to exercise deep-in-the-money options early. Faccio, Marchica, and Mura (2016) evaluate whether corporate risk-taking is affected by CEO gender. They observe a subsequent decrease in risk-taking of a given firm around the transition from a male to a female CEO. Moreover, firms with a female CEO make less risky financing and investment choices. Niessen-Ruenzi and Ruenzi (2019) report that female equity fund managers are more risk-averse, follow a less extreme investment style, invest more consistently, and trade less than their male counterparts do.

Although empirical evidence supports less risk-taking behavior among women, we find controversies in the related literature. Atkinson, Baird, and Frye (2003) find that fixed income mutual funds managed by male and female managers do not differ in terms of performance, risk, and other fund characteristics. Berger, Kick, and Schaeck (2014) show that three years following an increase in female board representation, portfolio risk increases marginally.

Another prominent and extensively tested behavioral bias among genders that affects investment decisions is overconfidence. Barber and Odean (2001) investigate the trading behavior of male and female investors and find that men trade more frequently and earn annual risk-adjusted net returns that are smaller than those earned by women. They conclude that “men being more overconfident than women” drives their results. It is observed that women in general shy away from competition (Niederle & Vesterlund, 2007). Huang and Kisgen (2013) find that female executives make more value-enhancing decisions for their shareholders as they are involved in less frequent acquisitions and debt issuance. On the contrary, Nekby, Thoursie, and Vahtrik (2008) show that women selected to participate in male-dominated environments are likely to be highly competitive. Deaves, Lüders, and Luo (2009) do not find any gender differences regarding overconfidence or trading activity. They propose that women who are attracted to “male” disciplines may be different from the overall female population. Following the literature of aggressive trading by overconfident men, we expect that male insiders are more likely to carry out biased trades and suffer higher losses than female insiders.

H1a: Biased trade losses are higher among male than female insiders.

It is argued that male dominance at top corporate levels remains a barrier, hindering females' progress to the top echelons of power (Athey, Avery, & Zemsky, 2000). Human capital theory developed by Becker (1964) recognizes the importance of an individual’s cumulative stocks of education, experiences, and skills in enhancing cognitive and productive capabilities. Tharenou, Latimer, and Conroy (1994) document that women have traditionally made fewer investments in education and work experience as reflected by lower pay and promotion. As a result, a commonly held assumption is that women possess inadequate human capital for board and top executive positions (Burke & Mattis, 2000). In addition, Oakley (2000) suggests that the gatekeepers, dominated by male, do not offer women same opportunities, such as training and development, pay and promotion. Therefore, women executives must possess substantial human capital stocks in order to be considered and bring the unique characteristics to the board (Kesner, 1988).

In addition to the assumption of females having insufficient human capital stocks, their underrepresentation is also related to the status characteristics theory documented in Biernat and

Kobrynowicz (1997), that standards of ability set are higher for low-status groups, i.e. women, compared to high-status groups, i.e. men. Thus, women are forced to provide more evidence to be perceived as being of high ability. Subsequently, women are underrepresented at top executive positions. Even reaching at the top position, they suffer from their limited connection with formal and informal networks. Ibarra (1992) describes that, compared to females, males use their network ties quite effectively to improve their position in the firm. Lyness and Thompson (2000) report that women are excluded from informal networks, and their information disadvantage is stronger in firms where they are underrepresented. Moreover, due to better connections, the effect of forecasting accuracy and recommendation impact is twice as large for male analysts than that of their female counterparts (Fang & Huang, 2017).

Inci, Narayanan, and Seyhun (2017) analyze gender differences in insider trading profitability among different executive positions. They report that limited access to informal networks might be the possible explanation that female insiders tend to possess less material information, earn less abnormal profits, and trade less than their male counterparts. Mobbs, Tan, and Zhang (2018) report that, when female outside directors buy their company stocks, their informational disadvantage is largely driven by geographic distance, unrelated work experience, and lack of firm-specific board experience. This partially explains why they earn lower abnormal returns than male outside directors. Following this line of literature, we hypothesize that limited connections and information disadvantage of female insiders are highly likely to explain their higher biased trades and resultant losses, than male insiders.

H1b: Biased trade losses are higher among female than male insiders.

Based on the literature reviewed, we test gender differences in prospect theory value biased trading decisions of insiders and provide possible explanations of the results.

2.3 Data and Methodology

2.3.1 Data

We obtain insider trading data for the United States (U.S.) firms from the comprehensive source of 2iQ Research - Global Insider Transaction Data. To avoid survivorship or selection bias, 2iQ Research uses Standard and Poor Broad Market Index (S&P BMI) benchmark for orientation. 2iQ Research consists of all listed stocks that have at least USD 100 million in float-adjusted market capitalization and value traded of at least USD 50 million for the past 12 months. Our sample contains all regular open market "equity" transactions (i.e., buy and sell transactions of top executives of firms). We include transactions of only top insiders who are classified "A" in the insider-level category by 2iQ Research. "A" insiders include those with membership on the executive board, chairpersons, and the top 5% beneficial owners of the company's stock.[4] The study ignores transactions of insiders with indirect connections (e.g., immediate family member or controlled corporations). Option exercises, subscription to new shares, stock awards, transactions by beneficial owners, and private transactions are excluded from the data set. In the sample, we include only common and ordinary shares. It contains the unique transaction ID, company name, insider ID, insider name, insider relation to the company, number of shares traded, price, value of shares traded, trade date, input/reporting date to the U.S. Securities and Exchange Commission (SEC), holdings, and the exchange on which the company is listed. By applying an initial filter, we have 307,516 observations of insider trades of publicly traded firms from January 1, 2000 to December 31, 2016.

Data on stock market returns and prices for firms with insider trading and have share codes 10 and 11 are retrieved from the Center for Research in Security Prices (CRSP). The sample comprises of 279,278 insider trades by 15,599 top executives of 5,920 firms. To deal with potential outliers and

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[4] Insiders' category "B" of 2iQ Research consists of upper level management (e.g., executive committee and the top 20% beneficial owners of the company. In this category, the number of insider trades is 201,000, carried out by 29,942 insiders (with initial filters). Insiders' category "C" contains non-executives, supervisory board, and board of directors. The number of insider transactions is 294,556 in this category, carried out by 39,218 insiders (with initial filters). We describe that top "A" insiders are smaller in number, but they more frequently involved in insider trading as compared with the other two categories.

misreporting, we follow the recommendations of Inci, Narayanan, and Seyhun (2017). We exclude insider transactions when on the trade date: (i) the insider transaction price is higher than twice the closing price of the stock; (ii) the number of shares of the insider transaction is higher than the daily volume of trade of the stock; and (iii) the number of shares of the insider transaction is higher than the outstanding number of shares for the stock. The final sample consists of 223,755 insider transactions by 11,488 top executives in 4,198 publicly listed firms from 2000 to 2016.[5]

To identify the gender of executives, we use the FactSet database. FactSet maintains a wide range of personal-level data including gender, education, date-of-birth, employment history, existing job's address, email address, and others. We manually match the names of our sample executives with FactSet individuals' names by verifying their employment history and insider trading information as available in the FactSet database. We identify and allocate the FactSet identifier to each executive in our sample and retrieve the required data points, including gender. We identify the gender of executives, without an appropriate match on FactSet, by exploring their profile and biography on Bloomberg, LinkedIn, or Google's database.

For firm-specific control variables, we obtain the monthly trading volume, shares outstanding, and market capitalization data from the CRSP database. Data on annual book-to-market ratio is obtained from Compustat. To measure excess returns, we use data retrieved from Kenneth French's data library.[6] Several websites are used to obtain data on the macro-level market factors. Data on CBOE VIX is obtained from Global Financial Data[7] and investors' sentiments data, from the AAII.[8] The monthly unemployment data for the U.S. is from the Bureau of Labor Statistics.[9]

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[5] We consider an insider who works for more than one firm during our sample period as more than one observation.
[6] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
[7] Available at https://www.globalfinancialdata.com/
[8] Available at http://www.aaii.com/
[9] Available at https://www.bls.gov/

2.3.2 Variables Definition and Model Development

In this section, we describe our main variables, along with the model used to measure losses from biased trades.

2.3.2.1 Prospect Theory Value (PTV)

Barberis, Mukherjee, and Wang (2016) report that individual investors form a mental representation regarding a stock's riskiness by observing its past returns distribution and evaluate outcomes according to cumulative prospect theory. The main effect of the probability-weighting function of the cumulative prospect theory is to overweight the tail events of any distribution. Their model describes that, in the cross section, investors are attracted to a stock with a high PTV, which results from very positively skewed past returns. Such an overvalued stock earns lower subsequent returns.

In this study, we expect that PTV of insiders' stocks is likely to influence their trading decisions. Following Barberis, Mukherjee, and Wang (2016), the PTV is measured by allocating probability weights to the past five years' (60 months) return distribution of the insider's stock:

$$PTV_{i,t} = \sum_{i=-m}^{-1} v(Retex_i) \left[w^-\left(\frac{i+m+1}{60}\right) - w^-\left(\frac{i+m}{60}\right)\right] + \sum_{i=1}^{n} v(Retex_i) \left[w^+\left(\frac{n-i+1}{60}\right) - w^+\left(\frac{n-i}{60}\right)\right] \tag{1}$$

where $PTV_{i,t}$ is the prospect theory value of every i^{th} stock traded by the insider at any point in time t, $Retex_i$ is the excess monthly return of the stock relative to the market, m is the maximum number of losses when $Retex_i$<0, and n is the maximum number of gains when $Retex_i$≥0 in the distribution of the past 60 months of excess returns on the i^{th} stock. Hence, $Retex_{-m}$ through $Retex_n$ is a distribution from the most negative return to the most positive. The distribution assigns an equal probability to each of the 60 historical excess returns of the stock, that is, (1/60). $v(Retex_i)$ is the value function, while $w^-(.)$ and $w^+(.)$ are the probability-weighting functions for losses and gains, respectively. $w^-(.)$ and $w^+(.)$ are explained by Tversky and Kahneman (1992) as follows:

$$w^{-}(P) = \frac{P^{\delta}}{(P^{\delta} + (1-P)^{\delta})^{1/\delta}}, \quad w^{+}(P) = \frac{P^{\gamma}}{(P^{\gamma} + (1-P)^{\gamma})^{1/\gamma}} \tag{2}$$

The degree to which an individual overweight tail is governed by the parameters γ and δ. Lower values of these parameters imply more overweighting of tails (Tversky & Kahneman, 1992). Based on the above expression, if the probabilities of extreme loss (p_{-m}) and extreme gain (p_n) are small, then $w^{-}(p_{-m})>p_{-m}$ and $w^{+}(p_n)>p_n$, so that the most extreme outcomes (outcomes in the tails) are overweighed. Following the value function of Tversky and Kahneman (1992), we use the following:[10]

$$v(Retex_i) = \begin{cases} -\lambda(-Retex_i)^{\alpha} & for \quad Retex_i < 0 \\ (Retex_i)^{\alpha} & for \quad Retex_i \geq 0 \end{cases} \tag{3}$$

The PTV is calculated for each stock on a monthly basis. Trade dates are converted to calendar months so that the PTV of each stock can be allocated to every insider trade. We measure the PTV for each insider stock (starting from January 1, 2000) by extracting its prior 60 months' (past five years) monthly returns.[11] For each stock *i* at any month *t*, this window keeps rolling for every month until the last month in 2016.[12] We then sort each window of these past 60 monthly returns in increasing order, starting with the most negative to the most positive. In Equation (1), *m* is the number of negative and *n* is the number of positive past monthly returns in each window of the i^{th} stock.[13] We consider *i* as a simple counter element with values ranging from 1 to 60 for each window of the sorted past 60 returns. Following Barberis, Mukherjee, and Wang (2016), we denote *i* to the counter element to show that it belongs to the window of past 60 returns of the i^{th} stock.

[10] Tversky and Kahneman (1992) estimate γ=0.61, δ=0.69, and λ=2.25 for their median subject. Using experimental data, they estimate α=0.88.
[11] The reason for starting the measurement of PTV from year 2000 is to match the insider transaction sample (available from 2000 to 2016).
[12] For example, for a particular stock, with reference to January 1, 2000, the selected past 60 monthly returns' window is from January 1, 1995 till December 31, 1999.
[13] "n= 60-m." For example, negatives are 10 so m=10 & n= (60-10).

2.3.2.2 Measurement of Biased Trade Loss

We develop a measure of behavioral bias according to the PTV. We describe that a trade is *biased* if insider stock's prospect theory value is greater (lower) than prospect theory value of the benchmark, the insider times a buy (sell) trade, and earns lower (greater) return over the next month. To select a benchmark for comparison, we assume that insiders time their buy or sell trade by comparing the PTV of their stock with a cross-sectional average PTV of other stocks in the market (benchmark).[14] . The next month's return from this trade (in absolute terms) is referred to as *loss* from the biased trade and is measured as follows:

$$Biased\_Trade\_Loss_{i,t} = |Retex_{i,t+1}|$$

$$= \begin{cases} PTV_{i,t} > AvgPTV_t \text{ and } Trade_{i,t} = Buy \text{ and } Retex_{i,t+1} < 0 \\ OR \\ PTV_{i,t} < AvgPTV_t \text{ and } Trade_{i,t} = Sell \text{ and } Retex_{i,t+1} > 0 \end{cases} \quad (4)$$

where $Biased\_Trade\_Loss_{i,t}$ is the absolute excess return of insider stock *i* at time *t+1* (i.e., the subsequent month of the insider trade), when any one of the mentioned conditions of biased trade is met, and "0" if otherwise. Time *t* is the calendar month of the insider trade. $PTV_{i,t}$ is the prospect theory value of insider stock *i* at time *t*. $AvgPTV_t$ is the cross-sectional average prospect theory value of other stocks in the market at time *t*. $Trade_{i,t}$ is the type of transaction (buy or sell) of insider stock *i* at time *t*.

Giving the title of "Bias" to prospect theory value induced trades is our subjective interpretation. The loss from such a trade is affected by the prospect theory value of the stock, instead of information. Therefore, we consider it as a mistake or error in trading decision and refer to it as *loss*. We develop the following model to test whether gender differences exist in the losses of prospect theory value-based trading decisions:

[14] Excess PTV = insider stock's PTV – cross-sectional average PTV.

$$
\begin{aligned}
&Biased\_Trade\_Loss_{i,t} \\
&\qquad = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Retex\_m_{i,t-1} + \beta_3\, Retex\_y_{i,(t-12,t-2)} \\
&\qquad + \beta_4\, Size_{i,t-1} + \beta_5\, Turnover_{i,t-1} + \beta_6 Book\_Mkt_{i,t-1} \\
&\qquad + \beta_7\, Age\_insider_{i,t} + \beta_8\, PhD_{i,t} + \beta_9 Grad_{i,t} + \beta_{10}\, MBA_{i,t} \\
&\qquad + \beta_{11} UnderGrad_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{5}
$$

where $Biased\_Trade\_Loss_{i,t}$ is the absolute excess return of insider stock *i* at time *t+1*. $Female_{i,t}$ is a dummy variable, which is equal to "1" if insider trade is made by a female executive, and "0" if it is made by a male executive at time *t*. $Retex\_m_{i,t-1}$ is the monthly return in excess of the market return of insider stock *i* at time *t-1*. $Retex\_y_{i,(t-12,t-2)}$ is the cumulative past monthly returns in excess of the market returns of insider stock *i* from *t-12* to *t-2*. $Size_{i,t-1}$ is the log of the monthly market capitalization of insider firm at time *t-1*. $Turnover_{i,t-1}$ is the monthly volume turnover of insider stock *i* at time *t-1*; it is equal to the number of shares traded divided by the number of shares outstanding. $Book\_Mkt_{i,t-1}$ is the book-to-market ratio of insider stock *i* at time *t-1*. $Age\_insider_{i,t}$ is the insider's age at the time of transaction, *t*. $PhD_{i,t}$, $Grad_{i,t}$, $MBA_{i,t}$, and $UnderGrad_{i,t}$ are dummy variables, where one of them is equal to "1" depending upon the highest degree earned by the insider, and the rest are equal to "0".

2.3.3 Summary Statistics

Figure 2.1 depicts the total number of male and female insider trades in each year, from January 2003 to December 2016 (we do not plot year 2000, 2001, and 2002 due to the unavailability of female insider trades). It also plots the proportion of prospect theory value biased trades by female and male insiders over our sample time period.[15] We observe that, in most of the years, the proportion of biased trades by female insiders is higher than the proportion of biased trades by male insiders.[16]

[15] See the numbers in the Appendix (Table A2).
[16] See a pattern of average prospect theory value biased trades and insider trades by female executives over time in the Appendix (Figure A1).

Figure 2.1. Comparison of Biased Insider Trades by Executive Gender

Figure 2.1 shows the total number of trades by male and female insiders, and the proportion of prospect theory value biased trades by male and female insiders in our sample from January 2003 – December 2016.

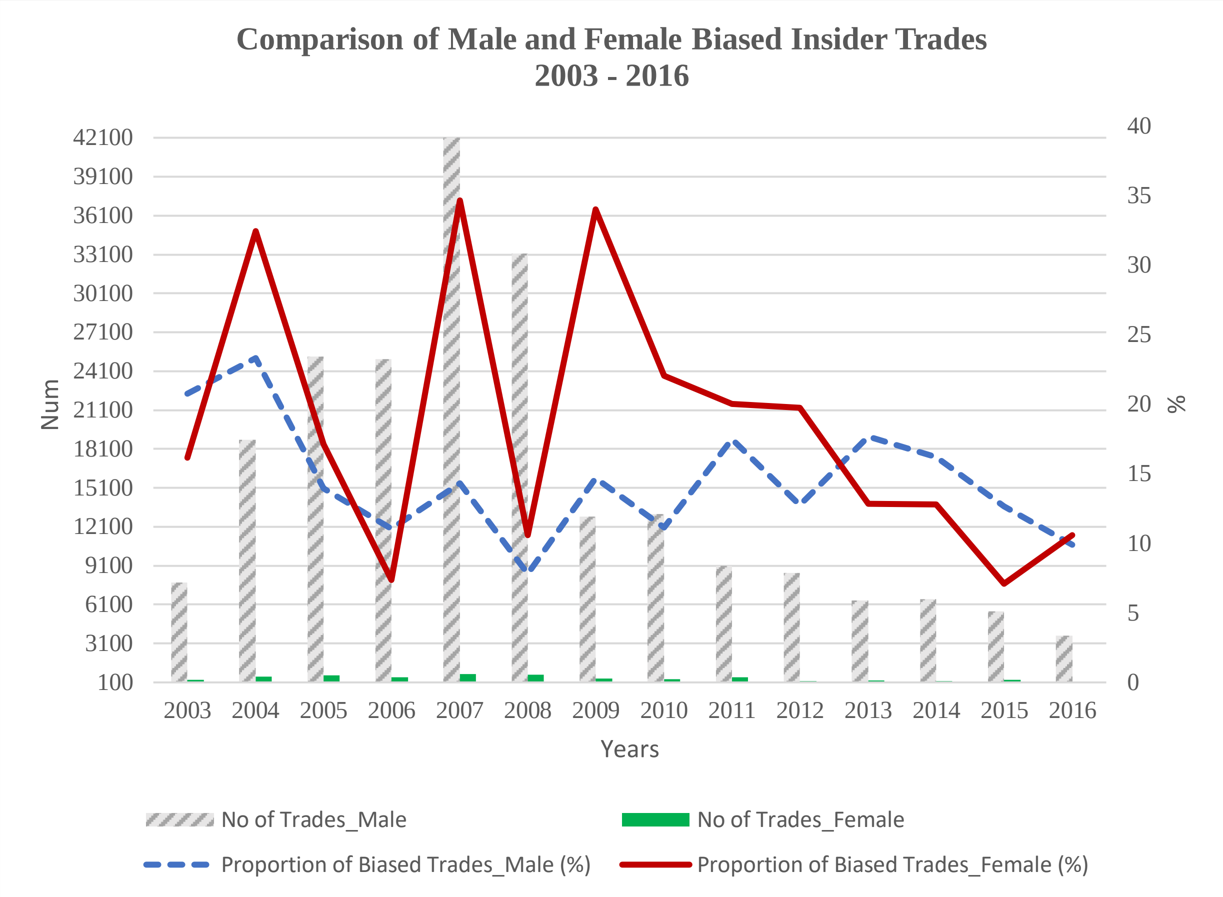

Table 2.1 provides detailed summary statistics of the insiders and their trades in the sample. Panel A of the table provides information about gender differences in the total number of insider transactions, number of executives, number of biased transactions and earned losses, number of buy and sell trades, average number of shares traded, and the dollar value of the trades. There are more firms with insider trading by males than those with insider trading by females. Firms with female insider trades represent only 14.41% of the sample firms. The limited number of women working at the corporate level is a prominent issue in terms of gender gap: only 5.71% of top executives in the sample are female. Moreover, this percentage goes down further when we observe that only 2.56% of the insider trades are made by female top executives. This supports Inci, Narayanan, and Seyhun's (2017) finding that female executives do not trade as frequently as their male counterparts do. We find that 14.01% of

the total transactions are prospect theory value biased. Moreover, we show that 20.02% (13.86%) of the total trades made by female (male) insiders are biased. Furthermore, average loss from these biased trades of female insiders (1.78%) is higher than that of their male counterparts (1.24%). This suggests that female insiders are more likely to make behaviorally biased trades and suffer more losses than males.

Panel A of Table 2.1 also reveals that top executives frequently make more sale transactions than purchases. However, female executives buy more insider stock (29.56%) than their male counterparts (22.08%) during the sample period. This suggests that male insiders, on average, not only trade (buy/sell) more shares but also trade at a higher dollar value than female insiders. The average dollar value of purchases by males (females) is $84,182 (54,962) and of sales is $302,742 (199,404).

Panel B of Table 2.1 provides in-depth descriptive statistics of male and female insiders in the three formal executive types: Chairperson, Chief_Officer, and Director (considered to be in decreasing order of seniority). We observe that the Chief_Officer category has the largest number of insiders of both genders (i.e., 8,929), with females representing 6.35% of the total Chief_Officer category. There is a larger percentage of female directors (7.14%) than female chairpersons or chief officers. Our results, in the context of a declining number of female insiders as seniority increases, are consistent with those of Inci, Narayanan, and Seyhun (2017). We note that there are only 2.39% of female insiders belonging to the Chairperson category.

Table 2.1. Summary Statistics

This table presents insider trading statistics of male and female executives in our sample for year 2000 to 2016. Panel A provides detailed characteristics of insider transactions, categorized by executives' gender. The last column of Panel A describes statistics for female insiders as a percentage of the total. We consider an insider who works for more than one firm during our sample period as more than one observation. Panel B provides statistics of the number of male and female insiders in three executive types, in decreasing order of seniority. We consider an insider who works for more than one firm or holds more than one position in the same firm during our sample period as more than one observation. Panel C provides descriptive statistics of all variables by grouping them based on the executives' gender. Biased_Trade_Loss is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. $Retex_{t+1}$ is a measure of the monthly return in excess of the market return at time t+1. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. The insiders and their trades are grouped in three categories of executive positions based on seniority (i.e., Chairperson, Chief_Officer and Director).

Panel A. Characteristics of Insider Transactions by Executive Gender

	Total	Trades by Males	Trades by Females	Female as a percentage of total (%)
Number of Firms	4,198	4,131	605	14.41%
Number of Executives	11,488	10,832	656	5.71%
Number of Transactions	223,755	218,017	5,738	2.56%
Number of Biased Transactions	31,359	30,210	1,149	3.66%
Percentage of Biased Transactions	14.01%	13.86%	20.02%	-
Average Loss from Biased Transactions	1.25%	1.24%	1.78%	-
Number of Transactions - Buy	49,828	48,132	1,696	3.40%
Percentage of Buy Transactions	22.27%	22.08%	29.56%	-
Number of Transactions - Sell	173,927	169,885	4,042	2.32%
Percentage of Sell Transactions	77.73%	77.92%	70.44%	-
Average Number of Shares Traded - Buy	8,032	8,051	7,470	-
Average Number of Shares Traded - Sell	9,834	9,916	6,418	-
Average Value($) of Shares Traded - Buy	83,188	84,182	54,962	-
Average Value($) of Shares Traded - Sell	300,340	302,742	199,404	-

Panel B. Number of Male and Female Insiders by Executive Type

Position	Total	Male	Female	Female (%)
Chairperson	2,464	2,405	59	2.39%
Chief_Officer	8,929	8,362	567	6.35%
Director	532	494	38	7.14%

Table 2.1. (continued)

Panel C. Descriptive Statistics of Variables by Executive Gender

Gender	Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
Male	Biased_Trade_Loss	218,017	0.012	0	0.061	0	1.949
Male	Retex_m	218,017	0.014	0.005	0.137	-0.798	6.893
Male	Retex_y	218,017	0.074	0.059	0.413	-3.873	2.942
Male	Size	218,017	14.152	14.170	2.153	8.062	17.702
Male	Turnover	218,005	2.108	1.725	1.811	0.020	9.819
Male	Book_Mkt	211,070	0.545	0.389	0.538	0.033	4.351
Male	Age_insider	212,361	56.852	57	9.208	20	91
Male	PhD	218,017	0.002	0	0.044	0	1
Male	Grad	218,017	0.023	0	0.149	0	1
Male	MBA	218,017	0.007	0	0.082	0	1
Male	UnderGrad	218,017	0.713	1	0.452	0	1
Male	Chairperson	218,017	0.522	1	0.499	0	1
Male	Chief_Officer	218,017	0.431	0	0.495	0	1
Male	Director	218,017	0.046	0	0.210	0	1
Female	Biased_Trade_Loss	5,738	0.018	0	0.049	0	0.529
Female	Retex_m	5,738	0.013	-0.001	0.151	-0.732	2.042
Female	Retex_y	5,738	0.018	0.054	0.377	-2.759	1.714
Female	Size	5,738	13.306	13.276	2.072	8.601	17.702
Female	Turnover	5,737	1.766	1.280	1.815	0.020	9.819
Female	Book_Mkt	5,446	0.624	0.484	0.630	0.033	4.351
Female	Age_insider	5,033	51.860	51	9.409	25	81
Female	PhD	5,738	0.027	0	0.163	0	1
Female	Grad	5,738	0.009	0	0.095	0	1
Female	MBA	5,738	0.012	0	0.107	0	1
Female	UnderGrad	5,738	0.594	1	0.491	0	1
Female	Chairperson	5,738	0.206	0	0.405	0	1
Female	Chief_Officer	5,738	0.696	1	0.460	0	1
Female	Director	5,738	0.098	0	0.297	0	1

Panel C of Table 2.1 provides the descriptive statistics of our main variables for both genders. It is evident that on average, the biased trade loss of females is higher (1.8%) than that of males (1.2%). We observe no gender difference in the past one-month's excess return. However, male insiders earn a larger past 12-months' cumulative excess return (7.4%) than female insiders (1.8%). Females and males are associated with similarly sized firms. Shares traded by male insiders have a higher turnover volume (Turnover) (2.11 times) compared with those of females (1.77 times). This result is consistent with the existing literature of overconfidence (e.g., Barber & Odean, 2001). On average, a higher book-to-market ratio of stocks traded by female insiders (0.62) compared with male insiders' traded stocks (0.55) depicts that females prefer to trade value stocks. Panel C shows that female insiders are younger than males, with an average age of 52, while for males, the average age is 57. Among male (female) insiders, 0.2% (2.7%) hold a doctoral degree, 2.3% (0.9%) have a graduate degree, 0.7% (1.2%) are MBAs, and 71.3% (59.4%) hold undergraduate degree as their highest earned degree. Panel C also provides information about gender difference in insider trading among three formal executive positions. Out of the 218,017 male transactions in the sample, 52% of the trades are made by those in the Chairperson category, whereas 43% and 4.6% of transactions belong to the Chief_Officer and Director categories, respectively. Conversely, out of the 5,738 total female transactions, 21% of the trades come from the Chairperson position, 70% from Chief_Officer, and 9.8% from the Director category.

Table 2.2 presents the correlation matrix of the key variables used in the study. We find that insider trades by female executives, last month's excess return, traded shares with high book-to-market ratio, senior insiders (in terms of their age), and insiders holding a Ph.D., Graduate, or Undergraduate degrees are positively and significantly correlated with biased trade losses. Meanwhile, the past 12-months' cumulative excess return and firm size are negatively and significantly correlated with the losses. Two of the variables, volume turnover and trades by insiders holding an MBA degree, are negatively but insignificantly correlated with the losses. Moreover, we observe that trades by female insiders are correlated positively and significantly with stocks that have high book-to-market ratio and insiders holding a Ph.D. or an MBA degree.

Table 2.2. Correlation Matrix

This table presents a correlation matrix for the main variables of insider transactions from year 2000 to 2016. Biased_Trade_Loss is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. $Retex_{t+1}$ is a measure of the monthly return in excess of the market return at time t+1. Female is a measure of trade by a female insider that is equal to 1 if the insider trading is carried out by the female at time t and 0 otherwise. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise.

Variable	Biased_Trade_Loss	Female	Retex_m	Retex_y	Size	Turnover	Book_Mkt	Age_insider	PhD	Grad	MBA
Female	0.014^{a}										
Retex_m	0.037^{a}	-0.001									
Retex_y	-0.042^{a}	-0.022^{a}	0.042^{a}								
Size	-0.118^{a}	-0.062^{a}	0.041^{a}	0.211^{a}							
Turnover	-0.002	-0.030^{a}	0.104^{a}	0.246^{a}	0.174^{a}						
Book_Mkt	0.069^{a}	0.023^{a}	0.0000	-0.154^{a}	-0.443^{a}	-0.073^{a}					
Age_insider	0.011^{a}	-0.081^{a}	0.003	-0.022^{a}	0.030^{a}	-0.035^{a}	0.049^{a}				
PhD	0.023^{a}	0.079^{a}	-0.007^{a}	-0.013^{a}	-0.011^{a}	0.047^{a}	-0.020^{a}	0.013^{a}			
Grad	0.023^{a}	-0.015^{a}	0.021^{a}	0.018^{a}	-0.051^{a}	-0.039^{a}	0.020^{a}	0.039^{a}	-0.008^{a}		
MBA	-0.003	0.009^{a}	-0.006^{a}	-0.014^{a}	-0.051^{a}	-0.027^{a}	0.043^{a}	-0.024^{a}	-0.004^{b}	-0.013^{a}	
UnderGrad	0.006^{a}	-0.042^{a}	-0.038^{a}	0.001	0.225^{a}	0.021^{a}	-0.066^{a}	-0.141^{a}	-0.080^{a}	-0.237^{a}	-0.130^{a}

^{a} $p < 0.01$, ^{b} $p < 0.05$, and ^{c} $p < 0.10$.

2.4 Empirical Results and Discussion

2.4.1 Effect of Prospect Theory Value on Future Returns of Insider Trades

Before moving to the analysis of gender of executives and their losses from prospect theory value biased trades, we examine whether prospect theory value of insider stock influences the future returns of insider trades. In the cross section of stock returns, Barberis, Mukherjee, and Wang (2016) provide empirical evidence that a stock whose past return distribution has a high (low) prospect theory value earns a low (high) subsequent return, on average. We examine this association in our setting of insider trading, where insiders decide to time their buy or sell transactions.

Table 2.3 shows the effect of the PTV on subsequent future returns (next month of the trade) of insider trades when they choose to buy or sell their company's stock. In Panel A, we categorize buy and sell transactions based on high (PTV of insider stock is greater than the benchmark PTV) or low (PTV of insider stock is smaller than the benchmark PTV) PTV of the stocks. The results show that on average, when insiders buy stocks having a high PTV, their subsequent future returns are lower by 0.34% than the future returns of buy trades of low PTV stocks. The finding is significant at the 5% level under the assumption of equal, as well as unequal, population variances. Likewise, on average, when insiders sell low PTV stocks, they lose 0.12% of future returns as compared with selling high PTV stocks. However, the higher future returns of low PTV stocks represent an opportunity loss for the insiders as they had already sold off their stocks. Assuming both equal and unequal population variances, the mean difference of this finding is significant at the 5% and 10% levels, respectively.

Panel B of Table 2.3 shows the regression results of the association between the PTV of insider stocks and the subsequent future returns earned by them. *Ex_PTV* is the variable of excess PTV. It represents the difference between the insider stock's PTV and the cross-sectional average PTV of other stocks in the market (benchmark) on the same day of trade (calendar month). A positive (negative) number represents a high- (low-) PTV insider stock. Column (1) presents results of the main model and shows a significantly negative relation between the dependent and independent variables. To give strength to the model, we introduce firm and insider-specific control variables. These results are presented in Column (2) of the table. While Column (3) exhibits the results considering all the control variables and firm fixed effect. The findings show that, when insiders time to buy or sell their stocks, the PTV negatively impacts subsequent future returns of such trades. These results are significant at the 1% level for all the regressions. After considering several firm level control variables, we find that firm size is negatively associated, whereas turnover and book-to-market ratio are positively associated with future returns. We also control for several insider level variables and find that insider age and undergraduate education are negatively associated, whereas graduation is positively related to future returns. All the findings are significant at the 1% level; the goodness of fit of the model in Column (3) is 24.28%.

Our findings are consistent with Barberis, Mukherjee, and Wang (2016). In the setting of the present study, insiders consider when to buy/sell their company's stock in order to make abnormal profits. However, it is evident that prospect theory value induced trades contribute negatively to the subsequent future returns. Hence, the results of Table 2.3 are consistent with the literature and provide support to our developed measure of prospect theory value biased trades and resultant losses. As, prospect theory value induced trades reduce subsequent returns, therefore, we consider these returns as *loss* for our further analysis.

Table 2.3. Prospect Theory Value and Future Returns

Panel A presents the mean differences of insider trades' subsequent future returns based on high or low PTV of an insider stock. High (low) PTV means that the PTV of an insider stock is greater (smaller) than the cross-sectional average PTV of other stocks in the market at time t. Panel B presents the findings of regression of insider trades' future returns on excess PTV (Ex_PTV) without, as well as with, firm- and insider-specific controls. The dependent variable is insider trades' return at time t+1. Ex_PTV is the difference between the PTV of the insider stock and the cross-sectional average PTV of other stocks in the market at time t. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. To ensure that extreme values are not affecting the results, all variables are winsorized at their 1 and 99 percentile levels. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

Panel A. Mean Difference

	Insiders' Future Returns from Buy Trades			Insiders' Future Returns from Sell Trades		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
High PTV	22,313	0.0084	0.1350	129,688	0.0043	0.0915
Low PTV	27,515	0.0118	0.1817	44,239	0.0055	0.1466
Difference	-	-0.0034**	0.1625	-	-0.0012*	0.1082

Panel B. Regression of Insider Trades' Future Returns

	No controls and no fixed effect (1)	All controls but no fixed effect (2)	All controls and fixed effect (3)
Ex_PTV	-0.1415*** (-12.01)	-0.1492*** (-12.75)	-0.1455*** (-11.67)
Retex_m	-	-0.0037 (-1.33)	0.0005 (0.27)
Retex_y	-	0.0020* (1.80)	0.0004 (0.42)
Size	-	-0.0043*** (-24.48)	-0.0036*** (-5.15)
Turnover	-	0.0041*** (21.29)	0.0024*** (10.55)
Book_Mkt	-	0.0022*** (2.61)	0.0059*** (7.63)
Age_insider	-	-0.0002*** (-6.44)	-0.0003*** (-5.77)
PhD	-	-0.0125* (-1.68)	-0.0097 (-1.27)
Grad	-	0.0154*** (7.41)	0.0315*** (10.18)
MBA	-	-0.0158*** (-4.95)	-0.0037 (-0.84)
UnderGrad	-	-0.0084*** (-13.22)	-0.0129*** (-12.07)
Firm-fixed Effect	NO	NO	YES
No. of Obs.	223,755	210,675	210,675
R-squared	0.0015	0.0176	0.2428

2.4.2 Effect of Female Insider Trading on Losses from Prospect Theory Value Biased Trades

We analyze insider trading by female and male executives to examine whether gender differences exist in the biased trade losses. Table 2.4 shows the regression results. To address the concern of any impact of firm related fixed factors on the results, we include a firm fixed effect model, where there are 4,198 firms in our sample. The regression results in Column (1) indicate that female insiders tend to suffer more losses (i.e. 0.65% or 65 basis points) from prospect theory value biased trades than male insiders do.

Hillier, Korczak, and Korczak (2015) provide evidence that not only firm- or trade-specific characteristics affect the performance of insider trading, but corporate insiders' attributes also have a strong influence in explaining a significant proportion of the variability in insider trading performance. Considering this view, we control for firm-specific characteristics (last month's excess return, cumulative past monthly excess returns from t-12 to t-2, firm size, turnover volume, and book-to-market ratio) and insider-specific characteristics (age and education). Controlling for firm-specific characteristics and insiders' demographics, along with firm fixed effects, Columns (2), (3), and (4) show a positive and significant relation between biased trade loss and female insider trading. The findings provide evidence that female insider trading is subject to higher bias and suffers more losses as compared with male insider trading.

In Column (4), we observe that the loss from biased trading is significantly higher for stocks that have a high excess return in the previous month, high cumulative excess returns in past months from t-12 to t-2, a high turnover volume, and a high book-to-market ratio. Moreover, higher prospect theory value loss is associated with stocks traded by senior insiders in terms of age and those holding an undergraduate degree. Meanwhile, the relation is significantly negative with firm size and trades by insiders with graduate degrees. It is observed that the control variables have a significant impact on the dependent variable. However, the coefficient of a higher loss of 0.47% (47 basis points) from biased trades by female insiders is still statistically significant at the 1% level.

It is expected that certain firms may endogenously pair with female insiders. Stocks traded by female insiders may thus be systematically different from those traded by male insiders. We explore whether this phenomenon explains the results of the study by considering a sub-sample of firms with insider trading by both female and male executives. We consider an insider who is affiliated with more than one firm during the sample period as more than one observation. There are 538 firms in our sample with 5,344 transactions by female insiders and 34,434 trades by male insiders. We observe a higher percentage of insider trades by female executives (i.e., 13.43% in our sub-sample of firms as compared with the full sample). This indicates that within mixed-gender firms, female executives have a higher tendency to carry insider trading as compared with firms that have single-gender executives. The total number of inside executives in these firms is 2,097; among them, 1,512 are males and 585 are females, depicting a higher proportion of female executives in such firms (i.e., 27.9% as compared with the full sample). Similarly, we report a higher number of biased transactions and resulting losses from female insider trading, compared with male insider trading. The percentage of number of biased transactions by female (male) executives is 20.32% (12.70%), and the average loss is 1.81% (1.07%).

Column (5) of Table 2.4 shows the results of the sub-sample of firms with insider trading by both genders. It reports that the trading losses increase by 0.41% (41 basis points) when female insiders carry out biased transactions compared to their male counterparts. This result is significant at the 1% level. There are changes in the signs of some control variables' coefficients; however, the results remain robust with a goodness of fit of 30.65%.

Table 2.4. Biased Trade Loss and Female Insider Trading

This table presents the findings of the regression of biased trade loss on female insider trades with firm- and insider-specific controls. The dependent variable, Biased_Trade_Loss (B_T_Loss), is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. $Retex_{t+1}$ is a measure of the monthly return in excess of the market return at time t+1. Female is a measure of trade by a female insider that is equal to 1 if the insider trading is carried out by the female at time t and 0 otherwise. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. To ensure that extreme values are not affecting the results, all variables are winsorized at their 1 and 99 percentile levels. The results are reported for the full sample, as well as for the subsample of firms with trades by both genders. The results are presented with firm-fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

$$\begin{aligned} B\_T\_Loss_{i,t} = {} & \alpha + \beta_1\, Female_{i,t} + \beta_2\, Retex\_m_{i,t-1} + \beta_3\, Retex\_y_{i,(t-12,t-2)} + \beta_4\, Size_{i,t-1} + \beta_5\, Turnover_{i,t-1} \\ & + \beta_6 Book\_Mkt_{i,t-1} + \beta_7\, Age\_insider_{i,t} + \beta_8\, PhD_{i,t} + \beta_9 Grad_{i,t} + \beta_{10}\, MBA_{i,t} \\ & + \beta_{11} UnderGrad_{i,t} + \varepsilon_{i,t} \end{aligned}$$

	Full Sample				Trades by both gender
	Fixed effect but no controls (1)	Firm controls and fixed effect (2)	Insider controls and fixed effect (3)	All controls and fixed effect (4)	All controls and fixed effect (5)
Female	0.0065***	0.0044***	0.0071***	0.0047***	0.0041***
	(6.15)	(6.21)	(6.05)	(6.10)	(5.33)
Retex_m	-	0.0011*	-	0.0016**	0.0191***
		(1.68)		(2.37)	(11.78)
Retex_y	-	0.0012***	-	0.0017***	0.0098***
		(4.19)		(5.84)	(14.28)
Size	-	-0.0086***	-	-0.0090***	-0.0141***
		(-36.16)		(-36.86)	(-27.72)
Turnover	-	0.0003***	-	0.0003***	-0.0006***
		(3.24)		(3.73)	(-3.03)
Book_Mkt	-	0.0016***	-	0.0015***	-0.0118***
		(5.76)		(5.31)	(-17.20)
Age_insider	-	-	0.0002***	0.0001***	-0.0001**
			(8.29)	(8.33)	(-2.19)
PhD	-	-	-0.0017	-0.0038	0.0024
			(-0.42)	(-1.34)	(0.63)
Grad	-	-	-0.0074***	-0.0073***	-0.0197***
			(-4.43)	(-6.45)	(-11.05)
MBA	-	-	-0.0020	-0.0026	0.0022
			(-0.81)	(-1.58)	(0.70)
UnderGrad	-	-	0.0019***	0.0018***	0.0056***
			(3.18)	(4.68)	(6.17)
Firm-fixed Effect	YES	YES	YES	YES	YES
No. of Obs.	223,755	216,503	217,394	210,675	36,449
R-squared	0.1668	0.2600	0.1651	0.2620	0.3065

The findings provide empirical evidence that gender differences exist in prospect theory value biased insider trading and that female insiders suffer higher losses compared to male insiders. We may not exclusively explain these results by the *overconfidence hypothesis*, which expects less profitable outcomes of trading by males due to their aggressive decisions. However, we can describe the consistency of our results with the *information access hypothesis*, which assumes that limited access to information may provide possible explanation of females' biased decisions and higher resultant losses. The literature provides evidence that uncertainty and lack of information contribute to higher behavioral bias.[17] There might be several factors influencing the association between female insiders and losses from biased trades, however, we propose that scarcity of information may serve as a possible explanation of our results. Consequently, we conduct additional tests to explore the role of access to information. We run the analyses in two settings, based on the level of information.

2.4.3 Equal Level of Information and Female Insiders' Losses from Prospect Theory Value Biased Trades

In this setting, the level of information is expected to be equal among all the executives, irrespective of their gender. We expect that in this setting, if information is equally dispersed, there ought to be no gender difference in losses from biased insider trades. We examine the association between female insiders and losses from biased trades under executives' similar formal titles, trade size, routine trades, and macro-level market uncertainty.

2.4.3.1 Female Insider Trading and Biased Trade Losses under Executives' Position

It is well documented that informativeness and abnormal future returns earned by insiders vary at different levels of the formal hierarchy.[18] The extant literature documents that chief financial officers (CFO) incorporate better quality information about their future earnings and make more profitable

[17] See for example, Feng and Seasholes (2005); Kumar (2009b); Fang and Huang (2017); Inci, Narayanan, and Seyhun (2017).
[18] See for example, Seyhun (1986); Ravina and Sapienza (2009); Knewtson and Nofsinger (2014).

trades than chief executive officers (CEO) (Wang, Shin, & Francis, 2012). The access to information ought to be equal within each formal title; therefore, we assume that the difference in losses from biased trades among male and female insiders is likely to attenuate within a similar executive position. However, Inci, Narayanan, and Seyhun (2017) conclude that female insiders face an informational disadvantage even within the same executive position, contributing to their lower abnormal returns than males. Consequently, we run our analysis under executives' positions to examine gender differences in biased trade losses.

We split our sample according to three executive positions: Chairperson, Chief_Officer, and Director (considered to be in decreasing order of seniority). We perform a regression of prospect theory value biased trade losses as the dependent variable against the cross products of gender (Male or Female) and the executive's position (Chairperson, Chief_Officer, or Director) as the independent variables. *Male×Director* is assigned as the benchmark category. The results are provided with firm fixed effect. Table 2.5 Column (1) shows the regression results of the full sample of insider trading. It is evident that under all executive positions, female insiders suffer more biased trade losses than males do. The coefficients of the cross product of *Female×Director* and *Female×Chairperson* are positive and significant at the 10% level, whereas the positive coefficient of *Female×Chief_Officer* is significant at the 1% level. Table 2.5 indicates the significance of the differences among the coefficients of male and female insiders under each executive position. It is noticeable that the biased trades' loss is significantly higher among female than those among male insiders under the Chief_Officer (0.9%) and Director (0.7%) positions. These differences are significant at the 1% and 10% levels, respectively. At the top executive level of Chairperson, we do not find any significant gender differences in biased trades. This is consistent with the notion that the most senior executives are highly informed (Tavakoli, McMillan, & McKnight, 2012).

In Table 2.5 Column (2), we present the results of a sub-sample of firms with insider trades by both genders. The findings are consistent with our full sample. We report higher biased trade losses for female insider trades, compared to male trades. Moreover, the coefficients are significant, at the 1%

level in the Chairperson and Chief_Officer positions, and at the 10% level in the Director position. Our results suggest that higher biased trade losses of female insiders might be explain by the argument of Inci, Narayanan, and Seyhun (2017), that females have limited access to information even within a similar executive position.

Table 2.5. Biased Trade Loss and Female Insider Trading under Executives' Position

This table presents the findings of the regression of biased trade loss on female insider trades under three executive positions. The dependent variable, Biased_Trade_Loss (B_T_Loss), is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. The independent variables are the cross products of gender (Female or Male) and executive positions (Chairperson, Chief_Officer, and Director). Male×Director is considered as the benchmark category. Column (1) shows findings of the full sample of insider trades, whereas in Column (2) the results are for the sub-sample of firms with trades by both genders. The results are presented with firm fixed effects. In the bottom of the table, the significance of the difference in the female and male coefficients for three executive positions is tested with F-test. The t-statistics are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

$$B\_T\_Loss_{i,t} = \alpha + \beta_1 Male \times Director_{i,t} + \beta_2\, Female \times Director_{i,t} + \beta_3\, Female \times Chairperson_{i,t} + \beta_4\, Male \times Chairperson_{i,t} + \beta_5\, Female \times Chief\_Officer_{i,t} + \beta_6\, Male \times Chief\_Officer_{i,t} + \varepsilon_{i,t}$$

	Full Sample	Trades by both gender
	(1)	(2)
Constant	-0.0066	-0.0048
	(-0.12)	(-0.33)
Female×Director	0.0070*	0.0051*
	(1.69)	(1.81)
Female×Chairperson	0.0047*	0.0047**
	(1.89)	(2.51)
Male×Chairperson	0.0066***	-0.0029**
	(8.24)	(-2.45)
Female×Chief_Officer	0.0118***	0.0103***
	(8.39)	(7.88)
Male×Chief_Officer	0.0029***	0.0048***
	(3.58)	(4.12)
Firm-fixed Effect	YES	YES
No. of Obs.	223,755	39,778
R-squared	0.1673	0.2816

Significance of (Female-Male) coefficient differences with t-value in brackets

Chairperson	-0.0019	0.0076***
	(-0.80)	(4.66)
Chief_Officer	0.0090***	0.0055***
	(7.37)	(6.77)
Director	0.0070*	0.0051*
	(1.69)	(1.81)

2.4.3.2 Female Insider Trading and Biased Trade Losses Conditional on Trade Size

In the studies on asset pricing, it is argued that trade size itself is unlikely to influence security prices, as every market participant is considered to possess the same access to information. Nevertheless, if some market participants are more informed than others, the uninformed ones may make adverse trading decisions (Glosten & Milgrom, 1985). It is evident in the literature that large trades are more informative than small trades. Highly informed investors choose to trade in large size to earn greater trading profits (Easley & O'hara, 1987). There is an extensive literature on the association between trade size and investors' information (Chakravarty, 2001; Dufour & Engle, 2000; Easley, Kiefer, & O'Hara, 1997). Literature provides theoretical argument that trade size is associated with higher confidence of traders with high precision of information quality, and they earn abnormal profits (Grossman & Stiglitz, 1980).

Subsequently, we run our analysis conditioned on trade size. We divide our sample in trade terciles and examine the association between female insiders and prospect theory value biased trade losses. We expect that gender difference in losses may reduce in a given trade size, if all executives possess equal access to information. However, Inci, Narayanan, and Seyhun (2017) report that even after controlling for trade size, male insiders earn greater profits than females; this indicates an informational advantage of male insiders over females. If we find gender differences in biased trader losses, it might be explained by the informational disadvantage of female insiders.

We divide our sample into trade size terciles according to dollar values. We consider that within each tercile the trade size is approximately equal. Table 2.6 shows regression results of female trades and losses from the biased trades under each tercile of the trade size. We repeat the regression analysis shown in Table 2.4 and present the results in Column (1), (2), and (3) based on the Lowest, Middle, and Highest trade sizes, respectively. Using the full sample, we introduce in Column (4) an interaction term, *Female×TSize,* which is the product of Trade size terciles and a Female dummy.

Table 2.6. Biased Trade Loss and Female Insider Trading Conditional on Trade Size

This table presents the findings of the regression of biased trade loss on female insider trades, controlling for trade size. The full sample is divided into three terciles based on the dollar value of the trade size, and the results are shown for each tercile. The dependent variable, Biased_Trade_Loss (B_T_Loss), is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. Female is a measure of trade by a female insider that is equal to 1 if the insider trading is carried out by the female at time t and 0 otherwise. The variable $Female \times TSize$ is the cross product of a female dummy and the trade size terciles (Lowest, Middle, and Highest). Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. To ensure that extreme values are not affecting the results, all variables are winsorized at their 1 and 99 percentile levels. The results are presented with firm-fixed effects. The t-statistics are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

$$B\_T\_Loss_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2 Trade\_Size_{i,t} + \beta_3 Female \times TSize_{i,t} + \gamma\ Controls + \varepsilon_{i,t}$$

	Full Sample			
	Lowest (1)	Middle (2)	Highest (3)	Interaction (4)
Female	0.0034**	0.0046***	0.0047***	0.0036***
	(2.06)	(3.46)	(4.33)	(3.43)
Trade_Size	-	-	-	-0.0007***
				(-5.04)
Female×TSize	-	-	-	0.0012*
				(1.65)
Retex_m	0.0015	0.0073***	-0.0031***	0.0017**
	(1.16)	(6.25)	(-2.78)	(2.51)
Retex_y	0.0040***	0.0003	0.0009**	0.0017***
	(6.53)	(0.60)	(2.00)	(5.89)
Size	-0.0110***	-0.0112***	-0.0063***	-0.0089***
	(-18.73)	(-25.46)	(-19.31)	(-36.05)
Turnover	0.0001	0.0009***	0.0007***	0.0003***
	(0.47)	(6.63)	(6.10)	(3.77)
Book_Mkt	-0.0016***	-0.0033***	-0.0027***	0.0015***
	(-3.02)	(-5.41)	(-4.64)	(5.23)
Age_insider	0.0002***	0.0001***	0.0001**	0.0001***
	(5.87)	(2.72)	(2.28)	(8.55)
PhD	0.0017	-0.0020	-0.0105**	-0.0036
	(0.25)	(-0.51)	(-2.47)	(-1.30)
Grad	-0.0151***	-0.0059***	-0.0040**	-0.0073***
	(-6.13)	(-3.25)	(-2.40)	(-6.49)
MBA	-0.0046	0.0004	-0.0017	-0.0027*
	(-1.40)	(0.12)	(-0.75)	(-1.64)
UnderGrad	0.0028***	0.0032***	0.0006	0.0018***
	(3.01)	(5.01)	(1.21)	(4.59)
Firm-fixed Effect	YES	YES	YES	YES
No. of Obs.	69,411	70,480	70,784	210,675
R-squared	0.2929	0.3316	0.2935	0.2621

By applying firm fixed effects and controlling for firm- and insider-specific characteristics, we find a significantly positive relation between female insider trades and the biased trade losses. In the lowest tercile, the magnitude of the positive coefficient is the smallest (at 0.34%), and significant at the 5% level, compared with the middle and highest terciles. In the middle and highest terciles, the positive coefficients are significant at the 1% level. In Column (4), the positive coefficient of *Female×TSize*, at 0.12%, is significant at the 10% level. Thus, consistent with the argument, we demonstrate that limited access to information may possibly explain higher biased trade losses in female insider trading.

2.4.3.3 Female Insider Trading and Biased Trade Losses under Routine Trades

The existing literature describes that insiders engage in opportunistic trading to exploit private information and earn abnormal profits (Ali & Hirshleifer, 2017). Opportunistic insiders trade whenever they receive superior information regarding their company; therefore, these trades do not follow a specific pattern or timing. Whereas, routine trades are unlikely to incorporate better quality information about their future earnings. Therefore, these routine traders trade on particular dates and their transactions follow a regular pattern. As routine trades are not indicative of a firm's future prospects, they earn lower returns compared to opportunistic trades (Cohen, Malloy, & Pomorski, 2012). Hence, under the category of routine trades, we argue that availability of superior information is highly unlikely, and all insiders possess equal quality information. As a result, we expect to observe no gender difference in biased trade losses under routine trades' category.

We follow the same technique developed by Cohen, Malloy, and Pomorski (2012) to categorize the sample into different classes of insiders based on their trading patterns. We examine whether female insiders' tendency to suffer higher losses from biased trades relative to their male counterparts differ under routine category. Our sample is divided into *Routine* trades (trades made by insiders at least once in the preceding three years and in the same calendar month each year), *Opportunistic* trades (trades for which there is no definite pattern in the preceding three years), and *Non-classified* trades (all remaining trades with no history of trades in the preceding three years). Cohen, Malloy, and Pomorski (2012) indicate that non-classified trades show the same characteristics as opportunistic trades.

Table 2.7. Biased Trade Loss and Female Insider Trading under Routine Trades

This table presents the findings of the regression of biased trade loss on female insider trades when insider trades are classified as routine, opportunistic, and non-classified. The dependent variable, Biased_Trade_Loss (B_T_Loss), is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. Female is a measure of trade by a female insider that is equal to 1 if the insider trading is carried out by the female at time t and 0 otherwise. $Female \times Routine$ is the product of the routine trade and a female dummy variable. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. To ensure that extreme values are not affecting the results, all variables are winsorized at their 1 and 99 percentile levels. The results are presented with firm-fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

$$B\_T\_Loss_{i,t} = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Routine_{i,t} + \beta_3\, Female \times Routine_{i,t} + \gamma\, Controls + \varepsilon_{i,t}$$

	Full sample		
	All controls but no fixed effect (1)	Fixed effect but no controls (2)	All controls and fixed effect (3)
Female	0.0028***	0.0062***	0.0046***
	(4.31)	(5.81)	(5.90)
Routine	-0.0019***	-0.0105***	-0.0074***
	(-5.59)	(-12.05)	(-12.29)
Female×Routine	0.0129**	0.0123*	0.0110**
	(2.06)	(1.74)	(2.35)
Retex_m	-0.0033***	-	0.0016**
	(-3.46)		(2.28)
Retex_y	0.0003	-	0.0016***
	(1.00)		(5.45)
Size	-0.0028***	-	-0.0088***
	(-47.05)		(-35.71)
Turnover	0.0008***	-	0.0003***
	(11.73)		(3.74)
Book_Mkt	0.0007*	-	0.0016***
	(1.76)		(5.71)
Age_insider	0.0001***	-	0.0001***
	(9.43)		(9.17)
PhD	0.0301***	-	-0.0037
	(12.05)		(-1.32)
Grad	0.0118***	-	-0.0073***
	(12.60)		(-6.48)
MBA	-0.0013	-	-0.0026
	(-1.19)		(-1.64)
UnderGrad	0.0039***	-	0.0019***
	(17.81)		(4.84)
Firm-fixed Effect	NO	YES	YES
No. of Obs.	210,675	223,755	210,675
R-squared	0.0236	0.1673	0.2626

In Table 2.7, we report the results of the relationship of routine trades made by female insiders and the biased trade losses. We introduce an interaction term, *Female×Routine*, which is the product of Routine trades and the Female dummy variable. Column (1), controlling for firm and insider-level variables, and Column (2), with fixed effects, show that routine trades are negatively and significantly related to the losses from biased trades. However, when routine trades are made by female executives, the losses increase. In Column (3), we consider firm-fixed effects as well as all the control variables. The results report a significant 0.74% decrease in the losses when insiders are routine traders. Interestingly, the results show a positive relation between prospect theory value biased trade losses and routine trades by female insiders. There is an increase of 1.1% in the loss from biased trading when female insiders carry out routine trades and follow a regular pattern of trading. As shown in Column (3), this outcome is significant at the 5% level with a goodness of fit of 26.26%.

Our results demonstrate that female insiders are subject to a higher prospect theory value bias, irrespective of the trading patterns. Even under routine trades category, where exploitation of superior non-public information is not observed, female insiders' decisions are influenced by prospect theory value of the stock and they suffer with higher losses than male insiders.

2.4.3.4 Female Insider Trading and Biased Trade Losses in Macro-level Market Uncertainty

We run our analysis under uncertain market situation. There are various macro-level uncertainty variables, however, we focus on the factors which directly influence investment behaviors of investors and market participants. When uncertainty is high for investors, the signals conveyed from insider trading might be received differently from market participants. Hence, we expect that under uncertain market situation, insiders ought to trade on equal informational level and convey similar signals. If exploiting firm's fundamental information and earning abnormal returns are avoided during uncertain market situation, we may expect to see no gender difference in the losses of biased trades. Following Kumar (2009b), our study considers four proxies to measure macro-level market uncertainty: (i) market volatility *(Vlty)*, measured as the cross-sectional average of monthly standard deviation of the stocks' daily returns; (ii) investors sentiment *(Sntmt)*, a monthly index measured by the American Association of Individual Investors (AAII); (iii) national unemployment rate *(Unempl)*, a monthly measure obtained from the U.S. Bureau of Labor Statistics; and (iv) CBOE volatility index *(VIX)*, a monthly measure obtained from Global Financial Data.

To examine the relation of female insiders and losses from biased trades under uncertain market conditions, we introduce four interaction terms; *Female*×*Vlty*, *Female*×*Sntmt*, *Female*×*Unempl*, and *Female*×*VIX*, which are the products of Female dummy variable and macro-level market uncertainty proxies. Table 2.8 provides the results with and without control variables and fixed effects. Column (1) is based on the basic model with no controls and fixed effects. Column (2) includes all firm and insider level control variables, without firm fixed effect, and shows that most of the uncertainty proxies, except VIX, are positively and significantly associated with the loss. Column (3), with fixed effects for firm, reports that the biased trades' loss is significantly larger when market volatility, investor sentiment, and unemployment rate are high, or VIX is low. Under market uncertainty conditions, other than market volatility, the losses from biased trades made by inside female executives increase. Among these measures, the coefficient of investor sentiment is the strongest.

In Column (4) of Table 2.8, we present results based on all control variables and firm fixed effects. It is evident that, when the market is volatile, biased trades' losses by female insiders are reduced by 0.39%, while under high sentiment and VIX index, female insider trades are subject to higher losses compared to trades by male insiders. The positive estimate of *Female*×*Unempl* is not statistically significant. The findings of higher losses by female insider trades are supported only under increased investors' sentiments and VIX. Due to mixed signs of coefficients, the results are not conclusive.

As a result, in our first setting of informational level, higher losses of female insiders' biased trading, compared to male trading, indicate that tendency of females to be influenced by their heuristics is higher than males and limited information availability potentially contribute to this association.

Table 2.8. Biased Trade Loss and Female Insider Trading under Macro-Level Market Conditions

This table presents the findings of the regression of biased trade loss on female insider trades under various uncertain market conditions. The dependent variable, Biased_Trade_Loss (B_T_Loss), is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. Female is a measure of trade by a female insider that is equal to 1 if the insider trading is carried out by the female at time t and 0 otherwise. The uncertainty variables include Market Volatility (Vlty), Investors Sentiment Index (Sntmt), National unemployment rate (Unempl), and Volatility Index (VIX). These variables are measured at time t-1. $Female \times Vlty$, $Female \times Sntmt$, $Female \times Unempl$, and $Female \times VIX$ are the product of female dummy variable and above mentioned uncertainty variables respectively. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. To ensure that extreme values are not affecting the results, all variables are winsorized at their 1 and 99 percentile levels. The results are presented with firm fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

$$B\_T\_Loss_{i,t} = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Vlty_{i,t-1} + \beta_3\, Sntmt_{i,t-1} + \beta_4\, Unempl_{i,t-1} + \beta_5 VIX_{i,t-1} + \beta_6\, Female \times Vlty_{i,t} + \beta_7\, Female \times Sntmt_{i,t} + \beta_8\, Female \times Unempl_{i,t} + \beta_9\, Female \times VIX_{i,t} + \gamma\, Controls + \varepsilon_{i,t}$$

	Whole Sample			
	No controls and no fixed effect (1)	All controls but no fixed effect (2)	Fixed effect but no controls (3)	All controls and fixed effect (4)
Female	0.0090***	0.0107***	0.0077*	0.0001
	(2.58)	(3.60)	(1.76)	(0.05)
Vlty	0.0039***	0.0024***	0.0037***	0.0010***
	(15.64)	(9.79)	(11.13)	(4.23)
Sntmt	0.0029***	0.0054***	0.0055***	0.0040***
	(5.19)	(9.87)	(6.54)	(7.04)
Unempl	0.0023***	-0.00001	0.0027***	-0.0002**
	(14.95)	(-0.15)	(24.96)	(-2.45)
VIX	-0.0003***	-0.0001***	-0.0002***	0.0001**
	(-9.65)	(-3.18)	(-4.33)	(2.38)
Female×Vlty	-0.0033**	-0.0053***	-0.0053***	-0.0039***
	(-2.46)	(-4.18)	(-2.86)	(-3.04)
Female×Sntmt	-0.0155***	-0.0036	0.0106**	0.0265***
	(-4.11)	(-0.91)	(2.11)	(7.19)
Female×Unempl	0.00001	-0.0005	-0.0001	0.0005
	(0.03)	(-0.99)	(-0.17)	(1.17)
Female×VIX	0.0003**	0.0006***	0.0007***	0.0006***
	(2.24)	(4.17)	(2.93)	(3.53)
Retex_m	-	-0.0031***	-	0.0017**
		(-3.20)		(2.41)
Retex_y	-	0.0004	-	0.0014***
		(1.22)		(4.80)
Size	-	-0.0027***	-	-0.0081***
		(-46.43)		(-32.33)
Turnover	-	0.0007***	-	0.0001*
		(11.26)		(1.74)

Table 2.8. (continued)

	No controls and no fixed effect	All controls but no fixed effect	Fixed effect but no controls	All controls and fixed effect
	(1)	(2)	(3)	(4)
Book_Mkt	-	0.0006	-	0.0017***
		(1.51)		(5.81)
Age_insider	-	0.0001***	-	0.0001***
		(9.77)		(8.09)
PhD	-	0.0298***	-	-0.0009
		(12.34)		(-0.31)
Grad	-	0.0122***	-	-0.0072***
		(13.06)		(-6.34)
MBA	-	-0.0016	-	-0.0024
		(-1.47)		(-1.49)
UnderGrad	-	0.0039***	-	0.0018***
		(18.13)		(4.64)
Firm Fixed Effect	NO	NO	YES	YES
No. of Obs.	223,755	210,675	223,755	210,675
R-squared	0.0054	0.0254	0.1714	0.2631

2.4.4 Trades Induced by Superior Information and Female Insiders' Losses from Prospect Theory Value Biased Trades

In this setting, we consider the trades which are made when superior or high-quality information is available. For this setting, higher losses of female insiders' biased trades are expected to diminish because the trades are influenced by superior information. We consider the sub-sample of buy trades and firms with high proportion of female insider transactions.

2.4.4.1 Female Insider Trading and Biased Trade Losses for Buy Trades

It is evident in the literature that insiders may sell due to reasons other than profit maximization, such as diversification or rebalancing of portfolio, liquidity, wealth, income, or tax-loss selling (Huddart & Ke, 2007). Insiders' buy trades mostly reflect some good news concerning a company's prospects and insiders earn abnormal returns in future. Lakonishok and Lee (2001) show that insider buying strongly predicts future long-term returns. Jeng, Metrick, and Zeckhauser (2003) find abnormal performance of over 6% annually after insider buying, as opposed to no significant abnormal performance for insider selling. Kallunki, Nilsson, and Hellstrom (2009) report that insiders tend to buy stocks that earn high positive abnormal returns on non-trading days, with returns that are greater than selling. Although insiders have an information advantage over other investors or market participants, there is always litigation risk associated with insider buy trades. Therefore, insiders are more likely to be cautious when timing their purchases than their sales because of the risk of regulatory monitoring (Seyhun, 1998). Jeng, Metrick, and Zeckhauser (2003) explain that CEO trades are closely scrutinized by regulators, therefore they trade more cautiously. We argue that if access to information explains our results, then a reduction in losses of female insiders' biased trades is expected for superior information induced buy trades.

Table 2.9 shows the regression results of the relationship between losses of prospect theory value biased trades and insider trading by females when they buy their company's stock. Columns (1) and (2) present the results of the full sample, whereas Columns (3) and (4) include firms with trades by both genders. We use two different models for this test. First, we consider only buy transactions and investigate the association between female trades and losses. Second, we analyze an interaction term, *Female×Buy*, which is the product of Buy trades and a Female dummy. We test the relationship with firm-fixed effects as well as with firm- and insider-specific characteristics. Columns (1) and (3) present the regression results for buy transactions only, where it is evident that the coefficient of female trades and the losses is insignificant. This validates the supposition that our finding of higher biased trade losses by female insiders is inconsistent when we control for buy trades. Similarly, Columns (2) and (4) exhibit negative coefficients of the *Female×Buy* variable that are significant at the 1% level.

We argue that female insiders decide to buy their company's stock when they have access to relatively higher quality internal information, resulting in a significant decrease in biased trade loss. Hence, we suggest that information availability plays an important role in explaining our results.

Table 2.9. Biased Trade Loss and Female Insider Trading under Buy Transactions

This table presents the findings of the regression of biased trade loss on female insider trades when female executives decide to buy the insider stock. We present results for buy transactions only, as well as for the interaction between female and buy insider trades using the full sample. The dependent variable, Biased_Trade_Loss (B_T_Loss), is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. Female is a measure of trade by a female insider that is equal to 1 if the insider trading is carried out by the female at time t and 0 otherwise. $Female \times Buy$ is the product of buy transaction and a female dummy variable. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. To ensure that extreme values are not affecting the results, all variables are winsorized at their 1 and 99 percentile levels. The results are reported for the full sample, as well as for the subsample of firms with trades by both genders. The results are presented with firm-fixed effects. The t-statistics are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

$$B\_T\_Loss_{i,t} = \alpha + \beta_1 \, Female_{i,t} + \beta_2 \, Buy_{i,t} + \beta_3 \, Female \times Buy_{i,t} + \gamma \, Controls + \varepsilon_{i,t}$$

	Full sample		Trades by both genders	
	Buy Transactions All controls and fixed effect (1)	Interaction All controls and fixed effect (2)	Buy Transactions All controls and fixed effect (3)	Interaction All controls and fixed effect (4)
Female	-0.0006	0.0075***	-0.0007	0.0076***
	(-0.32)	(8.43)	(-0.27)	(8.49)
Buy	-	0.0056***	-	0.0126***
		(14.08)		(12.60)
Female×Buy	-	-0.0098***	-	-0.0117***
		(-6.01)		(-6.88)
Retex_m	0.0165***	0.0029***	0.0561***	0.0222***
	(10.45)	(4.11)	(15.03)	(13.53)
Retex_y	0.0068***	0.0024***	0.0237***	0.0110***
	(10.12)	(8.01)	(15.80)	(15.89)
Size	0.0062***	-0.0085***	-0.0148***	-0.0132***
	(10.91)	(-34.20)	(-11.57)	(-25.89)
Turnover	0.0027***	0.0002***	0.0014**	-0.0008***
	(11.76)	(2.93)	(2.12)	(-4.01)
Book_Mkt	-0.0083***	0.0014***	-0.0130***	-0.0125***
	(-14.71)	(5.05)	(-8.87)	(-18.17)
Age_insider	-0.00004	0.0001***	-0.00002	-0.0001**
	(-1.00)	(8.77)	(-0.23)	(-1.99)
PhD	-0.0035	-0.0047*	-	-0.0013
	(-0.45)	(-1.69)		(-0.35)
Grad	-0.0143***	-0.0076***	-0.0308***	-0.0205***
	(-5.50)	(-6.76)	(-7.41)	(-11.51)
MBA	-0.0066*	-0.0028*	0.0084	0.0002
	(-1.81)	(-1.72)	(0.92)	(0.07)
UnderGrad	-0.0010	0.0015***	0.0037	0.0047***
	(-0.89)	(3.89)	(1.41)	(5.14)
Firm-fixed Effect	YES	YES	YES	YES
No. of Obs.	44,476	210,675	8,616	36,449
R-squared	0.3361	0.2628	0.2769	0.3097

2.4.4.2 Female Insider Trading and Biased Trade Losses in Firms with Higher Female Proportion

We have reported in our descriptive statistics that 5.71% of the executives are female, but they are responsible for only 2.56% of the total insider transactions. It is evident that they are underrepresented in the firms, especially at the top corporate level. Moreover, their lack of connections and limited access to informal networks become a hurdle for females to collect useful, material information and for making profitable decisions (Fang & Huang, 2017; Inci, Narayanan, & Seyhun, 2017; Mobbs, Tan, & Zhang, 2018). We anticipate that the impact of these factors may diminish in firms where the proportion of female insiders is comparatively higher than males. A greater number of females at top positions reflects stronger ties and networks among them, which ultimately improve their learning, work related experience, and the availability of useful information. Following Inci, Narayanan, and Seyhun (2017), we consider the proportion of female insider trades in a firm as a proxy of the proportion of female insiders. If access to information contributes to our results, in such firms we expect a decrease in the positive association between female insiders and their biased trades' losses.

Table 2.10 displays the findings of female insider trading and biased trade losses in the sub-sample of firms with a higher proportion of female insiders (i.e., where the proportion of female insider trading is at the 95th percentile and above). First, we measure the proportion of female insider trades in each firm within our full sample. Subsequently, by using these proportions, we consider the sub-sample of firms in which the female insider trades' proportion is at the 95th percentile and above. Columns (1), (2), and (3) of Table 2.10 present the results of the sub-sample of firms selected from the full sample. In Column (4), the sub-sample is chosen from the firms with insider trades by both genders.

Considering firm fixed effects and all the control variables, the regression results show that, when we limit our sample to the firms in which the proportion of female insider trading is at the 95th percentile and above, no significant positive relation exists between female insiders and biased trade losses. This finding is consistent with the argument that when females are higher in number, the informational disadvantage is reduced. Hence, female insiders no longer suffer higher losses from the prospect theory value biased trades.

Table 2.10. Biased Trade Loss and Female Insider Trading in Higher-Female-Proportion Firms

This table presents the findings of the regression of biased trade loss on female insider trades in firms with female trades that are in the 95th percentile of all female trades. We measure the proportion of female insider trades by taking the number of female trades divided by the total number of trades by both gender in each firm. Using these proportions, we take into account the sub-sample of firms in which female insider trades' proportion is in the 95th percentile and above. The dependent variable, Biased_Trade_Loss (B_T_Loss), is a measure of loss from prospect theory value biased trades and is equal to $|Retex_{t+1}|$ if either of the two conditions mentioned in Equation (4) is met at time t and 0 otherwise. Female is a measure of trade by a female insider that is equal to 1 if the insider trading is carried out by the female at time t and 0 otherwise. Retex_m is the monthly return in excess of the market return at time t-1. Retex_y is the cumulative past monthly returns in excess of the market returns from t-12 to t-2. Size is the log of the monthly market capitalization at time t-1. Turnover is the monthly volume turnover at time t-1; it is equal to the number of shares traded divided by the number of shares outstanding. Book_Mkt is the book-to-market ratio at time t-1, measured as (total assets - total liabilities) divided by (closing price*number of shares outstanding). Age_insider is the insider's age at the time of transaction t. PhD equals 1 if the insider has doctoral degree and 0 otherwise. Grad equals 1 if the insider has a graduate degree and 0 otherwise. MBA equals 1 if the insider has a Master of Business Administration degree and 0 otherwise. Undergrad equals 1 if the insider has an undergraduate degree and 0 otherwise. To ensure that extreme values are not affecting the results, all variables are winsorized at their 1 and 99 percentile levels. The results are reported for the full sample, as well as for the subsample of firms with trades by both genders. The results are presented with firm-fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels.

$$B\_T\_Loss_{i,t} = \alpha + \beta_1\ Female_{i,t} + \gamma\ Controls\ +\ \varepsilon_{i,t}$$

	Full Sample			Trades by both gender
	All controls but no fixed effect	Fixed effect but no controls	All controls and fixed effect	All controls and fixed effect
	(1)	(2)	(3)	(4)
Female	-0.0029**	0.0011	-0.0008	-0.0055
	(-2.37)	(1.23)	(-0.75)	(-1.33)
Retex_m	-0.0295***	-	-0.0269***	0.0363***
	(-4.63)		(-7.44)	(3.39)
Retex_y	0.0011	-	0.0010	0.0210***
	(0.65)		(0.64)	(4.45)
Size	-0.0039***	-	-0.0061***	-0.0079**
	(-14.79)		(-4.74)	(-2.07)
Turnover	0.0077***	-	0.0014***	-0.0070***
	(13.37)		(2.92)	(-3.00)
Book_Mkt	-0.0009	-	-0.0078***	0.0294***
	(-0.88)		(-4.15)	(3.90)
Age_insider	0.0002***	-	-0.00003	-0.0003
	(3.50)		(-0.46)	(-0.85)
PhD	0.0700***	-	0.0007	0.0169
	(15.84)		(0.22)	(0.93)
Grad	-0.0272*	-	-0.0649*	-
	(-1.66)		(-1.78)	
MBA	-0.0081***	-	-0.0029	-0.0206
	(-2.76)		(-0.39)	(-0.66)
UnderGrad	0.0006	-	-0.0003	-0.0039
	(0.48)		(-0.17)	(-0.43)
Firm-fixed Effect	NO	YES	YES	YES
No. of Obs.	4,430	5,507	4,430	1,074
R-squared	0.3307	0.6287	0.6689	0.2738

2.5 Conclusion

Behavioral biases affect the profitability of insider trading. This study is the first to provide empirical evidence of gender differences in insider trading from the perspective of prospect theory. Using a sample of U.S. top executives' insider trades, first, we document that insider trades earn lower returns in the subsequent month when insiders time to buy (sell) stock with a prospect theory value higher (lower) than that of other firms. Second, female insiders carry out prospect theory value biased trades and suffer losses higher than the losses their male counterparts suffer. It is evident that the number of insider transactions, past 12-months' cumulative return, share turnover, number of shares traded, and dollar-value of male trades are greater than female trades, on average. Our regression results cannot be explained by the *overconfidence hypothesis* as the results show that female executives carry higher number of biased trades and suffer more losses than males. These results support the *information access hypothesis* and imply that the information disadvantage to female executives may explain their higher biased trade losses.

We follow the literature that limited information contributes to higher behavioral biases, and that due to male dominance female insiders may have access to limited information, as compared to their male counterparts. We test these arguments in two different settings; first, where the access to information is considered to be equal for all the executive, second, where trades are induces by superior information availability. For our first setting, we run the analysis within executives' formal titles, trade size, routine trades, and macro-level market uncertainty. For second setting, buy trades and firms with high proportion of female insider trades are examined. We find that the significant positive association between female insiders and prospect theory value biased trades' losses exist even in the situations where information is supposed to be equally dispersed, indicating limited access of information to female insiders. Whereas, this association is significantly diminished when trades are induced by superior material information. Consequently, these findings indicate that access to information potentially contributes in explaining higher biased trade losses of female insiders.

CHAPTER 3

GENDER AND MUTUAL FUND LIQUIDITY

This chapter consists of the second essay of the thesis which investigates fund managers' preference for liquidity and analyzes the difference in portfolio liquidity among male and female managers. Using a sample of 1,932 U.S. domestic open-end single managed active equity funds from January 2000 to December 2017, the results show that preference of female fund managers to hold liquid portfolio is higher than male managers.

The brief introduction and motivation of the study is given in section 3.1. Section 3.2 provides the literature review and hypotheses formation, while Section 3.3 establishes the research methodology and specifies the details of our data. Section 3.4 presents the applications of diagnostic tests, analysis, and discussion of results. Section 3.5 reports the findings of endogeneity analysis. Section 3.6 provides the conclusions. An appendix to this chapter and the relevant reference list are provided at the end of the thesis.

Gender and Mutual Fund Liquidity

Abstract

This study demonstrates that the gender of mutual fund managers affects the liquidity of a portfolio. Female managers prefer higher portfolio liquidity than their male counterparts. Funds managed by single female managers are 8-25% more liquid than single male managed funds. Contrary to the excessive trading hypothesis that expects a higher liquidity preference of overconfident male fund managers, the findings support the inclination of female fund managers for the price efficiency hypothesis. Funds experience an increased liquidity when they transition to a female manager.

Keywords: Mutual funds, Fund manager's gender, Preference for portfolio liquidity, Information transparency, Transition funds.

3.1 Introduction

This study focuses on fund managers' preference for liquidity and examines the role of gender in selecting a liquidity-preferred portfolio. Liquidity is one of the preferred stock characteristics for portfolio holdings of mutual funds (e.g., Falkenstein, 1996; Gompers & Metrick, 2001; Pinnuck, 2004). The prime reason for mutual funds to hold liquid securities is to build a safety cushion to manage liquidity risk in the event of a crisis. Fund managers can sell their liquid stocks first to reduce exposure and leverage, quickly and at a lower cost (Scholes, 2000). Recent studies provide insight that expectation of future market volatility and fund withdrawals encourage fund managers to sell their illiquid stocks first to preserve liquidity (e.g., Ben-Rephael, 2017; Huang, 2015; Vayanos, 2004). Do male and female fund managers exhibit a similar preference for portfolio liquidity? Several studies have concluded that there are no significant differences in the risk-adjusted performance of male and female fund managers.[19] However, it is intriguing to analyze the liquidity choice of fund managers for portfolio holdings based on their gender.

The gender of finance professionals is an important personality trait associated with differences in investment decisions. Earlier studies suggest that gender disparities exist in investment behaviors e.g., risk taking, conservatism, and overconfidence.[20] We find strong empirical evidence that women have a stronger preference for stocks' information transparency than men. With the inclusion of female directors on corporate boards, stock price informativeness improves and the level of information asymmetry in the stock market diminishes (Abad et al., 2017; Gul, Srinidhi, & Ng, 2011). Following this strand of literature, we expect a difference in liquidity preference among male and female fund managers.

We develop two competing hypotheses in this regard: the *excessive trading hypothesis;* and the *price efficiency hypothesis.* The *excessive trading hypothesis* expects that, due to their overconfident investment behavior, male fund managers are involved in more frequent trading than female managers

[19] See for example, Atkinson, Baird, and Frye (2003); Niessen-Ruenzi and Ruenzi (2019).
[20] See for example, Beckmann and Menkhoff (2008); Huang and Kisgen (2013); Levi, Li, and Zhang (2014); Faccio, Marchica, and Mura (2016); Niessen-Ruenzi and Ruenzi (2019).

(Barber & Odean, 2001; Niessen-Ruenzi & Ruenzi, 2019). The excessive turnover in their portfolios, and aggressively moving money into new securities, increase transaction costs (Chan & Lakonishok, 1995). Therefore, the preference to trade in liquid stocks is higher for male managers as compared to their female counterparts. On the contrary, following the literature on female attraction for transparent information, the *price efficiency hypothesis* expects that, compared to male fund managers, females are more likely to prefer liquid stocks for which price adjustment to information occurs in a timely manner. Lang, Lins, and Maffett (2012) suggest that transaction costs are lower, and liquidity is higher, for firms with better transparency.

We find a contradictory view in the literature regarding behavioral disparities among gender. A number of studies indicate that it is usual to observe a vivid difference in the investment behaviors of individual or household investors and professional managers (Dwyer, Gilkeson, & List, 2002). The managers belong to a category of highly experienced and qualified investors; therefore, they are most likely to behave in a similar way. Following this aspect of the literature and considering the importance of portfolio liquidity decisions, it is plausible that there exists no disparity in the choices of male and female fund managers when investing in liquid assets. Fund managers have a familiarity with risk as they are specialists in risk management. Additionally, they usually have advanced financial education and market knowledge. These two forces alleviate the gender effect on behavioral preferences of fund managers.[21] The self-selection mechanism among females on becoming fund managers can be another reason to assume that females are equally confident and competitive as their male counterparts.[22] The ongoing ranking of fund managers by market participants, and some investors' gender bias towards female managed funds, are also reasons to assume that female and male fund managers tend to perform similarly.[23]

[21] Hibbert, Lawrence, and Prakash (2013) suggest that financial education mitigates the gender difference in risk aversion.
[22] Nekby, Thoursie, and Vahtrik (2008) show that women selected to participate in male-dominated environments are likely to be highly competitive.
[23] Niessen-Ruenzi and Ruenzi (2019) document significantly lower inflows in female-managed funds than in male-managed funds because some investors with strong gender bias invest significantly less in female-managed funds.

To the best of our knowledge, we are the first to investigate mutual fund managers' liquidity preference for portfolio holdings, influenced by their gender. This study not only explores the controversial research area of gender but also deals with potential endogeneity issues. It is likely that some fund management companies discriminate in their selection of a fund manager based on gender, or females may self-select specific type of funds, e.g. growth funds or income funds, etc. Hence, the investment objective of a fund affects a stockholding's liquidity, rather than it being affected by the gender of the fund manager. It should also be noted that female representation is uneven across different types of funds. Their underrepresentation in some funds with specific objectives can lead to spurious results. On the other hand, institutional ownership affects a stock's liquidity (Agarwal, 2007; Rubin, 2007). One major concern of this study is whether a fund manager has picked stocks based on their liquidity, or their inclusion in the fund portfolio has given rise to the stocks' liquidity. Therefore, it is difficult to establish a fund manager's preference for liquidity. The concern of time-invariant fund specific characteristics that might be correlated with omitted explanatory variables gives rise to endogeneity issues. In this scenario, a simple regression model may not be sufficient to justify the outcomes. We, therefore, apply propensity scores matching and difference-in-differences approaches to substantiate the authenticity of our results.

First, we compare the liquidity preference of funds managed by female managers to a (propensity score) matched sample of peers run by male managers, that are indistinguishable in terms of investment objectives, time, fund, and manager level characteristics. Second, we compare the portfolio liquidity preference of the same funds, as managed by managers of different gender. We consider a sample of funds experiencing a transition from one manager to another, including male to male, female to female, male to female, and female to male fund manager (referred to as "transition funds"). Third, we apply propensity scores matching on the transition funds. Finally, we apply a difference-in-differences approach on the transition funds to compare fund liquidity before and after transitions from male to female manager, with a control sample of male to male transition funds.

We conduct one additional test to rule out any endogeneity concerns. The test relies on the instrumental variable approach, in which we use a “state level gender equality index” as an instrument for a fund managed by a female manager (Di Noia, 2002). We assume that the friendlier a state is toward female equality the more likely a fund (with its headquarters in that state) is to have a female manager. The results support our hypothesis of a stronger female preference for portfolio liquidity relative to males.

Using a sample of 1,932 U.S. domestic open-end single managed equity funds from January 2000 to December 2017, 10% (on average) of which are run by single female managers, the results show that the preference of female fund managers for holding liquid portfolios is higher than for male managers. Our outcomes provide support to the *price efficiency hypothesis* as opposed to the *excessive trading hypothesis*. The findings are consistent with the literature that finds that females are involved in less frequent trading than their male counterparts. However, the net result of liquidity preference among male and female fund managers does not indicate higher liquidity demand by male managers. Price delay may result from lack of liquidity or investors’ inattention towards a stock (Hou & Moskowitz, 2005). The results show that female fund managers favor stocks for which their prices incorporate market and firm specific information in a timely manner. Subsequently, female fund managers’ inclination toward price-efficient stocks may explain their preference for higher portfolio liquidity. The findings of propensity scores matching, and difference-in-differences methodologies provide empirical evidence that a significant increase in portfolio liquidity occurs around the change from male to female fund manager, as compared to otherwise similar peers. The results from a two-stage least squares (2SLS) instrumental variable (IV) design are consistent with the main findings of the study. Moreover, the outcomes depict that, on average, female managed funds are smaller in size and have lower flows and fund returns. We also present the impact of female fund managers on portfolio liquidity across investment styles and over time. We run a main regression model by controlling for various stock-level variables that are likely to affect portfolio liquidity and find that the results support our hypothesis.

The literature on liquidity and asset pricing states that the expected return of an illiquid stock is higher to compensate for its higher trading cost (Amihud & Mendelson, 1986). One possible explanation for our results is the tradeoff between liquidity and fund returns. The liquidity preference of female fund managers gives them the benefits of managing a less risky portfolio and protecting from excessive trading costs when the market is volatile. However, a liquidity preferred portfolio has a higher tendency to deteriorate fund performance due to lower returns. There exists empirical evidence that mutual fund investors reward superior performing funds by increasing flows into these funds (e.g., Fant & O'Neal, 2000; Sirri & Tufano, 1998). Therefore, it is not surprising if fund managers attract fund flows by holding less-liquid stocks and reporting higher fund return performance. Our results show that female fund managers prefer to hold more liquid assets, which reduces the riskiness of the portfolio; however, female managed funds have, on average, lower flows and returns as compared to male managed funds. Although our preliminary analysis depicts negative returns when the fund is female managed, the association is not statistically significant.[24]

So far, the preference for portfolio liquidity among male and female mutual fund managers remains unexplored. Our study relates to several strands of literature. First, it contributes to the existing studies that report liquidity as one of the important characteristics of stockholdings, preferred by institutional investors (e.g., Del Guercio, 1996; Falkenstein, 1996; Gompers & Metrick, 2001). Second, our results are consistent with the notion that behavioral disparities among gender exist even in professional settings (e.g., Faccio, Marchica, & Mura, 2016; Ho et al., 2015; Huang & Kisgen, 2013). Third, the analysis of liquidity preference among male and female fund managers is a contribution to the existing literature on the gender of mutual fund managers (e.g., Beckmann & Menkhoff, 2008; Niessen-Ruenzi & Ruenzi, 2019). Fourth, our findings support the literature on females' inclination towards informationally transparent stocks, and the positive association between stock price efficiency and liquidity (e.g., Abad et al., 2017; Callen, Khan, & Lu, 2013; Diamond & Verrecchia, 1991; Gul,

[24] We present the findings for fund risk and return in Table B6 in the Appendix. The use of more structured proxies to measure fund performance will undoubtedly provide greater insight; however, it is beyond the scope of this study and is best left for future research.

Srinidhi, & Ng, 2011; Lang, Lins, & Maffett, 2012). Finally, this study discusses the fact of stock liquidity and return tradeoff (Amihud & Mendelson, 1986).

The rest of the paper is structured as follows. Section 3.2 provides the literature review and hypotheses formation, while Section 3.3 establishes the research methodology and specifies the details of our data. Section 3.4 presents the applications of diagnostic tests, analysis, and discussion of the results. Section 3.5 reports the analysis of the endogeneity issues. Section 3.6 provides the conclusions.

3.2 Literature Review and Hypotheses Development

3.2.1 Liquidity and Mutual Funds

Institutional investors, including fund managers, exhibit specific preferences for various stock characteristics, with liquidity being one of them. Del Guercio (1996) examines the impact of the prudent-man laws on the holding preferences of mutual funds and banks. By analyzing the reported portfolio holdings of 941 institutional managers, the study finds that bank managers significantly tilt their portfolios towards “prudent” (quality) stocks. The constraints of the prudent-man rule induce bank managers to prefer large-capitalization stocks with low book-to-market ratios. Mutual fund managers appear to display a slight preference for low book-to-market stocks and a stronger avoidance of high book-to-market stocks, in both large and small stocks.

Transaction costs erode a fund’s performance and managers wishing to maximize fund performance will prefer highly liquid stocks to minimize implicit transaction costs. Falkenstein (1996) analyzes a cross-section of U.S. mutual fund equity holdings to determine fund managers’ preferences for various stock characteristics. Examining equity holdings of about 1000 funds for the years 1991 and 1992, he finds strong preferences for stocks with high liquidity (low transaction cost), information flow, and high idiosyncratic volatility. The study also highlights that small-cap funds show a preference towards small-cap stocks, which are relatively low in liquidity. Gompers and Metrick (2001) extend the previous work on institutional investors’ preferences for stock features by analyzing a 17-year panel

(1980 to 1996) of U.S. 13F institutional investors with at least US$100 million under management. They find that such large institutions prefer large market-capitalization stocks and highly liquid stocks that have low past returns.

Using data of equity portfolio holdings of 35 Australian active equity fund managers from 1990 to 1997, Pinnuck (2004) finds strong evidence that fund managers prefer large, liquid, and low volatility stocks. Brands, Gallagher, and Looi (2006) consider 36 active Australian institutional equity managers over the period from 2000 to 2001 and examine their preferences for securities according to stock size. The study shows significant preferences for stocks with higher stock price variance, lower transaction costs, larger market-capitalization, preferences towards value stocks, securities with higher analyst coverage and stocks with a lower standard deviation in analyst earnings forecasts. For small stock holdings, stock volatility and analyst coverage are of greater importance. On the other hand, there is evidence that over time institutional investors have shifted their aggregate preferences towards smaller and riskier securities (Bennett, Sias, & Starks, 2003). The study suggests that institutional investors' informational advantages are greatest in smaller-capitalization securities.

Mutual fund managers' preference for liquidity and trading of stocks based on their liquidity provide managers with a safety cushion during changes in expected market volatility or redemptions. Liquid stocks can easily be converted into cash during market stress to cater for redemptions in the fund. Therefore, fund managers are likely to adjust the liquidity of their portfolios in response to changes in expected volatility. Huang (2015) examines fund managers' changes in portfolio decomposition and finds that fund managers hold more cash, and their holdings are more inclined towards liquid stocks, during periods when expected market volatility is high. Such liquidity preferences are stronger for funds that face high exposure to investor withdrawals during volatile times. Huang argues that this is due to strategic liquidity planning by fund managers and it can serve as a shock absorber when large investor redemptions occur during volatile periods. The evidence suggests that this type of dynamic behavior contributes to higher fund returns.

There are different predictions regarding which assets should be sold first in crisis, either liquid or illiquid. Scholes (2000) supports the view that fund managers sell their liquid securities first, quickly and at a lower cost. Clarke, Cullen, and Gasbarro (2007) provide evidence that, when fund managers face redemptions, they avoid selling their less-liquid assets because this would lead to a greater downward price pressure on the illiquid stocks. They find that low liquidity funds exhibit a higher preference for selling their more-liquid stocks when they experience redemptions. However, during volatile times when withdrawals become more likely, if fund managers act strategically, they sell their illiquid assets first to preserve liquidity. Vayanos (2004) concludes that, in crisis, fund managers increase their preference for liquidity, they reduce illiquid stocks' holding, stocks' liquidity premia, and illiquid assets' market betas increase. Consistent with this view, Ben-Rephael (2017) analyses the aggregate liquidation of equity mutual funds during ten periods of extreme market volatility, defined by a significant positive jump in VIX, from 1986 to 2009. The findings show that mutual funds reduce their aggregate shareholdings of illiquid stocks during volatile periods. The cross-sectional analysis suggests that larger redemptions from funds that hold less-liquid stocks contribute to the aggregate reduction in illiquid stocks' holdings, which may contribute to the relatively large decline of illiquid stock prices.

While it appears that many researchers are convinced that portfolio liquidity plays an important role in dealing with fund redemptions, there exists another strand of literature which recognizes that liquidity provision to fund investors and liquidity-motivated trading have an adverse impact on fund performance. The studies narrate that fund managers respond to unanticipated investors' flow and engage in trading to control liquidity, which is detrimental to fund performance. The liquidity-motivated trading by fund managers not only results in transaction costs, but also significant trading losses (e.g., Alexander, Cici, & Gibson, 2007; Edelen, 1999; Nanda, Narayanan, & Warther, 2000). Clarke, Cullen, and Gasbarro (2007) suggest that, until the following three- and six-month periods, redeeming funds that sell their more liquid stocks statistically and economically underperform redeeming funds that sell their less liquid stocks, during the period of inflows. In contrast, inflow funds that purchase more liquid stocks underperform those that purchase less liquid ones. Massa and Phalippou (2004) conclude that fund performance is unrelated to portfolio liquidity.

Managing portfolio liquidity is crucial for fund managers due to various fund- and market-specific reasons. However, the degree of male and female fund managers' preference for liquidity is still unexplored. This study conducts an empirical analysis to analyze gender aspects in liquidity choices.

3.2.2 Gender, Behavioral Differences, and Liquidity Preference of Male Fund Managers

In the behavioral finance literature, there are several studies exploring behavioral disparities among gender regarding financial decision making in different settings.

Using a psychological survey experiment on shareholders, security analysts, institutional investors, and general businesspersons, Estes and Hosseini (1988) find that women are significantly less confident than men in investment decisions. Sunden and Surette (1998), using data from the 1992 and 1995 *Surveys of Consumer Finances*, find that gender and marital status have a combined effect on the allocation decisions of defined contribution (DC) retirement plans. The results show that women, either single or married, tend to allocate their investments to the retirement plan more conservatively than men. The failure of women to invest adequate funds in stocks results in lower retirement wealth. Similarly, Jianakoplos and Bernasek (1998) use surveys and other economic data to conclude that single women are more risk averse in financial decision making than single men.

Powell and Ansic (1997) design two computerized laboratory experiments to examine the gender differences in risk preferences. They find that females are less risk seeking than males in financial decision making, regardless of the degree of familiarity, frame, or cost. Moreover, the results show that males overvalue, and females undervalue, their current position in the currency market because females are less confident than males. However, Schubert et al. (1999) attribute the higher risk aversion of females than males to the setting of financial design. They explain the inability of survey data to capture enough differences in relevant factors, like the investment opportunity set. They find no variances in risk taking behavior in men and women facing investment and insurance related decisions in a controlled setting.

Investment decision making by professionals at the corporate level provides a perfect setting to explore behavioral differences among gender, because it is a homogeneous group of individuals with comparable levels of financial expertise and knowledge. Huang and Kisgen (2013) document that the propensity to make acquisitions is lower in companies with female CFOs. They indicate that female executives are more risk averse in investment and capital structure decisions than male executives. Berger, Kick, and Schaeck (2014) and Adams and Ragunathan (2017) state that the portfolio risk of banks with more female directors on their boards is higher than that of banks with fewer female directors. Faccio, Marchica, and Mura (2016) evaluate whether corporate risk-taking is affected by CEO gender. They observe a subsequent decrease in risk-taking of a given firm around the transition from a male to a female CEO. Ho et al. (2015) document that female CEOs are more ethical and risk averse, hence firms with female CEOs report more conservative earnings. On the contrary, Sila, Gonzalez, and Hagendorff (2016) find no evidence that boardroom gender diversity affects a firm's equity risk.

There are studies exploring the characteristics of mutual fund managers and their impact on fund performance. Chevalier and Ellison (1999a) examine the manager's age, the average composite SAT score at the manager's undergraduate institution, and whether the manager has an MBA. They find that only the undergraduate college attended by the manager is relevant to fund performance. Atkinson, Baird, and Frye (2003) analyze a sample of fixed-income mutual fund managers and compare male and female managers to determine whether there is a difference in performance, risk, or other characteristics. They conclude that there is no significant difference in fund performance. However, female managers receive lower fund inflows into funds that they are managing. In a related study, Beckmann and Menkhoff (2008) test the survey responses of 649 fund managers in the U.S., Germany, Italy, and Thailand, and demonstrate that female fund managers are more risk averse and less overconfident than male managers. Recently, Niessen-Ruenzi and Ruenzi (2019) report that female equity fund managers are more risk averse, follow a less extreme investment style, have more consistent investments, and trade less than their male counterparts. Their study documents no gender difference in fund performance, but female managed funds receive significantly lower inflows than male managed funds.

One of the personality characteristics that influences investment decisions is overconfidence. Odean (1999) finds that individual investors tend to trade excessively, are more risk taking, and make poor investment decisions. To analyze gender differences in overconfidence, Barber and Odean (2001) use account data from a large brokerage firm and examine the common stock investments of male and female investors. They find that men trade 45% more than women, which results in lower net returns than for women. They attribute the performance and trading activity of men to overconfidence in their investment abilities. Grinblatt and Keloharju (2009) evaluate trading data of Finnish investors and document that men trade substantially more than women at all age groups. Huang and Kisgen (2013) find that male executives exhibit higher overconfidence as compared to females as they are involved in more frequent acquisitions and debt issuance. Hence, male executives earn lower returns for these corporate decisions than their female counterparts. On the contrary, Nekby, Thoursie, and Vahtrik (2008) show that women selected to participate in male-dominated environments are likely to be highly competitive. Deaves, Lüders, and Luo (2009) provide experimental evidence that overconfidence drives trading but do not find any gender differences regarding overconfidence or trading activity of finance and economics students.

Following the literature that finds men being more overconfident than women, we expect that male fund managers trade more actively than their female counterparts. These male managed high turnover funds face greater trading costs (Chan & Lakonishok, 1995). Subsequently, male fund managers prefer more liquid stocks in their portfolios to reduce trading costs.

H1a: Portfolio liquidity preference is higher among male than female fund managers.

3.2.3 Stock Price Efficiency and Liquidity Preference of Female Fund Managers

We conjecture that the preference for portfolio liquidity is higher for female fund managers than males. There is limited empirical work in the literature relating to the effect of gender on liquidity preference. Ahmed and Ali (2017) consider a sample of 944 Australian firms from 2008 to 2013 to investigate the relation between gender diverse boards and stock liquidity. They conclude that the efficient monitoring of female directors explains higher stock liquidity. They use three proxies to measure stock liquidity; Amihud’s (2002) illiquidity measure, liquidity ratio, and stock turnover, and find a positive and significant association between boardroom gender diversity and stock liquidity. Similarly, Loukil, Yousfi, and Yerbanga (2019) explore French firms between 2002 and 2012 to analyze the impact of gender diversity on boards on stock market liquidity, by distinguishing the effects of women inside and independent directors. They find that stock market liquidity is positively and significantly associated with the presence of women directors.

In this study, we explore the potential explanation of the tendency of female fund managers to prefer more liquid stocks in their portfolio than their male counterparts. The monitoring role of females on corporate boards and the resulting improved informativeness of stock prices have been examined in detail in the finance literature. The extant literature provides evidence that liquidity is higher for a stock with efficient prices. We argue that females’ liking for price efficient stocks may explain their higher preference for liquid stocks. There is no literature in the investment field regarding inclination of females towards information efficiency, therefore, we support our argument from corporate finance literature.

Adams and Ferreira (2009) describe how gender diverse boards are effective controllers. Female directors provide better monitoring of managers’ actions by promoting better board attendance, and joining monitoring positions on audit, nominating, and corporate governance committees. The literature shows that the boards performing an effective job of monitoring their managers’ actions, improve the quality and the frequency of information released by management. Subsequently, higher board quality is related to lower information asymmetry (e.g., Ajinkya, Bhojraj, & Sengupta, 2005; Karamanou & Vafeas, 2005).

We find empirical evidence in the literature that the presence of female directors on boards improves transparency and increases the quality and quantity of public/private disclosure. A valuable study by Gul, Srinidhi, and Ng (2011) explains that stock prices are more informative when boards are gender diverse. They argue that gender diversity improves stock price informativeness through the mechanism of increased public disclosure in large firms, and by encouraging private information collection in small firms. The strong monitoring role of female directors make stock prices more efficient in timely incorporation of market and firm specific information. Upadhyay and Zeng (2014) test a sample of S&P 1500 firms from the years 2000 through 2003 and show that board diversity (gender and ethnicity) is negatively associated with corporate opacity. The index to measure the corporate information environment includes analyst following, analyst forecast error, bid–ask spread, and share turnover. Their findings provide the insight that board diversity creates a more transparent information environment. Similarly, in the Spanish market using data from 2004 through 2009, Abad et al. (2017) find that the gender diversity on boards is negatively associated with the level of information asymmetry in the stock market. They use proxies for information asymmetry i.e., relative bid-ask spread, price impact measure, and PIN; estimated from high-frequency data along with a system GMM panel methodology. Consequently, it is obvious that transparency and price informativeness inspire female professionals.

The existing studies indicate a strong relationship between information asymmetry and stock liquidity. Diamond and Verrecchia (1991) show that revealing public information to reduce asymmetry of information, increases the liquidity of a firm's securities. The effect is stronger for large firms who want to appeal to large holdings by institutional investors, and these investors are more concerned about future liquidity. Therefore, these large firms receive the largest benefit from reduced information asymmetry and a decreased cost of capital. Ng (2011) shows that higher information quality lowers liquidity risk, which results in a reduced cost of capital. The negative association between information quality and liquidity risk is stronger in times of large, unexpected changes in market liquidity. Moreover, Lang, Lins, and Maffett (2012) use a sample across 46 countries over the period of 1994 to 2007 and conclude that transaction costs are lower, and liquidity is higher, for firms with better transparency. The transparency is measured as less evidence of earnings management, better accounting standards, higher quality auditors, more analyst following, and more accurate analyst forecasts. Enhanced quality of information increases the speed with which information is incorporated into prices, termed as price efficiency. We observe that various studies on price efficiency attempt to capture different dimensions of liquidity as controls and indicate that high liquidity stocks tend to have less price delay (e.g., Callen, Khan, & Lu, 2013; Hou & Moskowitz, 2005; Saffi & Sigurdsson, 2011).

Following the literature, we expect that preference for informationally transparent stocks with efficient prices may explain female fund managers' liquidity choices. A stock's price efficiency is associated with high liquidity; therefore, we conjecture that preference for portfolio liquidity is higher for female fund managers than for their male counterparts.

H1b: Portfolio liquidity preference is higher among female than male fund managers.

3.3 Data and Methodology

3.3.1 Data

This study considers U.S. domestic actively managed open-end equity funds from January 2000 to December 2017. It follows the methodology of Kacperczyk, Sialm, and Zheng (2008) to merge mutual funds' characteristics data from the Center for Research in Security Prices (CRSP) Survivorship Bias-Free Mutual Fund Database with holdings data from Thomson Reuters and stock prices data from the Center for Research in Security Prices (CRSP). The set from the Thomson Financial database, known as CDA/Spectrum S12 for mutual funds holdings, covers almost all historical domestic mutual funds plus about 3,000 global funds that hold a fraction of assets in stocks traded in U.S. and Canadian stock markets.[25] Based on Investment Objective Codes (IOC), we exclude non-equity funds from the holdings data, i.e., international, municipal bonds, bond and preferred, and balanced funds. The study deals with the two main issues of the S12 dataset, which are "late reporters", i.e., cases where a fund rarely shows RDATE (the date for which the holdings are actually held by the fund) holdings that correspond to the same quarter as the FDATE vintage (the date when the holdings are filed), and "stale data", i.e., where the same RDATE based holdings are shown in two or more consecutive FDATE vintages. We keep the holdings of the first given FDATE and the most recent RDATE for a portfolio. According to the mutual funds disclosure policy in 2004, funds are required to disclose their holdings quarterly instead of semiannually. We assume that, for funds that report semiannual holdings or if the gap between disclosure dates is more than 6 months, the most recently available filing is unchanged until the next filing is reported (the cut off for the holding period is 6 months). The monthly prices from CRSP are obtained to allocate a dollar value to the monthly holdings. We exclude the holdings if their CUSIPs cannot be linked to the CRSP stock database.

While selecting domestic equity funds from CRSP, we focus on funds with the following Lipper class or Lipper objectives: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, or CA, EI, G, GI, MC, MR, SG. If both of them are missing, we select funds with the following Strategic Insight objectives: AGG, GMC, GRI, GRO, ING, or SCG. If Lipper class, objectives, and Strategic Insight objectives are not available for a fund, we choose funds with the following objectives of Wiesenberger Fund Type Code: G, G-I, AGG, GCI, GRI, GRO, LTG, IEQ, MCG, SCG. If none of these objectives is given and the fund has a CS policy (common stocks primarily held by the fund), then the fund is included.[26] Moreover, following Kacperczyk, Sialm, and Zheng (2008), we ignore funds that, on average, hold less than 80%, or more than 105%, in stocks. As the study considers actively managed equity funds, we exclude index funds based on the provided

[25] See for example, Wharton Research Data Services (2008) – User's Guide.

[26] The description for the fund classifications from Lipper class or Lipper objectives, Strategic Insight objectives, and Wiesenberger Fund Type Codes is given in the Appendix (Table B7, B8, and B9, respectively).

index_fund_flag and their names that contain the following words: INDEX, INDE, INDX, IDX, S&P, MSCI, ETF, ISHARES, DOW JONES, INTERNATIONAL.

Following Solomon, Soltes, and Sosyura (2014), the study uses the MFLINKS table, which is developed by Wharton Research Data Services (WRDS) in collaboration with Professor Russ Wermers (University of Maryland's Robert H. Smith School of Business), to match portfolio holdings with mutual fund characteristics. The MFLINKS table uses "wficn" as the fund identifier, whereas the CRSP "fundno" identifier is used for each share class. Therefore, we aggregate multiple fundno share classes into one wficn. The annual expense and turnover ratio of fund share classes are converted to their monthly equivalent. The share class observations reporting negative monthly net assets, turnover ratio, or expense ratio are ignored. We sum monthly net assets of all share classes with the same wficn to derive the monthly total net assets of a fund. For the analysis, we compute the value-weighted average for the monthly fund return and expense ratio. For fund age and the turnover ratio, we consider the oldest share class. To avoid incubation bias, we exclude a fund's monthly observations where the date of the observation is prior to the inception date of the fund reported in CRSP and we also eliminate observations where funds' names are missing.[27] From a fund's aggregated holding data, we exclude funds that hold fewer than ten stocks or manage less than US$1 million in the previous month (Kacperczyk, Sialm, & Zheng, 2005). We require a fund to have at least one year of monthly returns.

After matching the samples from CRSP and Thomson Reuters by wficn and monthly dates, we impose an additional filter to eliminate observations with errors. Following Pastor, Stambaugh, and Taylor (2020), we measure the ratio of a fund's total net assets attained by adding up the net assets of CRSP share classes to the assets obtained by adding up the fund's holdings from Thomson Reuters. We eliminate any fund-month observation if the ratio exceeds 2.0 (i.e., 200%), or is less than 0.5 (i.e., 50%). We have a matched sample of 3,165 domestic equity funds with 376,362 fund-month observations.

We collect data on fund managers' characteristics from the Morningstar Direct (MS) database. In MS, "secid" is the unique identifier for a fund share class, whereas "fundid" uniquely identifies a

[27] See for example, Elton, Gruber, and Blake (2001); Evans (2004).

fund. Therefore, different share classes of the same fund have different secids, tickers, and CUSIPs, but the same fundid. For the purpose of matching, we use qualitative attributes like wficn, crsp_fundno, 8-digit CUSIP, name, ticker, and inception date of fund share classes of our completely matched CRSP and Thomson Reuters sample. First, we use the CUSIP of each share class to find a match in MS and obtain the relevant fundid.[28] Second, we verify the matching accuracy of the obtained fundid with crsp_fundno, and attain the missing fundid (if given) from the matched/merged list of CRSP and MS funds developed by Pastor, Stambaugh, and Taylor (2015).[29] At this stage, our matched CRSP and Thomson Reuters sample of share classes has the matched fundid as well. Third, we make sure that all matched MS share classes with the same fundid also have a unique wficn. We encounter the following issues:

(i) Almost 25% (or below) of the matched MS share classes with the same wficn have different fundid (e.g. there are 5 share classes belonging to a fund and have equal wficn. Out of these 5, 4 share classes have identical fundid, whereas 1 class's fundid does not match with the rest),

(ii) Almost 50% of the matched MS share classes with the same wficn have different fundid (e.g. there are 6 share classes belonging to a fund and have equal wficn. Out of these 6, 3 share classes have identical, whereas 3 have varying fundids),

(iii) Almost 75% (or above) of the matched MS share classes with the same wficn have different fundid (e.g. there are 8 share classes belonging to a fund and have equal wficn. Out of these 8, only 2 share class have identical fundid, whereas other 6 classes belong to diverse fundids), and

(iv) Some share classes with a particular fundid belong to more than one wficn.

[28] Due to the unavailability of CUSIP in the Morningstar Direct database, we provided the list of CUSIPs of CRSP and Thomson Reuters matched fund share classes to the MS support team, who then supplied us with the fundid of all matched CUSIPs.

[29] Lucian A. Taylor has been very kind to provide the data of matched CRSP and MS share classes (including crsp_fundno, secid, and fundid). The comprehensive matching process, till the end of year 2014, is described in their paper (Pastor, Stambaugh, & Taylor, 2015). We find some discrepancies in their matched fundid and the ones we obtain from MS, due to different study time windows. For our analysis, we mostly rely on fundid retrieved from MS, as they fulfill our matching criteria.

We manually deal with these issues by verifying with "Manager history" from MS, as well as the name and inception date of the oldest share class from MS and our matched CRSP and Thomson Reuters sample (Patel & Sarkissian, 2017). The data point of manager history provides managers' names and dates of joining and leaving the fund from the date of its origination. Therefore, all share classes belonging to one fund have a similar management history. To deal with the first matching issue, for every unique wficn, we keep management information of the share classes that are in majority and have the same fundid.[30] For the second issue, we consider the management history of the share classes with varying fundid. We cross-verify the joining date of the very first fund manager with the inception date of the oldest share class having unique wficn. We consider the management information of the share class if the joining date is the same or very shortly after the inception date. We also look at the name and inception date of this share class to see if they match with the information of the oldest share class of unique wficn. We address the third issue by excluding such funds because share classes have different fundids as well as management history and inception dates. Finding an exact match in this case is not feasible. To deal with the fourth issue, we cross-check monthly net assets, names, and inception dates of the share classes with fundid with the ones having unique wficn. Then, based on the above-mentioned selection process, we finalize the management information of these funds.[31]

At this stage, we have the share class aggregated fund characteristics, management history, and stock holdings for every unique wficn identifier, which forms the basis for further analysis. The resulting dataset contains 3,109 unique equity funds with 372,551 fund-month observations. We then hand-collect the data for various attributes of fund managers, including gender, year of graduation, tenure with the fund, earned degrees, and professional certifications. To specify whether a fund is managed by a male or female manager at the end of every month, we utilize the managers' joining and resigning dates information provided in the "Manager history" data point. In this study, all managers and their characteristics are recorded according to whether they have been serving, joined, or left the

[30] In all such cases, name and inception date of the oldest share class with fundid are exactly matched with the oldest share class of the allocated unique wficn.

[31] During the selection process to deal with all the matching issues, we have verified inception dates of all funds with the year when their first manager(s) started managing the fund, given in the manager history data point.

fund during the sample period, i.e, January 2000 to December 2017. Managers who have resigned before January 2000 or started managing the fund after December 2017 are not the focus of this research. We also remove fund-month observations for which manager name or tenure date is unavailable. Similarly, we discard funds that are team managed but do not provide any description of their team members.

Morningstar provides a “People” tab for every fund which contains management information. We identify the gender of managers with the help of the title prefixing their names (i.e., Mr., Ms., and Mrs., etc.). If the titles are missing, we search for terms like “he”, “his”, “him”, “she”, or “her” in their biography. Moreover, we record the graduation year when managers earn their first undergraduate degree, and the titles of all their degrees and certifications. If none of this information is available in MS, we look for their executive profile and biography in Bloomberg, LinkedIn, Facebook, Zoominfo, and the fund management company’s website.

We identify sole managed, team managed, and a combination of single and team managed funds in our sample. Following Patel and Sarkissian (2017), we classify a fund as single or team managed based on the number of manager(s) managing the fund at the end of every month. If there is only one manager with the fund at the end of a month, we consider the fund as single managed for that month. If two or more fund managers’ names are given, we classify the fund as team managed for that specific month. We also categorize all the funds as team managed if they use expressions like “management team”, or “multiple managers” instead of one manager’s name. Management teams may overshadow individual member’s decisions, which makes it difficult to analyze the impact of gender on decision choices. We therefore concentrate the analysis on single managed funds only. Our final sample covers 1,932 unique funds with 124,363 fund-month observations.

Finally, to derive liquidity measures, we retrieve the data of daily stock return, price, volume, bid price, ask price, and market capitalization from the CRSP stock database.

3.3.2 Variables Definition and Model Development

In this section, we describe our main variables and models used to measure the liquidity preference of mutual fund managers based on their gender.

3.3.2.1 Dependent Variable – Portfolio Liquidity

We use three proxies to measure fund liquidity: Portfolio liquidity developed by Pastor, Stambaugh, and Taylor (2020), Amihud's (2002) measure, and the bid-ask spread.

3.3.2.1.1 Portfolio Liquidity:

The measure of portfolio liquidity is introduced by Pastor, Stambaugh, and Taylor (2020) and consists of the liquidity of stocks held in the portfolio and the degree to which the portfolio is diversified. The measure defines the fundamental concept of portfolio liquidity and trading cost as follows:

$$L = \left(\sum_{i=1}^{N} \frac{w_i^2}{m_i} \right)^{-1} \tag{1}$$

where N is the number of stocks in the portfolio, w_i is the portfolio's weight on stock i, and m_i is the weight on stock *i* in a market-cap-weighted benchmark portfolio containing N_m stocks. The market-cap-weighted benchmark portfolio is the overall market. We use monthly data from the CRSP stock database to calculate portfolio liquidity and denote it as $Port\_Liq\_PST$.

3.3.2.1.2 Amihud Illiquidity:

To measure fund liquidity, we use the illiquidity measure of Amihud (2002), which is the daily ratio of absolute stock returns to the dollar volume of the stock. The Amihud measure is widely used in the literature as one of its main advantages is that it can be calculated for a large number of stocks at a daily frequency. It is a consistent measure of price impact and a reliable proxy for a stock's liquidity due to its' high correlation with the alternative price impact measures of liquidity which use intra-day data (e.g., Korajczyk & Sadka, 2008).

Following Karolyi, Lee, and Van Dijk (2012) and Lee, Tseng, and Yang (2014), we add a constant to the Amihud measure and take the natural log to reduce the impact of outliers. We multiply this measure by "-1" to interpret our regression results in terms of liquidity, instead of illiquidity. Finally, the measure is multiplied by 10^6 to observe the impact of observations with a very small number of liquidity measure.

$$Amihud_{i,d} = \left[-\log\left(1 + \frac{|\,R_{i,d}\,|}{P_{i,d}\,VO_{i,d}}\right)\right] \times\ 10^6 \qquad (2)$$

where $R_{i,d}$ is the return in absolute terms, $P_{i,d}$ is the closing price, and $VO_{i,d}$ is the trading volume of stock *i* on day *d*. Before calculating the measure, we exclude all stock-day observations with CRSP reported returns less than "-1", reported price and trading volume equal to "0" or missing, and we consider the absolute value of price. To obtain monthly stock liquidity, we average daily liquidity in every month of a year, under the condition that the stock has at least 11 daily observations per month. Our fund liquidity is the value weighted average of the monthly stock liquidity of all the stock holdings of a fund in a given month. To eliminate outliers, we winsorize this measure at the 1% and 99% levels and denote it as $Port\_Liq\_Amhd$.

3.3.2.1.3 Bid-Ask Spread:

Our third proxy, bid-ask spread, is the daily quoted bid-ask spread of a stock divided by its midpoint (Chordia, Roll, & Subrahmanyam, 2000; Chordia, Roll, & Subrahmanyam, 2001). Bid-ask spread may be considered as the price the market-makers demand for providing liquidity services. Hence, a greater bid-ask spread signals higher stock illiquidity. We multiply this measure by "-1" to interpret our regression results in terms of liquidity, instead of illiquidity.

$$Spread_{i,d} = \left[\frac{Ask_{i,d} -\ Bid_{i,d}}{\left(\frac{Ask_{i,d} +\ Bid_{i,d}}{2}\right)}\right] \times -1 \qquad (3)$$

where $Ask_{i,d}$ is the adjusted ask price, and $Bid_{i,d}$ is the adjusted bid price of stock *i* on day *d*. Before calculating the measure, we exclude all stock-day observations having CRSP reported bid or ask prices less than or equal to "0". To eliminate outliers, we exclude the observation if the daily spread is less than 0.2% (0.002) or more than 50% (0.5). To obtain monthly stock liquidity, we average daily spread in every month of a year, under the condition that the stock has at least 11 daily observations per month. Our fund liquidity is the value weighted average of the monthly stock liquidity of all the stock holdings of a fund in a given month. We denote this measure as $Port\_Liq\_Sprd$.

3.3.2.2 Independent and Control Variables

We use the female dummy as the independent variable, which is equal to "1" if the fund is single female managed, and "0" if it is single male managed in the given month.

We control for the following fund characteristics: fund size, which is the natural log of total net assets of the fund in millions of dollars at the end of a given month; fund return is defined as the asset-based value weighted average of the returns of all the share classes; fund expense ratio typically includes accounting, administrator, advisor, auditor, board of directors, custodial, distribution (12b-1), legal, organizational, professional, registration, shareholder reporting, sub-advisor, and transfer agency fees, excluding the fund's brokerage costs or any investor sales charges, and we measure it as the value weighted average of the net expense ratio of all the share classes; fund turnover ratio is the minimum of the fund's dollar buys and sells during the fiscal year, scaled by the fund's average total net assets; fund age is the natural log of fund age, measured as the difference between a fund's inception year and the current year. We also use fund flow, defined as the net growth in total net assets of funds, as a percentage of their total net assets, adjusted for returns. Following Sirri and Tufano (1998), we measure fund flow as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \quad (4)$$

where $TNA_{i,t}$ is the total net assets of share class *i* at month *t*, and $R_{i,t}$ is the return of share class *i* earned in month *t* on assets under management. $TNA_{i,t-1}$ is share class *i*'s total net assets at the end of last month. Our measure of fund flow is the aggregated monthly flow of all share classes belonging to the fund.

The demographic characteristics of managers may affect their decision choices; therefore, we control for the manager's age and qualifications. Considering Bachelors (undergrad), Masters (grad), and Ph.D. (doctoral) degrees, we consider the highest degree earned by the manager. MBA is a dummy variable, which is equal to "1" if the manager holds a Master of Business Administration degree, and "0" otherwise. In our model, we include a dummy variable for professional certification, which is equal to "1" if the fund manager has a professional certification like CFA or CPA, and "0" otherwise. Following Chevalier and Ellison (1999a), we measure manager age by assuming that a manager is 21 years old at the time of completion of his/her undergraduate degree. It is the natural log of manager age in years at year *t*.

3.3.2.3 The Model

The objective of this study is to analyze the relationship between fund liquidity and the gender of the fund manager. We run the following regression model including various controls for fund and manager attributes:

$$\begin{aligned} Port\_Liq_{i,t} = \; & \alpha + \beta_1\, Female_{i,t} + \beta_2\, Ret_{i,t} + \beta_3\, Size_{i,t} + \beta_4\, Exp_{i,t} \\ & + \beta_5\, TOratio_{i,t} + \beta_6\, Flow_{i,t} + \beta_7\, Fund\_Age_{i,t} \\ & + \beta_8\, Undergrad_{i,t} + \beta_9\, Grad_{i,t} + \beta_{10}\, PhD_{i,t} + \beta_{11}\, MBA_{i,t} \\ & + \beta_{12}\, Cert_{i,t} + \beta_{13}\, Mgr\_Age_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where $Port\_Liq_{i,t}$ is one of the three proxies used to measure liquidity of fund *i* at time *t*. $Female_{i,t}$ is a dummy variable, which is equal to "1" if fund *i* is managed by a single female manager, and "0" if it is single male managed at time *t*. Fund return $Ret_{i,t}$, size $Size_{i,t}$, expense ratio $Exp_{i,t}$, turnover ratio $TOratio_{i,t}$, flow $Flow_{i,t}$, and age $Fund\_Age_{i,t}$ are characteristics of fund *i* at time *t*. $Undergrad_{i,t}$, $Grad_{i,t}$, and $PhD_{i,t}$ are dummy variables, where one of them is equal to "1" depending upon the highest degree earned by the manager, and the rest are equal to "0". $MBA_{i,t}$ is a dummy variable, which is equal to "1" if the manager of fund *i* holds an MBA degree at time *t*, and "0" otherwise. $Cert_{i,t}$ is a dummy variable equal to "1" if the manager of i^{th} fund is a member of a professional certification body at time t, and "0" otherwise. $Mgr\_Age_{i,t}$ is used to control the age of the manager of fund i at time t.[32]

3.3.3 Summary Statistics

Our final sample consists of 124,363 fund-month observations, of which 112,982 (90.85%) are for single male managed funds, and 11,381 (9.15%) are for single female managed funds. The total number of domestic equity funds in our sample is 1,932. We observe that 113 (5.85%) are only female managed funds and 1,658 (85.82%) are only male managed fund, whereas 161 (8.33%) are funds managed by single male and single female managers at different times. Overall, 86.91% funds are managed by a single male manager and 13.09% funds are single female managed during our sample period.[33] On the manager level, we have 1,790 managers in our sample; 1,596 (89.16%) of them are male, and 194 (10.84%) are female. During our sample period, the average number of funds managed by a female manager is 1.5 and a male manager manages 2.0 funds on average. The average number of unique male (female) fund managers per month is 380 (39).

Figure 3.1 depicts the total number of single female and male managed funds in each year, from January 2000 to December 2017. It also plots the proportion of single female managed funds over our sample time period. We observe that the proportion of single female managed funds has decreased over our sample period from the maximum of 11.15% in 2001 to the minimum of 7.68% in 2012.[34] Consistent with the previous studies, we notice an overall diminishing trend in the total number of single managed funds (Patel & Sarkissian, 2017), including male and female managed funds, which indicates higher preference for team managed funds in the U.S. mutual fund industry.

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[32] The data of manager age contains a big number of missing observations because of the unavailability of graduation year of many fund managers. This reduces our sample significantly. Our main results, however, are not affected by the inclusion of this variable.
[33] We count the same fund twice, if it is managed by both genders.
[34] See the numbers in the Appendix (Table B2).

Figure 3.1. Distribution of Single Managed Funds by Manager Gender

Figure 3.1 shows the total number of single male and female managed funds and the proportion of female managed funds from January 2000 – December 2017. The data is collected from Morningstar Direct database.

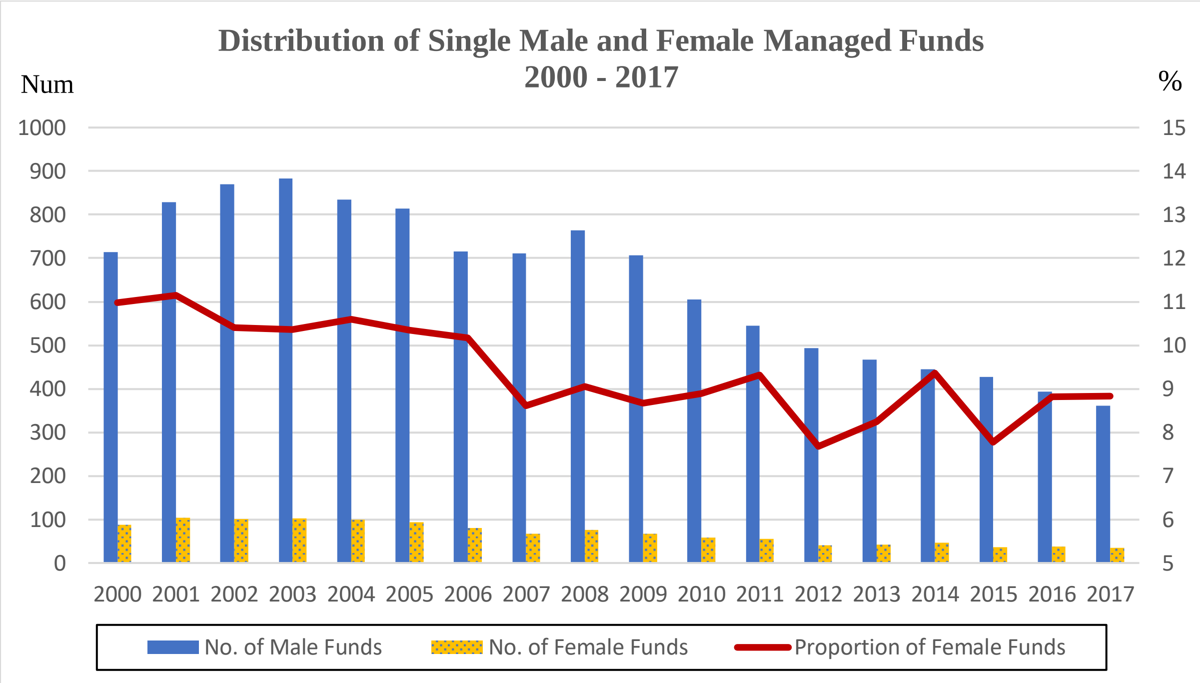

Table 3.1 displays the means and mean differences between female and male managed funds, regarding the fund as well as manager level characteristics used in our baseline model in Equation (5). The comparison of the three proxies of portfolio liquidity reports that female managed funds have a significantly higher Pastor, Stambaugh, and Taylor's portfolio liquidity, as well as Amihud's portfolio liquidity, than male managed funds. However, on average, there is no significant gender difference in the bid-ask spread's portfolio liquidity.[35] The mean of fund returns is lower for female funds than for male funds. We witness a significant difference in the total net assets (in millions of dollars) of female and male managed funds. On average, female managers manage smaller size funds compared to their male counterparts (Niessen-Ruenzi & Ruenzi, 2019). The average expense ratio of female funds is slightly higher, while the mean turnover ratio is also more than for male managed funds. Consistent with the literature, the findings show that female managed funds have significantly lower flows than

[35] Port_Liq_Sprd is measured in basis points.

male managed funds (Niessen-Ruenzi & Ruenzi, 2019). As females manage smaller sized funds, the number of stocks held in their portfolio is also less than in male managed portfolios.

Table 3.1. Summary Statistics

This table presents average fund and manager characteristics for all observations in our sample from year 2000-2017. Column (1) shows descriptive statistics for all pooled observations, Column (2) for female managed funds, and Column (3) for male managed funds. Column (4) indicates the difference between the average characteristics of female and male managed funds. The number of fund-month observations is displayed in columns' titles. $Port\_Liq\_PST$ is a measure of monthly portfolio liquidity introduced by Pastor, Stambaugh, and Taylor (2020) and described in Equation (1). $Port\_Liq\_Amhd$ is a measure of monthly portfolio liquidity which is the value weighted average of Amihud liquidity of all the stocks held by a fund at time t. The illiquidity measure of Amihud (2002) is the daily ratio of absolute stock return to dollar volume of the stock, described in Equation (2). $Port\_Liq\_Sprd$ is a measure of monthly portfolio liquidity which is the value weighted average of Bid_Ask Spread of all the stocks held by a fund at time t. This illiquidity measure is the daily quoted bid-ask spread of a stock divided by its midpoint, described in Equation (3). $Female$ is a dummy variable equal to 1 if fund is single female managed at time t, and 0 if it is single male managed. Ret is a measure of monthly fund return and equal to the value weighted average of returns of all the share classes of a fund at time t. $Size$ is a measure of monthly fund size and equal to the natural log of total net assets of all the share classes of a fund in million dollars at time t. Exp is a measure of monthly fund expense ratio and equal to the value weighted average of net expense ratio of all the share classes of a fund at time t. $TOratio$ is a measure of monthly fund turnover ratio and equal to the minimum of the fund's dollar buys and sells during the fiscal year, scaled by the fund's average total net assets. The annual measure is divided by 12 to convert to monthly frequency. $Flow$ is a measure of monthly fund flow and equal to the net growth in total net assets of a fund, as a percentage of its total net assets adjusted for returns at time t, described in Equation (4). $Fund\_Age$ is a measure of monthly fund age and equal to the natural log of the difference between fund's inception date and the date at time t. $Undergrad$ is a dummy variable and equal to 1 if the undergraduate degree is the highest that a fund manager has earned, and 0 otherwise. $Grad$ is a dummy variable and equal to 1 if the graduate degree is the highest that a fund manager has earned, and 0 otherwise. PhD is a dummy variable and equal to 1 if the PhD degree is the highest that a fund manager has earned, and 0 otherwise. MBA is a dummy variable and equal to 1 if a fund manager has obtained a Master of Business Administration degree, and 0 otherwise. $Cert$ is a dummy variable and equal to 1 if a fund manager has obtained a professional qualification (e.g. CFA or CPA), and 0 otherwise. Mgr_Age is a measure of monthly fund manager's age and equal to the natural log of the difference between completion date of manager's undergraduate degree and the date at time t. Significance is calculated based on a two-sided t-test. ***, **, and * denote 99%, 95%, and 90% significance levels.

	Sample Mean (N = 124,363) (1)	Female Funds (N = 11,381) (2)	Male Funds (N = 112,982) (3)	Difference (Female-Male) (4)
Port_Liq_PST	0.0381	0.0407	0.0378	0.0029***
Port_Liq_Amhd	-0.0104	-0.0046	-0.0110	0.0063***
Port_Liq_Sprd	-24.5700	-24.5597	-24.5755	0.0158
Ret	0.0044	0.0032	0.0045	-0.0013**
TNA (mil $)	1376.9553	678.2136	1447.3415	-769.1278***
Exp	0.0011	0.0012	0.0011	0.0001***
TOratio	0.0763	0.0774	0.0762	0.0012*
Flow	0.6858	0.2751	0.7272	-0.4521**
Fund_Age	14.5307	14.6777	14.5159	0.1618
N_Stocks	112.3043	86.9736	114.8560	-27.8824***
Undergrad	0.8328	0.8597	0.8301	0.0296***
Grad	0.1402	0.1315	0.1411	-0.0096***
PhD	0.0257	0.0066	0.0276	-0.0210***
MBA	0.5735	0.5589	0.5749	-0.0160***
Cert	0.5807	0.6409	0.5747	0.0662***
Mgr_Age	47.8083	47.4425	47.8470	-0.4045***

Regarding managers' characteristics, Table 3.1 shows that female fund managers are significantly less likely to hold a graduate or Ph.D. degree, whereas they are highly likely to hold an undergraduate degree as their highest earned degree. The likelihood of female fund managers holding an MBA degree is also less, however, having professional certification is significantly higher than for their male counterparts. The mean age of female fund managers is lower than that of male fund managers.[36]

Table 3.2 presents the correlation matrix of our main variables. Panel A confirms a positive and significant correlation between all three measures of portfolio liquidity. This positive correlation is significant at the 1% level. Panel B exhibits the coefficients of correlation between all three proxies of portfolio liquidity, and the independent and control variables. We observe that except for Port_Liq_Sprd, the other two measures of portfolio liquidity are positively and significantly related to the Female variable. This shows that female managed funds are connected to higher liquidity, at the 1% level of significance. Further examination of the control variables explains that large size funds are more liquid because the TNA variable is positively related to the three measures of portfolio liquidity, and this relation is significant at the 1% level. The funds with a smaller expense ratio, and old funds (in age) are significantly correlated to higher portfolio liquidity. Moreover, the results show that funds managed by those with a graduate degree are related to higher portfolio liquidity, while those holding a Ph.D. degree are associated with lower liquidity.

Finally, Panel C reports the correlation between the independent, and fund and manager-specific control variables. We find that fund returns, fund size, number of stocks held in the portfolio, manager's age, year of graduation, Ph.D., and MBA degrees are negatively and significantly correlated to female managed funds. The association is positive and significant for the fund expense ratio, manager with undergrad degree, and professional certification variables. Panel C shows that the fund and

[36] For female and male managed funds, we provide detailed summary statistics of fund and manager level characteristics in the Appendix (Table B3).

manager level characteristics mentioned in our baseline model in Equation (5) are positively or negatively correlated to each other.

Table 3.2. Correlation Matrix

This table presents correlation matrix for the fund and manager characteristics from year 2000 to 2017. Panel A provides the results of correlation among the three measures of portfolio liquidity. Panel B presents the correlation matrix for the three measures of portfolio liquidity, gender of fund manager, and other fund and manager level characteristics. Panel C depicts correlation among the gender of fund manager, and other fund and manager level characteristics. See Table B1 in the appendix for the explanation of all the variables.

Panel A. Correlation Matrix for Portfolio Liquidity Measures

	Port_Liq_PST	Port_Liq_Amhd
Port_Liq_Amhd	0.146[a]	
Port_Liq_Sprd	0.056[a]	0.321[a]

Panel B. Correlation Matrix for Portfolio Liquidity and All Variables

	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
Female	0.015[a]	0.048[a]	0.0001
Ret	-0.015[a]	0.002	0.101[a]
TNA	0.203[a]	0.038[a]	0.043[a]
Exp	-0.250[a]	-0.090[a]	-0.089[a]
TOratio	-0.109[a]	0.016[a]	-0.069[a]
Flow	0.007[b]	0.003	0.004
F_Age	0.115[a]	0.081[a]	0.136[a]
N_Stocks	0.366[a]	-0.135[a]	-0.003
Undergrad	-0.006[b]	-0.022[a]	0.006[b]
Grad	0.014[a]	0.025[a]	0.007[b]
PhD	-0.012[a]	-0.005[c]	-0.027[a]
MBA	0.065[a]	-0.046[a]	-0.017[a]
Cert	-0.029[a]	0.037[a]	-0.005[c]
Age_mgr	-0.076[a]	-0.040[a]	0.067[a]

Table 3.2. (continued)

Panel C. Correlation Matrix for All Variables

	Female	Ret	TNA	Exp	TOratio	Flow	F_Age	N_Stocks	Undergrad	Grad	PhD	MBA	Cert
Ret	-0.007[b]												
TNA	-0.045[a]	0.011[a]											
Exp	0.042[a]	-0.016[a]	-0.195[a]										
TOratio	0.004	-0.032[a]	-0.083[a]	0.205[a]									
Flow	-0.003	-0.003	0.017[a]	-0.008[a]	0.000								
F_Age	0.003	0.016[a]	0.245[a]	-0.157[a]	-0.101[a]	0.011[a]							
N_Stocks	-0.035[a]	0.016[a]	0.083[a]	-0.195[a]	-0.067[a]	0.000	-0.016[a]						
Undergrad	0.023[a]	0.001	-0.082[a]	0.011[a]	-0.018[a]	-0.008[a]	0.012[a]	0.011[a]					
Grad	-0.008[a]	-0.001	0.094[a]	-0.032[a]	0.020[a]	0.008[a]	-0.004	-0.013[a]	-0.901[a]				
PhD	-0.038[a]	0.001	-0.009[a]	0.012[a]	0.001	0.000	-0.021[a]	0.006[b]	-0.362[a]	-0.066[a]			
MBA	-0.009[a]	0.014[a]	0.073[a]	-0.072[a]	-0.037[a]	0.001	0.022[a]	0.107[a]	0.249[a]	-0.212[a]	-0.113[a]		
Cert	0.039[a]	0.001	-0.007[a]	-0.070[a]	-0.025[a]	0.004	0.007[b]	-0.094[a]	0.061[a]	-0.043[a]	-0.039[a]	0.073[a]	
Age_mgr	-0.012[a]	0.012[a]	0.003	0.051[a]	-0.151[a]	-0.005	0.145[a]	-0.049[a]	-0.033[a]	-0.008[b]	0.110[a]	-0.011[a]	-0.036[a]

[a] $p < 0.01$, [b] $p < 0.05$, and [c] $p < 0.10$.

3.4 Empirical Results and Discussion

3.4.1 Effect of Gender on Preference for Portfolio Liquidity

We start our empirical analysis by examining the impact of a fund manager's gender on portfolio liquidity and present the results in Table 3.3. Panel A displays the results of the pooled regression, where each of the portfolio liquidity measures is regressed on the female dummy variable, without controlling for fund or manager level characteristics. To address the concern of any impact of time and fund related fixed factors, we include a year and fund fixed effects model, where the number of funds is 1,932 and we have 18 years' data. To make the small coefficients presentable, throughout the analysis we measure bid-ask spread portfolio liquidity in basis points.[37] The positive and significant coefficients for all three proxies indicate higher portfolio liquidity for female managed funds.

The results of Panel A may be affected by the possibility of unobserved omitted fund, as well as manager-specific variables. These characteristics may explain a significant portion of the variability in portfolio liquidity preference of fund managers. Therefore, in Panel B, we present the findings of the model given in Equation (5), which controls for the relevant fund and manager level attributes.[38] Columns (1) to (3) show that Pastor, Stambaugh, and Taylor's portfolio liquidity (Port_Liq_PST) is significantly higher for female managed funds. The results indicate that the liquidity of female managed funds is 25% higher than the average liquidity of male managed funds, and this positive difference is significant at the 1% level.[39] We also observe that fund return, expense, and turnover ratio are negatively related to Port_Liq_PST, whereas fund size and age are positively and significantly associated with it. There is no strong association between Port_Liq_PST and only manager level controls. Nevertheless, the combined results of all the control variables in Column (1) describe that Port_Liq_PST is significantly higher for the funds that are managed by managers having undergraduate or graduate

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[37] The Port_Liq_Sprd is scaled by 10^4.
[38] See for example, Solomon, Soltes, and Sosyura (2014); Niessen-Ruenzi and Ruenzi (2019).
[39] The coefficients of regressions between female and the three measures of portfolio liquidity are interpreted in comparison with the average portfolio liquidity of male managed funds, i.e., coefficient/mean Port_Liq of male managed funds (separately for each Port_Liq measure).

degrees. All these associations are significant at the 1% level and the goodness of fit of the models is around 84%.

Columns (4) to (6) of Panel B display a significantly positive association between Amihud's portfolio liquidity and female managed funds. The female managed funds report 11% higher Port_Liq_Amhd than the average liquidity of male managed funds and this positive relationship is significant at the 1% level. The findings in Column (4) report significantly higher Port_Liq_Amhd for funds with large size, higher turnover ratios, that are managed by a manager who holds an undergraduate or graduate or Ph.D. degree, and who has professional certification. Conversely, old funds and funds managed by a manager with an MBA degree have lower portfolio liquidity. The goodness of fit of these three models is around 62%.

We find consistent results for the third proxy of liquidity. Columns (7) to (9) provide evidence that female managed funds prefer higher bid-ask spread portfolio liquidity compared to male managed funds. The liquidity of single female managed funds is 8% higher than the mean portfolio liquidity of single male managed funds and is significant at the 1% level. The fund and manager-specific control variables show a significant association with Port_Liq_Sprd. Similar to Port_Liq_Amhd, fund size and turnover ratio are positively associated with Port_Liq_Sprd, whereas fund age, expense ratio, and manager with an MBA degree are negatively associated with the measure. The overall goodness of fit of these models is around 72%.[40]

[40] We have a large number of missing data for the control variable of manager age, i.e. Mgr_Age. The inclusion of this variable significantly reduces the number of observations for our regression analysis. Although the results do not change with this variable, we present the findings in the Appendix (Table B4).

Table 3.3. Fund Manager Gender and Preference for Portfolio Liquidity

This table presents the findings of the regression of portfolio liquidity on the gender of single managed funds. Panel A exhibits the results without the fund and manger level controls. Panel B shows the findings of the regression model given in Equation (5). The dependent variable is portfolio liquidity, $Port\_Liq$. We use three proxies $Port\_Liq\_PST$, $Port\_Liq\_Amhd$, and $Port\_Liq\_Sprd$ to measure portfolio liquidity. The independent variable is $Female$ which is equal to 1 if fund is single female managed at time t, and 0 if it is single male managed. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of the fund and manager level control variables. See Table B4 in the appendix for the regression results with the control variable of Mgr_Age.

$$Port\_Liq_{i,t} = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Ret_{i,t} + \beta_3\, Size_{i,t} + \beta_4\, Exp_{i,t} + \beta_5\, TORatio_{i,t} + \beta_6\, Flow_{i,t} + \beta_7\, Fund\_Age_{i,t} + \beta_8\, Undergrad_{i,t} + \beta_9\, Grad_{i,t} + \beta_{10}\, PhD_{i,t} + \beta_{11}\, MBA_{i,t} + \beta_{12}\, Cert_{i,t} + \beta_{13}\, Mgr\_Age_{i,t} + \varepsilon_{i,t}$$

Panel A. Gender and Portfolio Liquidity without Controls

	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
	(1)	(2)	(3)
Female	0.0099***	0.0006**	1.2630***
	(16.69)	(2.12)	(3.02)
Year-fixed Effect	YES	YES	YES
Fund-fixed Effect	YES	YES	YES
No. of Obs.	124,363	124,363	124,363
Adj. R-squared	0.8429	0.6171	0.7205

Panel B. Gender and Portfolio Liquidity with Controls

	Port_Liq_PST			Port_Liq_Amhd			Port_Liq_Sprd		
	All controls	Fund controls	Manager controls	All controls	Fund controls	Manager controls	All controls	Fund controls	Manager controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	0.0095***	0.0095***	0.0099***	0.0012***	0.0011***	0.0008***	1.9918***	2.092***	1.2376***
	(15.44)	(15.54)	(16.57)	(4.05)	(3.52)	(2.76)	(4.40)	(4.65)	(2.94)
Ret	-0.0048***	-0.0048***	-	0.0024	0.0024	-	9.5592***	9.4985***	-
	(-3.94)	(-3.98)		(1.43)	(1.43)		(6.51)	(6.47)	
Size	0.0054***	0.0054***	-	0.0041***	0.0041***	-	4.0280***	4.0246***	-
	(41.84)	(41.79)		(24.21)	(24.19)		(30.05)	(30.02)	

Panel B. Gender and Portfolio Liquidity with Controls (continued)

	Port_Liq_PST			Port_Liq_Amhd			Port_Liq_Sprd		
	All controls	Fund controls	Manager controls	All controls	Fund controls	Manager controls	All controls	Fund controls	Manager controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exp	-1.6139***	-1.6079***	-	0.8876	0.8857	-	-1945.3000***	-1964.2000***	-
	(-4.26)	(-4.26)		(1.50)	(1.50)		(-3.76)	(-3.80)	
TOratio	-0.0163***	-0.0159***	-	0.0128***	0.0125***	-	7.0946***	7.6553***	-
	(-11.57)	(-11.41)		(5.23)	(5.11)		(5.37)	(5.79)	
Flow	0.0206	0.0207	-	-0.0018	-0.0017	-	-9.0872	-8.9632	-
	(1.06)	(1.07)		(-0.77)	(-0.72)		(-1.35)	(-1.32)	
Fund_Age	0.0023***	0.0021***	-	-0.0024***	-0.0023***	-	-5.8234***	-6.0324***	-
	(4.03)	(3.80)		(-5.03)	(-4.84)		(-12.24)	(-12.66)	
Undergrad	0.0040***	-	-0.0004	0.0030*	-	0.0005	-7.2871*	-	-2.1912
	(3.00)		(-0.32)	(1.71)		(0.36)	(-1.71)		(-0.72)
Grad	0.0049***	-	-0.0007	0.0032*	-	-0.0001	-6.4583	-	-2.0399
	(3.41)		(-0.56)	(1.82)		(-0.07)	(-1.51)		(-0.67)
PhD	-0.0001	-	-0.0024	0.0081***	-	0.0054***	-13.1000***	-	-8.5473***
	(-0.05)		(-1.60)	(4.39)		(3.51)	(-2.99)		(-2.66)
MBA	0.0002	-	0.0000	-0.0007**	-	-0.0011***	-0.5895**	-	-1.0124***
	(0.43)		(0.07)	(-2.22)		(-3.62)	(-2.01)		(-3.62)
Cert	0.0004	-	0.0000	0.0008***	-	0.0016***	-0.0280	-	0.3074
	(0.82)		(0.06)	(3.53)		(6.90)	(-0.08)		(0.96)
Year-fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fund-fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of Obs.	113,855	113,855	124,363	113,855	113,855	124,363	113,855	113,855	124,363
Adj. R-squared	0.8475	0.8475	0.8429	0.6252	0.6251	0.6173	0.7233	0.7232	0.7207

Based on the results presented in Table 3.3, we conclude that the gender of mutual fund managers does affect the choice of portfolio liquidity, and female fund managers have a higher preference for liquidity than male managers (Ahmed & Ali, 2017). The coefficients of all three measures of portfolio liquidity exhibit a significantly positive relationship to female managed funds, even after controlling for fund and manager-specific characteristics, and including year and fund fixed effects. By combining the results of the three proxies of the liquidity portfolio, it is evident that the funds managed by single female managers are 8% to 25% more liquid than single male managed funds. Consistent with Pastor, Stambaugh, and Taylor (2020), the overall results demonstrate that funds with more liquid portfolios are larger and cheaper. The coefficients of two of the proxies indicate that funds managed by managers having a graduate degree are positively, while managers holding an MBA degree are negatively, related to portfolio liquidity.[41]

3.4.1.1 Impact of Female Managers' Preference for Portfolio Liquidity Across Investment Objectives

Morningstar categorizes mutual funds in different investment objectives based on the type of stocks they invest in, e.g., growth or value stocks. The existing literature provides evidence that these investment styles or objectives significantly influence trading costs (Chan & Lakonishok, 1995) and a fund's preference for various stock characteristics (Falkenstein, 1996). Yan (2008) tests the association between fund size and performance across investment styles and concludes that the negative relation between size and performance is more pronounced among growth and high turnover funds. Hence, we analyze the impact of female fund managers on portfolio liquidity across various investment objectives.

We consider six investment objectives that represent most equity holdings. These categories are Growth, Aggressive growth, Growth-income, Equity-income, Income, and Small company funds. Our study analyzes single managed funds; therefore, we have only eight funds in the Income group. Due to a small number of observations, we combine Income funds with Equity-income funds. To explore the effect of investment styles on the relation between female fund managers and portfolio

[41] We run our main regression analysis by controlling for various stock-specific characteristics that may affect a fund manager's preference to hold the stock. The results are consistent and presented in the Appendix (Table B5).

liquidity, we include interaction terms between Female and Investment style dummy variables in the baseline model. For comparison, we consider Growth funds as a benchmark category.

Table 3.4 presents the findings of female fund managers' preference for portfolio liquidity across major investment objectives, with fund and manager-specific control variables and year and fund fixed effects. Combining the results of all three proxies of portfolio liquidity, we document that the effect of female managers on portfolio liquidity is weaker for Aggressive-growth compared to the benchmark. As explained by Yan (2008), growth funds have a high need for immediacy in their trades and they tend to have short-term trading strategies. Subsequently, their liquidity is lower, or transaction costs are higher (Chan & Lakonishok, 1995).

We find that the positive relation between female managers and portfolio liquidity is significantly lower when funds belong to the Small-company investment style. Falkenstein (1996) explains that Small-company funds cater for demand from investors who have preferences for small companies. These funds targeting small sized firms exhibit a much weaker preference for higher liquidity. Small stocks are illiquid and, when female managers manage funds with a Small-company investment objective, the higher preference for liquidity declines.

The effects of Growth-income and Equity-income investment objectives are not conclusive due to the mixed significance and signs of coefficients for all three proxies of portfolio liquidity. The results of Table 3.4 suggest that investment styles of funds play a significant role in either strengthening or weakening the preference for portfolio liquidity by female fund managers.

Table 3.4. Preference for Portfolio Liquidity by Female Fund Managers Across Styles

This table presents the findings of the regression of portfolio liquidity on the single female managed funds across four investment styles. The dependent variable is portfolio liquidity, $Port\_Liq$. The variable $Female \times Agg\_Growth$ is the cross product of female fund dummy and fund's aggressive growth style dummy variables. $Female \times Growth\_Income$ is the cross product of female fund dummy and fund's growth income style dummy variables. $Female \times EQ\_Income$ is the cross product of female fund dummy and fund's equity income style dummy variables. $Female \times Sm\_Comp$ is the cross product of female fund dummy and fund's small company style dummy variables. Female×Growth is the benchmark category. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables.

$$Port\_Liq_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2 Female \times Agg\_Growth_{i,t} + \beta_3 Female \times Growth\_Income_{i,t} + \beta_4 Female \times EQ\_Income_{i,t} + \beta_5 Female \times Sm\_Comp_{i,t} + \gamma Controls_{i,t} + \varepsilon_{i,t}$$

	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
	(1)	(2)	(3)
Female	0.0121***	0.0017***	2.4455***
	(14.53)	(4.76)	(4.53)
Female×Agg_Growth	0.0008	-0.0012*	-3.5139***
	(0.51)	(-1.66)	(-2.68)
Female×Growth_Income	0.0018	-0.0017***	1.0368
	(0.83)	(-3.76)	(0.66)
Female×EQ_Income	-0.0116***	0.0026***	-0.7520
	(-5.45)	(3.98)	(-0.36)
Female×Sm_Comp	-0.0143***	-0.0029**	-3.1656**
	(-15.85)	(-2.10)	(-2.46)
Ret	-0.0048***	0.0024	9.5655***
	(-3.92)	(1.43)	(6.52)
Size	0.0054***	0.0041***	4.0321***
	(41.99)	(24.22)	(30.11)
Exp	-1.6159***	0.8906	-1934.5000***
	(-4.27)	(1.51)	(-3.74)
TOratio	-0.0164***	0.0128***	7.0292***
	(-11.62)	(5.22)	(5.32)
Flow	0.0209	-0.0019	-0.0009
	(1.07)	(-0.80)	(-1.34)
Fund_Age	0.0023***	-0.0024***	-5.8203***
	(4.12)	(-5.01)	(-12.23)
Undergrad	-0.0052***	0.0010	-9.4537**
	(-4.47)	(0.54)	(-2.12)
Grad	-0.0042***	0.0013	-8.5747*
	(-3.38)	(0.66)	(-1.92)
PhD	-0.0098***	0.0063***	-15.3000***
	(-6.68)	(3.08)	(-3.35)
MBA	0.0000	-0.0007**	-0.5906**
	(0.10)	(-2.23)	(-2.01)
Cert	0.0003	0.0008***	-0.0562
	(0.64)	(3.42)	(-0.17)
Year-fixed Effect	YES	YES	YES
Fund-fixed Effect	YES	YES	YES
No. of Obs.	113,855	113,855	113,855
Adj. R-squared	0.8477	0.6252	0.7233

3.4.1.2 Impact of Female Managers' Preference for Portfolio Liquidity Over Time

Bennett, Sias, and Starks (2003) report a shift in the preferences of institutional investors from large capitalization stocks to smaller and riskier stocks. They suggest that over time institutional investors have moved towards smaller securities because these stocks offer "green pastures". Keeping this view in mind, we expect a change in the preference for portfolio liquidity by female fund managers over time. The aggregate change in the preferences of all the classes of institutional investors may affect the positive relation between female fund managers and portfolio liquidity during our sample time window.

Over time, we may expect the strength of this relationship to move either in a positive or negative direction. On the one hand, we have documented the fact of a diminishing proportion of single female managed funds in our sample from 2000 to 2017. This is a signal that there are few female managers who are solely responsible for making all the investment decisions. Due to the pressure of continuous scrutiny by investors, competitors, and the media they are likely to increase their preference for holding more liquid stocks in the portfolio, which helps them to trade with a lower transaction cost and sell these stocks quickly when the market is volatile. On the other hand, as explained by Niessen-Ruenzi and Ruenzi (2019) and presented in the descriptive statistics of our study, female managed funds receive lower flows from investors compared to male managed funds. In this situation, the female preference for holding more liquid stocks in the portfolio will contribute to a decreased fund return and performance. Ultimately, this can be damaging for their reputation and career. Subsequently, they may choose to reduce their preference for portfolio liquidity over time.

To test these assumptions, we create a Trend variable for the years from 2000 to 2017. In our baseline model, we introduce an interaction term between the Female and Trend variables; the outcomes are shown in Table 3.5. In column (1), the positive and significant coefficient of the interaction term indicates that the preference of female fund managers for Pastor, Stambaugh, and Taylor's portfolio liquidity is getting stronger over time and they are highly inclined towards holding liquid stocks. In contrast, the negative coefficients of the interaction term in columns (2) and (3) show that, over time, female managers are associated with a reduced impact on the Amihud and bid-ask spread's portfolio liquidity measures. The coefficients of the three measures of portfolio liquidity are contradictory, rendering them inconclusive regarding the strengthening or weakening of the impact of female managers on portfolio liquidity over time.

Table 3.5. Preference for Portfolio Liquidity by Female Fund Managers Over Time

This table presents the findings of the regression of portfolio liquidity on the single female managed funds over time during our sample period. The dependent variable is portfolio liquidity, $Port\_Liq$. The variable $Female \times Trend$ is the cross product of female fund dummy variable and yearly trend variable. The trend variable takes the value 1 for year 2000 and increases annually till year 2017. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables.

$$Port\_Liq_{i,t} = \alpha + \beta_1 \, Female_{i,t} + \beta_2 \, Female \times Trend_{i,t} + \gamma \, Controls_{i,t} + \varepsilon_{i,t}$$

	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
	(1)	(2)	(3)
Female	0.0074***	0.0041***	3.6907***
	(7.84)	(8.55)	(4.84)
Female×Trend	0.0003***	-0.0004***	-0.2288***
	(3.80)	(-6.95)	(-3.25)
Ret	-0.0048***	0.0024	9.5808***
	(-3.97)	(1.45)	(6.53)
Size	0.0054***	0.0041***	4.0134***
	(41.98)	(24.08)	(30.03)
Exp	-1.6003***	0.8686	-1956.7000***
	(-4.21)	(1.47)	(-3.79)
TOratio	-0.0162***	0.0126***	6.9869***
	(-11.51)	(5.16)	(5.29)
Flow	0.0206	-0.0019	-0.0009
	(1.06)	(-0.78)	(-1.36)
Fund_Age	0.0023***	-0.0024***	-5.8237***
	(4.03)	(-5.04)	(-12.24)
Undergrad	0.0031**	0.0043**	-6.5232
	(2.26)	(2.33)	(-1.56)
Grad	0.0040***	0.0044**	-5.6977
	(2.70)	(2.43)	(-1.36)
PhD	-0.0010	0.0095***	-12.3000***
	(-0.63)	(4.90)	(-2.85)
MBA	0.0001	-0.0007**	-0.5743**
	(0.38)	(-2.13)	(-1.96)
Cert	0.0003	0.0009***	0.0031
	(0.74)	(3.75)	(0.01)
Year-fixed Effect	YES	YES	YES
Fund-fixed Effect	YES	YES	YES
No. of Obs.	113,855	113,855	113,855
Adj. R-squared	0.8475	0.6253	0.7233

3.4.2 Female Fund Managers and Preference for Portfolio Liquidity

To explain female fund managers' preference for liquidity, we develop and test two contrasting hypotheses. For the *excessive trading hypothesis,* H1a, we measure aggressive trading by using the proxy of the fund Turnover ratio (Niessen-Ruenzi & Ruenzi, 2019). The fund turnover ratio is the minimum of the fund's dollar buys and sells during the fiscal year, scaled by the fund's average total net assets. The higher turnover ratio depicts excessive trading by the fund. To examine the relation between a fund manager's gender and trading style, we run the model given in Equation (6).[42]

$$
\begin{aligned}
TOratio_{i,t} = {} & \alpha + \beta_1\, Female_{i,t} + \beta_2\, Ret_{i,t} + \beta_3\, Size_{i,t} + \beta_4\, Exp_{i,t} + \beta_5\, Flow_{i,t} \\
& + \beta_6\, Fund\_Age_{i,t} + \beta_7\, Undergrad_{i,t} + \beta_8\, Grad_{i,t} + \beta_9\, PhD_{i,t} \qquad (6) \\
& + \beta_{10}\, MBA_{i,t} + \beta_{11}\, Cert_{i,t} + \beta_{12}\, Mgr\_Age_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

where the variables are as defined in Section 3.3.

Table 3.6, columns (1) and (2) display the results with all fund and manager level control variables, as well as the year and fund fixed effects. Consistent with the literature, we find that female fund managers are less likely to be involved in excessive trading compared to their male counterparts. Our *excessive trading hypothesis* assumes that more overconfident male fund managers exhibit a high preference for liquidity to avoid high transaction costs resulting from aggressive trading. Our findings do not support this conjecture and provide empirical evidence that funds managed by single female managers tend to prefer higher portfolio liquidity compared to male managed funds.

We then test our *price efficiency hypothesis*, H1b, which expects that females' preference for information transparency explains their tendency to hold more liquid stocks in the portfolio. The literature on stock price efficiency describes that if the information environment of a firm is opaque, the stock price response to information is delayed. Callen, Khan, and Lu (2013) explain that due to a firm's uncertain environment and poor quality of accounting/financial information, its stock price will be more delayed in incorporating newly arriving value-relevant information. Hence, in our study, we

[42] The description of all the variables is presented in the Appendix (Table B1).

assume that female fund managers are more likely to hold stocks whose prices have less delay in responding to the new information.

Following Hou and Moskowitz (2005), we measure the delay variable. Firstly, from CRSP we obtain daily returns of all the stocks held by single managed funds in our sample from January 2000 to December 2017. Since our focus is to obtain weekly returns, we allocate a unique "week_id" to the daily dates that belong to a week from Wednesday to the following Tuesday. We take the natural logarithm of daily stock returns to convert them into continuous returns. We define weekly returns as the sum of daily continuous returns for every unique "week_id", and then convert them to simple weekly returns. The weekly market return from Fama and French (1993) is employed as the relevant news to which a stock responds.[43] As the measure of price delay requires a year of prior weekly returns history (52-weeks), our calculation begins from 1999. We consider the past 52 weeks of returns corresponding to the last week of every month. Moreover, we exclude firm-year-month observations if 25 weeks out of past 52 weekly stock returns are missing. To obtain the monthly Delay variable, at the end of every month of a year we run two regressions: first, for each stock's weekly returns on the contemporaneous market return; and second, for each stock's weekly returns on four weeks of lagged market returns over the past year.

$$r_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,t} \tag{7}$$

$$r_{j,t} = \alpha_j + \sum_{n=1}^{4} \delta_j^{(-n)} R_{m,t-n} + \varepsilon_{j,t} \tag{8}$$

where $r_{j,t}$ is the return on stock *j* in week *t*, $R_{m,t}$ is the market return in week *t*, and $R_{m,t-n}$ is the lagged market return from week *t-1* to week *t-4*. If the stock responds rapidly to market news, β_j significantly differs from zero, but none of the $\delta_j^{(-n)}$ will be different from zero. If the stock's price responds with a lag, then some of the $\delta_j^{(-n)}$ will be significantly different from zero.

[43] The market return is retrieved from the Kenneth R. French-Data Library.

Using the estimated R^2 from the regressions in Equations (7) and (8), we compute the measure of the monthly Price Delay for each stock as follows:

$$D = 1 - \frac{R^2_{\delta_j^{(-n)}=0, \forall\, n \in [1,4]}}{R^2} \tag{9}$$

where $R^2_{\delta_j^{(-n)}=0, \forall\, n \in [1,4]}$ is from the regression in Equation (7), which restricts $\delta_j^{(-n)}$=0 for lagged weekly market returns. R^2 is from the regression in Equation (8), with no restrictions.

In our study, we measure portfolio delay as the value weighted average of the monthly stock price delay of all the stock holdings of a fund in a given month. A higher value of this variable indicates that prices of majority of the stocks held in a portfolio are less efficient and incorporate new information with a delay. Whereas, if portfolio stocks' prices respond quickly, the value of delay variable is lower. We denote this measure as $Delay$ and run the model given in Equation (10).

$$\begin{aligned} Delay_{i,t} = {} & \alpha + \beta_1\, Female_{i,t} + \beta_2\, Ret_{i,t} + \beta_3\, Size_{i,t} + \beta_4\, Exp_{i,t} + \beta_5\, Flow_{i,t} \\ & + \beta_6\, Fund\_Age_{i,t} + \beta_7\, Undergrad_{i,t} + \beta_8\, Grad_{i,t} + \beta_9\, PhD_{i,t} \\ & + \beta_{10}\, MBA_{i,t} + \beta_{11}\, Cert_{i,t} + \beta_{12}\, Mgr\_Age_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{10}$$

where $Delay_{i,t}$ is the value weighted average delay of fund *i* in month *t*. The other variables are as defined in Section 3.3.

Table 3.6, Columns (3) and (4) show the findings of the regression model given in Equation (10) with fund and year fixed effects, and control variables. The results provide empirical evidence that funds managed by single female managers significantly reduce holding those stocks whose prices are not efficient in integrating available information. Consistent with the literature, female managers are more inclined towards price efficient stocks, and it signals their preference for firms with a good quality information environment. Hence, we cannot reject the *price efficiency hypothesis,* and conclude that high information efficiency of a stock possibly explains female managers' higher preference for liquid portfolios.

Table 3.6. Reason for Higher Portfolio Liquidity Preference of Female Fund Managers

Table 3.6, Columns (1) and (2) present the findings of the regression of fund turnover on the single female managed funds. The dependent variable is monthly turnover ratio, $TOratio$. Columns (3) and (4) report the findings of the regression of portfolio stock prices' delay on the single female managed funds. The dependent variable is monthly portfolio delay, $Delay$, which is the value weighted average of price delay of all the stocks held by a fund at time t. The price delay measure is one minus the ratio of the restricted R^2 over the unrestricted R^2. The independent variable is $Female$ which is equal to 1 if fund is single female managed at time t, and 0 if it is single male managed. $Flow$ is measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables.

$$TOratio_{i,t} = \alpha + \beta_1 Female_{i,t} + \gamma Controls_{i,t} + \varepsilon_{i,t}$$

$$Delay_{i,t} = \alpha + \beta_1 Female_{i,t} + \gamma Controls_{i,t} + \varepsilon_{i,t}$$

	TOratio		Delay	
	All controls with manager age	All controls without manager age	All controls with manager age	All controls without manager age
	(1)	(2)	(3)	(4)
Female	-0.0058***	-0.0020*	-0.0072**	-0.0095***
	(-3.54)	(-1.96)	(-2.41)	(-5.57)
Ret	0.0066	0.0009	-0.0183**	-0.0203***
	(1.29)	(0.25)	(-2.27)	(-3.62)
Size	-0.0079***	-0.0059***	-0.0072***	-0.0064***
	(-9.88)	(-14.50)	(-9.44)	(-13.83)
Exp	19.9253***	20.3350***	18.8691***	11.5427***
	(3.73)	(7.89)	(6.22)	(6.32)
Flow	0.0438	0.0205	-0.0080	-0.0106
	(1.46)	(1.03)	(-0.14)	(-0.22)
Fund_Age	-0.0058***	-0.0075***	0.0153***	0.0159***
	(-3.71)	(-6.37)	(6.01)	(9.49)
Undergrad	0.0216***	0.1363***	0.0213**	0.0563***
	(6.75)	(6.01)	(2.47)	(3.78)
Grad	0.0222***	0.1468***	0.0122	0.0518***
	(7.60)	(6.45)	(1.48)	(3.47)
PhD	0.0000	0.1019***	0.0000	0.0508***
	-	(4.47)	-	(3.32)
MBA	0.0077***	-0.0031***	-0.0001	0.0015
	(5.78)	(-3.96)	(-0.05)	(1.27)
Cert	-0.0076***	-0.0028***	0.0110***	0.0035***
	(-5.18)	(-3.27)	(4.24)	(2.67)
Mgr_Age	-0.0258***	-	-0.0056	-
	(-7.26)		(-0.86)	
Year-fixed Effect	YES	YES	YES	YES
Fund-fixed Effect	YES	YES	YES	YES
No. of Obs.	55,253	113,855	55,253	113,855
Adj. R-squared	0.7344	0.7056	0.6316	0.6267

3.5 Endogeneity Issues

The issue of non-random selection of female fund managers is obvious in our study. To address the concern that fund companies might assign female managers to funds that are more liquid, or females' self-selection of more liquid funds, we apply various approaches to mitigate any endogeneity concerns. In this section, we use the full sample as well as a sub-sample of funds that experience replacement of one manager with another manager. This sub-sample of "transition funds" consists of all fund-month observations of those funds experiencing at least one event of transition from either male to male, male to female, female to male, or female to female.

3.5.1 Propensity Score Matching and Univariate Analysis

Following Faccio, Marchica, and Mura (2016), we compare the liquidity of funds managed by female managers to the liquidity of a (propensity score) matched sample of peers run by male managers, that are indistinguishable in terms of various fund, as well as manager level characteristics. Each pair of matched funds manifests no observable differences in relevant attributes except for the gender of the manager.

To apply this methodology, we consider female managed funds as a treatment group, and male managed funds (within similar investment objective and date as the treatment group) belonging to a control group. We calculate propensity scores by running a probit regression where the dependent variable is a dummy and takes the value equal to "1" if the fund belongs to the treatment group, or "0" if the fund is from the control group. We consider the fund level characteristics as independent variables, i.e., fund return, fund size, expense ratio, turnover ratio, flow, and fund age. Particularly, the propensity score is estimated within the same fund investment objective and date. To find an adequately precise nearest neighbor match (with replacement) between the female managed funds and the peer funds in the control group, we only consider the pairs where the maximum difference between their propensity scores does not exceed 0.01 in the absolute term. Additionally, we select the unique pair with minimum difference between their propensity scores. We re-run the probit regression on post-match pairs of treatment and control groups. We find that the majority of the coefficients of fund level characteristics lose their significance, which confirms that the matched pairs are almost the same regarding their fund related attributes.

Table 3.7, Panel A reports the comparison of Port_Liq_PST, Port_Liq_Amhd, and Port_Liq_Sprd with the matched samples. The results show that average portfolio liquidity (for the three measures) of funds managed by female managers is higher than the portfolio liquidity of male managed funds, even when other relevant characteristics between the fund pairs are virtually equal. All mean differences in portfolio liquidity between the two groups are significant at the 1% level. Hence, we suggest that the gender-related differences in portfolio liquidity do not result from the observable differences in fund characteristics. In addition to the fund characteristics, there are also some observable manager-specific characteristics. Therefore, we obtain the propensity score as a function of fund and manager level characteristics (i.e., undergrad, grad, Ph.D., MBA, cert, and manager age), within the same fund investment objectives and date. Table 3.7, Panel B presents the comparison of portfolio liquidity between the matched funds, and the results support the outcomes in Panel A.

We implement the same propensity score matching approach to the sub-sample of transition funds. This sub-sample consists of all fund-month observations of those funds experiencing at least one event of transition from either male to male, male to female, female to male, or female to female. We consider only those transition funds where a manager is managing the fund at least for 13 months, after transition. All the fund-month observations are considered as the treatment group when these transition funds are managed by single female. When the transition funds are single male managed (within similar investment objective and date as the treatment group), they belong to the control group. As mentioned earlier, we calculate probability (propensity score) as a function of fund level, and then fund and manager level characteristics. The propensity score is estimated within the same fund investment objective and date. All other conditions are the same to match the treatment fund with an identical control fund, and to obtain unique pairs.

Table 3.7. Propensity Score Matching and Univariate Analysis for Female Managed Funds

This table presents the results of the propensity score matching approach and the univariate regression analysis of the three measures of portfolio liquidity and matched female and male managed funds. The propensity score is estimated within the same investment objective and time. Applying propensity scores to the whole sample, Panel A and B report the comparison of portfolio liquidity between the two gender groups that are similar in only fund level characteristics, and fund as well as manager level characteristics, respectively. Using propensity scores for the transition funds sample, Panel C and D show the comparison of portfolio liquidity between the two gender groups that are similar in only fund level characteristics, and fund as well as manager level characteristics, respectively. Significance is calculated based on a two-sided t-test. Panel E presents the findings of the univariate regression of portfolio liquidity on the female and matched male managed transition fund. The dependent variable is portfolio liquidity. The independent variable is $Female$ which is equal to 1 if transition fund belongs to the Treatment group, and 0 if it belongs to the matched Control group. $Port\_Liq\_Sprd$ is measured in basis points. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables

Panel A. Propensity Score Matching using Fund Level Characteristics – All funds

	Mean-Female Funds (N=10,282)	Mean-Male Funds (N=10,282)	Difference (Female-Male)	t-statistic
	(1)	(2)	(3)	(4)
Port_Liq_PST	0.0409	0.0353	0.00562***	7.02
Port_Liq_Amhd	-0.00482	-0.0135	0.0087***	18.51
Port_Liq_Sprd	-25.8000	-29.1000	3.3000***	6.35

Panel B. Propensity Score Matching using Fund and Manager Level Characteristics – All funds

	Mean-Female Funds (N=4,946)	Mean-Male Funds (N=4,946)	Difference (Female-Male)	t-statistic
	(1)	(2)	(3)	(4)
Port_Liq_PST	0.0489	0.0367	0.0122***	9.89
Port_Liq_Amhd	-0.0053	-0.0136	0.00834***	12.05
Port_Liq_Sprd	-25.8000	-30.1000	4.3000***	5.19

Panel C. Propensity Score Matching using Fund Level Characteristics – Transition funds

	Mean-Female Funds (N=5,267)	Mean-Male Funds (N=5,267)	Difference (Female-Male)	t-statistic
	(1)	(2)	(3)	(4)
Port_Liq_PST	0.0523	0.0427	0.00952***	8.05
Port_Liq_Amhd	-0.00291	-0.00814	0.00523***	10.81
Port_Liq_Sprd	-22.6000	-26.2000	3.6000***	5.18

Panel D. Propensity Score Matching using Fund and Manager Level Characteristics – Transition funds

	Mean-Female Funds (N=2,155)	Mean-Male Funds (N=2,155)	Difference (Female-Male)	t-statistic
	(1)	(2)	(3)	(4)
Port_Liq_PST	0.0638	0.0562	0.00759***	2.78
Port_Liq_Amhd	-0.0041	-0.00674	0.00264***	4.11
Port_Liq_Sprd	-27.1000	-29.4000	2.3000**	1.99

Table 3.7. (continued)

Panel E. Univariate Regression of Propensity Score Matched Transition Funds

	Fund level Characteristics			Fund and Manager level Characteristics		
	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0095***	0.0052***	3.5666***	0.0076***	0.0026***	2.3443**
	(8.05)	(10.81)	(5.18)	(2.78)	(4.11)	(1.99)
Constant	0.0428***	-0.0081***	-26.2000***	0.0562***	-0.0067***	-29.4000***
	(51.14)	(-23.78)	(-53.83)	(29.12)	(-14.82)	(-35.26)
No. of Obs.	10,534	10,534	10,534	4,310	4,310	4,310
Adj. R-squared	0.0060	0.0109	0.0025	0.0016	0.0037	0.0007

The findings presented in Table 3.7, Panels C and D are consistent with the earlier results. The comparison of the three proxies of portfolio liquidity confirms that even transition funds managed by females tend to hold more liquid portfolios compared to the otherwise matched male managed transition funds, even when the observable characteristics between the pairs are virtually identical.

Finally, following Huang and Kisgen (2013), we run univariate regressions on the matched sample of transition funds to examine the gender differences in portfolio liquidity. Table 3.7, Panel E reports that, in comparison with the matched male managed funds, female managed transition funds are positively and significantly associated with all three proxies of portfolio liquidity. Columns (1) to (3) are the regression results for the propensity score matched funds that are indistinguishable regarding the fund level characteristics, whereas Columns (4) to (6) are the findings of the matched funds with respect to fund and manager level characteristics.

3.5.2 Pooled Regression Analysis of Transition Funds

Following Faccio, Marchica, and Mura (2016), we run a traditional panel regression analysis on all fund-month observations of the transition funds by including the controls.[44] Omission of these controls

[44] It is not the matched sample. This regression is run to examine the association of female fund managers and portfolio liquidity in the sub-sample of transition funds.

might lead us to wrongly attribute the differences in portfolio liquidity to the disparities in fund manager gender. We control for time-invariant fund specific characteristics that might be correlated with omitted explanatory variables. Specifically, in the fixed effects regressions, we compare fund managers of different genders managing the same fund. Moreover, the transitions might be accompanied by changes in fund manager characteristics, other than gender. If we do not consider the effects of manager level characteristics on portfolio liquidity, we may wrongly attribute the change in portfolio liquidity observed at the time of a transition to gender. Hence, we run panel regression analysis with fund and year fixed effects, controlling for fund and manager-specific observable characteristics. We restrict our sample to the funds experiencing either male to female, or female to male transitions only.

The findings in Table 3.8, Panel A exhibit a significantly positive relationship between female managed funds and the three proxies of portfolio liquidity. The observable fund and manager level characteristics show significant association with the measures of portfolio liquidity. However, with all the controls and fixed effects, the results reveal that portfolio liquidity is higher when the fund is managed by a female manager than when the same fund is managed by a male manager.

Following Huang and Kisgen (2013), we repeat the above applied panel regression analysis with fixed effects and controls. For this analysis, we include in our sample all the funds experiencing either male to male, female to female, male to female, or female to male transitions during our sample period. The results of Table 3.8, Panel B strongly support the evidence of the higher preference in female managed funds for portfolio liquidity. This analysis mitigates the concerns that our findings might be due to time-varying characteristics, or fund and manager level omitted variables.

Table 3.8. Female Fund Manager and Preference for Portfolio Liquidity of Transition Funds

This table presents the findings of the regression of portfolio liquidity on the single female managed transition funds, the model is given in Equation (5). Panel A reports the results from Male to Female and Female to Male transition funds. Panel B shows the regression results using panel observations of all the transition funds, including Male to Female, Female to Male, Male to Male, and Female to Female. The dependent variable is portfolio liquidity, $Port\_Liq$. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables.

Panel A. Regression Analysis of Male to Female and Female to Male Transition Funds

	Port_Liq_PST		Port_Liq_Amhd		Port_Liq_Sprd	
	All controls with manager age	All controls without manager age	All controls with manager age	All controls without manager age	All controls with manager age	All controls without manager age
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0105***	0.0110***	0.0014*	0.0008**	2.0359**	0.2907
	(7.26)	(14.89)	(1.91)	(2.20)	(2.13)	(0.62)
Ret	-0.0056	-0.0087*	0.0072	0.0017	19.2000***	14.7000***
	(-0.79)	(-1.80)	(1.27)	(0.51)	(3.19)	(3.68)
Size	0.0034***	0.0053***	0.0056***	0.0031***	6.4965***	3.2863***
	(4.49)	(13.18)	(7.60)	(10.79)	(7.98)	(8.97)
Exp	-24.0376***	-10.6622***	5.6796**	4.1629***	-4386.3000	-1654.3000
	(-4.43)	(-3.79)	(2.49)	(2.96)	(-1.30)	(-0.89)
TOratio	-0.0550***	-0.0488***	0.0308***	0.0065***	12.3000	3.0688
	(-3.33)	(-8.48)	(5.22)	(3.37)	(1.29)	(0.94)
Flow	-0.0398	-0.0363	0.0148	0.0044	-0.0004	-0.0022
	(-0.31)	(-0.09)	(0.45)	(0.82)	(-0.04)	(-0.40)
Fund_Age	0.0444***	0.0255***	-0.0069***	-0.0024***	-11.9000***	-6.1508***
	(12.62)	(14.06)	(-4.94)	(-2.96)	(-3.83)	(-3.91)
Undergrad	-0.0122***	-0.0089***	0.0044***	0.0034**	-3.3749	-13.1000***
	(-3.16)	(-2.81)	(3.92)	(2.41)	(-1.16)	(-2.81)
Grad	0.0070*	-0.0058*	0.0084***	0.0061***	1.7614	-10.4000**
	(1.69)	(-1.74)	(4.89)	(4.05)	(0.63)	(-2.21)
PhD	0.0000	-0.0275***	0.0000	0.0288***	0.0000	-31.6000***
	-	(-7.10)	-	(6.74)	-	(-5.27)
MBA	0.0179***	0.0072***	-0.0006	0.00005	3.6683***	1.7126***
	(10.16)	(8.78)	(-0.58)	(0.10)	(3.19)	(3.33)
Cert	0.0466***	0.0090***	0.0025*	0.0023***	1.4353	-1.0359
	(19.39)	(8.47)	(1.75)	(4.38)	(1.03)	(-1.54)
Mgr_Age	-0.0288***	-	-0.0045**	-	-4.1164	-
	(-5.81)		(-2.37)		(-1.02)	
Year-fixed Effect	YES	YES	YES	YES	YES	YES
Fund-fixed Effect	YES	YES	YES	YES	YES	YES
No. of Obs.	5,961	12,095	5,961	12,095	5,961	12,095
Adj. R-squared	0.8677	0.8213	0.6958	0.7741	0.7590	0.7301

Table 3.8. (continued)

Panel B. Regression Analysis of Male to Female, Female to Male, Male to Male, and Female to Female Transition Funds

	Port_Liq_PST		Port_Liq_Amhd		Port_Liq_Sprd	
	All controls with manager age	All controls without manager age	All controls with manager age	All controls without manager age	All controls with manager age	All controls without manager age
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0084***	0.0124***	0.0020***	0.0006**	2.3727***	1.4103***
	(5.80)	(18.46)	(3.06)	(2.17)	(2.75)	(3.10)
Ret	-0.0094***	-0.0066***	0.0037	-0.0002	9.4526***	7.5954***
	(-2.64)	(-3.01)	(1.07)	(-0.09)	(2.88)	(3.68)
Size	0.0089***	0.0066***	0.0054***	0.0030***	4.8834***	3.3744***
	(18.14)	(30.25)	(12.66)	(15.49)	(12.95)	(17.96)
Exp	0.9191	-0.8512	1.0279	1.4092	807.7000	-135.0000
	(0.99)	(-1.24)	(0.92)	(1.57)	(0.72)	(-0.17)
TOratio	-0.0237***	-0.0398***	0.0322***	0.0193***	24.0000***	14.9000***
	(-4.87)	(-16.11)	(9.56)	(12.68)	(7.44)	(7.00)
Flow	-0.0206	0.0107	0.0002	-0.0042*	-0.0004	-0.0009
	(-0.31)	(0.15)	(0.01)	(-2.02)	(-0.24)	(-0.38)
Fund_Age	0.0235***	0.0067***	-0.0098***	-0.0043***	-10.2000***	-5.7300***
	(11.09)	(6.80)	(-9.71)	(-7.59)	(-7.20)	(-7.75)
Undergrad	0.0179***	0.0110***	-0.0014	0.0053***	0.8548	-11.3000**
	(5.74)	(6.78)	(-1.39)	(3.57)	(0.36)	(-2.40)
Grad	0.0044	0.0103***	-0.0020***	0.0049***	0.5707	-11.5000**
	(1.53)	(5.86)	(-2.83)	(3.26)	(0.26)	(-2.42)
PhD	0.0000	0.0071***	0.0000	0.0105***	0.0000	-17.2000***
	-	(3.90)	-	(6.46)	-	(-3.56)
MBA	-0.0034***	-0.0006	-0.0037***	-0.0023***	-3.0067***	-1.4303***
	(-3.26)	(-1.44)	(-5.21)	(-8.01)	(-3.82)	(-4.59)
Cert	0.0099***	0.0011**	0.0004	0.0012***	0.5817	0.7510**
	(8.20)	(2.27)	(0.91)	(4.74)	(0.91)	(2.06)
Mgr_Age	0.0111***	-	-0.0002	-	0.2020	-
	(4.13)		(-0.10)		(0.10)	
Year-fixed Effect	YES	YES	YES	YES	YES	YES
Fund-fixed Effect	YES	YES	YES	YES	YES	YES
No. of Obs.	21,886	47,518	21,886	47,518	21,886	47,518
Adj. R-squared	0.8395	0.8361	0.5653	0.5761	0.7220	0.7136

3.5.3 Difference-in-Differences Regression Analysis Considering Transition Events

We apply a difference-in-differences approach for our empirical examination comparing portfolio liquidity before and after transitions from a male to female fund manager with a control sample of male to male transition funds (Huang & Kisgen, 2013). We refer to the treatment group of funds with male to female transition as Female_Trans. The sample for this analysis is twelve months before and twelve months after a transition, excluding the month when transition occurs. We require a fund manager to be solely managing the fund for at least twelve months (the month he or she is hired and the eleven months following) to ensure that the manager has enough time to make important changes in portfolio composition. We exclude a transition event if observations are missing for twelve months before or after the transition. We run regression on the model given in Equation (11) with controls, and time and fund fixed effects:

$$\begin{aligned} Port\_Liq_{i,t+1} = {} & \alpha + \beta_1\, Female\_Trans_i \times Post_{i,t+1} + \beta_2\, Post_{i,t+1} + \beta_3\, Ret_{i,t} \\ & + \beta_4\, Size_{i,t} + \beta_5\, Exp_{i,t} + \beta_6\, TOratio_{i,t} + \beta_7\, Flow_{i,t} \\ & + \beta_8\, Fund\_Age_{i,t} + \beta_9\, Undergrad_{i,t} + \beta_{10}\, Grad_{i,t} \\ & + \beta_{11}\, PhD_{i,t} + \beta_{12}\, MBA_{i,t} + \beta_{13}\, Cert_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{11}$$

where $Port\_Liq_{i,t+1}$ is one of the three measures of portfolio liquidity measured at the end of month *t+1*. $Female\_Trans_i$ is a dummy variable which is equal to "1" if fund *i* is a male to female transition fund, and "0" if the fund is a male to male transition fund. $Post_{i,t+1}$ is a dummy variable which is equal to "1" if month *t+1* is after the transition, and "0" if it is before the transition. $Female\_Trans_i \times Post_{i,t+1}$ is an interaction term between transition funds and Post variables. Time *t+1* presents the months after transition, whereas *t* shows one month lagged observations of control variables, excluding the month of transition. All other control variables are as explained in Section 3.3.

Table 3.9. Difference-in-Differences Regression for Transition Funds

This table presents the findings of the difference-in-differences regression of portfolio liquidity after the event of Male to Female transition. The dependent variable is portfolio liquidity, $Port\_Liq$. $Female\_Trans$ is a dummy variable which is equal to 1 if fund is a male to female transition fund, and 0 if the fund is a male to male transition fund. $Post$ is a dummy variable which is equal to 1 if month t+1 is after the transition, and 0 if it is before the transition. $Female\_Trans \times Post$ is the cross product of transition funds and Post variables. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with and without fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables.

$$Port\_Liq_{i,t+1} = \alpha + \beta_1 \, Female\_Trans_i \times Post_{i,t+1} + \beta_2 \, Post_{i,t+1} + \gamma \, Controls_{i,t} + \varepsilon_{i,t}$$

	Port_Liq_PST		Port_Liq_Amhd		Port_Liq_Sprd	
	(1)	(2)	(3)	(4)	(5)	(6)
Female_Trans×Post	0.0133***	0.0069***	0.0041***	0.0001	1.5754***	1.3554
	(5.12)	(6.02)	(6.17)	(0.19)	(2.78)	(1.26)
Post	-0.0027**	-0.0011**	-0.0004	0.0002	0.9383***	2.6364***
	(-2.18)	(-2.28)	(-0.78)	(0.50)	(2.83)	(8.43)
Ret	-0.0253**	-0.0060	-0.0048	0.0007	-6.4226	7.1154**
	(-2.29)	(-1.57)	(-0.66)	(0.17)	(-1.38)	(2.03)
Size	0.0043***	0.0056***	-0.0003**	0.0065***	0.6694***	5.3207***
	(10.10)	(10.30)	(-2.43)	(8.07)	(4.94)	(10.70)
Exp	-28.4981***	-0.8991	-1.7258**	-4.0899***	139.8000	1085.7000
	(-8.75)	(-1.05)	(-2.25)	(-3.81)	(0.28)	(0.64)
TOratio	-0.1251***	-0.0448***	0.0406***	0.0084***	19.9000***	3.6957
	(-17.63)	(-9.18)	(12.99)	(2.64)	(8.99)	(1.08)
Flow	0.0266	0.0043	-0.0070	-0.0025	-0.0002	-0.0004
	(0.85)	(0.21)	(-0.47)	(-1.47)	(-1.22)	(-0.26)
Fund_Age	-0.0094***	-0.0081***	0.0023***	-0.0021	-1.1627***	-3.7455*
	(-7.20)	(-2.96)	(6.06)	(-1.19)	(-2.87)	(-1.87)
Undergrad	0.0412***	0.0117***	0.0108***	0.0074***	10.7000***	9.7681***
	(13.34)	(6.06)	(6.76)	(4.03)	(10.14)	(3.96)
Grad	0.0399***	0.0066***	0.0138***	0.0073***	11.2000***	10.4000***
	(12.56)	(3.01)	(8.46)	(4.05)	(10.23)	(4.06)
PhD	0.0246***	0.0079***	0.0147***	0.0052***	10.2000***	6.3305**
	(7.08)	(3.71)	(8.36)	(2.81)	(8.51)	(2.50)
MBA	0.0056***	-0.0025***	-0.0037***	-0.0017***	-1.3375***	-1.9400***
	(4.98)	(-3.65)	(-7.88)	(-3.54)	(-3.53)	(-4.07)
Cert	-0.0062***	-0.0016**	0.0052***	-0.0011***	1.5446***	0.9625*
	(-5.53)	(-2.32)	(9.97)	(-4.17)	(4.09)	(1.71)
Year-fixed Effect	YES	YES	YES	YES	YES	YES
Fund-fixed Effect	NO	YES	NO	YES	NO	YES
No. of Obs.	10,772	10,772	10,772	10,772	10,772	10,772
Adj. R-squared	0.1516	0.8758	0.1013	0.6250	0.6452	0.7440

The results from the difference-in-differences analysis are reported in Table 3.9. We do not include $Female\_Trans_i$ as a stand alone variable in the model specification, because the fixed effects have consumed the effects of this variable. In Columns (1) and (2), the positive and significant coefficient of $Female\_Trans \times Post$ indicates that female fund managers prefer higher Pastor, Stambaugh, and Taylor's portfolio liquidity, compared to male fund managers. The findings are significant at the 1% level and we report the t-statistics based on White standard errors. Columns (3) to (6) carry similar analysis for the Amihud and bid-ask spread's portfolio liquidity methods. These tests show some evidence that female managed funds are more liquid. The coefficient of the $Female\_Trans \times Post$ variable is positive and statistically significant, as shown in Columns (3) and (5).

3.5.4 Instrumental Variable Approach

We conduct one additional test to rule out any remaining endogeneity concerns. We implement an instrumental variable approach, where the instrument that we use is the state's level of gender status equality index, initially developed by Sugarman and Straus (1988) and updated by Di Noia (2002). The measure analyzes the extent to which females have the same access as men to economic resources, legal rights, and positions of political power in each of the 50 U.S. states. The state's gender equality index is a composite index to represent the cumulative effect of the economic, legal, and political indicators, and assigns each of the states a score for its gender status equality. The scores range from 33.6 (Alabama) to 73.1 (Washington), where higher values indicate more gender equality.

Following Huang and Kisgen (2013), we hypothesize that the more friendly a state is towards female equality, the more likely a fund with its headquarters located in that state is to appoint a female manager. Based on the fund's headquarter location, we allocate each fund the state's gender status equality value. The purpose for using this instrumental variable is that there is a high possibility that the measure is correlated with the decision to hire a female fund manager; however, it is highly unlikely that it will affect our portfolio liquidity proxies. The only way it may affect the outcome variables is through its direct relationship with the gender of the fund manager. Hence, this measure reasonably fulfills the requirements of an instrumental variable. We use two stage least squares (2SLS) instrumental variable (IV) design:

First stage:

$$
\begin{aligned}
Female_i = \; & \varphi + \gamma_1\, Equality\_Index_i + \gamma_2\, Ret_{i,t} + \gamma_3\, Size_{i,t} + \gamma_4\, Exp_{i,t} \\
& + \gamma_5\, TOratio_{i,t} + \gamma_6\, Flow_{i,t} + \gamma_7\, Fund\_Age_{i,t} \\
& + \gamma_8\, Undergrad_{i,t} + \gamma_9\, Grad_{i,t} + \gamma_{10}\, PhD_{i,t} + \gamma_{11}\, MBA_{i,t} \\
& + \gamma_{12}\, Cert_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{12}
$$

Second stage:

$$
\begin{aligned}
Port\_Liq_{i,t} = \; & \alpha + \beta_1\, Instrumented\_Female_i + \beta_2\, Ret_{i,t} + \beta_3\, Size_{i,t} \\
& + \beta_4\, Exp_{i,t} + \beta_5\, TOratio_{i,t} + \beta_6\, Flow_{i,t} + \beta_7\, Fund\_Age_{i,t} \\
& + \beta_8\, Undergrad_{i,t} + \beta_9\, Grad_{i,t} + \beta_{10}\, PhD_{i,t} + \beta_{11}\, MBA_{i,t} \\
& + \beta_{12}\, Cert_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{13}
$$

where $Port\_Liq_{i,t}$ is one of the three measures of portfolio liquidity measured at the end of month *t*. $Female_i$ is a dummy variable which is equal to "1" if the fund is single female managed, and "0" if it is single male managed. $Equality\_Index_i$ is the instrumental variable of the state's gender status equality index (Di Noia, 2002). $Instrumented\_Female_i$ is the fitted value of the female dummy variable from the first-stage regression. All other control variables are as explained in Section 3.3.

Column (1) of Table 3.10 reports the results of first-stage regression and concludes that the gender equality index is significantly associated with the decision to have a female manager to manage the fund. The association is significant at the 1% level. The F-statistic is 38.58, which confirms the strength of the instrument. Columns (2) to (4) of Table 3.10 depict the outcomes of the second-stage analysis and confirm our main findings of the study. In our analysis, the positive coefficient of Port_Liq_Sprd is insignificant; however, the rest of the two measures are positively and significantly related to female managed funds.

Table 3.10. Preference for Portfolio Liquidity - Instrumental Variable Approach

This table presents the findings of the two stage least squares regression. Column (1) reports the results from the first-stage ordinary least squares regression with the female dummy as dependent variable. $Equality\_Index$ is the state's gender equality index. F-statistics from the first-stage regression is given at the bottom of the table. Columns (2), (3) and (4) show the results for the second-stage regressions with the three measures of portfolio liquidity as the dependent variables. $Instrumented\_Female$ is the fitted value of the female dummy from the first-stage regression. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with year and fund style fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables.

$$Female_i = \varphi + \gamma_1\, Equality\_Index_i + \gamma\, Controls_{i,t} + \varepsilon_{i,t}$$

$$Port\_Liq_{i,t} = \alpha + \beta_1\, Instrumented\_Female_i + \gamma\, Controls_{i,t} + \varepsilon_{i,t}$$

		Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
	First stage	Second stage	Second stage	Second stage
	(1)	(2)	(3)	(4)
Instrumented_Female	-	0.0661***	0.0321***	0.4700
		(6.91)	(4.73)	(0.10)
Ret	-0.0224	-0.0182***	-0.0053**	1.6000
	(-1.35)	(-6.06)	(-2.04)	(0.87)
Size	-0.0048***	0.0053***	0.0011***	0.8200***
	(-9.03)	(49.63)	(16.47)	(18.01)
Exp	27.8319***	-24.1122***	-5.5284***	-1160.8000***
	(13.19)	(-32.65)	(-13.70)	(-5.37)
TOratio	-0.0103	-0.0280***	0.0231***	12.2300***
	(-1.04)	(-14.23)	(13.07)	(12.98)
Flow	-0.1000	0.0347	0.0059	-0.0008
	(-0.78)	(1.48)	(1.26)	(-1.12)
Fund_Age	0.0112***	-0.0039***	0.0005***	-0.2000*
	(8.27)	(-11.98)	(3.02)	(-1.76)
Undergrad	-0.0066	-0.0203***	-0.0202***	-0.3000
	(-0.28)	(-6.38)	(-15.76)	(-0.09)
Grad	-0.0096	-0.0179***	-0.0197***	-0.0871
	(-0.40)	(-5.56)	(-15.07)	(-0.03)
PhD	-0.0769***	-0.0230***	-0.0209***	-6.2000**
	(-3.13)	(-6.74)	(-13.29)	(-2.09)
MBA	-0.0080***	0.0058***	-0.0028***	-1.6000***
	(-4.45)	(17.33)	(-11.77)	(-10.93)
Cert	0.0294***	-0.0093***	0.0018***	0.3300*
	(16.69)	(-21.77)	(5.85)	(1.77)
Equality_Index	0.0036***	-	-	-
	(18.91)			
Year-fixed Effect	YES	YES	YES	YES
Style-fixed Effect	YES	YES	YES	YES
No. of Obs.	112,842	112,842	112,842	112,842
Adj. R-squared	0.0157	0.1770	0.0981	0.6340
F-statistics	38.58	-	-	-
[p-value]	[0.00]			

3.6 Conclusion

This study provides empirical evidence that preference for portfolio liquidity differs among male and female fund managers. Using a sample of 1,932 U.S. domestic open-end single managed equity funds from January 2000 to December 2017, the results show that the preference of female fund managers to hold liquid portfolios is significantly higher than for male managers. This evidence is consistent with the *price efficiency hypothesis* and infers that female fund managers are likely to incline towards stocks whose prices incorporate available information efficiently. Hence female managers' preference for informationally transparent stocks possibly explains their higher tendency to hold liquid stocks in the portfolio. Consistent with the literature, this study reports lower portfolio risk of female managed funds. We document that, on average, female managed funds are smaller in size, earn lower return, receive lesser flow, and hold a smaller number of stocks in their portfolio compared to male managed funds. Moreover, female fund managers have a higher likelihood of holding an undergraduate degree and professional certification than male fund managers.

Further, the analysis of change in portfolio liquidity around manager transitions indicates that portfolio liquidity increases after a male to female transition as compared to a male to male transition. We run multiple tests to mitigate endogeneity concerns. Our findings are in line with the literature which suggests that professional women at the top positions are different from their male counterparts. Additionally, this study provides a new insight regarding gender differences in one of the preferred stock characteristics for portfolio holdings of mutual funds. The study highlights the concerns regarding negatively affected fund performance due to the potential tradeoff between liquidity and return, however, further detailed analysis is required to reach a conclusion on this issue.

As female managers prefer higher portfolio liquidity, the lower stocks' return might affect their funds' performance. It is not surprising if male fund managers attract fund flows by holding less-liquid stocks and reporting higher fund return performance. Therefore, fund investors and management companies should scrutinize the performance of male managed funds by analyzing the riskiness and percentage of asset allocation to illiquid stocks in their portfolio holdings.

CHAPTER 4

FEMALE FUND MANAGERS AND COLLECTIVISM

This chapter presents the third essay of the thesis which investigates the impact of gender of fund managers on the degree of active investment of funds. The study uses Morningstar Direct database to collect the data for U.S. domestic open-end single and team managed active equity funds from January 2004 to December 2014. The results describe that funds with a higher fraction of female managers in management team track the benchmark more closely than other funds. These findings provide an insight that female managers tend to manage funds less actively.

Section 4.1 provides the research question and motivation of the study. Section 4.2 presents the literature review and hypotheses formation. Section 4.3 comprises of establishing methodology and specifying the details of our data. The application of diagnostic tests, analysis, and discussion of results is given in Section 4.4. Section 4.5 includes description of additional tests and results. Section 4.6 provides the conclusions of the study. An appendix to this chapter and the relevant reference list are provided at the end of the thesis.

Female Fund Managers and Collectivism

Abstract

Collectivism is one of the important dimensions of female self-construal which makes women more social, interdependent, relational, and allocentric to each other than do men, as shown in the psychology literature. Consistent with the collectivism argument, we find that funds with a higher proportion of female managers track a multifactor benchmark more closely. This suggests female fund managers invest less actively than their male counterparts. The results indicate reduced diversification benefits of investing in funds managed by a higher fraction of female managers. Female fund managers herd more, take less risk, and are less overconfident than their male counterparts.

Keywords: Mutual funds, Proportion of female fund managers, Active investing, Diversification benefit, Investment behaviors.

4.1 Introduction

The self-construal of gender, explained in the psychology literature, motivates this study. Interdependent and independent self-construal refer to different cognitive depictions of the self that people may hold. Past research states that interdependence is one of the important dimensions of female self-construal, which makes women more social, relational, and allocentric with each other than men (Cross & Madson, 1997; Kashima et al., 1995). Women view their close relationships, social roles, and group memberships as central to their sense of self. The thoughts and actions of people in their surroundings or in the groups to which they belong determine the behaviors of women. The studies describe that their affiliative tendencies prefer collective group goals more than private goals. They thus have a lower requirement of being unique (Yamaguchi, Kuhlman, & Sugimori, 1995). Hence, this study investigates the impact of collective self-construal of female fund managers on their fund investment strategy. We argue that the interdependent self-attribute of female fund managers potentially contributes to the degree with which their funds track the market benchmark.

Active mutual fund managers decide to capitalize on their stock picking skills or timing abilities to outperform the chosen benchmark. In contrast, passive portfolio management is a strategy that fully tracks the returns of an index or market benchmark. There exists a wide strand of literature on active versus passive funds' performance.[45] However, our study considers only actively managed funds and their managers' goal is to beat the market benchmark. Under the category of active investment, we may expect fund managers to be less or more active, based on personality traits, skills, or behaviors. Nevertheless, the impact of gender of mutual fund managers on the degree of active investment is yet to be explored. Additionally, the use of gender self-construal to explain the investment strategy of fund managers has not been studied. Furthermore, Lutton and Davis (2015) report that only 9.4% of fund managers in U.S. mutual funds are women, and most of them manage funds in gender diverse teams. We follow the gender literature which suggests that females influence the decisions of the team to which they belong (e.g., Adams & Ferreira, 2009; Gul, Srinidhi, & Ng, 2011; Jurkus, Park, & Woodard, 2011).

[45] See for example, Elton, Gruber, and Blake (1996); Guercio and Reuter (2014); Crane and Crotty (2018).

We thus expect that funds managed by a high proportion of female managers would co-move to a greater extent against a benchmark than other funds.

The literature on the efficient frontier reports that investors are interested in exploring whether the minimum-variance frontier of a set of benchmark assets is different from the minimum-variance frontier of the benchmark assets plus a set of additional test assets (Huberman & Kandel, 1987). The benefits of diversification improve when adding a new set of assets can allow the investor to improve the minimum-variance frontier from a set of benchmark assets. The literature on mean-variance spanning tests in different settings is extensive (e.g., Cumby & Glen, 1990; De Roon, Nijman, & Werker, 2001; Kan & Zhou, 2001). Following De Roon and Nijman (2001), we apply a mean-variance spanning test of the efficient frontier to analyze whether a collective self-construal influences the diversification gains of investing in funds managed by more female managers. By using the Sharpe optimization model of performance, the results indicate that economic benefits of diversification diminish 1.86% when a high fraction of female managers manage the fund. This suggests that funds sacrifice their reward-to-performance focus due to the collectivism of female managers.

In addition to the personality attributes, we examine the contribution of investment behaviors linked to the gender of mutual fund managers to the co-movement of fund returns with benchmark returns. The issue of gender differences in investment behaviors is an unsolved puzzle. There exist a number of studies suggesting that there are no significant differences in the cognitive skills and resulting performance, among male and female professionals.[46] On the contrary, the literature reports that females behave significantly different from their male counterparts in terms of management, leadership style, and decision making.[47] In the field of finance, there are a number of studies providing empirical evidence that females are more risk averse and less overconfident than males; therefore, investment decisions differ among gender (Barber & Odean, 2001; Faccio, Marchica, & Mura, 2016). Following Niessen and Ruenzi (2006), this study explores possible contribution of gender differences in risk-taking, overconfidence, and investment styles to the degree of active investing strategy of female

[46] See for example, Atkinson, Baird, and Frye (2003); Nekby, Thoursie, and Vahtrik (2008).
[47] See for example, Chapman (1975); Carland and Carland (1991); Powell and Ansic (1997).

managers. Considering the collective self-construal of females, we expect that female fund managers exhibit higher herding behavior compared to their male counterparts. We hypothesize that these investment behaviors of female fund managers potentially explain funds' co-movement with the benchmark.

To test how closely funds track the market benchmark, we use the measure of a fund's strategy or activity, R^2, developed by Amihud and Goyenko (2013). This measure is the proportion of fund returns variance that is explained by the variation in the benchmark factors' returns. A lower R^2 depicts divergence of the returns of funds from the returns of benchmark factors. The literature on investors' behavior and stock price co-movement uses R^2 as a measure of synchronicity.[48] Hence, our study applies the measure of fund activity to analyze gender differences in fund activeness and uses self-construal and investment behaviors as possible explanations of the results.

Using a sample of 1,565 U.S. domestic open-end single and team managed active equity funds from January 2004 to December 2014, the results show that funds with a higher fraction of female managers in the management team track the benchmark more closely than other funds. These findings provide the insight that female managers tend to manage funds less actively. The results support our conjecture that funds with a higher proportion of female managers in the team herd more in a popular sector, and assets' representation in their portfolio holdings follows the trends of the benchmark holdings. Consequently, higher herding contributes to less active fund management. The findings of our study indicate that less risk-taking behavior (Niessen & Ruenzi, 2006) and less overconfidence (Barber & Odean, 2001) among female fund managers possibly explain their less active investing strategy. Unlike Niessen and Ruenzi (2006), our findings do not show a significant relationship between female fund managers and investment style extremity. However, a less extreme investment style significantly increases R^2.

Although the collective self of females may explain their higher tendency to herd, reputational concern is likely to explain part of their herding behavior. The literature documents that managers

[48] See for example, Jin and Myers (2006); Eun, Wang, and Xiao (2015).

mimic the investment decisions of other managers because they face a reputational cost for acting differently from the herd (Scharfstein & Stein, 1990). Managers imitate strategies of the crowd to enhance the market's perception of their ability (Avery & Chevalier, 1999), or as a response to their career concerns (Chevalier & Ellison, 1999b). The scope of our study does not include the investigation of reputational herding of female managers; hence, there is no empirical evidence to justify this explanation. We run several additional tests to check the robustness of the outcomes. We use the time-varying conditional correlation of fund returns by applying the dynamic conditional correlation (DCC) model of Engle (2002) as an alternative measure of R^2. All the results are consistent with time-varying correlation. In our main model, we consider managerial characteristics such as the manager's age, professional certification, education, and tenure. Moreover, we control for the size of the fund management team and time varying fund characteristics. By categorizing funds based on their size, the results indicate that the positive relation between the proportion of female fund managers and a fund's correlation with the benchmark becomes stronger as the fund size increases.

Our findings contribute to the psychology literature of collective self-construal of women (e.g., Kashima et al., 1995; Markus & Kitayama, 1991). To the best of our knowledge, this is the first study which explores the role of the gender of fund managers in funds' co-movement with the index, using the activity measure of R^2. The existing studies on fund managers' gender explore characteristics and investment behaviors of male and female managers who are the sole managers of funds. Few notable studies analyze behavioral differences among teams and single managed funds. Our research contributes to the mutual fund literature on gender diversity of fund managers and team managed funds (e.g., Atkinson, Baird, & Frye, 2003; Bär, Kempf, & Ruenzi, 2010; Bär, Niessen-Ruenzi, & Ruenzi, 2009; Niessen & Ruenzi, 2006). The application of the mean-variance frontier spanning test is a contribution to the related literature (e.g., De Roon & Nijman, 2001; Kan & Zhou, 2001). Moreover, the finding of reduced economic benefits of diversification for funds managed by a higher proportion of female managers is a contribution to the existing literature, which suggests lower performance of female professionals compared to males (e.g., Adams & Ferreira, 2009).

The rest of the study is structured as follows. Section 4.2 provides the literature review and hypotheses formation. Section 4.3 comprises of establishing methodology and specifying the details of our data. The application of diagnostic tests, analysis, and discussion of results is given in Section 4.4. Section 4.5 includes the description of additional tests and results. Section 4.6 provides the conclusions of the study.

4.2 Literature Review and Hypotheses Development

4.2.1 Activeness of Mutual Funds, Behavioral Biases, and R^2

The existing mutual fund literature that examines active management of funds and subsequent performance includes a detailed study by Wermers (2003). It uses the S&P500 tracking error (the standard deviation of the difference of the fund return and its benchmark return) as a measure of active management and investigates fund performance. Kacperczyk, Sialm, and Zheng (2005) analyze industry concentration of mutual funds as a measure of activity management and examine its impact on fund performance. The study investigates whether or not funds with concentrated stock holdings or large factor bets in industries perform better than other funds. Cremers and Petajisto (2009) and Cremers et al. (2011) show that an increased active share (deviation of a fund's stock holdings from the average holdings in the fund's index) enhances fund performance. Kacperczyk and Seru (2007) find that funds whose stock holdings are related to company-specific information that differs from analysts' expectations, demonstrate better performance. However, the study of Amihud and Goyenko (2013) introduces a simple but robust measure of R^2 to analyze the selectivity of a fund and to predict fund performance. The measure of R^2 is the proportion of fund returns variance that is explained by the variation in benchmark factors' returns.

The behavioral finance literature uses the measure of R^2 extensively. Price synchronicity or co-movement explains the extent to which stock returns move together with market returns. Barberis, Shleifer, and Wurgler (2005) explain return co-movement by modelling an environment where investors make portfolio decisions by grouping assets according to their styles and then invest funds at the category level. The correlated demand by moving funds from one category to another induces common factors in the returns of otherwise unrelated assets. Secondly, they argue that investors prefer to trade only a subset of all securities. Hence, any change in these investors' risk aversion or sentiments (e.g., Baker & Wurgler, 2006) brings about common factors in the returns of these securities. Green and Hwang (2009) describe stock price co-movement with investors' sentiments before and after the event of stock split. Stock returns co-move more with correlated trading among retail investors (Kumar & Lee, 2006), as well as among institutional investors (Pirinsky & Wang, 2004). Moreover, studies have shown the impact of cross-country variations in the protection of private property rights and information opaqueness on stock return co-movement (Jin & Myers, 2006; Morck, Yeung, & Yu, 2000). Eun, Wang, and Xiao (2015) have made another important contribution to the literature explaining behavioral biases in the context of different cultures and their impact on synchronicity.

In addition to active management, mutual fund literature describes the impact of several investment styles, stock picking talent, and characteristics of fund managers on fund performance. Wermers (1997) concludes that fund managers possess stock picking ability, which allows them to choose stocks that outperform their benchmarks before expense deduction. Fund managers process information about firm-specific and economy-wide shocks, they pick stocks in boom, and time the market in recession (Kacperczyk, Nieuwerburgh, & Veldkamp, 2014). Chevalier and Ellison (1999a) consider different demographics of fund managers including education, experience, and age to examine their impact on fund performance.

Following the studies which analyze the influence of trading behaviors of fund managers on fund returns, we expect that investment behaviors of fund managers are highly likely to influence the investing strategy of funds.

4.2.2 Gender Behaviors in Mutual Funds and Mixed-Gender Teams

Atkinson, Baird, and Frye (2003) contribute to the literature of gender diversity in mutual funds. They compare the performance and investment behavior of single female managed fixed income mutual funds with single male managed fixed income funds. The study does not find significant differences in fund performance, risk, and other characteristics of the funds managed by male and female managers. However, it concludes that funds managed by female managers receive smaller net asset flows from investors compared to male managed funds. Niessen and Ruenzi (2006) conduct univariate as well as multivariate analysis to compare the performance of single female managed equity funds with single male managed funds. The findings show that female fund managers take less risk, consistently use a less extreme investment style, and are less overconfident than male fund managers. Niessen-Ruenzi and Ruenzi (2019) report no gender difference in fund performance, but single female managed funds receive significantly lower inflows than single male managed funds.

Bär, Kempf, and Ruenzi (2010) compare the investment behavior of fund management teams with single-person managed funds. While analyzing the impact of different characteristics of fund managers as control variables, they find that female fund managers exhibit similar investment behavior to that of teams. They follow significantly less extreme investment styles with respect to all style dimensions. They hold less industry concentrated portfolios. There are less extreme performance outcomes among female managers than among male managers. Bär, Niessen-Ruenzi, and Ruenzi (2009) describe that gender diversity is negatively related to fund performance, while information gains (tenure and educational diversity) lead to positive fund performance. In an experiment study, Bogan, Just, and Dev (2013) examine gender composition of fund management teams and its impact on investment decision making behavior. They state that having a male presence in the team increases the risk seeking and loss aversion of the team. These studies indicate the importance of gender composition in fund management teams. Apesteguia, Azmat, and Iriberri (2012) compare the economic performance of gender mixed teams with single gender teams by playing a large business game with three members in each group. Involving undergraduate and MBA students, the study concludes that the best performing team consists of two men and one woman. They explain that gender diversity is positively associated with good team dynamics, as the different skills and knowledge of participating men and women contribute to prudent decisions.

There are some conflicting evidences in the literature regarding the influential ability and decision-making power of males and females in mixed gender teams. Carli (2001) states that men are more influential than women in mixed gender groups because they are highly competent, assertive, and task oriented. Moreover, the gender effect on influence is not primarily due to behavioral biases among gender, but due to resistance by men to women's influence. Men particularly resist the influence of a competent woman, unless they are likely to benefit from her competence. Men are likely to have higher status roles than women, hence, they are more influential (Eagly, 1983).

Campbell and Mínguez-Vera (2008) show that having a higher proportion of female directors on the corporate boards of Spain tends to improve the monitoring quality of the board and firm financial performance. Adams and Ferreira (2009) find that the presence of female directors on a board plays a monitoring role in mitigating agency costs. Moreover, they show the peer effect of female directors on their male counterparts in terms of correcting their attendance issues. Our study expects that female managers in either single managed or team managed funds exhibit different investment behaviors than their male counterparts.

4.2.3 Self-Construal and Behavioral Disparities in Gender

There is a consensus in academic literature that a woman possesses cognitive skills and personality characteristics which differentiate her from men. Psychology literature conceptualizes the self-construal of individuals and proves that these internal traits are regulators of one's behavior. The individual-self is described as independent, separate, self-contained individual, producer of one's actions, and autonomous. On the contrary, the collective construal is described as interdependent, relational, a sense of connectedness with others, and communal (Markus & Kitayama, 1991). Individuals containing individualistic self-construal prefer to be distinctive in different situations, while others' emotions and actions largely regulate the behavior of collective-self individuals (Cross, Hardin, & Gercek-Swing, 2010). Considering the two self-definitions, women are thought to be more collective and relational than men. Women are more likely to describe themselves in connection with others, while men describe themselves independent of others (Kashima et al., 1995).

The self-schema also plays another important role in determining the overall characteristic of an individual. The self-schema refers to a long lasting and stable set of memories that summarize a person's beliefs, experiences and generalizations about the self, in specific behavioral domains. A person may have a self-schema based on any aspect of himself or herself as a person, including physical characteristics, personality traits and interests, as long as they consider that aspect of their self-important to their own self-definition. As documented in Konrad et al. (2000), gender self-schemas are developed from childhood, male self-schemas are based on roles, norms, values, and beliefs that are perceived to be appropriate for men, such as achievement, aggression, autonomy, dominance, endurance, exhibition, and income provider. Female self-schema, on the other hand, are based on similar aspects that are perceived to be appropriate for women, such as abasement, affiliated to others, deference, homemaker, and nurturance (Konrad et al., 2000).

In the literature on gender, it is a prevalent belief that women are more risk averse in financial decision making than men. Jianakoplos and Bernasek (1998) explain that in financial decision-making single women are more risk averse than single men. Byrnes, Miller, and Schafer (1999) have carried out a meta-analysis of 150 studies and conclude that in various situations there is a greater risk-taking tendency in male participants, as compared to female participants. Dwyer, Gilkeson, and List (2002) argue that investors' gender affects investment decisions in mutual funds as females demonstrate less risk taking than males when considering risky investments. However, the impact of gender on risk taking significantly weakens when investor knowledge of financial markets and investments is controlled in the regression equation.

Puetz and Ruenzi (2011) find that overconfident managers are optimistic about their trading abilities and are involved in excessive trading, which leads to a higher turnover ratio. Moreover, they find that, among the funds in the top decile of performers sorted on a Carhart four factor alpha, low turnover funds outperform high turnover funds by up to 1.9% per annum. Barber and Odean (2001) categorize investors based on their gender and find that men are more overconfident than women, are involved in excessive trading, and risk-adjusted live trading affects the performance of men more than women. In a laboratory experiment, Niederle and Vesterlund (2007) find that men select their compensation scheme by preferring a competitive tournament twice as much as women. Their study concludes that men are more overconfident than women.

Despite possessing leadership qualities, there are few females at managerial positions in the corporate world. Among many other explanations, “gender-based stereotyping” and the closed circle of the “old boy network” are strong social forces that are slow to change, and work as barriers to female promotion or joining top management positions (Oakley, 2000). Niessen and Ruenzi (2006) state that female managers encounter discrimination by gender stereotyping investors and experience 18% lower fund inflow than male managed funds. In this situation, one wrong investment move by female fund managers can boost gender-based criticism and bring harm to their reputation. According to Scharfstein and Stein (1990), managers who are concerned about their reputations mimic the investment strategies of other managers in the market. Chevalier and Ellison (1999b) analyze the termination-performance relation of young fund managers and their impact on fund performance. Their study concludes that career concern and the termination-performance relation are incentives for young managers to herd. Popescu and Xu (2014) provide empirical evidence that institutional herding is driven by the reputational concerns of institutional managers.

Following the literature, we expect that investment behaviors of female fund managers influence their decisions, hence, they invest in accordance with the market.

H1: Funds with a higher proportion of female fund managers than male managers closely track the market benchmark.

The collective self-construal explains the tendency of female fund managers to herd the market and make conventional investment decisions. Herd behavior contributes to return co-movement (Eun, Wang, & Xiao, 2015). The lower risk-taking investment style of female fund managers may explain lower riskiness of a portfolio. This results in less volatile fund returns (small beta), which are likely to move with benchmark returns. The study conjectures that funds with a high proportion of less overconfident female managers have a moderate turnover ratio and consistent returns. It signals that fund returns are less likely to deviate from the benchmark index.

H2: Investment behaviors of female fund managers are highly likely to explain their less active investing strategy than male managers.

4.3 Data and Methodology

4.3.1 Data

The study considers the U.S. domestic open-end single and team managed active equity funds from January 2004 to December 2014. We collect our sample from the Morningstar Direct database. We exclude index funds and consider equity funds with more than US$1 million assets under management (Lou, 2012). We also exclude international funds, sector funds, balanced funds, all fixed income funds, and precious metal funds. We focus on the following four investment objectives of funds: Aggressive Growth, Growth, Growth and Income, and Income. The data is free of survivorship bias as it includes all surviving and non-surviving funds. We ignore share class observations reporting negative monthly net assets, turnover ratios, or expense ratios. To avoid incubation bias, we exclude fund's monthly observations where the date of the observation is prior to the inception date of the fund reported in Morningstar (Elton, Gruber, & Blake, 2001). We require a fund to have at least one year of monthly returns.

To avoid multiple counting, we aggregate all share classes belonging to the same fund by using their FundId. FundId is an identification code of Morningstar, which is similar for all the share classes that belong to the same fund. We sum monthly net assets of all share classes with the same FundId to derive the monthly total net assets of a fund. For the analysis, we compute the value-weighted average for the monthly fund return and expense ratio. We repeat the turnover ratio of fund share classes to obtain the monthly frequency. Finally, we have a sample of 1,565 U.S. domestic open-end equity funds with a total of 5,964 share classes. In the Aggressive Growth category there are 46 funds (152 share classes), the Growth category has 1,273 funds (4,804 share classes), the Growth and Income category has 241 funds (1,000 share classes), and the Income category has 5 funds (8 share classes).

We collect fund managers' data from Morningstar Direct. We record all the relevant information manually including the manager's name, qualification, professional certification, graduating year, and tenure with the fund. Morningstar provides a data point; "Manager History"; which we utilize to specify the name and gender of each fund manager in each month from year 2004 to 2014. The data point of "Manager History" provides managers' names and dates of joining and leaving the fund, since the fund is originated. We identify managers' gender through the title prefixing their names (e.g. Mr., Ms., and Mrs., etc.). Executive profiles and biographies are gathered from Bloomberg, LinkedIn, Facebook, Zoominfo, and fund management companies' websites for all those managers with missing information in Morningstar Direct.

In our sample, there are funds that are single male or female managed for a specific time period, which are later managed by team of managers. We ignore the funds which do not provide any description of their team members, and only mention that they are "Team Managed". We keep all those managers and their characteristics who either have been serving, joined or left the fund during our sample time window, i.e., January 2004 - December 2014. Managers who have resigned before January 2004, or started managing the fund after December 2014, are not the focus of this analysis. We also remove fund-month observations for which manager name or tenure date is unavailable. The final sample of this study contains 206,580 fund-month observations from January 2004 to December 2014. The total number of U.S. domestic open-end equity funds for the sample is 1,565, and we collect the information of around 9,000 fund managers.

We retrieve monthly data of sector concentration from Morningstar Direct. By knowing how heavily a fund invests in each sector, it is easy to measure how much sector risk a fund manager has taken on. Morningstar has introduced a sector structure that divides the stock universe into three major Super Sectors; 1) Cyclical, 2) Defensive, and 3) Sensitive. Across each of these three super sectors, there are a total of eleven economic sectors. The cyclical super sector includes the basic materials, consumer cyclical, financial services, and real estate sectors. In the defensive super sector are the consumer defensive, healthcare, and utilities sectors. Finally, in the sensitive super sector, there are the communication services, energy, industrials, and technology sectors. Morningstar calculates a fund's sector exposure based on the amount of assets invested in stocks in each sector.[49] We measure the monthly fund net exposure in each of the three super sectors as the percentage difference between the long and short positions of fund investments. Net exposure is the measure of the extent to which a fund's portfolio is vulnerable to market fluctuations.[50]

4.3.2 Variables Definition and Model Development

4.3.2.1 Measure of R^2

The study uses R^2 as a measure of fund strategy or activity (Amihud & Goyenko, 2013). The literature on stock price synchronicity widely uses R^2 (Eun, Wang, & Xiao, 2015; Jin & Myers, 2006; Roll, 1988). We derive R^2 by regressing individual fund's monthly excess returns on returns of a multifactor benchmark model. R^2 is the proportion of the variability in fund returns that is explained by the variation in these factors' returns. Higher R^2 shows that the fund tracks benchmark factors closely. We use the benchmark model of factor-mimicking portfolios (4 factor model) presented by Carhart (1997). It includes the 3 factor model of Fama and French (1993): RM-RF (market excess return), SMB (small minus big size stocks), HML (high minus low book-to-market ratio stocks), and the momentum factor MOM (winner minus loser stocks) of Carhart (1997). We retrieve R^2 from the following annual time series regression for each fund:

[49] Morningstar (2010).
[50] Morningstar provides four data points for sector concentration, Equity Econ Super Sector % (Long), (Short), (Net) and (Long Rescaled). Long Rescaled takes the long positions, and re-weights them to sum to 100%. The data point "Rescaling Factor" helps to interpret these numbers, as it shows the number that equals the Long-Rescaled value divided by the actual Long positions.

$$R_{i,m,t} - R_{f,m,t} = \alpha + \beta_{i,M,t}(R_{M,m,t} - R_{f,m,t}) + \beta_{i,S,t}SMB_{m,t} + \beta_{i,H,t}HML_{m,t} + \beta_{i,MO,t}MOM_{m,t} + \varepsilon_{i,m,t} \tag{1}$$

where $(R_{i,m,t} - R_{f,m,t})$ is fund *i*'s excess return over the risk-free rate in month *m* of year *t*. $(R_{M,m,t} - R_{f,m,t})$ denotes the excess return of the market over the risk-free rate in month *m* of year *t*. $SMB_{m,t}$ is the return difference between small and large capitalization stocks, $HML_{m,t}$ is the return difference between high and low book-to market ratio stocks, and $MOM_{m,t}$ is the return difference between stocks with high and low previous year's returns, in month *m* of year *t*.[51]

The value of the resulting R^2 from the time series regression, i.e., Equation (1), varies between 0 and 1. Following Eun, Wang, and Xiao (2015), we apply logistic transformation to the bounded explanatory variable. The bounded outcomes have a non-standard distribution. We obtain the logit-normal distribution by applying logistic transformation on a normally distributed random variable.

$$Transformed\ R^2 = Ln\left(\frac{R_i^2}{1 - R_i^2}\right) \tag{2}$$

where R_i^2 is the return activity measure for individual fund *i* derived from Equation (1).[52]

4.3.2.2 Measure of Female Proportion and Fund-specific Characteristics

We measure the monthly fraction of female fund managers by dividing the number of females to the total number of managers (male and female) in the management team of individual funds in each month.

We control for the following fund characteristics: fund size is measured as the natural log of total assets under management of the fund in millions of dollars at the end of a given month; Morningstar defines the net expense ratio as the percentage of fund assets paid for operating expenses and management fees, however, we measure it as the value weighted average of the net expense ratio

[51] We retrieve the market, size, value, and momentum portfolio returns from the website of Kenneth R. French. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[52] As an initial analysis, the study assumes that $Transformed\ R^2$ for each fund in each year remains constant throughout the months of the year.

of all the share classes; and, following Sirri and Tufano (1998), we measure monthly fund level net flow, which is the net growth in fund assets beyond reinvested dividends:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \tag{3}$$

where $TNA_{i,t}$ is the total net assets of fund *i* at time *t* and $R_{i,t}$ is the return of fund *i* earned on assets under management. This measure assumes that flows for the fund arise at the end of the period.

4.3.2.3 The Model

This study aims to examine the relation between the female proportion in the management team and fund returns tracking the returns of benchmark factors. We run the following model, with fund level controls, to test our main hypothesis:

$$T\left(R_{i,t}^2\right) = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $T\left(R_{i,t}^2\right)$ is the transformed R^2 measured in Equation (2). $Female_{i,t}$ is the monthly proportion of female fund managers in fund *i* at time *t*. $Size_{i,t}$ is the monthly size, $Exp_{i,t}$ denotes the monthly net expense ratio (%), and $Flow_{i,t}$ is the monthly net flow (%) of fund *i* at time *t*.

4.3.3 Summary Statistics

The study provides information about the total number of funds, number of male and female managers, and proportion of female managers in management teams in each year of our sample period.[53] Figure 4.1 depicts that the number of female fund managers is increasing each year from 2004 to 2014. However, the ratio of female to male managers is diminishing over time, from 11.27% in 2004 to 9.51% in 2014. There is a minor decrease in the proportion of female managers in fund management teams. We observe the minimum level in the female proportion (i.e. 8.092%) in 2012, and it starts improving from the following year.

[53] See Table C2 in the Appendix.

Figure 4.1. Trends of Female Managers Participation in Mutual Funds

Figure 4.1 shows total number of female fund managers, their ratio to male managers, and proportion in mixed gender management teams of mutual funds over the sample period of 2004-2014.

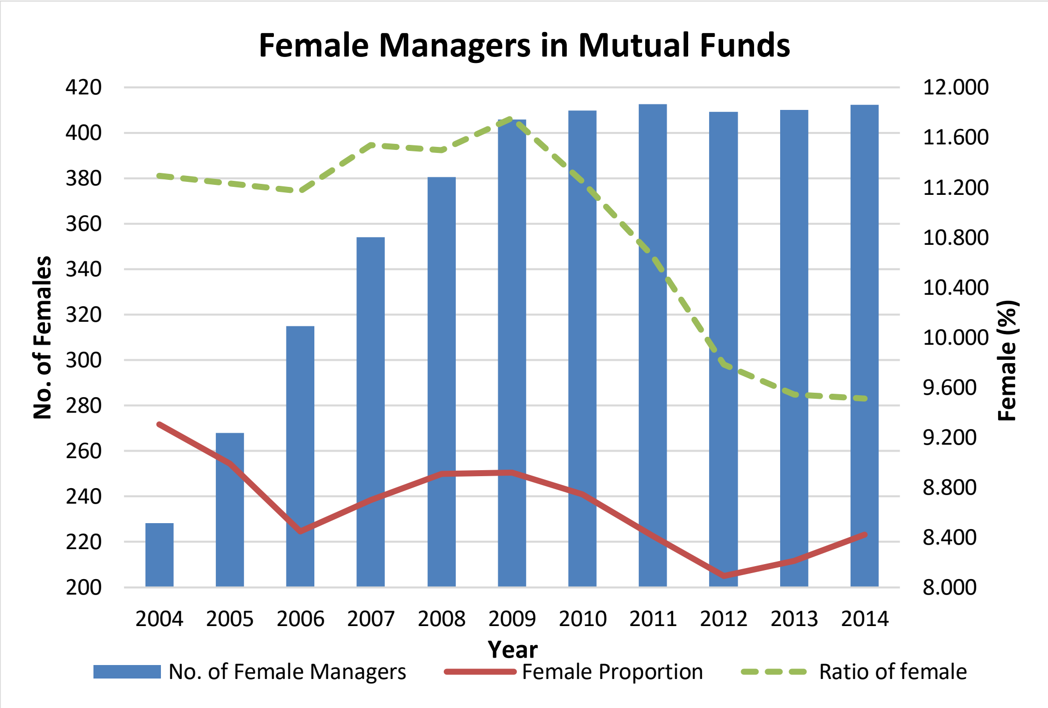

Figure 4.2 shows that from 2004 to 2014, on average, male only managed funds (single as well as team) are 78.4%, female only managed funds (single as well as team) are 2.59%, and teams with mixed gender manage 19% of the sample funds. We observe a small but obvious increase in funds managed by mixed gender teams over the study period, i.e., 17.7 % in 2004 increasing to 18.9% in 2014. However, it is noticeable that the funds managed by only female managers are decreasing over time i.e., 3.96% in 2004 falling to 2.52% in 2014.

Figure 4.2. Gender Balance of Mutual Fund Managers from 2004-2014

Figure 4.2 shows percentage of the sample funds managed by male only (single or team), female only (single or team), and mixed gender teams over the sample period of 2004-2014.

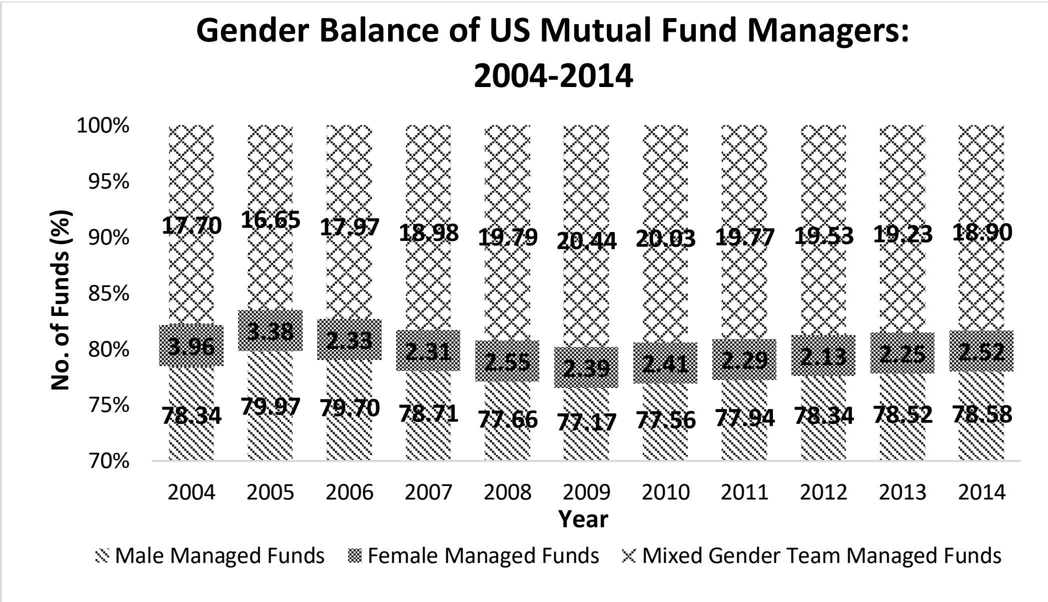

Table 4.1 presents the summary statistics for the variables of this study. See Table C1 in the appendix for the detail explanation of all the variables. The mean (median) of R^2 for the sample is 0.937 (0.948). According to Q1, 25% of R^2 is less than or equal to 92.4%. The results of this measure are limited within the interval of 0 and 1, therefore, we apply logistic transformation to R^2. The mean (median) of the transformed R^2, $T(R^2)$, is 2.416 (2.360). The average proportion of female managers in the sample funds is 0.083 or 8.3%. It is evident that 75% of the female proportion in fund management teams is less than or equal to 10.4%. The mean (median) of the measure of herding, SecDev, is 13.280 (11.955). Total risk has a mean (median) of 1.832 (1.754), while 25% of the risk is below 1.56%, and 75% is less than or equal to 2.03%. The mean (median) of the measure for overconfidence, i.e., TOratio, is 76.690 (61.817). The mean of the style extremity measure, i.e., AggSE, is 1.035 with 50% of style extremity less than or equal to 0.924.

Table 4.1. Summary Statistics

This table presents summary statistics of the main variables of this study. The sample consists of 206,580 fund-month observations from January 2004 to December 2014. R^2 is the measure of fund activity introduced by Amihud, and Goyenko (2013), it is the proportion of the variability in fund returns that is explained by the variation in market factors' returns. $T(R^2)$ is the logistic transformation of R^2. $Female$ is the measure of female proportion and equal to the number of female managers divided by the total number of managers in fund's management team at time t. $SecDev$ is the measure of herding (%) and equal to the square root of the sum of squared differences between portfolio concentration of fund i in each of the three super sectors and the average concentration in each sector among all the funds in fund i's investment segment in the same year t. $UnsysRisk$ is the measure of unsystematic risk (%) and equal to the annual standard deviation of fund return residuals obtained from Carhart's (1997) four factor model. $SysRisk$ is the measure of systematic risk (%) and equal to the annual beta retrieved from regressing fund's excess return on the excess return of market. $Risk$ is the measure of total risk (%) and equal to the sum of systematic and unsystematic risk of fund at time t. $TOratio$ is the measure of overconfidence (%) and equal to the lesser of annual purchases or sales and dividing by average net assets of fund in time t. $AggSE$ is the measure of aggregate style extremity (%) and equal to the mean of style extremity of three style dimensions i.e., size, value, and momentum in time t. $Size$ is the measure of fund size and equal to the natural log of total assets under management of fund in time t. Exp is the measure of expense ratio (%) and equal to the value weighted average of net expense ratio of all the share classes of a fund at time t. $Flow$ is the measure of fund flow and equal to the growth in fund's assets under management in time t.

	Mean	Median	Std. dev.	Q1	Q3
R^2	0.937	0.948	0.051	0.924	0.966
$T(R^2)$	2.416	2.360	0.782	1.964	2.868
Female	0.083	0.000	0.166	0.000	0.104
SecDev	13.280	11.955	6.694	8.674	15.879
SysRisk	0.989	1.000	0.119	0.949	1.042
UnsysRisk	0.842	0.780	0.387	0.580	1.028
Risk	1.832	1.754	0.416	1.557	2.027
TOratio	76.690	61.817	70.903	35.670	92.550
AggSE	1.035	0.924	0.483	0.744	1.194
Size	8.279	8.300	0.875	7.683	8.886
Exp	1.128	1.100	0.432	0.821	1.301
Flow	0.013	0.005	0.019	-0.004	0.022

Table 4.2 describes the correlation between the variables. The correlation between $T(R^2)$ and female proportion is significantly positive. Moreover, the correlation between $T(R^2)$ and the herding measure is negative and significant. The correlation between risk and $T(R^2)$ is significantly negative. The measures of overconfidence and style extremity are both correlated negatively and significantly with $T(R^2)$. Among the fund-specific variables, expense ratio and flow are negatively, while fund size is positively correlated with $T(R^2)$, and all of these correlations are significant. On the other hand, the correlation coefficients of these behavior measures and female proportion are significantly negative.

Table 4.2. Correlation Matrix

This table presents correlation matrix of the variables in this study. The sample consists of 206,580 fund-month observations from January 2004 to December 2014. See Table C1 in the appendix for the explanation of all the variables.

	$T(R^2)$	Female	SecDev	SysRisk	UnsysRisk	Risk	TOratio	AggSE	Size	Exp
Female	0.067[a]									
SecDev	-0.262[a]	-0.068[a]								
SysRisk	-0.009[c]	-0.013[c]	-0.038[a]							
UnsysRisk	-0.596[a]	-0.057[a]	0.293[a]	0.113[a]						
Risk	-0.487[a]	-0.046[a]	0.245[a]	0.485[a]	0.924[a]					
TOratio	-0.089[a]	-0.023[a]	0.063[a]	0.058[a]	0.245[a]	0.238[a]				
AggSE	-0.233[a]	-0.017[a]	0.274[a]	0.096[a]	0.422[a]	0.409[a]	0.164[a]			
Size	0.119[a]	-0.007[a]	-0.096[a]	0.054[a]	-0.157[a]	-0.118[a]	-0.129[a]	-0.154[a]		
Exp	-0.291[a]	0.005[b]	0.169[a]	-0.024[a]	0.319[a]	0.273[a]	0.136[a]	0.200[a]	-0.406[a]	
Flow	-0.049[a]	-0.010[a]	0.035[a]	-0.019[a]	0.017[a]	0.008[a]	0.004	0.045[a]	-0.129[a]	-0.005[b]

[a] $p < 0.01$, [b] $p < 0.05$, [c] $p < 0.10$

4.4 Empirical Results and Discussion

4.4.1 Effect of Female Proportion on Fund R^2

We start our empirical analysis by examining the impact of the proportion of female fund managers on fund R^2 and present the results in Table 4.3. Using Equation (4), Column (1) of Table 4.3 reports that fund returns closely track the returns of the multifactor benchmark when there is a higher proportion of female managers in the management team. The goodness of fit of the baseline model is 9.26%. The finding is consistent with our argument that collective self-construal of female managers possibly contributes to their tendency of investing in accordance with the market. Hence, female fund managers manage funds less actively.

The significantly positive relationship between female proportion and R^2 holds even after controlling for each fund-specific variable in Columns (2), (3) and (4). The findings describe that fund size has a significantly positive impact on fund R^2, indicating that the returns of large funds co-move more with the benchmark in comparison to small funds. In contrast, the expense ratio and fund flow affect R^2 negatively and the results are statistically significant at the 1% level. This signals that less actively managed funds are less costly and receive lower flows in comparison to actively managed funds. We present the results with adjusted standard errors for fund and month clustering. We conclude that the presence of female managers, either in single or mixed-gender team management, does affect the investing strategy of funds. The outcome of our study is consistent with the literature on gender, which argues that females influence the decisions of teams. Hence, their corporate decisions are different from males (Adams & Ferreira, 2009; Jurkus, Park, & Woodard, 2011; Liu, Wei, & Xie, 2014).

Table 4.3. Female Proportion and Fund R^2

This table presents the findings of regression of fund's R^2 on female proportion, including fund level controls. R^2 is retrieved from the annual time series regression of Carhart's (1997) four factor model given in Equation (1). The dependent variable is the transformed R^2 explained in Equation (2). The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$T(R_{i,t}^2) = \alpha + \beta_1 \, Female_{i,t} + \beta_2 \, Size_{i,t} + \beta_3 \, Exp_{i,t} + \beta_4 \, Flow_{i,t} + \varepsilon_{i,t}$$

	Fund R^2			
	All Controls	Fund Size Control	Expense Control	Flow Control
	(1)	(2)	(3)	(4)
Female	0.3848***	0.3920***	0.3830***	0.3892***
	(4.32)	(4.12)	(4.32)	(3.99)
Size	-0.0075	0.1583***	-	-
	(-0.36)	(7.68)		
Exp	-0.7795***	-	-0.7720***	-
	(-12.98)		(-13.96)	
Flow	-1.2664***	-	-	-1.0633***
	(-7.85)			(-6.28)
Constant	4.2039***	1.9159***	4.1208***	3.2589***
	(18.90)	(10.99)	(45.92)	(60.74)
No. of Obs.	164,645	170,464	167,293	167,620
Adj. R-squared	0.0926	0.0188	0.0892	0.0069

4.4.2 Effect of Female Proportion on Economic Benefits of Diversification

In this study we perform a mean-variance spanning test to investigate the effect of investing in funds on the minimum-variance frontier and apply a performance measure to assess the economic gains of diversification when a high fraction of female managers manages funds. Huberman and Kandel (1987) describe the concept of mean-variance spanning. They suggest that a set of K risky assets (benchmark assets) spans a larger set of K+N risky assets (test assets) if the minimum-variance frontier of both sets of assets is identical. Modern portfolio theory states that when there exists a risk-free asset, and unlimited lending and borrowing at the risk-free rate is allowed, investors who care only about the mean and variance of their portfolios will only be interested in the tangency portfolio of the risky asset (the one that maximizes the Sharpe ratio). We use the spanning tests of the tangency portfolio (De Roon &

Nijman, 2001; Kan & Zhou, 2001). The tangency portfolio relates to the changes in the Sharpe ratio that correspond to the shift in the optimal risky portfolio when the test asset is added to the set of benchmark assets. The Sharpe ratio of the tangency portfolio gives the largest mean return per unit of standard deviation risk attainable for the assets.

In our study, we consider the benchmark portfolio of assets based on Carhart's (1997) four factors (i.e., RMRF, SMB, HML, MOM). We assess the additional gains when we add funds in the benchmark portfolio. Firstly, we examine the benchmark case of diversification and measure the maximum Sharpe ratio for the addition of every fund in the benchmark. Then, to test whether the maximum Sharpe ratio of the optimal benchmark portfolio is different from the Share ratio of every fund, we take the difference between the Sharpe ratios. A difference between the Sharpe ratios, computed for the optimal benchmark and the funds, indicates that investors can enhance their returns per unit of risk by diversifying their investments in the funds. This assesses the magnitude of diversification benefit. Finally, to examine the impact of having a high proportion of female managers in a fund's management team on the diversification benefits of the fund, we use the following model:

$$\begin{aligned} Div\_Benefit_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2\, Team\_Size_{i,t} \\ + \beta_3\, Fund\ Charateristics_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where $Div\_Benefit_{i,t}$ is the difference between the Sharpe ratios computed for the optimal benchmark and each fund *i* in time *t*. The other variables are as defined in Section 4.3.

According to the findings in Table 4.4, the diversification gains of funds managed by a higher fraction of female fund managers are 1.86% lower than other funds. The results are significant after controlling for fund-specific characteristics and time and segment (i.e. find investment objective) fixed effects. The benefits are 1.64% smaller than other funds when we control for team size and fund-specific time varying variables. Hence, we conclude that less active investing of female managers reduces the rewards of diversification. Investors who want to enhance their returns per unit of risk by diversification will not be attracted to the funds that have more females than males in their management teams.

Table 4.4. Female Proportion and Economic Benefits of Diversification

This table presents the findings of regression of diversification benefits on female proportion, including team size and fund level controls. The dependent variable is $Div\_Benefit$, which is the difference in the Sharpe Ratio of optimized benchmark and our sample funds. The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. Column (1) controls for all fund level characteristics. Column (2) presents the results with team size and time lagged fund level variables. $Team\_Size$ is equal to the total number of managers in fund management team in time t. We winsorize the fund level control variables at 1% and 99%. We include fixed effect at time and segment level. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$Div\_Benefit_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2\, Team\_Size_{i,t} + \beta_3\, Fund\ Charateristics_{i,t-1} + \varepsilon_{i,t}$$

	Diversification Benefits	
	(1)	(2)
Female	-0.0186***	-0.0164***
	(-3.48)	(-3.10)
Size	-0.0194***	-
	(-6.67)	
Exp	-0.0175***	-
	(-4.39)	
Flow	0.2626***	-
	(8.68)	
Team_Size	-	0.0014**
		(2.35)
Size_lag	-	-0.0193***
		(-6.60)
Exp_lag	-	-0.0229***
		(-5.14)
Flow_lag	-	0.2555***
		(8.49)
Year-fixed Effect	YES	YES
Segment-fixed Effect	YES	YES
No. of Obs.	164,794	163,290
Adj. R-squared	0.1434	0.1486

4.4.3 Effect of Investment Behaviors of Female Managers on Fund R^2

The existing research studies explore the impact of several investment behaviors of gender on investment decisions. We consider three behaviors, mostly studied in the context of fund managers, and examine their impact on fund activity.

4.4.3.1 Effect of Herding on R^2

The psychology literature states that the actions of people in a group, which women belong to, influence the behavior of women due to their collective self-construal. Therefore, we expect that, compared to male fund managers, females are less likely to make unique decisions which are against the common investment strategies of the group (i.e., the market benchmark). Mimicking the strategies of other managers explains higher herding. Bo, Li, and Sun (2016) provide evidence that boards with more female directors make investment decisions closer to their peers in the same industry. There exists empirical evidence that herd behavior potentially contributes to return co-movement (Eun, Wang, & Xiao, 2015).

To measure fund herding, we use a proxy developed by Chevalier and Ellison (1999b). The measure is Sector deviation, which estimates sectors' concentration within a fund's portfolio that deviates from those sectors that are most popular in the specific year. Sector deviation, $SecDev$, is the square root of the sum of the squared differences between a fund's portfolio concentration in each of the three super sectors (reported by Morningstar) and the average exposure in each sector among all the funds in that fund's investment segment in the same year. Small $SecDev$ indicates that a fund manager is less likely to concentrate the portfolio in sectors which are not popular among other funds.[54] We measure Sector deviation as follow$s$:

$$SecDev_{i,t} = \sqrt{\sum_{k=1}^{n} (w_{i,k,t} - \overline{w}_{k,t})^2} \tag{6}$$

where $SecDev_{i,t}$ is the measure of herding for fund *i* at time *t*. *n* is equal to 3 (number of super sectors). $w_{i,k,t}$ is the investment weight/concentration of fund *i* in each of the three super sectors *k* in year *t*, while $\overline{w}_{k,t}$ is the average weight in each of the sectors *k* in year *t* among all the funds in fund *i*'s investment segment (growth, aggressive growth, growth and income, income).

[54] Since the equity funds adopt different investment styles, the herding measure is estimated at the investment segment level.

We hypothesize that female fund managers herd more in popular sectors. First, we run the following model to test the relationship between the fraction of female managers and fund herding:

$$SecDev_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2 Size_{i,t} + \beta_3 Exp_{i,t} + \beta_4 Flow_{i,t} + \varepsilon_{i,t} \qquad (7)$$

where $SecDev_{i,t}$ is the proxy of herding of fund *i* at time *t*. The other variables are as defined in Section 4.3.

Second, we test our hypothesis that fund herding explains higher R^2 in the following model:

$$T\left(R_{i,t}^2\right) = \alpha + \beta_1 SecDev_{i,t} + \beta_2 Size_{i,t} + \beta_3 Exp_{i,t} + \beta_4 Flow_{i,t} + \varepsilon_{i,t} \qquad (8)$$

Table 4.5 presents the results of the influence of female managers on fund herding. Column (1) displays the results with all fund level controls. It is shown that when a high fraction of female managers manages funds, their portfolio concentration in each of the three super sectors strongly mimics the average exposure in each sector by all other funds. The negative coefficients in Columns (1) to (4) indicate that a fund's sector deviation decreases with more female managers serving in the fund management team. This negative relation is significant at the 1% level. We conclude that female fund managers exhibit higher herding behavior than their male counterparts. One of the explanations of their herding behavior might be the reputational concern. According to Scharfstein and Stein (1990), managers who are concerned about their reputations, mimic investment strategies of other managers in the market. Popescu and Xu (2014) reports that reputational concerns of institutional managers drive institutional herding. The underrepresentation of female fund managers may increase strict scrutiny of their decisions by the market participants. Any unique decision can damage their reputation; therefore, female fund managers may prefer to herd the popular investment strategies of their peers. We do not provide empirical evidence in this regard because the topic of reputational herding is beyond the scope of this study.

Table 4.5. Female Proportion and Fund Herding

This table presents the findings of regression of fund herding on female proportion, including fund level controls. The dependent variable is fund herding, which is measured as Sector Concentration Deviation, $SecDev$, explained in Equation (6). The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$SecDev_{i,t} = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t}$$

	Sector Concentration Deviation			
	All Controls	Fund Size Control	Expense Control	Flow Control
	(1)	(2)	(3)	(4)
Female	-2.8225***	-2.8349***	-2.8182***	-2.8024***
	(-4.82)	(-4.86)	(-4.78)	(-4.77)
Size	-0.1878	-0.8972***	-	-
	(-0.97)	(-5.22)		
Exp	3.0858***	-	3.2105***	-
	(6.74)		(7.76)	
Flow	4.6360***	-	-	5.3526***
	(3.83)			(4.45)
Constant	11.4115***	20.9310***	9.7379***	13.3127***
	(5.99)	(14.54)	(19.28)	(67.60)
No. of Obs.	164,794	171,307	167,521	168,083
Adj. R-squared	0.0353	0.0138	0.0334	0.0059

The results in Table 4.6, Columns (1) to (4), show that Sector concentration deviation is negatively related to $T(R^2)$ and the association is statistically significant at the 1% level. The negative effect is consistent and statistically significant with the controls of all fund-specific variables in Columns (2) to (4). These findings show that, when funds deviate their investment concentration from the popular sectors, their returns do not closely track the benchmark returns. We conclude that funds with a high fraction of female managers herd more in the poplar sectors, and their returns tend to closely track market returns.

Table 4.6. Herding and Fund R^2

This table presents the findings of regression of fund's R^2 on herding, including fund level controls. R^2 is retrieved from the annual time series regression of Carhart's (1997) four factor model given in Equation (1). The dependent variable is the transformed R^2 explained in Equation (2). The independent variable is fund herding, which is measured as Sector Concentration Deviation, $SecDev$, explained in Equation (6). We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$T(R^2_{i,t}) = \alpha + \beta_1 \, SecDev_{i,t} + \beta_2 \, Size_{i,t} + \beta_3 \, Exp_{i,t} + \beta_4 \, Flow_{i,t} + \varepsilon_{i,t}$$

	Fund R^2			
	All Controls	Fund Size Control	Expense Control	Flow Control
	(1)	(2)	(3)	(4)
SecDev	-0.0309***	-0.0356***	-0.0310***	-0.0369***
	(-14.70)	(-15.65)	(-14.68)	(-15.95)
Size	-0.0126	0.1270***	-	-
	(-0.66)	(6.99)		
Exp	-0.6826***	-	-0.6710***	-
	(-11.89)		(-12.80)	
Flow	-1.1407***	-	-	-0.8816***
	(-7.22)			(-5.38)
Constant	4.5735***	2.6807***	4.4460***	3.7740***
	(21.83)	(16.80)	(49.19)	(57.74)
No. of Obs.	165,181	171,035	167,864	168,156
Adj. R-squared	0.1350	0.0780	0.1323	0.0710

4.4.3.2 Effect of Risk-taking Behavior on R^2

To analyze the risk-taking behavior of fund managers, the study follows Chevalier and Ellison (1999a) and measures the systematic and unsystematic risk of a fund. The systematic risk, $SysRisk$, is the annual market beta coefficient ($\beta_{i,M,t}$) of Carhart's (1997) four factor model described in Equation (1). On the other hand, the unsystematic risk, $UnsysRisk$, is the annual standard deviation of each fund's return residuals from the model in Equation (1). In Equation (1), $\beta_{i,M,t}$ is the annual measure of systematic risk of fund *i* in year *t*, which describes the sensitivity of a fund's excess returns with the volatility in market excess returns. $\varepsilon_{i,m,t}$ is the return residual of fund *i* in month *m* of year *t*. We expect negative association between fund returns co-movement with the benchmark and riskiness. The less risky fund is expected to show higher R^2.

We use the following model to test the impact of investment riskiness on fund returns' co-movement with the benchmark:

$$T\left(R_{i,t}^{2}\right) = \alpha + \beta_1\, Risk\_Measures_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t} \qquad (9)$$

where $Risk\_Measures_{i,t}$ are the three measures of fund riskiness: $UnsysRisk_{i,t}$ which is the annual standard deviation of fund *i*'s return residuals in year *t*; $SysRisk_{i,t}$, which is the annual $\beta_{i,M,t}$ of fund *i* from Equation (1); and $Risk_{i,t}$, which is the total risk of fund *i* in year *t* measured as the sum of systematic and unsystematic risk. The other variables are as defined in Section 4.3.

Table 4.7 presents the results of the association between level of riskiness and fund activity. After controlling for fund level characteristics, we observe that all three measures of fund riskiness show a negative relation with R^2 and the relation is significant at the 1% level. The outcomes support the hypothesis that risky investments decrease the tracking of funds' returns with the benchmark returns. High risk-taking behavior of fund managers may explain the outperformance from the benchmark.

The literature on gender behaviors argues that female fund managers show less risk-taking behavior than male managers (Atkinson, Baird, & Frye, 2003; Niessen & Ruenzi, 2006). We analyze the effect of the proportion of female managers on fund riskiness, and the results are consistent with the literature. We present the results in Table C3 in the Appendix. The findings provide empirical evidence that the total risk of a fund diminishes when more female managers are in the management team and the association is statistically significant at the 1% level. Hence, we conclude that the lesser risk-taking behavior of female fund managers than of male managers is more likely to be dominant in a team's decision making.

Table 4.7. Risk and Fund R^2

This table presents the findings of regression of fund's R^2 on riskiness of fund investments, including fund level controls. R^2 is retrieved from the annual time series regression of Carhart's (1997) four factor model given in Equation (1). The dependent variable is the transformed R^2 explained in Equation (2). The independent variable is fund's risk level, which is measured as $UnsysRisk$, $SysRisk$, and $Risk$ using Equation (1). We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$T(R_{i,t}^2) = \alpha + \beta_1 \, UnsysRisk_{i,t} + \beta_2 \, Size_{i,t} + \beta_3 \, Exp_{i,t} + \beta_4 \, Flow_{i,t} + \varepsilon_{i,t}$$

$$T(R_{i,t}^2) = \alpha + \beta_1 \, SysRisk_{i,t} + \beta_2 \, Size_{i,t} + \beta_3 \, Exp_{i,t} + \beta_4 \, Flow_{i,t} + \varepsilon_{i,t}$$

$$T(R_{i,t}^2) = \alpha + \beta_1 \, Risk_{i,t} + \beta_2 \, Size_{i,t} + \beta_3 \, Exp_{i,t} + \beta_4 \, Flow_{i,t} + \varepsilon_{i,t}$$

	Fund R^2		
	(1)	(2)	(3)
UnsysRisk	-1.2526***	-	-
	(-15.25)		
SysRisk	-	-0.4681***	-
		(-5.76)	
Risk	-	-	-0.8832***
			(-14.40)
Size	-0.0300**	-0.0132	-0.0114
	(-2.12)	(-0.63)	(-0.71)
Exp	-0.3230***	-0.7776***	-0.4582***
	(-7.13)	(-13.32)	(-9.16)
Flow	-1.0521***	-1.2470***	-1.1916***
	(-6.46)	(-7.84)	(-7.13)
Constant	4.9625***	3.8170***	5.5260***
	(29.08)	(16.63)	(26.33)
No. of Obs.	165,181	165,181	165,181
Adj. R-squared	0.3691	0.0954	0.2720

4.4.3.3 Effect of Overconfidence on R^2

A small turnover ratio suggests a less overconfident manager and less trading activity than peers (Barber & Odean, 2001). Morningstar describes the turnover ratio as a measure of the fund's trading activity, and computes the measure by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year), and dividing this by the average monthly net assets. We hypothesize that funds with excessive buying and selling of securities are less likely to follow the benchmark.

Therefore, a higher turnover ratio, $TOratio$, reduces a fund's R^2. The following model tests our argument:

$$T(R^2_{i,t}) = \alpha + \beta_1\, TOratio_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t} \quad (10)$$

where $TOratio_{i,t}$ is the turnover ratio of fund *i* at time *t.* The other variables are as defined in Section 4.3.

Table 4.8. Trading and Fund R^2

This table presents the findings of regression of fund's R^2 on trading activity, including fund level controls. R^2 is retrieved from the annual time series regression of Carhart's (1997) four factor model given in Equation (1). The dependent variable is the transformed R^2 explained in Equation (2). The independent variable is fund's trading activity, which is measured by turnover ratio, $TOratio$. We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$T(R^2_{i,t}) = \alpha + \beta_1\, TOratio_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t}$$

	Fund R^2			
	All Controls	Fund Size Control	Expense Control	Flow Control
	(1)	(2)	(3)	(4)
TOratio	-0.0023***	-0.0020***	-0.0017***	-0.0012***
	(-2.75)	(-4.32)	(-2.73)	(-4.99)
Size	-0.0117	0.1528***	-	-
	(-0.58)	(7.56)		
Exp	-0.7623***	-	-0.7508***	-
	(-12.82)		(-13.73)	
Flow	-1.2418***	-	-	-1.1431***
	(-7.53)			(-6.59)
Constant	4.3140***	2.0816***	4.1911***	3.3956***
	(19.75)	(11.86)	(45.79)	(55.09)
No. of Obs.	161,359	165,129	163,787	162,657
Adj. R-squared	0.0891	0.0209	0.0859	0.0105

Table 4.8 presents that the turnover ratio is negatively associated with R^2 and the association is statistically significant at the 1% level. The findings are consistent with controlling for every fund specific variable and indicate that funds diverge from the benchmark due to excessive and frequent trading by managers. The existing research studies provide evidence that females are less overconfident than males in their corporate decisions (Huang & Kisgen, 2013) and they are less likely to be involved in aggressive trading (Barber & Odean, 2001). Niessen-Ruenzi and Ruenzi (2019) support this

argument by analyzing the trading behavior of male and female fund managers. Our results are consistent with the literature that female fund managers are less aggressive in trading activities. We present the results in Table C4 in the Appendix. The findings show that a 1% increase in the fraction of female managers is related to a 0.1% (monthly) decrease in a fund's turnover ratio, with this result being significant at the 10% level. Hence, we suggest that the aggressive trading behavior of male team members is tamed as the proportion of less overconfident female fund managers goes up.

4.4.3.4 Effect of Investment Style Extremity on R^2

To capture the investment style of a fund manager, the study considers the measure of investment style extremity. We define this measure as taking a large bet on the size, value, or momentum factor (Bär, Kempf, & Ruenzi, 2010; Niessen & Ruenzi, 2006). To measure style extremity, we first compute the annual factor loading ($\beta_{i,S,t}, \beta_{i,H,t}, \beta_{i,MO,t}$) on Carhart's (1997) four factor model described in Equation (1). Style extremity ($SE_{i,t}^F$) is the absolute difference between the fund's factor weightings ($\beta_{i,t}^F$) and the style benchmark ($\bar{\beta}_{i,t}^F$). The style benchmark is the average factor weightings of all the funds in fund *i*'s investment segment and the style factor in the same year *t*. To normalize this extremity, the style extremity measure is divided by the average absolute difference of the corresponding market segment in the respective year. This process gives three extremity values for each fund, corresponding to the three style factors (SMB, HML, and MOM). The style extremity measure is comparable across style, segments, and time after normalization (Bär, Kempf, & Ruenzi, 2010). We measure style extremity with a normalization process in the following model:

$$SE_{i,t}^F = \frac{|\beta_{i,t}^F - \bar{\beta}_{i,t}^F|}{\frac{1}{n}\sum_{j=1}^{n} |\beta_{j,t}^F - \bar{\beta}_{i,t}^F|} \tag{11}$$

where $SE_{i,t}^F$ is the style extremity of fund *i* in year *t* for each of the three style dimensions (*F*=1, 2, 3). Fund *i*'s factor loading for each of the style dimensions *F* in year *t* is denoted by $\beta_{i,t}^F$, while the style benchmark is $\bar{\beta}_{i,t}^F$. *j* stands for the corresponding market segment, and *n* is the number of funds in this corresponding segment in year *t*.

To get an aggregate measure for extremity for each fund, following Niessen and Ruenzi (2006), we average three individual extremity measures as follows:

$$AggSE_{i,t} = \frac{1}{3} \sum_{F} SE_{i,t}^{F} \qquad (12)$$

where $AggSE_{i,t}$ is the average extremity of fund *i* in year *t*, which is by definition equal to "1", and any higher measure will show an extreme style.

We expect that higher bets and a more extreme investment style by fund managers result in the funds' divergence from the benchmark. We test this conjecture in the following model:

$$T\left(R_{i,t}^{2}\right) = \alpha_{i,t} + \beta_1\, AggSE_{i,t} + \beta_2\, FSize_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t} \qquad (13)$$

where $AggSE_{i,t}$ is the aggregate style extremity measure of fund *i* in year *t*, which is aggregated for the three style dimensions. The other variables are as defined in Section 4.3.

Table 4.9 displays the regression outcomes of Equation (13) and indicates that investment style extremity is negatively related to R^2. This relation is significant at the 1% level after controlling for all fund specific characteristics. The goodness of fit of the model in Column (1) is 13.04%. The findings suggest that funds are less likely to track the benchmark if managers take larger bets on the size, value, or momentum factor.

Niessen and Ruenzi (2006) report that female fund managers exhibit a less extreme investment style in comparison to their male counterparts. We present the results in Table C5 in the Appendix. Our results describe that the association between the fraction of female fund managers and style extremity is negative, however, the findings are not statistically significant. Therefore, our findings are not conclusive. Our study considers female fund managers in single as well as management teams, while Niessen, and Ruenzi (2006) analyze single managed funds. This might be one of the reasons for the difference in outcomes.

Table 4.9. Style Extremity and Fund R^2

This table presents the findings of regression of fund's R^2 on investment style extremity, including fund level controls. R^2 is retrieved from the annual time series regression of Carhart's (1997) four factor model given in Equation (1). The dependent variable is the transformed R^2 explained in Equation (2). The independent variable is fund's aggregated style extremity, which is measured in Equation (12). We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$T(R^2_{i,t}) = \alpha + \beta_1 \, AggSE_{i,t} + \beta_2 \, Size_{i,t} + \beta_3 \, Exp_{i,t} + \beta_4 \, Flow_{i,t} + \varepsilon_{i,t}$$

	Fund R^2			
	All Controls	Fund Size Control	Expense Control	Flow Control
	(1)	(2)	(3)	(4)
AggSE	-0.4002***	-0.4282***	-0.3946***	-0.4669***
	(-17.69)	(-16.34)	(-17.33)	(-18.62)
Size	-0.0261	0.1104***	-	-
	(-1.40)	(6.03)		
Exp	-0.6805***	-	-0.6598***	-
	(-12.22)		(-12.87)	
Flow	-1.1474***	-	-	-0.8283***
	(-7.38)			(-5.12)
Constant	4.6762***	2.7784***	4.4173***	3.7536***
	(22.79)	(17.31)	(48.39)	(57.90)
No. of Obs.	165,171	171,024	167,853	168,146
Adj. R-squared	0.1304	0.0672	0.1268	0.0648

4.5 Additional Investigation

In this section, we describe some additional tests to support the relation between degree of active management of funds and the female proportion in their management team.

4.5.1 Time-varying Fund Correlation and Market Model

For the analysis, we retrieve annual R^2 from the time series regression of Carhart's (1997) four factors model and use this as a measure of activeness. As an alternate measure, we calculate the time varying conditional correlation of fund returns by applying the dynamic conditional correlation (DCC) model of Engle (2002). We replace the measure of activeness, i.e., R^2, with monthly time varying conditional correlation and re-run all the regression models for robustness.

Table 4.10 presents the findings of regressions with time varying conditional correlation as the dependent variable. All fund specific characteristics are the same. Column (1) displays the findings of the model given in Equation (4), where female proportion is the independent variable. Column (2) presents the findings of the association between fund herding and fund correlation with the market. Columns (3) to (5) show the results of the impact of funds' riskiness, trading activity, and style extremity on funds' time-varying conditional correlation, respectively. All the results are consistent with the previously explained relations and are significant at the 1% level. We observe a significant improvement in the overall goodness of fit of each model. The goodness of fit of the main model, i.e., Column (1), improves from 9.26% (with R^2) to 16.69% (with time varying correlation). We conclude that our results are robust even with an alternate measure of the dependent variable.

We again calculate the measures of fund risk level by using the Market model given below:

$$R_{i,m,t} - R_{f,m,t} = \alpha + \beta_{i,M,t}\left(R_{M,m,t} - R_{f,m,t}\right) + \varepsilon_{i,m,t} \tag{14}$$

where $(R_{i,m,t} - R_{f,m,t})$ is the excess return of fund *i* over the risk free return in month *m* of year *t*. $(R_{M,m,t} - R_{f,m,t})$ is the excess return of market *M* in month *m* of year *t*. $\beta_{i,M,t}$ is the annual measure of systematic risk of fund *i* in year *t*, which describes the sensitivity of a fund's excess returns to the volatility in market excess returns. $\varepsilon_{i,m,t}$ is the return residual of fund *i* in month *m* of year *t*.

We run the model given in Equation (9). The dependent variable is the time varying conditional correlation of fund returns, and we calculate the three risk measures; unsystematic, systematic, and total risk; from the market model given in Equation (14). The results are robust and indicate that high riskiness of funds possibly explains a diminishing correlation between funds and the benchmark returns.[55]

[55] We present the results in Table C6 in the Appendix.

Table 4.10. Female Proportion, Investment Behaviors, and Time-varying Conditional Correlation

This table presents the findings of regression of fund returns correlation on female proportion, herding, risk level, trading activity, and style extremity of fund, including fund level controls. The dependent variable is DCC, which is the dynamic conditional correlation of fund returns measured by using the model of Engle (2002). In Column (1), the independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. In Column (2), the independent variable is fund herding, which is measured as Sector Concentration Deviation, $SecDev$, explained in Equation (6). In Column (3), the independent variable is fund's risk level, which is measured as total risk, $Risk$, using Equation (1). In Column (4), the independent variable is fund's trading activity, which is measured by turnover ratio, $TOratio$. In Column (5), the independent variable is fund's aggregated style extremity, which is measured in Equation (12). We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

	Fund Time-varying Conditional Correlation				
	(1)	(2)	(3)	(4)	(5)
Female	0.3519***	-	-	-	-
	(4.55)				
SecDev	-	-0.0298***	-	-	-
		(-15.11)			
Risk	-	-	-0.6331***	-	-
			(-17.73)		
TOratio	-	-	-	-0.0015***	-
				(-3.36)	
AggSE	-	-	-	-	-0.4407***
					(-18.66)
Size	0.0023	-0.0034	-0.0014	-0.0095	-0.0194
	(0.10)	(-0.15)	(-0.07)	(-0.46)	(-0.95)
Exp	-0.7625***	-0.6701***	-0.5330***	-0.7313***	-0.6550***
	(-13.41)	(-12.36)	(-10.97)	(-13.19)	(-12.75)
Flow	-0.8920***	-0.7720***	-0.8597***	-0.8971***	-0.7741***
	(-6.81)	(-6.11)	(-7.05)	(-6.75)	(-6.39)
Constant	3.2476***	3.6107***	4.2111***	3.4602***	3.7744***
	(13.92)	(16.89)	(23.12)	(17.24)	(18.89)
No. of Obs.	164,794	165,331	165,181	161,493	165,171
Adj. R-squared	0.1669	0.2423	0.3383	0.1799	0.2570

4.5.2 Manager and Time-varying Fund Level Characteristics, Team Size, and Fixed Effects

In our analysis, endogeneity exists due to the possibility of unobserved omitted variables of manager or fund-specific characteristics. To deal with these concerns, we consider fund managers' demographics along with the segment and time fixed effects (Chevalier & Ellison, 1999b; Niessen & Ruenzi, 2006).

We develop a model that controls for a manager's characteristics like age, professional certification, education, and tenure. We also consider time-varying fund-specific characteristics and control for one-month lagged fund size, net expense ratio, and fund flow. The literature about mutual funds suggests that team size affects the behaviors of team members and the resulting performance of fund managers (Bär, Kempf, & Ruenzi, 2010; Bär, Niessen-Ruenzi, & Ruenzi, 2009). Therefore, our study controls for the team size of sample funds. The model below includes the segment and time fixed effects of the funds:

$$\begin{aligned} DCC_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2\, Age_{i,t} + \beta_3\, Grad_{i,t} + \beta_4\, PhD_{i,t} + \beta_5\, Cert_{i,t} \\ + \beta_6\, Tenure_{i,t} + \beta_7\, Size_{i,t-1} + \beta_8\, Exp_{i,t-1} + \beta_9\, Flow_{i,t-1} \\ + \beta_{10}\, Team\_Size_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{15}$$

where $DCC_{i,t}$ is the time varying conditional correlation of fund *i*'s returns in time *t*. $Age_{i,t}$ is the average age of all managers managing fund *i* in time *t*. Following Chevalier and Ellison (1999a), we assume that a manager is 21 years old at the time of completion of his/her undergraduate degree. $Grad_{i,t}$ is a dummy variable that takes the value "1" if the fund has a manager with a graduate degree, and "0" otherwise. $PhD_{i,t}$ is a dummy variable that takes the value "1" if the fund has a manager with a Ph.D. degree, and "0" otherwise. $Cert_{i,t}$ is a dummy variable for professional certification that takes the value "1" if the fund has a manager with professional certification like CFA or CPA, and "0" otherwise. $Tenure_{i,t}$ is the average tenure of all the managers in fund *i* in time *t*. $Size_{i,t-1}$, $Exp_{i,t-1}$, and $Flow_{i,t-1}$ are one month lagged fund-specific variables. $Team\_Size_{i,t}$ is the total number of managers in fund *i*'s management team in time *t*. We consider year and segment (Aggressive Growth, Growth, Growth and Income, and Income) fixed effects in the model.

Table 4.11 presents the results of the model in Equation (15). Column (1) shows the relationship between female proportion and the correlation of fund returns with market returns, controlling for all manager level and lagged fund-level characteristics. The association is positive and significant at the 1% level. Column (2) displays the results by considering the size of funds' teams. The findings show that a high fraction of female managers in management team contributes to a higher correlation of fund returns, even after controlling for team size and lagged fund level variables.

We analyze the relation between fund correlation and the measures of investment behaviors by considering team size and lagged fund specific characteristics. We develop the following model:

$$DCC_{i,t} = \alpha + \beta_1 Investments_{i,t} + \beta_2\, Size_{i,t-1} + \beta_3\, Exp_{i,t-1} + \beta_4\, Flow_{i,t-1} + \beta_5\, Team\_Size_{i,t} + \varepsilon_{i,t} \tag{16}$$

where $Investments_{i,t}$ denotes to the measures of herding, risk, trading activity, and style extremity of fund *i* in time *t*. Other fund specific variables are already explained.

Table 4.12, Column (1) shows the findings of the impact of herding on the correlation of fund returns. Columns (2) to (4) are the results of the associations between funds' correlation and risk, the turnover ratio, and the investment extremity style. All the findings, except the measure of overconfidence, are consistent with our main results. Hence, we conclude that unobserved manager, or fund related, traits do not affect the findings of this study.

Table 4.11. Female Proportion and Fund Correlation

This table presents the findings of regression of fund returns correlation on female proportion, including team size, manager level, and time lagged fund level controls. The dependent variable is DCC, which is the dynamic conditional correlation of fund returns measured by using the model of Engle (2002). The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. In Column (1), we control for fund level characteristics which are one month lagged, and manager level characteristics. Age is the average age of all managers managing a fund in time t, $Grad$ is a dummy variable and equal to 1 if the fund has a manager with graduate degree, and 0 otherwise, PhD is a dummy variable and equal to 1 if the fund has a manager with Ph.D. degree, and 0 otherwise, $Cert$ is a dummy variable and equal to 1 if the fund has a manager with professional certification, and 0 otherwise, $Tenure$ is the average tenure of all the managers in a fund in time t. In Column (2), we control for one month lagged fund level variables, and $Team\_Size$ which is equal to the total number of managers in fund management team in time t. We winsorize the fund level control variables at 1% and 99%. We include fixed effect at time and segment level. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$DCC_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2 Age_{i,t} + \beta_3 Grad_{i,t} + \beta_4 PhD_{i,t} + \beta_5 Cert_{i,t} + \beta_6 Tenure_{i,t} + \beta_7 Size_{i,t-1} + \beta_8 Exp_{i,t-1} + \beta_9 Flow_{i,t-1} + \beta_{10} Team\_Size_{i,t} + \varepsilon_{i,t}$$

	Fund Time-varying Conditional Correlation	
	(1)	(2)
Female	0.0076***	0.0056***
	(4.26)	(3.70)
Age	0.0001	-
	(1.24)	
Grad	0.0065***	-
	(2.94)	
PhD	0.0040***	-
	(3.06)	
Cert	-0.0033**	-
	(-2.12)	
Tenure	-0.0005***	-
	(-3.50)	
Size_lag	0.0004	-0.0003
	(0.45)	(-0.36)
Exp_lag	-0.0133***	-0.0129***
	(-6.34)	(-6.86)
Flow_lag	-0.0222	-0.0258*
	(-1.56)	(-1.85)
Team_Size	-	0.0008***
		(6.31)
Year-fixed Effect	YES	YES
Segment-fixed Effect	YES	YES
No. of Obs.	129,269	163,290
Adj. R-squared	0.9747	0.9729

Table 4.12. Investment Behaviors and Fund Correlation

This table presents the findings of regression of fund returns correlation on herding, risk level, trading activity, and style extremity of fund, including team size and time lagged fund level controls. The dependent variable is DCC, which is the dynamic conditional correlation of fund returns measured by using the model of Engle (2002). In Column (1), the independent variable is fund herding, which is measured as Sector Concentration Deviation, $SecDev$, explained in Equation (6). In Column (2), the independent variable is fund's risk level, which is measured as total risk, $Risk$, using Equation (1). In Column (3), the independent variable is fund's trading activity, which is measured by turnover ratio, $TOratio$. In Column (4), the independent variable is fund's aggregated style extremity, which is measured in Equation (12). The control variable $Team\_Size$ is equal to the total number of managers in fund management team in time t. We winsorize the fund level control variables at 1% and 99%. We include fixed effect at time and segment level. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$DCC_{i,t} = \alpha + \beta_1 Investments_{i,t} + \beta_2\, Size_{i,t-1} + \beta_3\, Exp_{i,t-1} + \beta_4\, Flow_{i,t-1} + \beta_5\, Team\_Size_{i,t} + \varepsilon_{i,t}$$

	Fund Time-varying Conditional Correlation			
	(1)	(2)	(3)	(4)
SecDev	-0.0007***	-	-	-
	(-4.65)			
Risk	-	-0.0271***	-	-
		(-5.79)		
TOratio	-	-	-0.0011	-
			(-1.17)	
AggSE	-	-	-	-0.0138***
				(-6.42)
Size_lag	-0.0004	-0.0001	-0.0005	-0.0009
	(-0.46)	(-0.01)	(-0.62)	(-1.19)
Exp_lag	-0.0126***	-0.0103***	-0.0126***	-0.0123***
	(-6.90)	(-5.40)	(-6.59)	(-6.89)
Flow_lag	-0.0247*	-0.0283**	-0.0266*	-0.0247*
	(-1.78)	(-1.99)	(-1.89)	(-1.73)
Team_Size	0.0008***	0.0008***	0.0009***	0.0008***
	(6.36)	(5.10)	(6.29)	(5.87)
Year-fixed Effect	YES	YES	YES	YES
Segment-fixed Effect	YES	YES	YES	YES
No. of Obs.	163,290	163,185	159,716	163,176
Adj. R-squared	0.9729	0.9730	0.9729	0.9729

4.5.3 Effect of Fund Size

For the purpose of analyzing the possible impact of fund size on the association between female proportion and the correlation of fund returns with the benchmark, we categorize the sample funds according to their fund size. The quantiles are as follows: below 33.33%, between 33.33% and 66.66%, and above 66.66%. We classify funds into small, medium, and large sized groups. We use the model in Equation (4), with $DCC_{i,t}$ as the dependent variable. Table 4.13 shows the findings of the regression for the three categories of fund size. The results support our main conjecture that funds managed by a high proportion of female managers have a higher correlation with the benchmark. The coefficients of female proportion are positive and significant in small, medium, and large sized funds. Moreover, we observe a persistent increase in the coefficient of female proportion, which indicates that the relationship among the main variables becomes stronger as fund size increases.

One of the possible explanations of this result is the fact that large funds tend to appoint more female managers. As described by Niessen and Ruenzi (2006), mainly large funds and well-established families employ female managers because they have reputational concerns, and they are more likely to be sued in anti-discrimination lawsuits. Moreover, large funds have big institutional investors who often appreciate work force diversity in the firms they do business with. Hence, large sized funds have more female managers; hence, these funds' returns correlate more with the benchmark.

Table 4.13. Effect of Fund Size on Female Proportion and Fund Correlation

This table presents the findings of regression of fund returns correlation on female proportion under three quantiles of fund size, including fund level controls. The dependent variable is DCC, which is the dynamic conditional correlation of fund returns measured by using the model of Engle (2002). The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. *Q1* consists of funds with fund size below 33.33%, *Q2* includes funds with fund size between 33.33% - 66.66%, *Q3* is based on funds with fund size above 66.66%. We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

	Fund Time-varying Conditional Correlation		
	Q1	Q2	Q3
Female	0.2408*	0.2839**	0.3028**
	(1.79)	(2.31)	(2.23)
Size	0.1526*	-0.0805*	-0.1532***
	(1.83)	(-1.70)	(-3.49)
Exp	-0.5169***	-0.8587***	-0.9265***
	(-7.24)	(-9.19)	(-9.22)
Flow	-0.3918**	-1.0974***	-1.2341***
	(-2.28)	(-5.51)	(-4.34)
Constant	1.7466***	4.0990***	4.8458***
	(2.64)	(9.24)	(10.70)
No. of Obs.	43,164	57,706	63,195
Adj. R-squared	0.1389	0.1439	0.1391

4.6 Conclusion

This study provides empirical evidence that female fund managers influence fund investing strategy. Although less than 10% of all mutual fund managers are women and the majority of them work in mixed gender teams, their collective self-construal plays an important role in the investment decisions. The findings report that funds with a higher proportion of female managers in the team closely track the benchmark. Hence, female fund managers follow less active investing strategies compared to their male counterparts. We apply the Sharpe optimization model of performance in the mean-variance spanning test. The results demonstrate that a marginal change in the risk-to-reward measure (diversification benefits) decreases with funds that are managed by more female than male managers. Hence, the collective self-construal of female managers possibly explains the reduction in funds' activity, making them less attractive to investors.

To support the main findings, we analyze the impact of various investment behaviors of the gender of mutual fund managers on funds' activity. Consistent with the collectivism argument, the results show that female fund managers herd more by concentrating investments in the most popular sectors. The funds which herd more have returns that closely track the returns of the multifactor benchmark. Consistent with the literature, we find that female fund managers are more risk averse and less overconfident than male managers. Risky investments increase the activity of funds because they generate higher returns and are likely to beat the benchmark. Therefore, less risk-taking behavior and less aggressive trading potentially explain a higher R^2. We also find that a less extreme investment style tends to significantly decrease fund activity. The results are robust to various additional tests. We suggest a future research to investigate the impact of the collective self-construal of female directors and executives on corporate decisions.

CHAPTER 5

CONCLUSION

This chapter concludes the thesis by providing a summary of the main results of the three essays in Section 5.1. Section 5.2 documents potential directions for future research.

5.1 Major Findings and Conclusion

Women are underrepresented at leadership positions and the gender gap persists globally. The existing literature regarding the advantages of female inclusion in investment decisions suggests that higher gender diversity is associated with positive outcomes for employers. However, several studies have documented no significant difference in the decision making or skills of male and female professional investors. Moreover, the literature on gender provides empirical evidence that gender stereotype market participants undermine the performance of professional females and encourage gender bias in investment industry. The gender gap exists in top positions and efforts are required to address this issue. This thesis explores investment behaviors of females who have reached to the top positions of investment industry or at the executive positions of corporations and possess strength in decision making. The three studies in the thesis examine whether females' investment preferences and trading behaviors are different from those of their male counterparts, and also examine the role of various factors that possibly contribute to the disparities between male and female investment decisions.

In the first essay, we observe that only 5.71% of top executives in our sample are female. Moreover, this percentage decreases further when we observe that female top executives are involved in only 2.56% of the insider trades. Using a sample of U.S. top executives' insider trades, the findings show that female insiders carry biased trades based on prospect theory value and earn losses higher than their male counterparts. On average, the number of insider transactions, past 12-months' cumulative returns, share turnover, the number of shares traded, and the dollar-value of male trades are greater than for female trades. We document that insiders earn lower returns in the subsequent month when they buy (sell) stock with a prospect theory value higher (lower) than other firms. This finding is consistent with the literature that trades based on prospect theory value negatively impact subsequent returns.

We follow the literature that limited information contributes to higher behavioral biases, and that due to male dominance female insiders may have access to limited information, as compared to their male counterparts. Our results demonstrate that information disadvantage to female executives might be the possible explanation of their higher biased trades and resultant losses. The availability of information within an executive category is expected to be equal for all executives, irrespective of their gender. However, we find that higher biased trade losses exist for female insiders with similar formal titles to their male counterparts. In a given trade size, where all inside traders are expected to be equally informed, we find higher losses for females from prospect theory value trades, compared to males. Our findings are consistent in the settings of routine and opportunistic/non-classified trades, and macro-level market uncertainty factors; where the level of information is believed to be the same for all insiders.

If female insiders' access to poor quality information is a possible explanation of their higher biased trades, then we may observe a decrease in their losses for the trades based on superior information. We consider firms with a high proportion of female insider transactions. This serves as a proxy for a high proportion of female insiders, who would reduce the impact of situational factors that may lead to an informational disadvantage. In such a setting, the association between female insiders and biased trade losses is insignificant, demonstrating that informal networks may give an informational advantage to male insiders. Moreover, insiders' buy transactions are based on superior internal information, and market participants are likely to mimic these trades. The results show that losses from prospect theory value bias trades are reduced for female insiders when they carry buy trades.

The second essay uses a sample of single male and female managed active equity funds. We observe that the proportion of single female managed funds decreases over our sample period from the maximum of 11.15% in 2001 to the minimum of 7.68% in 2012. The total number of domestic actively managed equity funds in our sample is 1,932. We observe that 113 (5.85%) are female-only managed funds and 1,658 (85.82%) are male-only managed funds. Considering the importance of liquidity, essay two explores the liquidity preference of fund managers based on their gender. The results demonstrate that the preference of female fund managers for holding liquid portfolios is significantly higher than for male managers. On average, female managed funds are smaller in size, earn lower returns, receive lesser flow, and the portfolios consist of a smaller number of stocks compared to male managed funds.

The factor which potentially explains the preference of female fund managers to hold more liquid stocks is their endorsement of information transparency. We provide empirical evidence that female fund managers are attracted to stocks whose prices incorporate the available information efficiently. Their tendency to invest in price efficient stocks may serve as a channel to higher portfolio liquidity. Additionally, to deal with endogeneity concerns, we apply propensity score matching, difference-in-differences, and instrumental variable approaches on the whole sample, as well as on a sub-sample of transition funds. All the results support our hypothesis that a preference for portfolio liquidity is higher among female than male fund managers, and it is evident that portfolio liquidity significantly improves after a transition from a male to a female fund manager. The study highlights the concerns regarding negatively affected fund performance due to the potential tradeoff between liquidity and returns. However, further detailed analysis is required to reach any conclusions in this regard.

Essay three reports that the ratio of female to male managers has decreased over time from 11.27% in 2004 to 9.51% in 2014. Teams of mixed gender manage 19.6% of the funds in our sample. We report that less than 10% of all mutual fund managers are women and the majority of them prefer to work in mixed gender teams. Our study explores whether investment style of these few female fund managers, either in management teams or single managed funds, influences their fund's strategy and subsequent returns, or they follow the fund management style of their male counterparts. We use the measure of fund activeness, i.e., R^2, presented by Amihud and Goyenko (2013), which is the deviation of fund returns from index returns. The regression results provide evidence that fund returns track benchmark returns closely with a higher fraction of female managers in the fund management team. The results signal that female fund managers design fund investment strategies and portfolio composition in accordance with the benchmark index. Moreover, the study argues that the interdependent construct of female managers reduces the economic benefits of diversification of the funds.

Consistent with the hypothesis of the collective self-construal of women, the results demonstrate that female fund managers herd more by concentrating investments in the most popular sectors. A portion of their herding behavior can be explained by reputational concerns as they face strict scrutiny from market participants. However, we do not empirically explore the reputational aspects of herding. Furthermore, we analyze the investment behaviors of females, given in the literature, to test their impact on the less active investments of female managers. The findings are consistent with the literature that females are more risk averse and less overconfident than their male counterparts. Subsequently, these behaviors explain the close movement of fund returns with the benchmark returns.

Combining the findings of all three studies, we conclude that female professionals in top positions exhibit investment behaviors and make decisions that are significantly different from that of their male counterparts. We report that gender differences in investment decisions exist, either when females perform their services in a mixed gender team, or they are the sole decision makers. In this thesis, we have also examined the likely channels that may explain why females behave differently. Making insider trading decisions induced by prospect theory value, managing a portfolio of liquid stocks that are price efficient, and managing funds less actively by following the market benchmark closely provide strong signals that females tend to exhibit safe and careful investment behavior compared to male professionals.

The findings of this thesis have implications for investors, corporations, market participants, and policy makers. The literature suggests that traders and market participants receive signals from insider trades. Insider purchases indicate good news about firm fundamentals, and investors are highly likely to follow them for their trading decisions. Based on our findings, female insider trades may not always convey information, and likely to be based on heuristics. Therefore, market participants need to be cautious about the gender of executives who make insider trades in different timings. Although, female managed funds are less risky and satisfy liquidity needs of investors, especially during an event of crisis; they receive lower inflow as compared to male managed funds. It is not surprising if male fund managers attract fund flows by holding less-liquid stocks and reporting higher fund return performance. Therefore, fund investors and management companies should scrutinize the performance of male managed funds by analyzing the riskiness and percentage of asset allocation to illiquid stocks in their portfolio holdings.

Our findings report a decrease in the number of single managed funds, whereas, most of the female managers are managing funds in gender diverse teams. Hence, companies must put in all possible efforts to narrow gender gap in investment industry, e.g., raising awareness of gender stereotypes, providing an equal opportunity to join informational networks, and eliminating discrepancies in compensations and promotion systems to counter the prejudices that female professionals face. As women reach the higher decision-making position, they become increasingly scarce, making them more visible and subject to greater scrutiny (Ely, Ibarra, & Kolb, 2011). As a result, they may refrain from making bold decisions and outperform the benchmark in fund industry. Companies must provide the necessary resources, support, and mentoring to address these concerns. The pessimistic attitude of market participants towards women prevents them from taking powerful positions. Hence, policymakers must design career planning programs and implement practices which reduce any misperception of women's lower abilities and skills. Improved gender diversity and inclusion of more educated and skilled females in investment industry may contribute to achieving several macroeconomic goals through capitalizing on behavioral differences among the genders.

5.2 Future Research

We have conducted three research studies in detail. Specific time frame for completion of the degree and unavailability of some of the databases have placed limitations to our research work. Moreover, unobserved variables, and other possible channels contributing to our results are considered as limitation of this thesis. Consequently, there are some areas that could be addressed in possible future research. Our sample for the first study considers insider trading by only the A category of top executives of the U.S. firms. In future, inclusion of a wide range of executive classes will provide more insight into the risk preferences of insiders. Comparing information content of male and female insider trades is an important topic for study. Furthermore, other measures of bias e.g., disposition effect or anchoring bias, can be examined to document the tendency of biased trading among male and female insiders.

Focusing on the findings of our second study, analyzing the pros and cons of higher liquidity preferences of female fund managers in volatile market situations will be an interesting topic for study. Moreover, trading motivations of female fund managers can also be compared with those of male managers by examining their buying and selling patterns of liquid stocks. Additionally, there are many variations of asset allocations other than just equity funds; hence, it would be of interest to test the liquidity preferences of female fund managers in other fund categories.

In the third study, we use the activity measure of R^2 to examine the degree of active investing strategy of female fund managers. It will be more insightful to use a fund's holding-based measure, e.g., Active Share, to test whether fund stockholdings closely track benchmark holdings if there is a high proportion of female managers in the team. In our sample, most of the funds are team managed and the data does not provide information about the decision-making powers of each team member, or fund companies' policies in this regard. If such information can be accessed in future, it would provide thought-provoking results regarding the impact of male and female decisions in a team. In our sample, there are few single male and single female managed equity funds. In future, analyzing the degree of active investment of single managed funds will be more useful in commenting on females' investment style. Our study does not comment on the performance of less actively managed funds, hence, analyzing this relationship will be a useful topic to study.

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APPENDIX A. CHAPTER 2

The equations below follow Tversky and Kahneman (1992) who develop cumulative prospect theory to assign value to gains and losses by aggregating the product of value and probability weighting functions. Following Barberis, Mukherjee, and Wang (2016):

$$Value = \sum_{i=-m}^{n} \pi_i \; \upsilon(x_i) \tag{A1}$$

where υ (.) is value function:

$$\upsilon(x) = \begin{cases} x^{\alpha} & for \quad x \geq 0 \\ -\lambda(-x)^{\alpha} & for \quad x < 0 \end{cases} \tag{A2}$$

whereas π_i is probability weighting function:

$$\pi_i = \begin{cases} w^{+}\,(p_i + \cdots + p_n) - \; w^{+}\,(p_{i+1} + \cdots + p_n) & for \quad 0 \leq i \leq n \\ w^{-}\,(p_{-m} + \cdots + p_i) - \; w^{-}\,(p_{-m} + \cdots + p_{i-1}) & for \quad -m \leq i < 0 \end{cases} \tag{A3}$$

To obtain the probability weight for a loss ($Retex_i$<0), Barberis, Mukherjee, and Wang (2016) take the total probabilities of all losses equal to or worse than $Retex_i$, and the total probability of all losses strictly worse than $Retex_i$. They then apply a weighting function to each of the sum of these probabilities, i.e., w^{-}(.), and take the difference (Eq. A3). For a gain ($Retex_i$≥0), take total probabilities of all gains equal to or greater than $Retex_i$, and the total probability of all gains strictly greater than $Retex_i$. Then apply a weighting function to each of the sum of these probabilities, i.e. w^{+}(.), and take the difference (Eq. A3). The w^{+}(.) and w^{-}(.) are explained as below:

$$w^{+}(P) = \frac{P^{\gamma}}{\left(P^{\gamma} + \; (1-P)^{\gamma}\right)^{1/\gamma}}\,, \quad w^{-}(P) = \frac{P^{\delta}}{\left(P^{\delta} + \; (1-P)^{\delta}\right)^{1/\delta}} \tag{A4}$$

To measure PTV, probability weighting function of each outcome is as below:

$$\pi_i = \begin{cases} w^{+}\left(\dfrac{n-i+1}{60}\right) - \; w^{+}\left(\dfrac{n-i}{60}\right) & for \quad 0 \leq i \leq n \\ w^{-}\left(\dfrac{i+m+1}{60}\right) - \; w^{-}\left(\dfrac{i+m}{60}\right) & for \quad -m \leq i < 0 \end{cases} \tag{A5}$$

Equation (1) is measured as follows:

$$PTV_{i,t} = \sum_{i=-m}^{-1}[-\lambda(-Retex_i)^{\alpha}]\left[\frac{\left(\frac{i+m+1}{60}\right)^{\delta}}{\left(\left(\frac{i+m+1}{60}\right)^{\delta}+\left(1-\left(\frac{i+m+1}{60}\right)\right)^{\delta}\right)^{1/\delta}} - \frac{\left(\frac{i+m}{60}\right)^{\delta}}{\left(\left(\frac{i+m}{60}\right)^{\delta}+\left(1-\left(\frac{i+m}{60}\right)\right)^{\delta}\right)^{1/\delta}}\right]$$

$$+ \sum_{i=1}^{n}[(Retex_i)^{\alpha}]\left[\frac{\left(\frac{n-i+1}{60}\right)^{\gamma}}{\left(\left(\frac{n-i+1}{60}\right)^{\gamma}+\left(1-\left(\frac{n-i+1}{60}\right)\right)^{\gamma}\right)^{1/\gamma}} - \frac{\left(\frac{n-i}{60}\right)^{\gamma}}{\left(\left(\frac{n-i}{60}\right)^{\gamma}+\left(1-\left(\frac{n-i}{60}\right)\right)^{\gamma}\right)^{1/\gamma}}\right]$$

(A6)

Figure A1: Trend of Average Biased Trades and Average Female Insider Trades Over Time

This figure shows a pattern of average prospect theory value biased trades and insider trades by female executives in our sample from year 2002 to the end of 2016. Avg_Biased_Trades and Avg_Female_Trades are cross-section averages of biased and female insider trades, respectively, over time.

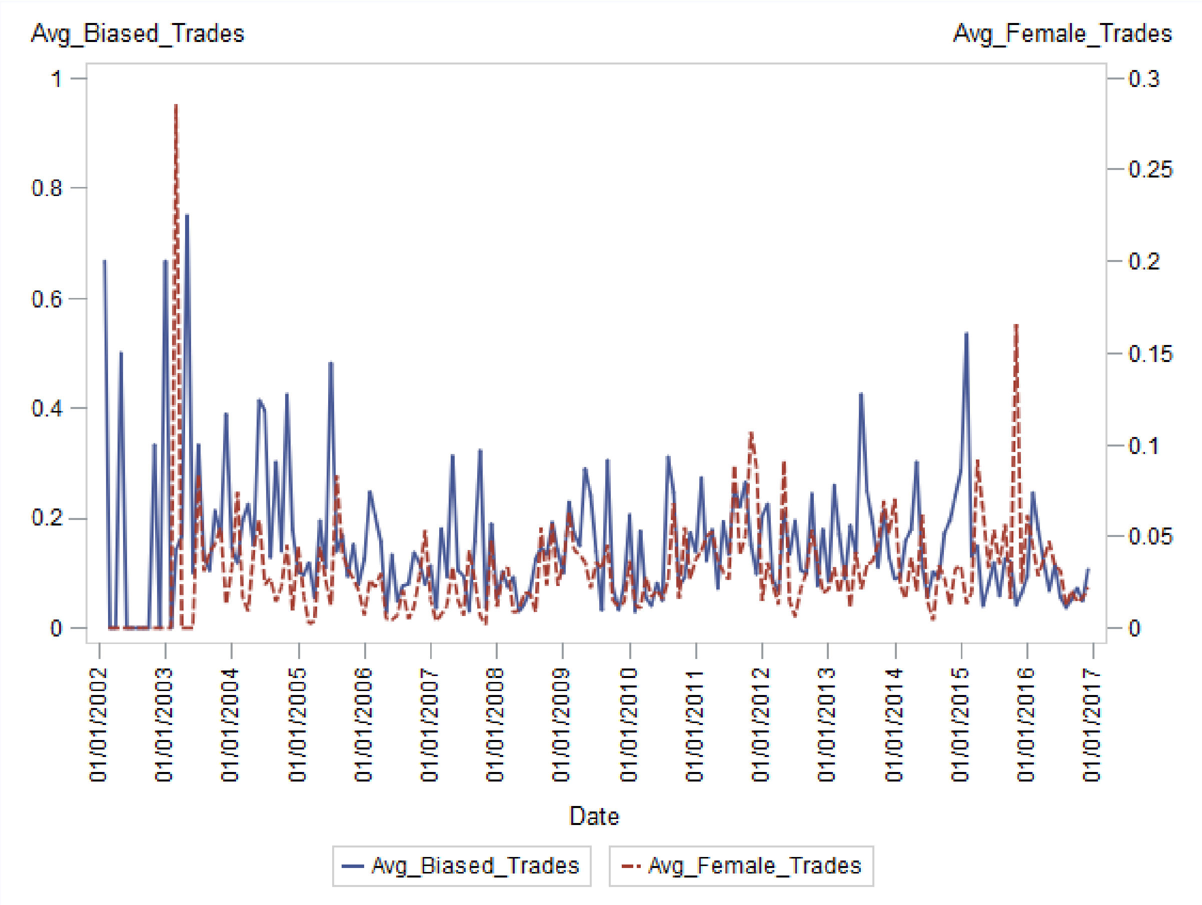

Table A1: Description of Variables

This table defines all the main variables of this study.

Variables	Description
$Biased\_Trade\_Loss$	Measure of loss from prospect theory value biased trades. Equal to $\lvert Retex_{t+1} \rvert$ if either of the two conditions mentioned in Equation (4) is met at time t, and 0 otherwise.
PTV	Measure of prospect theory value. Equal to insider stock's PTV, described in Equation (1).
$Retex_{t+1}$	Measure of monthly return in excess to market return at time t+1.
$Female$	Measure of trade by female insider. Equal to 1 if insider trading is carried by female at time t, and 0 otherwise.
$Retex\_m$	Past month return – Monthly return in excess to market return at time t-1.
$Retex\_y$	Past year return – Cumulative past monthly returns in excess to market returns from t-12, t-2. We take log of compounded monthly excess returns and aggregate from t-12, t-2.
$Size$	Log of monthly market capitalization at time t-1.
$Turnover$	Monthly volume turnover at time t-1. Equal to number of shares traded divided by number of shares outstanding.
$Book\_Mkt$	Book to Market ratio at time t-1. Equal to (total assets - total liabilities) divided by (closing price × number of shares outstanding). Book to Market ratio for June of year t is the book equity for the last fiscal year end in t-1 divided by market equity for December of t-1.
$Age\_insider$	Insider's age at the time of transaction.
PhD	Equals 1 if insider has doctoral degree, and 0 otherwise.
$Grad$	Equals 1 if insider has graduate degree, and 0 otherwise.
MBA	Equals 1 if insider has MBA degree, and 0 otherwise.
$UnderGrad$	Equals 1 if insider has undergraduate degree, and 0 otherwise.

Note: For linear regression, the variables are measured for the calendar month when insider transaction takes place.

Table A2: Comparison of Biased Insider Trades by Executive Gender

This table shows the total number of trades by male and female insiders, and the proportion of prospect theory value biased trades by male and female insiders from January 2003 – December 2016.

Year	No. of Trades_Male	No. of Trades_Female	No. of Biased Trades_Male	No. of Biased Trades_Female	Proportion of Biased Trades_Male (%)	Proportion of Biased Trades_Female (%)
2003	7,794	291	1,618	47	20.76	16.15
2004	18,796	570	4,383	185	23.32	32.46
2005	25,240	637	3,520	109	13.95	17.11
2006	25,049	490	2,767	36	11.05	7.35
2007	42,128	730	6,036	253	14.33	34.66
2008	33,165	718	2,590	76	7.81	10.58
2009	12,864	394	1,887	134	14.67	34.01
2010	13,105	345	1,457	76	11.12	22.03
2011	9,066	499	1,587	100	17.51	20.04
2012	8,523	218	1,088	43	12.76	19.72
2013	6,396	257	1,130	33	17.67	12.84
2014	6,527	203	1,058	26	16.21	12.81
2015	5,588	282	707	20	12.65	7.09
2016	3,716	104	368	11	9.90	10.58

APPENDIX B. CHAPTER 3

Table B1: Description of Variables

This table defines all the main variables of this study.

Variables	Description
$Port\_Liq\_PST$	Measure of monthly portfolio liquidity introduced by Pastor, Stambaugh, and Taylor (2020) and described in Equation (1).
$Port\_Liq\_Amhd$	Measure of monthly portfolio liquidity which is the value weighted average of Amihud liquidity of all the stocks held by a fund at time t. The illiquidity measure of Amihud (2002) is the daily ratio of absolute stock return to dollar volume of the stock, described in Equation (2).
$Port\_Liq\_Sprd$	Measure of monthly portfolio liquidity which is the value weighted average of Bid_Ask Spread of all the stocks held by a fund at time t. This illiquidity measure is the daily quoted bid-ask spread of a stock divided by its midpoint, described in Equation (3).
$Female$	Dummy variable equals to 1 if fund is single female managed at time t, and 0 if it is single male managed.
Ret	Measure of monthly fund return. Equal to the value weighted average of returns of all the share classes of a fund at time t.
$Size$	Measure of monthly fund size. Equal to the natural log of total net assets of all the share classes of a fund in million dollars at time t.
Exp	Measure of monthly fund expense ratio. Equal to the value weighted average of net expense ratio of all the share classes of a fund at time t.
$TOratio$	Measure of monthly fund turnover ratio. Equal to the minimum of the fund's dollar buys and sells during the fiscal year, scaled by the fund's average total net assets. The annual measure is divided by 12 to converted to monthly frequency.
$Flow$	Measure of monthly fund flow. Equal to the net growth in total net assets of a fund, as a percentage of its total net assets adjusted for returns at time t, described in Equation (4).
$Fund\_Age$	Measure of monthly fund age. Equal to the natural log of the difference between fund's inception date and the date at time t.
$Undergrad$	Dummy variable. Equal to 1 if the undergraduate degree is the highest that a fund manager has earned, and 0 otherwise.
$Grad$	Dummy variable. Equal to 1 if the graduate degree is the highest that a fund manager has earned, and 0 otherwise.
PhD	Dummy variable. Equal to 1 if the PhD degree is the highest that a fund manager has earned, and 0 otherwise.
MBA	Dummy variable. Equal to 1 if a fund manager has obtained a Master of Business Administration degree, and 0 otherwise.
$Cert$	Dummy variable. Equal to 1 if a fund manager has obtained a professional qualification (e.g. CFA or CPA), and 0 otherwise.
Mgr_Age	Measure of monthly fund manager's age. Equal to the natural log of the difference between completion date of manager's undergraduate degree and the date at time t.

Table B2: Distribution of Single Managed Funds by Gender

This table shows the total number of single male and female managed funds and the proportion of female managed funds in percentage from January 2000 – December 2017.

Year	Total Funds	No. of Male Funds	No. of Female Funds	Proportion of Female Funds (%)
2000	802	714	88	10.97
2001	933	829	104	11.15
2002	971	870	101	10.40
2003	985	883	102	10.36
2004	934	835	99	10.60
2005	908	814	94	10.35
2006	797	716	81	10.16
2007	778	711	67	8.61
2008	840	764	76	9.05
2009	773	706	67	8.67
2010	664	605	59	8.89
2011	601	545	56	9.32
2012	534	493	41	7.68
2013	509	467	42	8.25
2014	491	445	46	9.37
2015	463	427	36	7.78
2016	431	393	38	8.82
2017	396	361	35	8.84

Table B3: Detailed Summary Statistics by Manager Gender

This table provides descriptive statistics of fund and manager characteristics by grouping them based on the gender of mutual fund managers.

Gender	Variable	Obs.	Mean	Median	Std. Dev.	P1	P99
Male	Port_Liq_PST	112,982	0.0378	0.0174	0.0575	0.0003	0.2706
Male	Port_Liq_Amhd	112,982	-0.0110	-0.0005	0.0392	-0.2667	-0.00003
Male	Port_Liq_Sprd	112,982	-24.5800	-9.6100	36.3700	-178.9200	-1.8700
Male	Ret	112,982	0.0045	0.0093	0.0543	-0.1589	0.1310
Male	TNA (mil $)	112,982	1447.3415	188.5000	5172.5695	2.2000	23007.0000
Male	Exp	104,354	0.0011	0.0010	0.0005	0.0002	0.0027
Male	TOratio	103,456	0.0762	0.0517	0.0951	0.0025	0.4183
Male	Flow	112,982	0.7272	-0.0039	52.1456	-0.4217	1.4991
Male	Fund_Age	112,982	14.5159	11	13.6379	1	73
Male	N_Stocks	112,982	114.8560	69	236.7667	18	1255
Male	Undergrad	112,982	0.8301	1	0.3755	0	1
Male	Grad	112,982	0.1411	0	0.3481	0	1
Male	PhD	112,982	0.0276	0	0.1638	0	1
Male	MBA	112,982	0.5749	1	0.4944	0	1
Male	Cert	112,982	0.5747	1	0.4944	0	1
Male	Mgr_Age	54,308	47.8470	46	10.1299	29	73
Female	Port_Liq_PST	11,381	0.0407	0.0173	0.0538	0.0010	0.2751
Female	Port_Liq_Amhd	11,381	-0.0046	-0.0005	0.0179	-0.0875	-0.00004
Female	Port_Liq_Sprd	11,381	-24.5600	-10.1400	33.9100	-166.6200	-1.9100
Female	Ret	11,381	0.0032	0.0085	0.0537	-0.1597	0.1262
Female	TNA (mil $)	11,381	678.214	177.000	1673.642	2.200	8746.500
Female	Exp	10,482	0.0012	0.0011	0.0007	0.0004	0.0023
Female	TOratio	10,399	0.0774	0.0600	0.0629	0.0033	0.3108
Female	Flow	11,381	0.2751	-0.0051	10.0860	-0.4320	1.8819
Female	Fund_Age	11,381	14.6777	11	13.4503	1	68
Female	N_Stocks	11,381	86.9736	73	63.4785	23	294
Female	Undergrad	11,381	0.8597	1	0.3473	0	1
Female	Grad	11,381	0.1315	0	0.3380	0	1
Female	PhD	11,381	0.0066	0	0.0809	0	0
Female	MBA	11,381	0.5589	1	0.4965	0	1
Female	Cert	11,381	0.6409	1	0.4798	0	1
Female	Mgr_Age	5,744	47.4425	46	9.3257	30	68

Table B4: Fund Manager Gender and Preference for Portfolio Liquidity

(Manager age as control variable)

This table presents the findings of the regression of portfolio liquidity on the gender of single managed funds, including the control variable of Mgr_Age. The baseline regression model is given in Equation (5). The dependent variable is portfolio liquidity, $Port\_Liq$. The independent variable is $Female$ which is equal to 1 if fund is single female managed at time t, and 0 if it is single male managed. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of the fund and manager level control variables.

	Port_Liq_PST		Port_Liq_Amhd		Port_Liq_Sprd	
	All controls	Manager controls	All controls	Manager controls	All controls	Manager controls
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0050***	0.0047***	0.0023***	0.0010*	2.3774***	1.1760
	(3.89)	(3.71)	(3.79)	(1.69)	(3.00)	(1.55)
Ret	-0.0057***	-	0.0038	-	12.0000***	-
	(-3.05)		(1.42)		(5.09)	
Size	0.0067***	-	0.0076***	-	5.5560***	-
	(28.48)		(22.02)		(23.15)	
Exp	-2.6334***	-	0.3978	-	370.7000	-
	(-4.12)		(0.40)		(0.48)	
TOratio	-0.0093***	-	0.0260***	-	11.3000***	-
	(-4.70)		(9.48)		(6.27)	
Flow	0.0129	-	0.0025	-	-0.0006	-
	(0.38)		(0.58)		(-0.63)	
Fund_Age	0.0054***	-	-0.0051***	-	-8.1463***	-
	(5.61)		(-6.19)		(-10.32)	
Undergrad	0.0140***	0.0139***	0.0004	0.0047***	0.7830	4.4713**
	(5.00)	(5.08)	(0.36)	(5.07)	(0.35)	(2.03)
Grad	0.0043*	0.0035	0.0000	0.0031***	1.6267	3.8876*
	(1.68)	(1.41)	(0.05)	(4.15)	(0.78)	(1.91)
PhD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	-	-	-	-	-	-
MBA	-0.0023**	-0.0032***	-0.0017***	-0.0016**	-0.8741	-0.8674
	(-2.55)	(-3.51)	(-2.58)	(-2.35)	(-1.19)	(-1.21)
Cert	0.0109***	0.0101***	0.0004	0.0015***	-0.4664	0.1629
	(9.58)	(8.97)	(0.92)	(3.28)	(-0.75)	(0.27)
Mgr_Age	0.0170***	0.0227***	0.0010	0.0053***	0.9949	3.6087*
	(7.51)	(10.18)	(0.70)	(3.71)	(0.52)	(1.95)
Year-fixed Effect	YES	YES	YES	YES	YES	YES
Fund-fixed Effect	YES	YES	YES	YES	YES	YES
No. of Obs.	55,253	60,052	55,253	60,052	55,253	60,052
Adj. R-squared	0.8421	0.8359	0.6174	0.6040	0.7201	0.7175

Table B5: Fund Manager Gender and Preference for Portfolio Liquidity

(Stock characteristics as control variables)

This table presents the findings of the regression of portfolio liquidity on the gender of single managed funds, including stock level characteristics along-with the fund and manager level controls. The baseline regression model is given in Equation (5). The dependent variable is portfolio liquidity, $Port\_Liq$. The independent variable is $Female$ which is equal to 1 if fund is single female managed at time t, and 0 if it is single male managed. *Port_Liq_PST_lag* is a proxy of portfolio liquidity introduced by Pastor, Stambaugh, and Taylor (2020) and measured at time t-1. *Port_Liq_Amhd_lag* is a measure of portfolio liquidity which is the value weighted average of Amihud liquidity of all the stocks held by a fund at time t-1. *Port_Liq_Sprd_lag* is a measure of portfolio liquidity which is the value weighted average of Bid_Ask Spread of all the stocks held by a fund at time t-1. *Port_Vlty* is the value weighted average of the monthly percentile rank of volatility of all the stocks held by a fund at time t, where volatility is the standard deviation of daily stock returns. *Port_Div* is the value weighted average of the monthly percentile rank of dividend yield of all the stocks held by a fund at time t. *Port_Size* is the value weighted average of the monthly percentile rank of size of all the stocks held by a fund at time t, where size is the natural log of stock's market capitalization. *Port_Cumret* is the value weighted average of the monthly percentile rank of cumulative return of all the stocks held by a fund at time t, where cumulative return is measured for t-12, t-1. $Port\_Liq\_Sprd$ and $Flow$ are measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of the fund and manager level control variables.

	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
	(1)	(2)	(3)
Female	0.0008***	0.0005*	0.5336*
	(3.36)	(1.94)	(1.89)
Ret	0.0015***	0.0143***	18.5000***
	(3.31)	(11.05)	(23.27)
Size	0.0002***	0.0012***	0.9083***
	(5.62)	(10.32)	(11.41)
Exp	0.0701	1.1346***	-223.3000
	(0.58)	(2.70)	(-0.78)
TOratio	-0.0014***	0.0035**	0.7854
	(-2.70)	(2.19)	(0.96)
Flow	0.0125	-0.0006	-0.0005
	(0.88)	(-0.42)	(-1.49)
Fund_Age	0.0002	-0.0000	-0.8142***
	(1.52)	(-0.04)	(-2.61)
Undergrad	-0.0005	0.0011	-2.0490
	(-0.63)	(1.48)	(-0.82)
Grad	-0.0006	0.0012*	-1.8385
	(-0.71)	(1.68)	(-0.73)
PhD	-0.0011	0.0028***	-3.4094
	(-1.29)	(3.19)	(-1.33)
MBA	0.0001	-0.0003	-0.0695
	(0.90)	(-1.33)	(-0.37)
Cert	0.0001	0.0005***	-0.0225
	(0.44)	(2.65)	(-0.10)
Port_Liq_PST_lag	0.9265***	-	-
	(120.71)		
Port_Liq_Amhd_lag	-	0.6199***	-
		(60.61)	

Table B5: (continued)

	Port_Liq_PST	Port_Liq_Amhd	Port_Liq_Sprd
	(1)	(2)	(3)
Port_Liq_Sprd_lag	-	-	7589.8000***
			(107.61)
Port_Vlty	-0.0009**	0.0100***	-6.6277***
	(-1.99)	(8.55)	(-9.14)
Port_Div	-0.0034***	-0.0050***	0.9423
	(-7.84)	(-5.85)	(1.37)
Port_Size	0.0191***	0.0586***	14.6000***
	(6.88)	(13.86)	(9.15)
Port_Cumret	-0.0009***	-0.0011	-1.5257**
	(-2.91)	(-1.39)	(-2.44)
Year-fixed Effect	YES	YES	YES
Fund-fixed Effect	YES	YES	YES
No. of Obs.	112,184	112,184	112,184
Adj. R-squared	0.9826	0.7757	0.8933

Table B6: Female Fund Manager and Portfolio Risk and Return

Table B6, Columns (1) and (2) report the findings of the regression of portfolio risk on the single female managed funds. The dependent variable is monthly portfolio risk, $Port\_Risk$, which is the value weighted average of monthly volatility of all the stocks held by a fund at time t. Columns (3) and (4) present the findings of the regression of fund return on the single female managed funds. The dependent variable is monthly fund return, $Fund\_Ret$. The independent variable is $Female$ which is equal to 1 if fund is single female managed at time t, and 0 if it is single male managed. $Flow$ is measured in basis points. The results are presented with fund and year fixed effects. The t-statistics based on White robust standard errors are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table B1 in the appendix for the explanation of all the variables.

$$Port\_Risk_{i,t} = \alpha + \beta_1 \, Female_{i,t} + \gamma \, Controls_{i,t} + \varepsilon_{i,t}$$

$$Fund\_Ret_{i,t} = \alpha + \beta_1 \, Female_{i,t} + \gamma \, Controls_{i,t} + \varepsilon_{i,t}$$

	Port_Risk		Fund_Ret	
	All controls with manager age	All controls without manager age	All controls with manager age	All controls without manager age
	(1)	(2)	(3)	(4)
Female	-0.0005**	-0.0003*	-0.0012	-0.0011
	(-1.99)	(-1.94)	(-0.66)	(-1.00)
Ret	-0.0302***	-0.0324***	-	-
	(-31.05)	(-46.38)		
Size	-0.0005***	-0.0002***	0.0023***	0.0015***
	(-7.70)	(-5.12)	(4.84)	(5.17)
Exp	-1.1324***	-0.7550***	3.1664	3.5626***
	(-4.76)	(-5.06)	(1.46)	(2.60)
TOratio	0.0029***	0.0038***	0.0066	0.0009
	(2.81)	(6.06)	(1.30)	(0.25)
Flow	0.0019	0.0036	-0.0169	-0.0200
	(0.58)	(1.34)	(-0.54)	(-0.81)
Fund_Age	-0.0009***	-0.0009***	-0.0044***	-0.0039***
	(-4.39)	(-6.25)	(-2.64)	(-3.62)
Undergrad	0.0007	-0.0022	-0.0046	0.0120
	(1.44)	(-1.36)	(-1.10)	(0.84)
Grad	0.0021***	-0.0014	-0.0062	0.0100
	(4.47)	(-0.87)	(-1.60)	(0.70)
PhD	0.0000	-0.0025	0.0000	0.0140
	-	(-1.55)	-	(0.97)
MBA	0.0005***	0.0001	-0.0006	0.0005
	(2.62)	(0.62)	(-0.37)	(0.69)
Cert	-0.0001	-0.0000	-0.0019	-0.0003
	(-0.58)	(-0.17)	(-1.16)	(-0.38)
Mgr_Age	0.0023***	-	-0.0108***	-
	(4.34)		(-2.56)	
Year-fixed Effect	YES	YES	YES	YES
Fund-fixed Effect	YES	YES	YES	YES
No. of Obs.	55,253	113,855	55,253	113,855
Adj. R-squared	0.6446	0.6350	0.0917	0.0939

Table B7: Lipper Class or Lipper Objectives

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
A	Corporate Debt Funds A Rated	Funds invest primarily in corporate debt issues rated A or better or government issues.
ABR	Absolute-Return Funds	Funds that aim for positive returns in all market conditions. The funds are not benchmarked against a traditional long-only market index but rather have the aim of outperforming a cash or risk-free benchmark.
ACF	Alternative Credit Focus Funds	Funds that, by prospectus language, invest in a wide-range of credit-structured vehicles by using either fundamental credit research analysis or quantitative credit portfolio modelling trying to benefit from any changes in credit quality, credit spreads, and market liquidity.
AED	Alternative Event Driven Funds	Funds that, by prospectus language, seek to exploit pricing inefficiencies that may occur before or after a corporate event, such as a bankruptcy, merger, acquisition, or spinoff. Event Driven funds can invest in equities, fixed income instruments (investment grade, high yield, bank debt, convertible debt and distressed), options and other derivatives.
AGM	Alternative Global Macro Funds	Funds that, by prospectus language, invest around the world using economic theory to justify the decision-making process. The strategy is typically based on forecasts and analysis about interest rate trends, the general flow of funds, political changes, government policies, intergovernmental relations, and other broad systemic factors. These funds generally trade a wide range of markets and geographic regions, employing a broad range of trading ideas and instruments.
AL	Alabama Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Alabama, (double tax-exempt) or city, (triple tax-exempt).
ALT	Alternative Other Funds	Funds that, by prospectus language, seek total returns through the use of alternative investment strategies. These strategies include but are not limited to equity market neutral, long/short equity, global macro, event driven, credit focus or through the use of several different hedge-like strategies.
AMS	Alternative Multi-Strategy Funds	Funds that, by prospectus language, seek total returns through the management of several different hedge-like strategies. These funds are typically quantitatively driven to measure the existing relationship between instruments and in some cases to identify positions in which the risk-adjusted spread between these instruments represents an opportunity for the investment manager.
ARM	Adjustable Rate Mortgage Funds	Funds invest primarily in adjustable rate mortgage securities or other securities collateralized by or representing an interest in mortgages.
AU	Precious Metals Equity Funds	Funds invest primarily in shares of gold mines, gold-oriented mining finance houses, gold coins, or bullion.
AZ	Arizona Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Arizona, (double tax-exempt) or city, (triple tax-exempt).
B	Balanced Funds	Funds whose primary objective is to conserve principal by maintaining at all times a balanced portfolio of both stocks and bonds. Typically, the stock/bond ratio ranges around 60%/40%.
BBB	Corporate Debt Funds BBB-Rated	Funds invest primarily in corporate and government debt issues rated in the top four grades.

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
BBBL	Corporate BBB_Rated Debt Funds (Leveraged)	Funds that invest primarily in a basket of futures contracts with the aim of reduced volatility and positive returns in any market environment. Investment strategies are based on proprietary trading strategies that include the ability to go long and/or short.
BM	Basic Materials Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in manufacturing chemicals; construction materials;glass;paper,forest products, and related packaging products; and metals, minerals, and mining products including steel.
BT	Balanced Target Maturity Funds	Funds that invest to provide a guaranteed return of investment at maturity (targeted periods). A portion of the assets is invested in zero coupon U.S. Treasury securities, while the remainder is in equity securities for long-term growth of capital and income.
CA	Capital Appreciation Funds	Funds that aim at maximum capital appreciation, frequently by means of 100% or more portfolio turnover, leveraging, purchasing unregistered securities, purchasing options, etc. The funds may take large cash positions.
CAG	California Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in California (double tax-exempt) or city (triple tax-exempt).
CAI	California Insured Municipal Debt Funds	Funds invest primarily in those securities that are exempt from taxation in California, and are insured as to timely payment.
CAM	California Tax-Exempt Money Market Funds	Funds invest in municipal obligations of California, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
CAS	California Sh-Intmdt Municipal Debt Funds	Funds invest primarily in municipal debt issues that are exempt from taxation in California, with dollar-weighted average maturities of one to five years.
CAT	California Intermdt Municipal Debt Funds	Funds invest primarily in municipal debt issues that are exempt from taxation in California, with dollar-weighted average maturities of five to ten years.
CG	Consumer Goods Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in manufacturing and distributing consumer goods such as food, beverages, tobacco, and nondurable household goods and personal products.
CH	China Region Funds	Funds that concentrate investments in equity securities whose primary trading markets or operations are in the China region or in a single country within this region.
CMA	Commodities Agriculture Funds	Funds that invest primarily in agricultural commodity-linked derivative instruments or physicals.
CMD	Commodities Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in trading commodities such as food, grains,metals,foreign currencies, future contracts, and financial instruments, which can be interchangeable with another product of the same type.
CME	Commodities Energy Funds	Funds that invest primarily in energy-related commodity-linked derivative instruments or physicals.
CMG	Commodities General Funds	Funds that invest primarily in a blended basket of commodity-linked derivative instruments or physicals.
CMM	Commodities Base Metals Funds	Funds that invest primarily in base-metal commodity-linked derivative instruments or physicals.
CMP	Commodities Precious Metals Funds	Funds that invest primarily in precious-metal commodity-linked derivative instruments or physicals.
CMS	Commodities Specialty Funds	Funds that invest primarily in commodity-linked derivative instruments or physicals of sectors or strategies not previously mentioned. These include leveraged or short-biased offerings.
CN	Canadian Funds	Funds that concentrate investments in equity securities of Canadian companies.
CO	Colorado Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Colorado, (double tax-exempt) or city, (triple tax-exempt).
CPB	Core Plus Bond Funds	Funds that invest at least 65% in domestic investment-grade debt issues (rated in the top four grades) with any remaining investment in non-benchmark sectors such as high-yield, global and emerging market debt. These funds maintain dollar-weighted average maturities of five to ten years.
CRX	Currency Funds	Funds that invest in US and foreign currencies. This is achieved through the use of short term money market instruments; derivatives (forwards, options, swaps) and cash deposits.
CS	Consumer Services Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in providing consumer services, including the services segment of hotels, restaurants, and other leisure facilities; media production and services; and consumer retail and services.
CT	Connecticut Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Connecticut, (double tax-exempt) or city, (triple tax-exempt).

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
CTM	Connecticut Tax-Exempt Money Market Funds	Funds invest in municipal obligations of Connecticut state, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
CV	Convertible Securities Funds	Funds invest primarily in convertible bonds and/or convertible preferred stock.
DL	Equity Leverage Funds	Diversified and non-diversified equity funds that seek daily investment results of more than 100% of the daily performance of a stated benchmark through any combination of futures contracts, derivatives, and leverage.
DM	Developed Market Funds	Funds that invest primarily in equity securities whose primary trading markets or operations are in countries (or a single country) outside of the U.S. that are generally considered developed.
DSB	Dedicated Short Bias Funds	Funds that employ portfolio strategies that consistently create a net short exposure to the market. This objective also includes short only funds, i.e. funds that pursue short sales of stock or stock index options.
EI	Equity Income Funds	Funds that, by prospectus language and portfolio practice, seek relatively high current income and growth of income by investing primarily in dividend-paying equity securities. Funds' gross or net yield must be at least 125% of the average gross or net yield of the U.S. diversified equity fund universe.
EIEI	Equity Income Funds	Funds that, by prospectus language and portfolio practice, seek relatively high current income and growth of income by investing primarily in dividend-paying equity securities. This funds' gross or net yield must be at least 125% of the average gross or net yield of the U.S. diversified equity fund universe.
ELCC	Extended U.S. Large-Cap Core Funds	Funds that combine long and short stock selection to invest in a diversified portfolio of U.S. large-cap equities, with a target net exposure of 100% long.Typical strategies vary between 110% long and 10% short to 160% long and 60% short.
EM	Emerging Markets Funds	Funds that seek long-term capital appreciation by investing primarily in emerging market equity securities, where emerging market is defined by a country's GNP per capita or other economic measures.
EMD	Emerging Markets Debt Funds	Funds seek either current income or total return by investing primarily in emerging market debt securities, where emerging market is defined by a country's GNP per capita or other economic measures.
EML	Emerging Markets Local Currency Debt Funds	Funds that seek either current income or total return by investing at least 65% of total assets in emerging market debt issues denominated in the currency of their market of issuance.
EMN	Equity Market Neutral Funds	Funds that employ portfolio strategies that generate consistent returns in both up and down markets by selecting positions with a total net market exposure of zero.
EMP	Energy MLP Funds	Funds that invest primarily in Master Limited Partnerships (MLPs) engaged in the transportation, storage and processing of minerals and natural resources.
EU	European Region Funds	Funds that concentrate investments in equity securities whose primary trading markets or operations are concentrated in the European region or a single country within this region.
FL	Florida Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Florida, (double tax-exempt) or city, (triple tax-exempt).
FLI	Florida Insured Municipal Debt Funds	In closed-End Funds: Funds that invests primarily in securities that are exempt from taxation in Florida and are insured as to timely payment. Florida insured municipal debt funds will be classified in Single-State Insured Municipal Debt Funds, with objective of Florida Insured Municipal Debt Funds (FLI)
FLT	Florida Intermediate Municipal Debt Funds	Funds invest primarily in municipal debt issues that are exempt from taxation in Florida, with dollar-weighted average maturities of five to ten years.
FLX	Flexible Income Funds	Funds emphasize income generation by investing at least 85% of assets in debt issues and preferred and convertible securities.
FS	Financial Services Funds	Funds invest primarily in equity securities of companies engaged in providing financial services, including but not limited to banks, finance companies, insurance companies, and securities/brokerage firms.
FX	Flexible Portfolio Funds	Funds that allocate investments across various asset classes, including domestic common stocks, bonds, and money market instruments with a focus on total return.
G	Growth Funds	Funds that normally invest in companies with long-term earnings expected to grow significantly faster than the earnings of the stocks represented in the major unmanaged stock indices.
GA	Georgia Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Georgia, (double tax-exempt) or city, (triple tax-exempt).
GB	General Bond Funds	Funds do not have any quality or maturity restrictions. Intend to keep a bulk of their assets in corporate and government debt issues.

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
GEI	Global Equity Income Funds	Funds that, by prospectus language and portfolio practice, seek relatively high current income and growth of income by investing at least 65% or more of their portfolio in dividend-paying equity securities of domestic and foreign companies
GFS	Global Financial Service Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in providing financial services, including but not limited to banks,finance companies, insurance companies, and securities/brokerage firms.
GH	Global Health/Biotechnology Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in healthcare, medicine and biotechnology.
GI	Growth and Income Funds	Funds that combine a growth-of-earnings orientation and an income requirement for level and/or rising dividends.
GIF	Global Infrastructure Funds	Funds that invest primarily in equity securities of domestic and foreign companies engaged in an infrastructure industry, including but not limited to transportation, communication and waste management.
GL	Global Funds	Funds that invest at least 25% of their portfolio in securities traded outside of the United States and that may own U.S. securities as well.
GLCC	Global Large-Cap Core	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) greater than 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Large-cap core funds typically have an average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World BMI.
GLCG	Global Large-Cap Growth	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) greater than 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Large-cap growth funds typically have an above-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World BMI.
GLCV	Global Large-Cap Value	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) greater than 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Large-cap value funds typically have a below-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World BMI.
GLI	Global Income Funds	Funds invest primarily in U.S. dollar and non-U.S. dollar debt securities of issuers located in at least three countries, one of which may be the United States.
GM	General & Insured Municipal Debt Funds	Funds invest primarily in municipal debt issues in the top four credit ratings.
GMLC	Global Multi-Cap Core	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have 25% to 75% of their assets invested in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) above 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Multi-cap core funds typically have an average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup BMI.
GMLG	Global Multi-Cap Growth	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have 25% to 75% of their assets invested in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) above 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Multi-cap growth funds typically have an above-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup BMI.

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
GMLV	Global Multi-Cap Value	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have 25% to 75% of their assets invested in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) above 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Multi-cap value funds typically have a below-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup BMI.
GNM	GNMA Funds	Funds invest primarily in Government National Mortgage Association securities.
GNR	Global Natural Resources Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in natural resources.
GRE	Global Real Estate Funds	Funds that invest at least 25% but less than 75% of their equity portfolio in shares of companies engaged in the real estate industry that are strictly outside of the U.S. or whose securities are principally traded outside of the U.S.
GS	Global Small-Cap Funds	Fund that invest at least 25% of their portfolio in securities with primary trading markets outside the United States, and that limits at least 65% of their investments to companies with market capitalizations less than US $1 billion at the time of purchase.
GSMC	Global Small/Mid-Cap Core	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) less than 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Small/mid-cap core funds typically have an average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World BMI.
GSME	Global Small-/Mid-Cap Funds	Funds that, by portfolio practice, invest at lest 75% of their equity assets in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) below Lipper's global large-cap floor. Combines Global Small/Mid-Cap Value Funds, Global Small/Mid-Cap Core Funds and GLobal Small/ Mid-Cap Growth Funds into a new classification.
GSMG	Global Small/Mid-Cap Growth	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) less than 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Small/mid-cap growth funds typically have an above-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World BMI.
GSMV	Global Small/Mid-Cap Value	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies both inside and outside of the U.S. with market capitalizations (on a three-year weighted basis) less than 400% of the 75th market capitalization percentile of the S&P/Citigroup World Broad Market Index. Small/mid-cap value funds typically have a below-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World BMI.
GTK	Global Science/Technology Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in science and technology.
GUS	General U.S. Government Funds	Funds invest primarily in U.S. government and agency issues.
GUT	General U.S. Treasury Funds	Funds invest primarily in U.S. Treasury bills, notes, and bonds.
GX	Global Flexible Port Funds	Funds that allocate investments across various asset classes, including both domestic and foreign stocks, bonds, and money market instruments focused on total return. At least 25% of portfolio is invested in securities traded outside of the U.S.
H	Health/Biotechnology Funds	Funds invest primarily in shares of companies engaged in health care, medicine, and biotechnology.
HI	Hawaii Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Hawaii, (double tax-exempt) or city, (triple tax-exempt).
HM	High Yield Funds	Funds invest at least 50% of assets in lower rated municipal debt issues.
HY	High Current Yield Funds	Funds aim at high (relative) current yield from fixed income securities, have no quality or maturity restrictions, and tend to invest in lower grade debt issues.
I	Income Funds	Funds that normally seek a high level of current income through investing in income-producing stocks, bonds, and money market instruments.

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
ID	Industrial Funds	Funds that invest primarily in the equity securities of domestic and foreign companies engaged in manufacturing and distributing capital goods including aerospace and defense, construction, engineering, and building products; electrical equipment; industrial machinery; commercial services and supplies including printing, employment , environmental, and office services ; transportation services including airlines and couriers; and marine, road and rail, and transportation infrastructure.
IEI	International Equity Income Funds	Funds that, by prospectus language and portfolio practice, seek relatively high current income and growth of income by investing at least 65% or more of their portfolio in dividend-paying equity securities of foreign companies.
IF	International Funds	Funds that invest their assets in securities with primary trading markets outside of the United States.
IID	Intermediate Investment Grade Debt Funds	Funds invest primarily in investment grade debt issues (rated in top four grades) with dollar-weighted average maturities of five to ten years.
ILCC	International Large-Cap Core	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) greater than 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Large-cap core funds typically have an average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
ILCG	International Large-Cap Growth	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) greater than 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Large-cap growth funds typically have an above-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
ILCV	International Large-Cap Value	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) greater than 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Large-cap value funds typically have a below-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
IMD	Intermediate Municipal Debt Funds	Funds invest in municipal debt issues with dollar-weighted average maturities of five to ten years.
IMLC	International Multi-Cap Core	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have 25% to 75% of their assets invested in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) above 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Multi-cap core funds typically have an average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
IMLG	International Multi-Cap Growth	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have 25% to 75% of their assets invested in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) above 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Multi-cap growth funds typically have an above-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
IMLV	International Multi-Cap Value	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have 25% to 75% of their assets invested in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) above 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Multi-cap value funds typically have a below-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
IMM	Instl Money Market Funds	Funds invest in high quality financial instruments rated in top 2 grades w/ dollar-weighted average maturities < 90 days. Require high minimum investments & have lower total expense ratios relative to other MM funds. Intend to keep a constant NAV.

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
INI	International Income Funds	Funds invest primarily in non-U.S. dollar and U.S. dollar debt securities of issuers located in at least three countries, excluding the U.S., except in periods of market weakness.
INR	India Region Funds	Funds that concentrate their investments in equity securities with primary trading markets or operations concentrated in the India region.
IRE	International Real Estate Funds	Funds that invest at least 75% of their equity portfolio in shares of companies engaged in the real estate industry that are strictly outside of the U.S. or whose securities are principally traded outside of the U.S.
IS	International Small-Cap Funds	Funds that invest at least 65% of their assets in equity securities of non-United States companies with market capitalizations less than US $1 billion at time of purchase.
ISMC	International Small/Mid-Cap Core	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) less than 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Small/mid-cap core funds typically have an average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
ISMG	International Small/Mid-Cap Growth	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) less than 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Small/mid-cap growth funds typically have an above-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
ISMV	International Small/Mid-Cap Value	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies strictly outside of the U.S. with market capitalizations (on a three-year weighted basis) less than 400% of the 75th market capitalization percentile of the S&P/Citigroup World ex-U.S. Broad Market Index. Small/mid-cap value funds typically have a below-average price-to-cash flow ratio, price-to-book ratio, and three-year sales-per-share growth value compared to the S&P/Citigroup World ex-U.S. BMI.
ITE	Instl Tax-Exempt Money Market Funds	Funds invest in municipal obligations w/ dollar-weighted average maturities of less than 90 days. Funds require high minimum investments, have lower total expense ratios relative to other money market funds, intend to keep a constant NAV.
ITM	Instl U.S. Treasury Money Market Funds	Funds invest principally in U.S. Treasury obligations with dollar-weighted average maturities of < 90 days. Funds require high minimum investments and have lower total expense ratios relative to other money market funds. Intend to keep a constant NAV.
IUG	Intermediate U.S. Government Funds	Funds invest primarily in securities issued or guaranteed by the U.S. government, its agencies, or its instrumentalities, with dollar-weighted average maturities of five to ten years.
IUS	Instl U.S. Government Money Market Funds	Funds invest principally in financial instruments issued or guaranteed by the U.S. government., its agencies, or instrumentalities with dollar-weighted average maturities of < 90 days. Require high minimum investments, have lower total expense ratios relative to other MM funds. Intend to keep a constant NAV.
IUT	Inflation Protected Bond Funds	Funds that invest primarily in inflation-indexed fixed income securities. Inflation-linked bonds are fixed income securities that are structured to provide protection against inflation.
JA	Japanese Funds	Funds that concentrate investments in equity securities of Japanese companies.
KS	Kansas Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Kansas, (double tax-exempt) or city, (triple tax-exempt).
KY	Kentucky Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Kentucky, (double tax-exempt) or city, (triple tax-exempt).
LA	Louisiana Municipal Debt Funds	Funds limit assets to those securities that are exempt from taxation in Louisiana, (double tax-exempt) or city, (triple tax-exempt).
LCCE	Large-Cap Core Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) greater than 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Large-cap core funds have more latitude in the companies in which they invest. These funds typically have an average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P 500 Index.

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
LCGE	Large-Cap Growth Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) greater than 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Large-cap growth funds typically have an above-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P 500 Index.
LCVE	Large-Cap Value Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) greater than 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Large-cap value funds typically have a below-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P 500 Index.
LP	Loan Participation Funds	Funds that invest primarily in participation interests in collateralized senior corporate loans which have floating or variable rates.
LSE	Long/Short Equity Funds	Funds that employ portfolio strategies that combine long holdings of equities with short sales of equity, equity options, or equity index options, the fund may be either net long or net short depending on the portfolio manager's view of the market.
LT	Latin American Funds	Funds that concentrate investments in equity securities with primary trading markets or operations concentrated in the Latin American region or in a single country within this region.
MA	Massachusetts Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Massachusetts, (double tax-exempt) or city, (triple tax-exempt).
MAM	Massachusetts Tax-Exempt Money Market Fd	Funds invest in municipal obligations of Massachusetts state, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
MAT	Massachusetts Intermediate Muni Debt Funds	Funds invest primarily in municipal debt issues that are exempt from taxation in Massachusetts, with dollar-weighted average maturities of five to ten years.
MATA	Mixed-Asset Target 2010 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon not to exceed the year 2010.
MATB	Mixed-Asset Target 2020 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon from January 1, 2016 to December 31,2020.
MATC	Mixed-Asset Target 2030 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon from January 1, 2026 to December 31,2030.
MATD	Mixed-Asset Target 2035 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon from January 1, 2031 to December 31,2035.
MATE	Mixed-Asset Target 2050+ Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon exceeding the year 2045.
MATF	Mixed-Asset Target 2015 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon from January 1, 2011 to December 31,2015.
MATG	Mixed-Asset Target 2025 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon from January 1, 2021 to December 31,2025.
MATH	Mixed-Asset Target 2040 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon from January 1, 2036 to December 31,2040.
MATI	Mixed-Asset Target 2045 Funds	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon from January 1, 2041 to December 31,2045.
MATJ	Mixed-Asset Target Today Funds	Funds that, by portfolio practice, maintain a conservative mix of equity, bonds, cash, and cash equivalents designed to provide income to investors who are in or close to retirement.
MATK	Mixed-Asset Target 2055+	Funds that seek to maximize assets for retirement or other purposes with an expected time horizon exceeding December 31, 2050.
MC	Mid-Cap Funds	Funds that by prospectus or portfolio practice invest primarily in companies with market capitalizations less than $5 billion at the time of purchase.

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
MCCE	Mid-Cap Core Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) less than 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Mid-cap core funds have more latitude in the companies in which they invest. These funds typically have an average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P MidCap 400 Index.
MCGE	Mid-Cap Growth Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) less than 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Mid-cap growth funds typically have an above-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P MidCap 400 Index.
MCVE	Mid-Cap Value Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) less than 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Mid-cap value funds typically have a below-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P MidCap 400 Index.
MD	Maryland Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Maryland, (double tax-exempt) or city, (triple tax-exempt).
MDI	Insured Municipal Debt Funds	Funds invest primarily in municipal debt issues insured as to timely payment.
MFF	Alternative Managed Futures Funds	Funds that invest primarily in a basket of futures contracts with the aim of reduced volatility and positive returns in any market environment. Investment strategies are based on proprietary trading strategies that include the ability to go long and/or short.
MI	Michigan Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Michigan, (double tax-exempt) or city, (triple tax-exempt).
MIM	Michigan Tax-Exempt Money Market Funds	Funds invest in municipal obligations of Michigan state (double tax-exempt) or city (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
MLCE	Multi-Cap Core Funds	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have between 25% to 75% of their assets invested in companies with market capitalizations (on a three-year weighted basis) above 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Multi-cap core funds have more latitude in the companies in which they invest. These funds typically have an average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P SuperComposite 1500 Index.
MLGE	Multi-Cap Growth Funds	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have between 25% to 75% of their assets invested in companies with market capitalizations (on a three-year weighted basis) above 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Multi-cap growth funds typically have an above-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P SuperComposite 1500 Index.
MLVE	Multi-Cap Value Funds	Funds that, by portfolio practice, invest in a variety of market capitalization ranges without concentrating 75% of their equity assets in any one market capitalization range over an extended period of time. Multi-cap funds typically have between 25% to 75% of their assets invested in companies with market capitalizations (on a three-year weighted basis) above 300% of the dollar-weighted median market capitalization of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Multi-cap value funds typically have a below-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P SuperComposite 1500 Index.
MM	Money Market Funds	Funds invest in high quality financial instruments rated in top two grades with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
MN	Minnesota Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Minnesota, (double tax-exempt) or city, (triple tax-exempt).

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
MO	Missouri Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Missouri, (double tax-exempt) or city, (triple tax-exempt).
MR	Micro-Cap Funds	Funds that by prospectus or portfolio practice invest primarily in companies with market capitalizations less than $300 million at the time of purchase.
MSI	Multi-Sector Income Funds	Funds seek current income by allocating assets among different fixed income securities sectors, (not primarily in one sector except for defensive purposes), including U.S. & foreign governments, with a significant portion rated below investment grade.
MTAA	Mixed-Asset Target Allocation Aggressive Growth Funds	Fund of funds that, by portfolio practice, maintain at least 80% of assets in equity securities, with the remainder invested in bonds, cash, and cash equivalents.
MTAC	Mixed-Asset Target Alloc Consv Funds	Funds that by portfolio practice maintain a mix of between 20%-40% equity securities, with the remainder invested in bonds, cash, and cash equivalents.
MTAG	Mixed-Asset Target Alloc Growth Funds	Funds that by portfolio practice maintain a mix of between 60%-80% equity securities, with the remainder invested in bonds, cash, and cash equivalents.
MTAM	Mixed-Asset Target Alloc Moderate Funds	Funds that by portfolio practice maintain a mix of between 40%-60% equity securities, with the remainder invested in bonds, cash, and cash equivalents.
NC	North Carolina Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in North Carolina, (double tax-exempt) or city, (triple tax-exempt).
NJ	New Jersey Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in New Jersey, (double tax-exempt) or city, (triple tax-exempt).
NJM	New Jersey Tax-Exempt Money Market Funds	Funds invest in municipal obligations of New Jersey, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
NR	Natural Resources Funds	Funds invest primarily in natural resources stocks.
NY	New York Municipal Debt Funds	Funds that limit their assets to those securities that are exempt from taxation in New York, (double tax-exempt) or city, (triple tax-exempt).
NYI	New York Insured Municipal Debt Funds	Funds that invest at least 65% of their assets in those securities that are exempt from taxation in New York, and are insured as to timely payment.
NYM	New York Tax-Exempt Money Market Funds	Funds invest in municipal obligations of New York state, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep constant net asset value.
NYT	New York Intermdt Municipal Debt Funds	Funds invest primarily in municipal debt issues that are exempt from taxation in New York, with dollar-weighted average maturities of five to ten years.
OH	Ohio Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Ohio, (double tax-exempt) or city, (triple tax-exempt).
OHM	Ohio Tax-Exempt Money Market Funds	Funds invest in municipal obligations of Ohio state, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
OHT	Ohio Intermediate Municipal Debt Funds	Funds invest primarily in municipal debt issues that are exempt from taxation in Ohio, with dollar-weighted average maturities of five to ten years.
OR	Oregon Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Oregon, (double tax-exempt) or city, (triple tax-exempt).
OSS	Other States Short-Intmdt Muni Debt Funds	Funds invest in municipal debt issues with dollar-weighted average maturities of one to five years and are exempt from taxation on a specified city or state basis.
OST	Other States Intermediate Muni Debt Funds	Funds invest in municipal debt issues with dollar-weighted average maturities of five to ten years and are exempt from taxation on a specified city or state basis.
OTH	Other States Municipal Debt Funds	Funds invest in municipal debt issues with dollar-weighted average maturities of five to ten years and are exempt from taxation on a specified city or state basis.
OTM	Other States Tax-Exempt Money Market Funds	Funds invest in municipal obligations of other states, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep constant net asset value.
PA	Pennsylvania Municipal Debt Funds	Funds that limit assets to those securities that are exempt from taxation in Pennsylvania, (double tax-exempt) or city, (triple tax-exempt).

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
PAM	Pennsylvania Tax-Exempt Money Market Funds	Funds invest in municipal obligations of Pennsylvania state, (double tax-exempt) or city, (triple tax-exempt) with dollar-weighted average maturities of less than 90 days. Intend to keep constant net asset value.
PAT	Pennsylvania Intermediate Muni Debt Funds	Funds invest primarily in municipal debt issues that are exempt from taxation in Pennsylvania, with dollar-weighted average maturities of five to ten years.
PC	Pacific Region Funds	Funds that concentrate investments in equity securities with primary trading markets or operations concentrated in the Western Pacific Basin region or a single country within this region.
RE	Real Estate Funds	Funds invest primarily in equity securities of domestic and foreign companies engaged in the real estate industry.
S	Specialty/Miscellaneous Funds	Funds that limit fund investments to a specific industry (e.g., transportation, retailing, or paper, etc.) or one that has not been classified into an existing investment objective.
SC	South Carolina Municipal Debt Funds	Funds that limit their assets to those securities that are exempt from taxation in South Carolina (double tax-exempt) or city (triple tax-exempt).
SCCE	Small-Cap Core Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) less than 250% of the dollar-weighted median of the smallest 500 of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Small-cap core funds have more latitude in the companies in which they invest. These funds typically have an average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P SmallCap 600 Index.
SCGE	Small-Cap Growth Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) less than 250% of the dollar-weighted median of the smallest 500 of the middle 1,000 securities of the S&P SuperComposite 1500 Index. Small-cap growth funds typically have an above-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P SmallCap 600 Index.
SCVE	Small-Cap Value Funds	Funds that, by portfolio practice, invest at least 75% of their equity assets in companies with market capitalizations (on a three-year weighted basis) less than 250% of the dollar-weighted median of the smallest 500 of the middle 1,000 securities of S&P SuperComposite 1500 Index. Small-cap value funds typically have a below-average price-to-earnings ratio, price-to-book ratio, and three-year sales-per-share growth value, compared to the S&P SmallCap 600 Index.
SESE	Specialty Diversified Equity Funds	Funds that, by portfolio practice, invest in all market capitalization ranges without restriction. These funds typically have distinctly different strategies and performance, resulting in a low coefficient of determination (r-squared) compared to other U.S. diversified equity funds. Examples of specialty diversified equity funds include enhanced index funds and market short funds.
SFI	Specialty Fixed Income	Funds that by portfolio practice invest in fixed income strategies that are outside Lipper's other fixed income classifications. These funds typically have distinctly different performance and strategies, including the use of short positions and leverage.
SG	Small-Cap Funds	Funds that by prospectus or portfolio practice invest primarily in companies with market capitalizations less than $1 billion at the time of purchase.
SID	Short Investment Grade Debt Funds	Funds invest primarily in investment grade debt issues (rated in top four grades) with dollar-weighted average maturities of less than three years.
SII	Short-Intmdt Investment Grade Debt Funds	Funds invest primarily in investment grade debt issues (rated in top four grades) with dollar-weighted average maturities of one to five years.
SIM	Short-Intmdt Municipal Debt Funds	Funds invest in municipal debt issues with dollar-weighted average maturities of one to five years.
SIU	Short-Intermediate U.S. Government Funds	Funds invest primarily in securities issued or guaranteed by the U.S. government, its agencies, or its instrumentalities, with dollar-weighted average maturities of one to five years.
SMD	Short Municipal Debt Funds	Funds invest in municipal debt issues with dollar-weighted average maturities of less than three years.
SP	S&P 500 Index Objective Funds	Funds that are passively managed and commit by prospectus language to replicate the performance of the S&P 500 Index, including reinvested dividends. In addition, S&P 500 Index funds have limited expenses (advisor fee no higher than 0.50%).

Table B7: (continued)

CODE	OBJECTIVE CLASS NAME	DESCRIPTION
SPSP	S&P 500 Index Objective Funds	Funds that are passively managed and commit by prospectus language to replicate the performance of the S&P 500 Index, including reinvested dividends. In addition, S&P 500 Index funds have limited expenses (advisor fee no higher than 0.50%).
SSIM	Single-State Insured Municipal Debt Funds	In Open-End and Closed-End Funds;Funds that limit assets to those securities exempt from taxation in a specified state (double tax-exempt) or city (triple tax-exempt) and are insured as to timely payment. Due to the introduction of the Single-State Insured Municipal Debt Funds (SSIM) classification, the New York Insured Municipal Debt FUNDS (NYI) and California Insured Municipal Debt Funds (CAI) classifications will not be available after May 23, 2008. These classifications will be collapsed into the Single-State Insured Municipal Debt Funds classification; however, Lipper will continue to maintain the NYI and CAI objectives.
STB	Stable Value Funds	Funds that aim to provide income while limiting price fluctuations by investing primarily in guaranteed investment contracts (GICs) or wrapped bonds (synthetic GICs).
SUS	Short U.S. Government Funds	Funds invest primarily in securities issued or guaranteed by the U.S. government, its agencies, or its instrumentalities, with dollar-weighted average maturities of less than three years.
SUT	Short U.S. Treasury Funds	Fund invests primarily in U.S. Treasury bills, notes and bonds with dollar-weighted average maturitie of less than three years.
SWM	Short World Mulit-Market Income Funds	Funds that invest in non-U.S. dollar and U.S. dollar debt instruments and, by policy, keep a dollar-weighted average maturity of less than five years.
TEM	Tax-Exempt Money Market Funds	Funds invest in high quality municipal obligations with dollar-weighted average maturities of less than 90 days. Intend to keep a constant net asset value.
TK	Science & Technology Funds	Funds invest primarily in science and technology stocks.
TL	Telecommunication Funds	Funds invest primarily in equity securities of domestic and foreign companies engaged in the development, manufacture, or sales of telecommunications services or equipment.
TM	Target Maturity Funds	Funds invest principally in zero-coupon U.S. Treasury securities or in coupon-bearing U.S. government securities targeted to mature in a specific year.
TN	Tennessee Municipal Debt Funds	Funds that limit its assets to those securities that are exempt from taxation in Tennessee, (double tax-exempt) or city, (triple tax-exempt).
TX	Texas Municipal Debt Funds	Funds that limit their assets to those securities that are exempt from taxation in Texas (double tax-exempt) or city (triple tax-exempt).
USM	U.S. Mortgage Funds	Funds invest primarily in mortgages/securities issued or guaranteed as to principal and interest by the U.S. government and certain federal agencies.
USO	Ultra-Short Obligations Funds	Funds invest primarily in investment grade debt issues, or better, and maintains a portfolio dollar-weighted average maturity between 91 days and 365 days.
USS	U.S. Government Money Market Funds	Funds invest principally in financial instruments issued or guaranteed by the U.S. government, its agencies, or its instrumentalities, with dollar-weighted average maturities of less than 90 days. Intend to keep a constant NAV.
UST	U.S. Treasury Money Market Funds	Funds invest principally in U.S. Treasury obligations with dollar-weighted average maturities of less than 90 days. Intend to keep a constant net asset value.
UT	Utility Funds	Funds invest primarily in utility shares.
VA	Virginia Municipal Debt Funds	Funds that limit their assets to those securities that are exempt from taxation in Virginia, (double tax-exempt) or city, (triple tax-exempt).
VAT	Virginia Intermediate Municipal Debt Funds	Funds that invest at least 65% of its assets in municipal debt issues that are exempt from taxation in Virginia, with dollar-weighted average maturities of five to ten years.
WA	Washington Municipal Debt Funds	Funds that limit their assets to those securities that are exempt from taxation in Washington (double tax-exempt) or city (triple tax-exempt).
XJ	Pacific Ex Japan Funds	Funds that concentrate investments in equity securities with primary trading markets or operations concentrated in the Pacific region (including Asian countries) and that specifically does not invest in Japan.

Table B8: Strategic Insight Objectives

STRATEGIC INSIGHTS OBJECTIVE CODES - DETAILED

(Fund Style Table. Variable: si_obj_cd. Page 12)

CODE	CODE NAME
AGG	Equity USA Aggressive Growth
BAL	Asset Allocation USA Balanced
BGA	Tx Bd Pan Americas
BGC	Global Corporation Fixed Income
BGE	Tx Bd Global Emerging Market
BGG	Tx Bd Global Govt Bond
BGN	Tx Bd Global Bond General
BGS	Tx Bd Global Bond Short
CGN	Tx Bd Corp Bond General
CHQ	Tx Bd Corp High Quality
CHY	Tx Bd Corp High Yield
CIM	Tx Bd Corp Intermediate
CMQ	Tx Bd Corp Medium Quality
CPF	Asset Allocation USA Preferred
CPR	Tx Bd Corp Prime Rate
CSI	Tx Bd Strategic Income
CSM	Tx Bd Corp Short
CVR	Convertibles
ECH	Equity Greater China
ECN	Equity Canada
EGG	Equity Global Growth
EGS	Equity Global Small Company
EGT	Equity Global Total Return
EGX	Equity Global Equity Sector
EID	Equity Global Emerging Markets
EIG	Equity International Growth
EIS	Equity International Small Company
EIT	Equity International Total Return
EJP	Equity Japan
ELT	Equity Latin America
ENV	Equity USA Environmental
EPC	Equity Asia Pacific Including Japan
EPR	Asset Allocation USA Principle Return
EPX	Equity Asia Pacific Excluding Japan
ERP	Equity European
ESC	Equity Single Country
FIN	Equity USA Financial Sector
FLG	Asset Allocation Global Flexible
FLX	Asset Allocation USA Flexible
GBG	Global Bond General
GBS	Global Bond Short Maturity
GGN	Tx Bd USA Govt General
GIM	Tx Bd USA Govt Intermediate
GLD	Equity Gold
GLE	Global Equity
GMA	Tx Bd USA Govt Mortgage Adj Returns
GMB	Tx Bd USA Govt Mortgage Backed
GMC	Equity USA Midcaps
GRI	Equity USA Growth & Income
GRO	Equity USA Growth
GSM	Tx Bd USA Govt Short
HLT	Equity USA Health
IAZ	TxFr Bd Muni Intermediate AZ
ICA	TxFr Bd Muni Intermediate CA
ICO	TxFr Bd Muni Intermediate CO
ICT	TxFr Bd Muni Intermediate CT
IFL	TxFr Bd Muni Intermediate FL
IGA	TxFr Bd Muni Intermediate GA
IHI	TxFr Bd Muni Intermediate HI
IKS	TxFr Bd Muni Intermediate KS
IKY	TxFr Bd Muni Intermediate KY
IMA	TxFr Bd Muni Intermediate MA
IMD	TxFr Bd Muni Intermediate MD
IMI	TxFr Bd Muni Intermediate MI
IMN	TxFr Bd Muni Intermediate MN
IMT	TxFr Bd Muni Intermediate MT
IMX	Asset Allocation USA Income
INC	TxFr Bd Muni Intermediate NC
IND	TxFr Bd Muni Intermediate ND
ING	Equity USA Income & Growth
INJ	TxFr Bd Muni Intermediate NJ
INM	TxFr Bd Muni Intermediate NM
INY	TxFr Bd Muni Intermediate NY
IOH	TxFr Bd Muni Intermediate OH
IOR	TxFr Bd Muni Intermediate OR
IPA	TxFr Bd Muni Intermediate PA
ISC	TxFr Bd Muni Intermediate SC
ISD	TxFr Bd Muni Intermediate SD
ITN	TxFr Bd Muni Intermediate TN
ITX	TxFr Bd Muni Intermediate TX
IVA	TxFr Bd Muni Intermediate VA
IVT	TxFr Bd Muni Intermediate VT
IWA	TxFr Bd Muni Intermediate WA
IWV	TxFr Bd Muni Intermediate WV
JPN	Japanese Equity
LCA	TxFr Bd Muni Short CA

Table B8: (continued)

CODE	CODE NAME	CODE	CODE NAME
LFL	TxFr Bd Muni Short FL	MNM	TxFr Bd Muni NM
LKY	TxFr Bd Muni Short KY	MNY	TxFr Bd Muni NY
LMA	TxFr Bd Muni Short MA	MOH	TxFr Bd Muni OH
LMD	TxFr Bd Muni Short MD	MOK	TxFr Bd Muni OK
LMI	TxFr Bd Muni Short MI	MOR	TxFr Bd Muni OR
LNC	TxFr Bd Muni Short NC	MPA	TxFr Bd Muni PA
LNY	TxFr Bd Muni Short NY	MPR	TxFr Bd Muni PR
LTN	TxFr Bd Muni Short TN	MRI	TxFr Bd Muni RI
LVA	TxFr Bd Muni Short VA	MSC	TxFr Bd Muni SC
MAL	TxFr Bd Muni AL	MSD	TxFr Bd Muni SD
MAR	TxFr Bd Muni AR	MSM	TxFr Bd Fed Muni Short
MAZ	TxFr Bd Muni AZ	MTN	TxFr Bd Muni TN
MCA	TxFr Bd Muni CA	MTX	TxFr Bd Muni TX
MCO	TxFr Bd Muni CO	MUT	TxFr Bd Muni UT
MCT	TxFr Bd Muni CT	MVA	TxFr Bd Muni VA
MDE	TxFr Bd Muni DE	MVT	TxFr Bd Muni VT
MFL	TxFr Bd Muni FL	MWA	TxFr Bd Muni WA
MGA	TxFr Bd Muni GA	MWI	TxFr Bd Muni WI
MGN	TxFr Bd Fed Muni General	MWV	TxFr Bd Muni WV
MHI	TxFr Bd Muni HI	NTR	Equity Natural Resources & Energy
MHY	TxFr Bd Fed Muni High Yield	OPI	Option Income
MIA	TxFr Bd Muni IA	PAC	Pacific Equity
MID	TxFr Bd Muni ID	RLE	Equity USA Real Estate
MIL	TxFr Bd Muni IL	SBA	Tx MM Bank Govt & Agency
MIM	TxFr Bd Fed Muni Intermediate	SBE	Tx MM Bank Prime Euro
MIN	TxFr Bd Muni IN	SBP	Tx MM Bank Prime
MIS	TxFr Bd Fed Muni Insured	SBT	Tx MM Bank Govt
MKS	TxFr Bd Muni KS	SBY	Tx MM Bank Prime Euro Yank
MKY	TxFr Bd Muni KY	SCG	Equity USA Small Companies
MLA	TxFr Bd Muni LA	SCU	Tx MM Currency Funds
MMA	TxFr Bd Muni MA	SEC	Equity USA Misc Sectors
MMD	TxFr Bd Muni MD	SIA	Tx MM Instl Govt & Agency
MME	TxFr Bd Muni ME	SIE	Tx MM Instl Prime Euro
MMI	TxFr Bd Muni MI	SIP	Tx MM Instl Prime
MMN	TxFr Bd Muni MN	SIT	Tx MM Instl Govt
MMO	TxFr Bd Muni MO	SIY	Tx MM Instl Prime Euro Yank
MMS	TxFr Bd Muni MS	SPE	Tx MM Prime Euro
MMT	TxFr Bd Muni MT	SPR	Tx MM Prime
MNC	TxFr Bd Muni NC	SPY	Tx MM Prime Euro Yank
MND	TxFr Bd Muni ND	SUA	Tx MM Govt & Agency
MNE	TxFr Bd Muni NE	SUT	Tx MM Govt
MNH	TxFr Bd Muni NH	TAL	TxFr MM Muni AL
MNJ	TxFr Bd Muni NJ	TAZ	TxFr MM Muni AZ

Table B8: (continued)

CODE	CODE NAME
TBG	TxFr MM Fed Muni Bank Managed
TCA	TxFr MM Muni CA
TCT	TxFr MM Muni CT
TEC	Equity USA Technology
TFG	TxFr MM Fed Muni General
TFI	TxFr MM Fed Muni Instl
TFL	TxFr MM Muni FL
TGA	TxFr MM Muni GA
TMA	TxFr MM Muni MA
TMD	TxFr MM Muni MD
TMI	TxFr MM Muni MI
TMN	TxFr MM Muni MN
TNC	TxFr MM Muni NC
TNJ	TxFr MM Muni NJ
TNY	TxFr MM Muni NY
TOH	TxFr MM Muni OH
TPA	TxFr MM Muni PA
TTN	TxFr MM Muni TN
TTX	TxFr MM Muni TX
TVA	TxFr MM Muni VA
UTI	Equity USA Utilities

Table B9: Wiesenberger Objective Codes

CODE	DESCRIPTION
G	Growth
I	Income
SStability	
(ANNUAL VOLUMES 1991-93)	
AAL	Asset allocation
BAL	Balanced
CBD	Corporate bond
CHY	Corporate high-yield bond
ENR	Energy/Natural resources
FIN	Financial sector
GCI	Growth and current income
GOV	Government securities
GPM	Gold and precious metals
HLT	Health sector
IBD	International bond
IEQ	Equity income
IFL	Flexible income
INT	International equity
LTG	Long-term growth
MBD	Municipal bond
MCG	Maximum capital gains
MHY	Municipal high-yield
MMF	Money market fund
MSS	Municipal single state
MTG	Government mortgage-backed
OTH	Other (not classified)
SCG	Small capitalization growth
TCH	Technology sector
TFM	Tax-free money market
TMM	Taxable money market
UTL	Utilities

APPENDIX C. CHAPTER 4

Table C1: Description of Variables

This table defines all the main variables of this study.

Variables	Description
R^2	Measure of activity of fund introduced by Amihud, and Goyenko (2013), retrieved from an annual time series regression of Carhart's (1997) four factor model given in Equation (1). It is the proportion of the variability in fund returns that is explained by the variation in these factors' returns.
$T(R^2)$	Logistic transformation of R^2 for fund i at time t, explained in Equation (2).
$Female$	Measure of Female Proportion. Equal to number of female managers divided by the total number of managers in fund's management team at time t.
$SecDev$	Measure of Sector Concentration Deviation (%). Equal to the square root of the sum of squared differences between portfolio concentration of fund i in each of the three super sectors and the average concentration in each sector among all the funds in fund i's investment segment in the same year t.
$UnsysRisk$	Measure of Unsystematic Risk (%). Equal to the annual standard deviation of fund i's return residuals obtained from Carhart's (1997) four factor model.
$SysRisk$	Measure of Systematic Risk (%). Equal to the annual beta retrieved from regressing fund i's excess return on the excess return of market.
$Risk$	Measure of Total Risk (%). Equal to the sum of systematic and unsystematic risk of fund i at time t.
$TOratio$	Measure of Trading Activity (%). Equal to the lesser of annual purchases or sales (excluding all securities with maturities of less than one year) and dividing by average net assets in time t.
$AggSE$	Measure of Aggregate Style Extremity (%). Equal to the mean of style extremity of three style dimensions i.e., size, value, and momentum in time t.
$Size$	Measure of Fund Size. Equal to the natural log of total assets under management of fund i in time t.
Exp	Measure of Expense Ratio (%). Equal to the value weighted average of net expense ratio of all the share classes of a fund at time t.
$Flow$	Measure of Fund Net Flow. Equal to the growth in fund i's assets under management in time t, given in Equation (3)

Note: For linear regressions, instead of taking annual average of the variables with monthly data frequency, the annual measures are considered unchanged for all respective months of the year.

Table C2: Annual Distribution of Funds by Gender

This table presents the number of funds, number of male and female managers, ratio of female to male managers, and proportion of female managers in management teams across all the sample funds from January 2004 – December 2014.

Year	No. of funds	No. of female managers	No. of male managers	Ratio of female to male managers (%)	Female proportion in management teams (%)
2004	1,017	228	2,023	11.27	9.30
2005	1,079	268	2,386	11.23	8.99
2006	1,155	315	2,819	11.17	8.45
2007	1,207	354	3,067	11.54	8.70
2008	1,265	381	3,310	11.50	8.91
2009	1,302	406	3,453	11.75	8.92
2010	1,346	410	3,644	11.24	8.75
2011	1,401	413	3,876	10.65	8.41
2012	1,467	409	4,184	9.78	8.09
2013	1,522	410	4,297	9.54	8.21
2014	1,565	412	4,335	9.51	8.42

Table C3: Female Proportion and Risk-taking Behavior

This table presents the findings of regression of fund riskiness on female proportion, including fund level controls. The dependent variable is fund's risk level, which is measured as $UnsysRisk$, $SysRisk$, and $Risk$ using Equation (1). The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$UnsysRisk_{i,t} = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t}$$

$$SysRisk_{i,t} = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t}$$

$$Risk_{i,t} = \alpha + \beta_1\, Female_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t}$$

	Unsystematic Risk	Systematic Risk	Total Risk
	(1)	(2)	(3)
Female	-0.1483***	-0.0122	-0.1362***
	(-3.45)	(-1.11)	(-2.83)
Size	-0.0183	0.0134***	-0.0049
	(-1.53)	(3.86)	(-0.37)
Exp	0.3634***	-0.0015	0.3619***
	(12.25)	(-0.16)	(11.59)
Flow	0.1787**	-0.0786**	0.1001
	(2.02)	(-2.10)	(0.98)
Constant	0.5963***	0.8822***	1.4785***
	(5.21)	(25.69)	(11.92)
No. of Obs.	164,645	164,645	164,645
Adj. R-squared	0.1064	0.0038	0.0769

Table C4: Female Proportion and Overconfidence

This table presents the findings of regression of fund trading activity on female proportion, including fund level controls. The dependent variable is fund's trading activity, which is measured by turnover ratio, $TOratio$. The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$TOratio_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2 \, Size_{i,t} + \beta_3 \, Exp_{i,t} + \beta_4 \, Flow_{i,t} + \varepsilon_{i,t}$$

	Turnover Ratio			
	All Controls	Fund Size Control	Expense Control	Flow Control
	(1)	(2)	(3)	(4)
Female	-9.9430*	-9.8954*	-9.6174*	-9.9653*
	(-1.79)	(-1.75)	(-1.70)	(-1.79)
Size	-8.2923***	-12.2874***	-	-
	(-2.88)	(-3.97)		
Exp	18.7623***	-	25.6923***	-
	(2.51)		(3.40)	
Flow	-7.8048	-	-	6.4600
	(-0.54)			(0.48)
Constant	125.5378***	180.5051***	47.8703***	76.6737***
	(4.59)	(6.59)	(6.20)	(34.71)
No. of Obs.	161,004	164,822	163,469	162,303
Adj. R-squared	0.0253	0.0171	0.0189	0.0006

Table C5: Female Proportion and Style Extremity

This table presents the findings of regression of investment style extremity on female proportion, including fund level controls. The dependent variable is fund's aggregated style extremity, which is measured in Equation (12). The independent variable is $Female$ which is the number of female fund managers divided by the total number of managers managing the fund at time t. We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$AggSE_{i,t} = \alpha + \beta_1 Female_{i,t} + \beta_2\, Size_{i,t} + \beta_3\, Exp_{i,t} + \beta_4\, Flow_{i,t} + \varepsilon_{i,t}$$

	Aggregated Style Extremity			
	All Controls	Fund Size Control	Expense Control	Flow Control
	(1)	(2)	(3)	(4)
Female	-0.0550	-0.0565	-0.0555	-0.0513
	(-1.18)	(-1.20)	(-1.16)	(-1.09)
Size	-0.0475***	-0.1110***	-	-
	(-3.99)	(-8.71)		
Exp	0.2444***	-	0.2817***	-
	(7.47)		(8.82)	
Flow	0.3346***	-	-	0.5267***
	(3.63)			(5.06)
Constant	1.1155***	1.9346***	0.6767***	0.9927***
	(9.61)	(17.40)	(19.87)	(89.04)
No. of Obs.	164,635	170,453	167,282	167,610
Adj. R-squared	0.0464	0.0241	0.0402	0.0022

Table C6: Time-varying Conditional Correlation and Fund Risk with Market Model

This table presents the findings of regression of fund returns correlation on riskiness of fund, including fund level controls. The dependent variable is DCC, which is the dynamic conditional correlation of fund returns measured by using the model of Engle (2002). The independent variable is fund's risk level, which is measured as $UnsysRisk$, $SysRisk$, and $Risk$ using Equation (14). We winsorize the fund level control variables at 1% and 99%. The t-statistics based on clustered standard errors for time and fund are reported in parentheses. ***, **, and * denote 99%, 95%, and 90% significance levels. See Table C1 in the appendix for the explanation of the variables.

$$DCC_{i,t} = \alpha + \beta_1\ Risk\_Measures_{i,t} + \beta_2\ Size_{i,t} + \beta_3\ Exp_{i,t} + \beta_4\ Flow_{i,t} + \varepsilon_{i,t}$$

	Time-varying Conditional Correlation		
	(1)	(2)	(3)
UnsysRisk	-0.5289***	-	-
	(-16.83)		
SysRisk	-	-0.0229	-
		(-0.38)	
Risk	-	-	-0.4023***
			(-16.77)
Size	-0.0101	0.0022	-0.0013
	(-0.56)	(0.09)	(-0.07)
Exp	-0.5097***	-0.7608***	-0.5427***
	(-11.24)	(-13.33)	(-11.29)
Flow	-0.7862***	-0.9288***	-0.8625***
	(-6.71)	(-7.06)	(-7.13)
Constant	3.7658***	3.3018***	3.9945***
	(21.59)	(13.43)	(21.41)
No. of Obs.	165,181	165,181	165,181
Adj. R-squared	0.3578	0.1597	0.3111