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THE EFFECT OF FEMALE MANAGERS ON MUTUAL FUND PERFORMANCE DURING DOWN MARKETS

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by

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Abstract

Women in the finance industry have long been underrepresented. The mutual fund industry is no exception, with female managers in the United States falling stagnant at only 11% from 2000 to 2019. Given this low and stagnant number, this study seeks to understand if female managers impact mutual fund performance, specifically comparing down and up market periods. The data for this research was compiled from individual US mutual fund prospectus and fact sheet information in order to create a unique dataset containing the returns for every year between 2000 and 2019 as well as gender make-up, average experience, and team size of each management team. The funds in this data set include equity, fixed income, and blended portfolios. It is necessary to understand the performance of mutual funds as despite their continual underperformance in comparison to other actively managed investment classes, they remain a large industry. This study finds that gender is not a cause of this underperformance and therefore not a rational component for deciding management team makeup. These findings are consistent with previous literature that found no impact on performance due to gender in European equity mutual funds.

Acknowledgements

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1. Introduction

Traditionally, the asset management industry is a field dominated by men (Morris, 2020). This is particularly noticeable in the mutual fund industry, which consistently has low percentages of female managers. In both 2000 and 2019, the average percentage of female mutual fund managers measured globally was only 14% and was even smaller in the United States where it was 11% in both these years (Lallos 2020). In the finance industry overall, there has been a growth in the number of women and people of color who enter asset management. Some firms have begun to actively diversify their workforce through participation in both internal directives, as well as programs organized by organizations such as Girls Who Invest or Seizing Every Opportunity (SEO) which give college students experience in the asset management industry. This industry often focuses on finding a "trading edge" which describes "a technique, observation or approach that creates a cash advantage over other market players" (Farley 2020). This trading edge is developed through unique experiences and perspectives that allow an investor to see opportunities in the market where others do not. It is possible that diversity and growth in perspectives has the potential to help firms find promising new investments and increase their financial returns. This has helped influence the decision to increase their diversity.

The actively managed mutual fund industry is in particular need of such potential. This industry has long underperformed in comparison to other subfields of asset management, as well as benchmarks such as the S&P 500. Due to this underperformance, over the years actively managed mutual funds have lost investors to these other forms of investing (Pastor, Vortaz 2020). However, the niche remains large, manages tens of trillions of dollars, and is still attractive to investors due to the allocation of assets held by mutual funds. The

underperformance relative to other industries demonstrates a necessity to study what factors contribute to financial performance – both positively and negatively. It is important for firms to understand what factors influence returns for their funds in order to potentially make changes to improve their performance. In particular, studying mutual funds during recessions and bear markets can provide useful information in regard to what factors correlate with strong returns. Understanding what allows certain mutual funds to perform better than others reveals what factors are important to positive returns during both times of financial crisis and financial growth.

This thesis adds to the research on how female managers impact financial performance in the mutual fund industry. Specifically, I investigate how mutual funds with female managers differ from those that have no female managers, as well as analyze the way percentages of female managers on a team may impact returns. My efforts differ from previous research by analyzing a random sample of mutual funds from equity, fixed income, and blended asset classes during recessions and bear markets. I analyze what are the most significant factors in a mutual funds' ability to generate high returns, particularly during bear markets. Previous research has not considered how mutual funds perform during recessions in relation to structural characteristics such as percentage of female managers on the management team. I argue that by studying the industry in times of an unexpected economic shock, managers' skills are truly tested, and the returns of their fund will reflect all benefits or deficits they bring to the table.

This paper helps generate a greater understanding of mutual fund performance and characteristics in the United States over the last two decades. By comparing how the percentage of female managers as well as other structural characteristics of funds impact returns to the consistently low levels of female managers, I will investigate if the industry is acting rationally

and in its own self-interest. If female managers are a positive factor on firm performance, especially during crises such as recessions, then as rational actors firms should have been increasing the levels of female managers and moving forward would be incentivized to consider hiring more female managers. There has been much work in behavioral finance to explain why firms do not always act as rational actors. Kahneman and Tversky in their seminal work found that individuals had inconsistent preferences, which they used to develop an alternative theory of decision making under risk (Kahneman, Tversky 1979). This laid the groundwork for further research, particularly by Richard Thaler, who was able to demonstrate through series of experiments, that what he calls nudges effect the choices people make, something that would not happen to rational economic agents (Thaler 2018). The fact that firms do not act as rational agents could be used to explain why the mutual fund industry as a whole has not increased its percentages of female managers if it is shown that they are a statistically significant positive impact on returns.

My research contributes to the current literature in several ways. First, recent developments in diversity of firm ownership demonstrates larger trends that I will study within the mutual fund industry. From 2011 to 2017 there has been an upward trend of Assets Under Management (AUM) by women owned firms. In terms of financial performance, there was no statistical difference in diverse owned firms and non-diverse owned firms during this time, with diverse being defined as either owned by women or people of color (Lerner 2017). It is important to note that this research looked at ownership and not management. A study of European diversified equity mutual funds and gender also found no significant difference in the financial performance of funds managed by women compared to men (Babalos, Caporale, Philippas). The

European study focuses on Europe and on gender in mutual funds that invest in equity, as opposed to fixed income or other possible asset allocations.

Since mutual funds are publicly traded, data on management characteristics are publicly available. Management characteristics encompasses gender, industry experience, and team size. I use the gender of the managers to create a percentage of each management team of female managers. Similarly, I use industry experience to create an average team experience for each management team. I also collect data on returns for each individual fund collected on December 31st of each year from 2000 to 2019. In order to control for differences in structural asset class allocation, I collected data on the percentage breakdown of where assets are allocated in terms of equity, cash/cash equivalence, and fixed income. All of this data is publicly available on the fact sheets and websites of each firm that owns the mutual funds. Finally, I collected the historical returns of the S&P 500 and the three-month US-Treasury Bill for use in the Capital Asset Pricing Model (CAPM), which is used to measure the returns against the appropriate benchmarks.

2. Literature Review

In this section I review the existing literature on women's participation both in the labor force overall as well as their impact in the finance industry. In addition, I review literature examining the behavior of mutual funds during and around a financial crisis, focusing on the relationship between the participation of women as managers in the mutual fund industry to returns during down markets such as financial crises.

2.1. Women's Participation in the Labor Force

From the early 1920s until the present, women's labor force participation has consistently been growing. In 1920, married women first began to join the workforce in noticeable numbers,

starting a period of expansion that lasted until the 1960s (Goldin, 2014). Through the 1940s, an increased demand for clerical work and an increased supply of high school graduates further grew the number of women participating in the labor force. Periods of evolutionary change began to level out towards the end of the 1960s due to several factors such as the decreased stigma of working married women, the end of marriage bars, and the creation of part-time employment which pushed women's participation to its highest points. Yet despite these increases in labor force participation, women's income remained below that of their male counterparts. The fact that men were more likely to plan out future careers in their youth could account for this disparity (Goldin 2006).

At the same time, women's educational possibilities began to expand, making them more qualified to become participants in parts of the labor force that were previously inaccessible due to educational barriers. Yet, even with women's educational and skill levels beginning to match those of men, participation in the labor force plateaued in the 1990s and today remains low in certain fields. Women simply are not engaged in the same professions at the same numbers as men. This suggests additional barriers to entry that are not related to barriers in access to education and skill training. One argument for this has been that change must occur in the labor market itself, specifically relating to the ways that jobs are structured and the flexibility of labor hours. Currently, firms have an incentive to reward workers who are able to work long and set hours. This disproportionately affects the ability of women to participate in occupations that demand such structure, due to constraints such as childcare (Goldin 2014).

This disproportionate labor force participation between men and women can and often does negatively impact firms. In recent decades, diversity and inclusion have become standard corporate strategies. However, it is not simply for social justice reasons that businesses engage in

these practices. Diversity is increasingly being understood as a competitive advantage, specifically as an important way to create growth (Hunt, Yee, Prince, Dixon-Fyle 2018). In 2014, companies in the top quartile of gender diversity for executive teams were 15% more likely to experience profitability that was above average than companies in the fourth quartile. The expanded 2017 study demonstrated a 21% likelihood that continued to be statistically significant (Hunt, Yee, Prince, Dixon-Fyle 2018). Additionally, more women executives in line roles (revenue generating) is closely correlated with financial outperformance, even while women continue to be underrepresented in these roles (Krivkovich, Robinson, Starikova, Valentino, Yee 2017; Hunt, Yee, Prince, Dixon-Fyle 2018). Board diversity is also correlated with financial performance. A study using 1993 and 1998 financial performance data and the percentage of women and minorities on boards of directors of the 127 largest US companies found that board diversity is positively associated with the firm's financial performance (Erhardt, Werbel, Shrader 2003). Simply the presence of a woman on a team creates better performance in terms of sales and profits (Hoogendoorn, Oosterbeek, and van Praag 2013).

In the case of mutual funds two studies, one released in 2017 and one released in 2019 discuss diversity in the context of firm ownership. Women owned firms have seen an upward trend in Assets Under Management (AUM) from 2011 to 2017 (Lerner 2017). This upward trend in women ownership is at odds with the percentage of women management of mutual funds, which has remained at 14% from the end of 2000 to the end of 2019 (Morningstar). Both the 2017 and 2019 studies found that there was no statistical difference in diverse owned firms and non-diverse owned firms in terms of financial performance (Lerner 2017, 2019). This finding is consistent with other studies of mutual fund managers and gender diversity. One analysis focused specifically on European diversified equity mutual funds found that there was no

significant difference in the financial performance measured by returns of funds managed by women compared to men (Bablos, Caporale, and Philippas 2015). All three of these studies support a general trend in the literature that there is no significant statistical difference in performance of mutual funds between female and male managers. In another important angle, Baer, Niessen-Ruenzi, Ruenzi (2009) investigate diversity defined by education, gender, tenure, and age. The study focuses on the effect of team diversity on mutual fund performance and finds that a tradeoff exists between information gains and communication costs. In teams that are educationally and tenure diverse, information gains were strong, however in gender diverse teams, communication costs dominate. This focus on team performance is due to the fact that funds are increasingly being managed by a team, rather than by a single manager.

2.2. Mutual Funds and Financial Crises

My research centers around the impact of female managers on performance during down-markets. While there has not been research on how female managers impact returns during recessions, there is literature about the impact of recessions on mutual fund returns. A study of the 2008 financial crisis and mutual funds examined the behavior of managers in their financial performance in comparison to benchmark indices. In general, mutual fund managers who actively picked stocks outperformed managers who were secretly matching their funds to indexes. This pattern held true during the 2009 financial crisis. However, all mutual funds were hit severely during the 2008 financial crisis, leading to general underperformance compared to previous years with a strong recovery in 2009 (Petajist0 2018). This literature demonstrates that down-markets and their recovery periods offer a useful point of analysis to compare the impact of managers on returns. My paper expands on this literature to analyze if the gender of managers

impacts the returns of mutual funds during moments of economic downturn such as the 2008 financial crisis.

3. Theory

Mutual funds are important parts of investors' portfolios. Mutual funds can be purchased by any investor – either through a brokerage or directly from an investment firm that operates mutual funds. Because they can be purchased by anyone, they are registered with and regulated by the SEC who requires a certain level of information about their financial status to be published quarterly. Mutual funds can invest in any combination of stocks, bonds, and other assets. They also typically hold some amount of cash that is not invested. The mutual funds discussed in this paper are all actively managed, meaning they are run by managers who make trading decisions based on market analysis and are not simply buying holdings to match indexes such as the S&P 500. Funds that seek to match indexes are called passively managed funds and are not analyzed in this paper. Actively managed funds attempt to generate higher returns for their investors than one would get with a fund that matched indexes. These higher returns allow for actively managed funds to justify their management fees. Structurally, mutual funds pool together cash generated by investors purchasing a stock of the mutual fund, allowing for greater diversification as well as reducing the information and trading costs that investors would incur if they invested on their own. This diversification helps protect investors who buy mutual funds from losses that occur in bear markets and recessions. It is during these recessions and bear markets that actively managed mutual funds are put to the test and should rise to the occasion.

Earning extra-normal returns in financial markets is rare, especially for active traders (Barber, Lee, Liu, Odean, Zhang, 2017). Investors view this success in financial markets as driven by trading edge, which is the specific ways in which a fund, firm, or individual utilizes a

difference from others in order to notice opportunities in the market that others do not (Forbes 2020). The main opportunity to make money in financial markets is to find stocks whose listed value on the stock market is below an analyzed target price that represents the true value of the stock (Baresa, Bogdan, Ivanovic 2013). The edge that a firm, fund, or individual brings to better analyze price targets and find opportunities in the market is another important part of driving the returns that justify the fees that come with actively managed funds.

As discussed previously, there were no statistically significant effects of women managers on returns in various fund sectors and global regions. However, there is a distinct gap in the literature about potential impacts women may have during recessions and bear markets. Recessions are defined as two consecutive quarters of negative GDP growth. In financial markets, bear markets are typically described as a market atmosphere of widespread pessimism and negative investor sentiment that causes securities prices to fall 20% or more (Investopedia, 2020). Over the past twenty years – from 2000 to 2019 – in the United States there have been two recessionary periods and four clear moments of a bear market. The 2001 Dot-Com Bubble and the 2007-2009 Housing Crisis were both recessions and bear markets. In 2011 there was an unexpected and short-lived bear market that resulted in the overall industry ending the year flat. Additionally, in 2015-2016 a stock market sell-off resulted in another bear market.

Finally, it is necessary to address the role risk plays in portfolio allocation. Equity funds invest purely in stocks, which represent small ownership stakes in a company. Stocks often generate dividends, which are small amounts of money paid yearly to investors. Alternatively, fixed income funds invest in types of investment securities that pay a fixed interest payment until a maturity date, at which point the principal investment amount is repaid. One of the fundamental tradeoffs in finance is between risk and return: the greater the risk, the greater the

return, but also the greater the possibility of loss. Investing in equity has a higher level of risk than investing in fixed income, which means that it can either generate higher returns or larger losses for the investor (Campbell, Viceira 2005). Traditional portfolio theory suggests reducing risk through diversification (Sharpe, 1965). It is argued that portfolios with diversification of different kinds of assets will on average yield higher and longer-term returns. The classic portfolio diversification is a split between 40% fixed income and 60% equity. However, in reality investors choose how to invest based on their risk profile – if they are able to tolerate more risk they will invest more heavily in equities and if they want lower levels of risk they invest more in fixed income. Investors who are older and closer to retirement generally tolerate less risk and want safer investments, to ensure that they do not incur a significant loss in their retirement portfolio just before retiring. Younger investors have more time to recover and thus generally are able to tolerate more risk and can invest more heavily in equities.

Mutual funds are a specific type of financial asset that investors can buy. Firms will generally offer many different types of mutual funds, each with different investing goals. This allows them to cater to the varied risk tolerance potential investors may have. Each of the firms discussed in this paper offer funds that invest in either pure equity, pure fixed income, or in a blend that has a mix of equity and fixed income. While equity theoretically may allow for greater returns, not every mutual fund invests in equity because there is a market for investors who want to invest in fixed income or blended funds in order to mitigate the risk level of their portfolio.

4. Data Overview

The following sections provide an overview of the data components in this paper.

4.1. Mutual Funds

Overall, the mutual fund industry in the United States has hovered at approximately eight thousand mutual funds from 2000 to 2019 (Rudden 2020) as shown in Figure 1

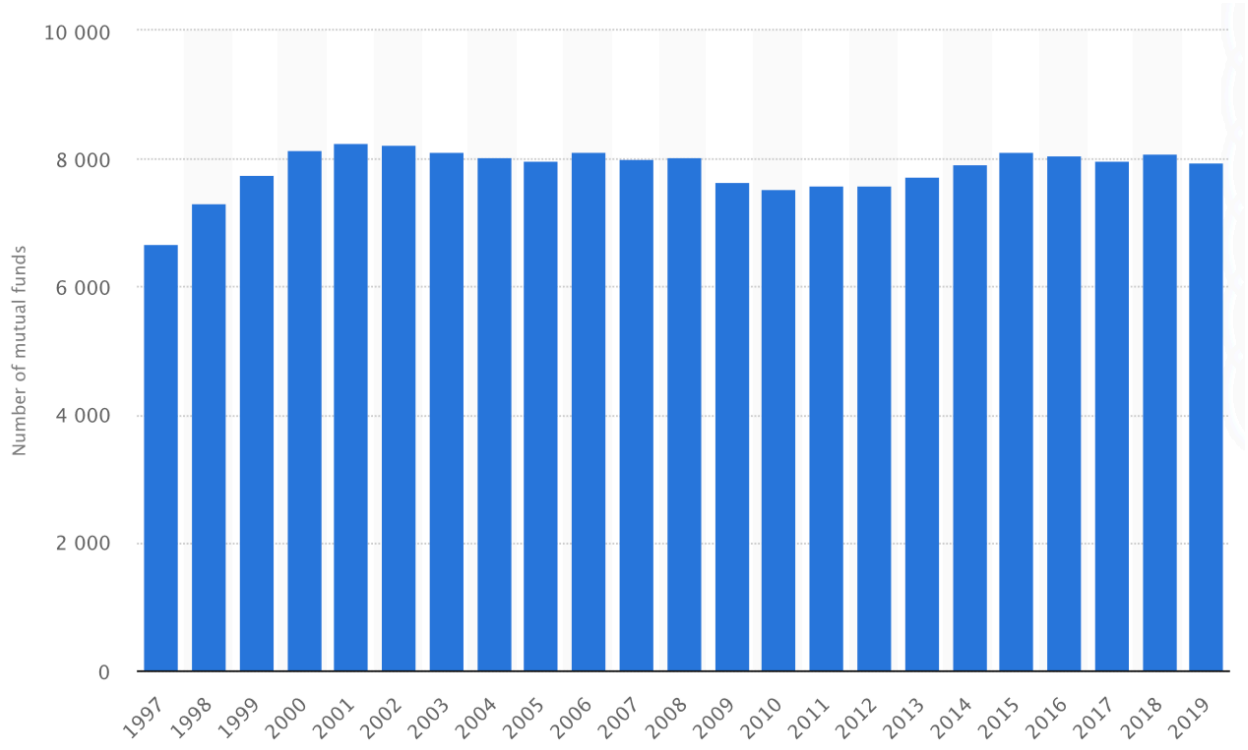

Figure 1

These funds are sold by several large companies who offer a variety of fund types for investors to choose from. Because these funds are available for direct investment by anyone in the public, details about management, investment choices, returns and other metrics of financial performance must be made publicly available through fact sheets and prospectus forms listed on the company's website. The data for this paper is composed of 133 randomly selected mutual funds drawn from several top financial firms. The data includes fund information for all years between 2000 and 2019 for each of the randomly selected funds.

I have selected only funds that have complete data from 2000 to 2019. These funds are likely more stable due to their age. This paper does not analyze funds that completely liquidated

during this time period, which could occur for reasons such as bankruptcy. This creates a selection bias, as I am only analyzing funds managed well enough to avoid bankruptcy. I also do not analyze newer funds that came into existence after 2000.

4.2. Female Managers

The central assumption of this paper is that the level of female managers in the mutual fund industry has remained constant between 2000 and 2019. The literature backs up this assumption on both a global and national level. Globally, from 2000 to 2019, the percentage of managers of mutual funds that are women was 14%, according to an analysis by financial reporting giant Morningstar. This number was even smaller for the United States, where only 11% of managers were women across all funds (Lallos 2020). This industry trend informed the collection of the data for this paper. As manager data for each year from 2000 to 2019 was not easily accessible information for each fund in this data set, the percent breakdown of gender on a management team as well as the presence of a woman on the team is held constant. The listed number of women on the management team at the end of 2019 is used as the constant for each year between 2000 and 2019.

4.3. Capital Asset Pricing Model

In order to effectively measure returns both within and across asset classes it is necessary to control them against a benchmark. A useful model in financial economics to measure returns is the Capital Asset Pricing Model (CAPM):

$$R_i = R_f + \beta_i\left(R_M - R_f\right) \tag{1}$$

R_i represents the return of security *i.* R_M is the return of the market and is greater than the return of the risk-free rate R_f. This model implies that a security's return has a linear relationship to the additional return generated by the market over the risk-free rate captured as the

$CAPM\ Multiplier\ \beta_i$. This model assumes $(R_M - R_f)$ is positive over long periods, as confirmed by observation in the market (Ross, Westerfield, Jaffe 2009). However, during a bear market, the term $(R_M - R_f)$ may become negative and this has an impact on interpretation of β_i which is discussed in section 5.1.

The CAPM model has been modified in order to create Jensen's alpha (Hamilton, Hoje, Statman, 1993). Jensen's alpha is used by financial economists to measure excess returns. The general model for this is:

$$R_i - R_f = \alpha_i + \beta_{iB}(R_B - R_f) + \varepsilon_I \quad (2)$$

Where R_B is the monthly return on a benchmark market portfolio and R_f is risk-free monthly return. β_{iB} is the proportion of fund *i*'s return related to the benchmark. The expected value of the residual return is α_i, which is constant. ε_I represents the deviation of the residual return from the mean. The dependent, $R_i - R_f$ represents the risk adjusted return as it describes the return of mutual fund *i* minus the risk-free rate. Additionally, it is important to note that the α_i or "alpha" for each fund is the mathematical representation of a "trading edge." It demonstrates the skill active investors have over a passive investment in the market. By adjusting for risk in finding the excess performance represented by $R_i - R_f$, increases in alpha represent increasing returns without additional risk, which is ideal for a fund. Jensen's alpha measures a fund manager's performance controlling for the returns of the S&P 500 and the risk-free US 3-month Treasury Bill.

4.4. Summary Statistics

To create the data set to study this industry, I collected data on management experience, team size, and gender as well as the returns for each fund. I also collected the percentage of

women on the management team, which I define as $PerMngWomen$. I then created a dummy variable called $Woman$ that captures whether each fund has a woman on their management team. Additional dummy variables include $EQFund$, which represents funds invested only in equity; $FXFund$, which represents funds only invested in fixed income; and $Blended$, which represents funds that contain a mix of both equity and fixed income. The variable $AvExp$ represents the combined average experience of a management team. $TeamSize$ represents the number of managers in the management team. I took the logs of these two variables, represented by $lgAvgExp$ and $lgTeamSize$, in order to measure the effects as a percentage. Using a version of CAPM discussed later in the model section, I created a multiplier called $CAPM\ Multiplier$, that controls a funds return against the S&P 500 and the three-month US T-Bill. Table 2 contains the relative summary statistics.

Table 2: Summary Statistics

	Observations	Mean	Std. Deviation	Min	Max
Fund	2660	67	38.4	1	133
Year	2660	-	-	2000	2019
Bear Market	2660	0.35	0.477	0	1
Recession	2660	0.2	0.4	0	1
Returns	2660	6.307	21.69	-804	74.44
CAPM Multipier	2660	-1.88	40.69	-391.2	695
S&P 500	2660	5.6	17.18	-38.49	29.6
US T-Bill	2660	1.62	1.73	0.03	5.82
PerMngWomen	2660	13.42	23.34	0	100
Woman	2660	0.368	0.48	0	1
Equity	2660	48.14	45.75	0	99.87
Cash	2660	3.2	4.42	-12.42	27.27
FxIncome	2660	48.64	46.22	0	112.3
EQ Fund	2660	0.331	0.47	0	1
FX Fund	2660	0.414	0.49	0	1
Blended	2660	0.256	0.44	0	1
Team Size	2660	3.69	2.94	1	18
AvgExp	2660	23.32	6.91	1	38.5
Log Team Size	2660	1.1	0.59	0	2.89
Log AvgExp	2660	3.07	0.47	0	3.65

4.5. Returns and CAPM Multiplier

Table 3 demonstrates the average returns for the mutual funds in the data set, the average CAPM multiplier across those same funds, the S&P 500 and the US T-Bill returns from 2000 to 2019.

Table 3: Averages

	Average Return	CAPM Multiplier	S&P 500 Return	US Treasury Bill	$(R_m - R_f)$	Bear Market
2000	-0.50	0.40	-10.14	5.82	-15.96	0
2001	0.22	0.19	-13.04	3.39	-16.43	1
2002	-3.88	0.22	-23.37	1.6	-24.97	0
2003	20.92	0.78	26.38	1.01	25.37	0
2004	10.34	1.18	8.99	1.37	7.62	0
2005	6.65	-23.33	3	3.15	-0.15	0
2006	11.87	0.80	13.62	4.73	8.89	0
2007	5.89	-1.86	3.52	4.35	-0.83	1
2008	-22.93	0.61	-38.49	1.37	-39.86	1
2009	25.09	1.07	23.45	0.15	23.3	1
2010	10.63	0.83	12.78	0.14	12.64	0
2011	1.29	-24.80	0	0.05	-0.05	1
2012	11.70	0.87	13.41	0.09	13.32	0
2013	13.58	0.46	29.6	0.06	29.54	0
2014	6.09	0.53	11.39	0.03	11.36	0
2015	-1.19	1.59	-0.73	0.05	-0.78	1
2016	6.64	0.69	9.54	0.32	9.22	1
2017	12.10	0.60	19.42	0.93	18.49	0
2018	-5.11	0.86	-6.24	1.94	-8.18	0
2019	16.76	0.56	28.88	1.55	27.33	0

The $Average\ Return$ represents the average return for the given year across all mutual funds in the data set. The $CAPM\ Multiplier$ is the average returns generated for all the funds using the modified CAPM discussed in section 4.3. Comparing the $Average\ Return$ and $the\ CAMP\ Multiplier$ to the S&P 500 and the three-month US Treasury Bill demonstrates the variations between risk-adjusted returns and raw returns against both the risk filled stock market represented by the S&P 500 and the risk-free US Treasury Bill. The US

Treasury Bill is considered risk free as the only risk of loss would come from the defaulting of the US government, which financial markets consider extremely unlikely. As discussed in the theory section, with greater risk there are greater returns. The lack of risk in US Treasury Bills is demonstrated by the small fluctuations between years in returns, and the fact that returns never drop below zero. The S&P 500 has more risk as it is composed of companies whose performance could lead to either great loss or great returns. This is demonstrated in the large differences in returns between years, with losses as much as 38.49% and gains as strong as 28.88% in comparison with the much smaller fluctuations in the US Treasury Bill. The column $(R_m - R_f)$ measures the difference between the S&P 500 (R_m) and the US Treasury Bill (R_f) and is the denominator used to adjust for risk levels to create the CAPM Multiplier. While both the $Average\ Return$ and $CAPM\ Multiplier$ involve risk, the $CAPM\ Multiplier$ measures performance adjusted against the risk levels of the S&P 500 and the US-Treasury Bill, and thus leads to generally lower fluctuations in returns.

5. Model

5.1. CAPM Multiplier

Before describing the details of the model, I need to expand on the CAPM model and how I am using it to measure the effectiveness of fund managers during market downturns. Equation (1) can be rewritten as shown:

$$CAPM\ Multiplier = (R_{it} - R_{ft})/(R_{mt} - R_{ft}) \quad (3)$$

With R_{it} standing for the annual returns of each individual fund, R_{ft} for the annual returns of the US T-Bill, and R_{mt} for the annual returns of the S&P 500. The $CAPM\ Multiplier$ I am using as the dependent variable measures returns with respect to the market gain relative to

the market risk-free gain. I use the S&P 500 and the three-month US T-Bill as the market gain and market risk free gain respectively. By controlling the annual returns of a fund against both the S&P 500 and the US T-Bill equation (3) represents the difference between active management and funds that are fully indexed.

It is necessary to understand how Jensen's alpha fits into this model. Note that when there is a bear market, the assumption that $\left(R_M - R_f\right)$ is positive no longer holds (see Table 3). In terms of equation (2), the proportion of the fund tied to the market β_{iB} has a larger impact on the residual returns than the constant α_i. This means the managers of the fund must create a negative $CAPM\ Multiplier$ in order to generate positive returns. Thus, for the purpose of this paper I am using the $CAPM\ Multiplier$ as the key component in measuring performance of the fund managers, especially in bear markets. Table 3 summarizes the results of computing the $CAPM\ Multiplier$ for each of the funds and its average across the funds for every year in the dataset.

5.2. Model Details

Previous literature demonstrates the positive effect the presence of women in a team can have financially (See: Hoogendoorn, Oosterbeek, and Praag 2013). I place this question within the mutual fund industry during periods of market downturn. I investigate if the simple presence as well as percentage of women managers running a mutual fund has an impact on returns, especially during recessions. In order to do this, I break down the measurement of returns against the percentage of women managers and women managers as a dummy variable into several regressions.

First, I measure this effect in the aggregate by measuring performance across all years looking at both the percentage of women managers as well as the presence of a woman on the management team. The model to measure this can be explained in the following two equations:

$$CAPM\ Multiplier = \beta_0 + \beta_1 PerMngWomen + \beta_2 lgAvgExp + \beta_3 lgTeamSize + \beta_4 Equity + \mu \quad (4)$$

$$CAPM\ Multiplier = \beta_0 + \beta_1 Woman + \beta_2 lgAvgExp + \beta_3 lgTeamSize + \beta_4 Equity + \mu \quad (5)$$

$PerMngWomen$ measures the percentage of women in a team for each fund held constant over the 20-year period. $Woman$ is a dummy variable where 1 represents a fund management team having at least one woman on their team. $lgAvgExp$ measures the log of the average experience of each team for each fund. It is likely that greater experience may make it easier to spot opportunities in the market. Additionally, it is also possible for those newer to the industry to bring in a fresh perspective that is useful to the team. $lgTeamSize$, which measures the log of the size of each team for each fund, is also necessary to analyze as bigger teams have more eyes to see market opportunities and bring different perspectives and experiences to the table. Finally, $Equity$ represents the percentage of assets invested in equity. Only the percentage of equity is necessary to demonstrate the fund allocation between equity and fixed income given that they total 100%. It is likely that the greater the amount of assets invested into equity, the greater the returns on the aggregate are. The reason for this is that equity generally involves greater risk and thus greater return potential. The addition of $Equity$ here helps to control for the goals of funds as some seek to invest more heavily in either equity or fixed income in order to offer investors a variety based on their risk profiles.

Given the importance of $Equity$ in returns, I run a regression where funds are separated by asset classes. This is done by adding in dummy variables where funds are separated out into either pure equity, pure fixed income, or blended funds. The variables added to the regression are $EQFund$ and $Blended$ which measure performance relative to fixed income funds. This also measures performance across all years. The two regression equations for this are as follows:

$$CAPM\ Multiplier = \beta_0 + \beta_1 PerMngWomen_{(c)} + \beta_2 lgAvgExp_{(c)} + \beta_3 lgTeamSize_{(c)} + \beta_4 EQFund + \beta_5 Blended + \mu \quad (6)$$

$$CAPM\ Multiplier = \beta_0 + \beta_1 Woman_{(c)} + \beta_2 lgAvgExp_{(c)} + \beta_3 lgTeamSize_{(c)} + \beta_4 EQFund + \beta_5 Blended + \mu \quad (7)$$

This captures the effect of female managers both as a percentage and as a dummy variable for a given asset class. Controlling for asset class reveals the relationship between managers and their skill as opposed to simply reflecting the risk and return trade-off. The returns of equity, blended, and fixed income funds are not directly comparable due to the fact that their different risk levels lead to very different ranges of potential returns. For example, an equity fund is able to earn significantly more returns than a fixed income fund due to the fact it carries more risk. By separating out funds into their asset classes, I am able to control for this effect and thus am able to examine the relationship between returns and the impact of female managers.

Finally, I run additional regressions measuring the effects during recessions and bear markets while continuing to control for asset allocation. This allows me to analyze more specifically the relationship between returns and women managers during recessionary and non-recessionary periods. This model is as follows:

$$CAPM\ Multiplier = \beta_0 + \beta_1 PerMngWomen_{(c)} + \beta_2 lgAvgExp_{(ct)} + \beta_3 lgTeamSize_{(ct)} + +\beta_4 EQFund_t + \beta_5 Blended_t + \mu \quad (8)$$

$$CAPM\ Multiplier = \beta_0 + \beta_1 Woman_{(ct)} + \beta_2 lgAvgExp_{(ct)} + \beta_3 lgTeamSize_{(ct)} + \beta_4 EQFund_t + \beta_5 Blended_t + \mu \quad (9)$$

$lgAvgExp$ represents the log of the average years of experience in the industry of the team for an individual mutual fund. I expect that the higher the average experience of the team, the higher the returns. $EQFund$ is a dummy variable that represents funds invested purely in equity. $Blended$ is a dummy variable that represents funds invested in both equity and fixed income. It is likely that the greater the amount of assets invested into equity, the greater the returns are. By using dummy variables, the goals of funds are controlled. Each of the variables are measured at *t* specific year levels controlling for asset class *c*. Each *t* time period chosen will reflect either a recessionary period, a bear market, or non-recessionary period for comparison. In order to measure time period, the variable Bear Market is used in the regression through an "if statement" command. Bear Market is a dummy variable where years in which a bear market occurred equals 1 and is used in the regression through an "if statement" command. All recessionary periods are also bear markets but there are additional bear markets that did not develop into recessions; therefore, the variable Bear Market is able to represent both of these periods of economic down markets.

6. Results

The results for each of the regressions are in line with previous literature. There is no statistically significant impact of women managers both as a percentage and as a dummy variable

on returns in any of the regressions. I breakdown the regressions into two sections that first measure the impact of female managers in the aggregate and then measure the results in down-markets compared to up-markets.

6.1. Results in the Aggregate

Table 4 looks at the effects of $PerMngWomen$ and $Woman$ on the $CAPM\ Multiplier$ in the aggregate. The first two regressions measure these effects in the aggregate without controlling fund type. The variable $Equity$ measures the impact of the amount of equity a fund has on the $CAPM\ Multiplier$. Regressions three and four measure the aggregate effects while controlling for fund type using the dummy variables $EQFund$ and $Blended$. $PerMngWomen$ and $Woman$, measuring the effect of female managers as a percentage and as a presence respectively, are not statistically significant in any of the four regressions. The log of $AvExp$, measured by $lgAvgExp$, is statistically significant at the 5% level and has a negative impact on returns in each regression. $Equity$ – the specific levels of equity each firm possess – is also statistically significant and has a small positive impact on returns. Similarly, the dummy variables $EQFund$ and $Blended$ are also statistically significant and positively impact returns. This is in line with the literature, as the greater risk equity represents generally leads to higher returns. In line with this, funds that are pure equity ($EQFund$) have a larger positive impact on returns then funds with some level of fixed income ($Blended$).

Table 4: Aggregated Regressions

Dependent variable:	(1) CAPM Multiplier All Years	(2) CAPM Multiplier All Years	(3) CAPM Multiplier Funds Controlled	(4) CAPM Multiplier Funds Controlled
R^2	0.0127	0.0128	0.0126	0.0128
Adj R^2	0.0112	0.0114	0.0108	0.0109
PerMngWomen	-0.009	-	-0.013	-
	(0.802)	-	(0.704)	
Woman	-	-1.422	-	-1.434
		(0.466)		(0.463)
lgAvgExp	-5.949	-5.743	-5.524	-5.333
	(0.001)	(0.001)	(0.002)	(0.003)
lgTeamSize	1.079	1.581	0.905	1.390
	(0.432)	(0.309)	(0.521)	(0.379)
Equity	0.078	0.079	-	-
	(0.00)	(0.00)		
EQFund	-	-	7.946	8.088
			(0.00)	(0.00)
Blended	-	-	6.037	6.158
			(0.004)	(0.003)
_Cons	11.6	10.74	10.108	9.263
	(0.030)	(0.242)	(0.063)	(0.098)
Number of Obs	2660	2660	2660	2660

Standard errors in ()
*p = 0.05

6.2. Down and Up Markets Compared

Table 5 compares the returns of the $CAPM\ Multiplier$ in both down and up market years. One concern is that there are only a few down-market periods in the years between 2000 and 2019. The smaller number of observations in down markets limits the explanatory power of the results for regressions for recessionary data. The easiest way to increase this explanatory power is to increase the number of funds in the dataset, something that would be useful for

additional research. As in the aggregate, neither the percentage ($PerMngWomen$) nor mere presence of women managers ($Woman$) are statistically significant. The log of average experience ($lgAvgExp$) has a statistically significant negative impact on the $CAPM\ Multiplier$ throughout both down and up market years. During down-market periods, this effect is more pronounced. The negative effect of increased experience seems counterintuitive, suggesting that perhaps measuring experience by taking the average of the experience of each team member is not the best way to measure experience. A fund being equity, as measured by $EQFund$, is also statistically significant at the 5% level and has a positive impact on returns during recessionary periods. A fund being a mixture of equity and fixed income, measured by $Blended$, is statistically significant during down-market periods and has a positive impact on returns.

Table 5: Down and Up Markets

Dependent variable:	(5) CAPM Multiplier Down Market	(6) CAPM Multiplier Up Markets	(7) CAPM Multiplier Down Market	(8) CAPM Multiplier Up Market
R^2	0.0445	0.0086	0.0452	0.0088
Adj R^2	0.0393	0.0057	0.0400	0.0059
PerMngWomen	-.055	0.010	-	-
	(0.551)	(0.521)		
Woman	-	-	-5.423	0.713
			(0.304)	(0.407)
lgAvgExp	-12.355	-1.845	-11.673	-1.920
	(0.009)	(0.016)	(0.014)	(0.014)
lgTeamSize	2.856	-0.146	4.670	-.376
	(0.454)	(0.814)	(0.274)	(0.014)
EQFund	27.185	-2.413	27.697	-2.471
	(0.00)	(0.003)	(0.00)	0.003)
Blended	19.571	-1.251	19.994	-1.293
	(0.001)	(0.173)	(0.000)	0.160)
_Cons	18.389	5.649	15.27	6.029
	(0.211)	(0.018)	(0.312)	(0.014)
Number of Obs	931	1729	931	1729

Standard errors in ()
*p = 0.05

As demonstrated in Tables 4 and 5, women as both a percentage ($PerMngWomen$) and as a dummy variable ($Woman$) have no statistically significant results. This is in line with previous literature that demonstrated that female managers had no statistically significant impact on European mutual fund returns. Another notable result comes from $lgAvgExp$ and $AvgExp$. Both these variables have a statistically significant result and had a negative impact on returns – something that is not intuitive. By taking the log, the results indicate that an increase in the percentage change in experience of a team leads to lower returns. This effect is especially

pronounced during recessionary periods. The results for $lgAvgExp$ seem counterintuitive. I had expected that as average experience increases, there would be a positive impact on returns. In both table 4 and table 5 however, average experience has a negative impact, and it is particularly pronounced during recessions. Finally, the R^2 and adjusted R^2 for each of the eight regressions are lower than results from previous literature. The study of European equity funds had an adjusted R^2 of 0.94 (Babalos, Caporale, Philippas 2015). The difference in these R^2 results may come from the fact that this research expands the types of mutual funds studied from pure equity funds to include blended and fixed income.

In order to test if there was a problem with the variable $lgAvgExp$ itself, I took the standard deviation of the years of experience for each management team. Table 7 in the Appendix shows these standard deviations for each firm and fund. The standard deviations for each fund have a large spread, with the minimum being 0 and the maximum being 23.335. This suggests that using the average experience is not the best way to capture the effect of years of experience of the fund managers. For further research, I would suggest breaking down funds into classes of experience based on standard deviation ranges. This was not possible with this dataset as this would have resulted in too few observations to make any meaningful interpretation of experience on performance.

Given this significant level of variation in average experience, I re-ran regressions five through eight using a new variable called $MaxExp$. This variable captures the effect of the person with the highest level of experience on the team. In these regressions, $EQFund$ remained statistically significant with a large positive effect during down market periods but had a small statistically significant negative impact during up markets. $Blended$ was only statistically significant during recessionary periods and had a large positive impact. Both $PerMngWomen$,

$Woman$, and $TeamSize$ remained statistically insignificant across all years. Unlike $lgAvgExp$, $MaxExp$ was only statistically significant during recessionary periods and had a very small negative impact. The $R^2$and adjusted R^2continued to be smaller than in previous literature. This does suggest that there is in fact some correlation between increased experience and a funds financial performance, however, this effect likely would be best captured through separating the average experience of all teams into classes based on the standard deviation of experience levels within the team.

Table 6: MaxExp – Down and Up Markets

	(9)	(10)	(11)	(12)
Dependent variable:	CAPM Multiplier Down Market	CAPM Multiplier Up Markets	CAPM Multiplier Down Market	CAPM Multiplier Up Market
R^2	0.0072	0.0070	0.0458	0.0072
		0.0041	0.0406	0.0044
Adj R^2	0.0044			
PerMngWomen	-0.0488	0.009	-	-
	(0.601)	(0.556)		
Woman	-	-	-4.202	0.733
			(0.435)	(0.404)
MaxExp	-0.739*	-0.076	-0.698*	-0.083
	(0.005)	(0.080)	(0.011)	(0.064)
lgTeamSize	6.012	0.094	7.190	-0.110
	(0.147)	(0.889)	(0.105)	(0.879)
EQFund	26.985*	-2.401*	27.379*	-2.468*
	(0.00)	(0.003)	(0.00)	(0.003)
Blended	19.283*	-1.170	19.627*	-1.227
	(0.001)	(0.080)	(0.011)	(0.133)
_Cons	-1.574	1.888	-3.396	2.205
	(0.837)	(0.130)	(0.672)	(0.093)
Number of Obs	931	1729	931	1729

Standard errors in ()
*p = 0.05

6.3. Correlation Analysis

The variables that should theoretically impact returns may also be highly correlated with each other, which could result in the problem of multicollinearity. Table 6 represents the results for the correlation test for multicollinearity.

Table 7: Correlation

	CAPM Multipler	PerMngWomen	Woman	Equity
CAMP Multipler	1			
PerMngWomen	-0.0053	1		
Woman	-0.0023	0.7563	1	
Equity	0.0896	0.0744	0.2104	1
Fx Income	-0.0918	-0.0591	-0.2005	-0.9954
EQ Fund	0.0635	0.0368	0.0924	0.7483
FX Fund	-0.0924	-0.1085	-0.2299	-0.8838
Blended	0.0357	0.0829	0.1599	0.1907
Team Size	0.0272	0.1189	0.5094	0.2335
AvgExp	-0.0758	0.1038	0.2464	-0.0567
lgTeamSize	0.0200	0.1320	0.5115	0.1751
lgAvgExp	-0.0662	0.1313	0.2434	0.0012

	FX Income	EQ Fund	Fx Fund	Blended
Fx Income	1			
EQ Fund	-0.7402	1		
FX Fund	0.8788	-0.5904	1	
Blended	-0.1937	-0.4121	-0.4921	1
Team Size	-0.2447	0.0574	-0.2650	0.2372
AvgExp	0.0656	-0.0404	0.1342	-0.1079
lgTeamSize	-0.1882	0.0197	-0.2323	0.2409
lgAvgExp	0.0163	0.0267	0.0632	-0.1696

Table 6 breaks down the correlations between the $CAPM\ Multiplier$, $PerMngWomen$, $Woman, Equity, FX\ Income, EQ\ Fund, FX\ fund, Blended, Team\ Size, AvgExp, lgTeamSize$ and $lgAvgExp$. The variables that represent years, including bear markets and recessions have been removed. None of these variables are highly correlated with the $CAPM\ Multiplier$, which is consistent for each of the variables except for $AvExp$ and $lgAvgExp$ as well as $Equity, EQfund$ and $Blended$. $Woman$ and $PerMngWomen$ are highly and positively

correlated, which supports the logic for separating these variables into separate regressions. Both $TeamSize$ and the $lgTeamSize$ have a small correlation effect with the variable $Woman$. $Equity$ has a very strong negative correlation with $Fixed\ Income$ and negative correlation with $FxFund$. Equity holds greater risk and therefore greater reward potential (captured through returns) while fixed income holds less risk and less potential reward. Equity and fixed income have inverse return potentials due to these different levels of risk the assets hold. The strong negative correlation (-0.995) between the variables $Equity$ and $Fixed\ Income$ is captured in Table 6. As returns attributed to equity increase, the impact of returns attributed to fixed income on the overall returns of a portfolio decreases.

7. Conclusion

Measuring female managers as both a percent ($PerMngWomen$) and a dummy variable ($Woman$) captures the effects of female managers both in higher percentages and as simply being present on a management team. These results in each of the regressions were not statistically different from zero, demonstrating that mutual fund management teams with women perform no better or worse than funds with more men on the team. The fact that someone is a woman does not contribute to trading edge or cause any difference in performance compared to men. My empirical results demonstrate that other factors may contribute to a fund's trading edge, such as the average experience of the team, but does not offer any additional insights into what may impact an individual's trading edge. The lack of difference in performance between funds with female managers compared to male managers suggests that gender is not an issue in causing underperformance in the mutual fund industry. However, the fact that gender is not an issue in fund underperformance does not explain why the number of women in the mutual fund industry remained stagnant over the past 20 years. Rationally, gender should not be a decision factor for

firms, suggesting that there must be additional issues causing the low and stagnant participation of women in the mutual fund industry. A potential argument about women having less experience would also not explain this effect, as the regressions demonstrate that increasing experience has a negative relationship with returns. As discussed in the literature review, Goldin writes about hidden factors that cause gender gaps in labor force participation. While not the focus of this paper, further research tying Goldin's theories into the mutual fund industry could yield insights into the stagnant female participation rate. Given the existence and purpose of organizations such as those mentioned in the introduction – Girls Who Invest and SEO – it is also possible that a lack of internship training and issues with recruitment contribute to this gender gap. This suggests that there is a labor supply issue rather than an issue of labor demand. Additionally, it is possible that there are positive impacts on a fund and on a firm that come with hiring more women managers, such as the ability to attract additional clients. Further research into how women contribute to client recruitment could potentially demonstrate incentives to help firms overcome the hidden factors leading to such low and stagnant levels of female participation in the industry.

Appendix

Table 1: Definitions

Terms	Definitions
Recession	A fall in GDP over two consecutive quarters.
Bear Market	A market atmosphere of widespread pessimism and negative investor sentiment that causes securities prices to fall 20% or more
Return	A change in price of an asset over time represented in percentage change
Trading Edge	A technique, observation or approach that creates a cash advantage over other market players
Assets Under Management	The total market value of the investments that a person or entity manages on behalf of clients
Equity	The value of the shares issued by a company
Fixed Income	Investment secuirty that pay invesotrs fixed interest or dividend payments until maturity date. Government and corporate bonds are most common types of fixed income products
Cash Equivilants	Short-Term Investments that are easily transferable into a known cash amount
Mutual Funds	A investment program funded by shareholders that trades in diversified holdings and is professionally managed

Table 8: Standard Deviations of Average Experience

Dodge&Cox	FranklinTempleton	FranklinTempleton	AmericanFunds	PrincipleFunds	JP Morgan
9.885	7.848	7.071	3.91	4.95	4.243
8.295	7.848	4.243	10.704	4.95	4.583
7.211	3.536	12.423	4.163	4.95	0
	7.071	0	8.102	4.95	0
	7.848	9.539	5.533	4.95	3.559
	0	12.423	6.989	3.536	3.536
	5.657	4.95	4.677	1.155	12.728
	7.071	0.707	5.172	2.121	4.726
	7.778	0.707	7.521	3.536	1.414
	7.071	8.544	8.182	0	6.083
	7.937	6.185	6.534	3.464	11.15
	8.846	7.047	5.622	2.121	6.733
	1.414	7.071	5.61	3.536	6.733
	7.937	8.083	8.107		6.733
	3.202	7.071	7.273		8.485
	1.414	3.536	6.344		6.733
	4.95	6.364	9.069		2.121
	4.95	5.916	4.619		0.707
	12.423	10.231	5.831		0
	4.95	11.21	8.042		8.485
	13.577	2.517	1		0
	12.23	23.335	11.314		1.673
	4.95	9.899	1.414		4.583
	3.215	7.071	4.243		1.673
	14.848	6.506			6.37
	3.215	13.614			6.37
	4.95	4.243			7.071
	7.55	4.95			6.506
	8.021	10.408			6.506
	6.083	2.828			10.017
	3.536	13.577			
		0			

Table 9: LgAvgExp Squared – Down and Up Markets

Dependent variable:	(5) CAPM Multiplier Down Market	(6) CAPM Multiplier Up Markets	(7) CAPM Multiplier Down Market	(8) CAPM Multiplier Up Market
R^2	0.0458	0.0087	0.0463	0.0089
Adj R^2	0.0406	0.0058	0.0411	0.0061
PerMngWomen	-0.053	0.010	-	-
	(0.568)	(0.521)		
Woman	-	-	-4.799	0.784
			(0.366)	(0.365)
lgAvgExp2	-2.776*	-0.386*	-2.632*	-0.408*
	(0.004)	(0.015)	(0.008)	(0.012)
lgTeamSize	3.026	-0.140	4.598	-0.394
	(0.427)	(0.821)	(0.281)	(0.571)
EQFund	26.499*	-2.501*	26.975*	-2.575*
	(0.00)	(0.002)	(0.00)	(0.002)
Blended	18.856*	-1.326	19.255*	-1.385
	(0.001)	(0.150)	(0.001)	(0.135)
_Cons	7.434	3.748*	5.105	4.122*
	(0.464)	(0.024)	(0.628)	(0.016)
Number of Obs	931	1729	931	1729

Standard errors in ()
*p = 0.05

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