Psychological and social effects on economic decision-making – Gender differences and insights from the COVID-19 pandemic

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Submitted by
Mengqiao Du, M.Sc.

Mannheim, Germany

Dean:	Joachim Lutz
Referent:	Prof. Dr. Alexandra Niessen-Ruenzi
Correferent:	Prof. Ernst Maug, Ph.D.
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ABSTRACT

This Ph.D. dissertation consists of three chapters in behavioral finance, financial intermediation, and labor and finance. The first chapter explores the shock of school closures caused by the COVID-19 pandemic to study the effect of domestic responsibilities on analyst forecasts and identifies the negative effect of unequal division of housework between gender on female analysts' work. The second chapter uses hand-collected data from Gallup surveys that cover more than 50 years to create a direct measure of counter-stereotypical female role models and shows that admiring counter-stereotypical female role models is associated with better career outcomes in terms of labor market participation and occupational choices. The third chapter analyzes how mutual funds' trading experiences bias their future repurchasing decisions and finds that mutual funds are less likely to repurchase a stock if they previously sold the stock for a loss rather than for a gain. We also find evidence that female fund managers are slightly less likely to suffer from this repurchasing bias.

EXECUTIVE SUMMARY

An increasing number of policies, e.g., mandatory gender quotas, are introduced to increase women's representation in competitive industries and high-level positions. However, people have limited time to work and limited capacity to process information. Helping women enter women-underrepresented professions may not help them perform well in these industries. The first chapter in the dissertation shows that even female analysts who self-select and survive in a competitive industry respond slower to new information from earnings announcements after the COVID-19 school closures. The chapter also finds that female analysts allocate more effort to firms that are more important for their careers. It is worth learning from female analysts' strategically allocating efforts in the face of domestic distractions. The findings also indicate that the gender gap in the labor market may be able to get closed by alleviating the imbalance in housework allocation between gender or by providing better external childcare services.

Despite this "grand convergence", women are still underrepresented in lucrative and competitive professions, such as STEM and finance. A lack of appropriate female role models that would otherwise nudge women into more lucrative occupations may enlarge the gender gap in competitive industries. The second chapter creates a systematic measure of counter-stereotypical female role models and shows that admiring counter-stereotypical female role models is associated with more women participating in the labor market, working in male-dominated and STEM industries, and taking managerial positions, which eventually alleviates the gender pay gap.

Fund managers have more expertise and experience than retail investors and more opportunities to learn about and correct trading biases. The third chapter examines whether their trading behavior is influenced by psychological biases. We show that fund managers are less likely to repurchase stocks that they have previously sold for a loss and that this trading pattern does not enhance performance. We also find evidence that female fund managers are slightly less likely to suffer from the repurchasing bias. Mutual fund trading behavior deserves scrutiny because it has a significant impact on investor welfare and the capital markets.

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Introduction

This Ph.D. dissertation consists of three chapters in behavioral finance, financial intermediation, and labor and finance. The common theme that runs through the three essays in this dissertation is to identify and quantify the effect of psychological and social factors on economic decision-making. People's economic decisions are subject to their cognitive constraints and are shaped by their past experiences and social environment, which makes the behavior of market participants deviate from the traditional framework in finance that assumes rational beliefs and decision making based on expected-utility preferences. The studies aim to understand how cognitive constraints influence economic decisions and gender inequality.

Chapter 1 aims to understand whether high-achieving women are still more likely to suffer from limited attention when faced with domestic responsibilities. Moreover, how do they minimize the influence of limited attention on their careers? I explore the shock of school closures due to the COVID-19 pandemic to study the effect of domestic responsibilities on analysts' forecasts. I find that school closures significantly reduce the forecast timeliness of female analysts rather than that of male analysts. School closures also negatively influence the forecast accuracy of female analysts, but the effect is only significant for forecasts on firms with relatively low institutional ownership. Analysts are dependent on institutional investors for performance ratings and commission revenues to the broker firms so forecasts for firms with high institutional ownership are more important for their careers. Hence, the negative effect of school closures on female analysts' forecast accuracy of firms with relatively high institutional ownership is mitigated. The findings indicate that female analysts are more likely to get distracted from work by domestic duties, but they strategically allocate their efforts to forecasts that are more important for their careers.

Chapter 2 creates a systematic measure of counter-stereotypical female role models based on a long time series of public opinion surveys and investigates its relation to occupational choices, fertility choices, and labor market outcomes for women in the US. We find that admiring counter-stereotypical female role models is associated with more women seeking full-time employment, working in male-dominated occupations such as STEM, and taking over managerial positions. Women in states with higher popularity of counter-stereotypical female role models are also more likely to seek higher education and to have their first child later in life. Moreover, the gender pay gap is smaller in these states.

Chapter 3 examines how personal trading experiences on a certain stock influence mutual fund managers' future trading decisions. We conjecture that even professional investors such as fund managers are inevitably influenced by emotions generated from their trading experiences. We find that mutual funds are more likely to repurchase stocks that they previously sold for a gain. We find some evidence that female fund managers are slightly less likely to suffer from the repurchasing bias. After switching to managing a different fund, fund managers still avoid repurchasing stocks they sold for a loss at a past fund. We do not find that mutual fund managers are biased against repurchasing past loser stocks because of superior information. Though less likely to be repurchased, repurchased losers outperform repurchased winners–and the fund itself–in the subsequent quarter.

CHAPTER 1

Locked-in at Home: Female Analysts' Attention at Work during the COVID-19 Pandemic

1.1 Introduction of Chapter 1

Despite the rise in women's labor market participation over the past decades, women are still underrepresented in competitive industries and high-level positions. Accordingly, policies are introduced to promote gender equality. For example, following Norway's lead in 2003, many European countries including Belgium, France, Germany, Iceland, Italy, and Portugal have adopted mandatory board quotas. Are policies helping women gain representation in top positions sufficient to alleviate the gender gap? Are there other obstacles that prevent professional women from being equally successful?

Among studies explaining the gender gap, Becker (1985) models the allocation of human capital between domestic and market work. The model indicates that women spend more time and effort in domestic work and have less time and effort per unit of time for market work, leading to the gender pay gap and occupational gender segregation. Are high-achieving women still more likely to suffer from limited attention when faced with domestic responsibilities?[1] Moreover, how do they minimize the influence of limited attention on their careers?

In this paper, I take advantage of a quasi-natural experiment in which schools are

[1] I do not distinguish the definition of attention and effort in this paper, as common in the psychology literature (e.g., Kahneman (1973)). Attention and effort both refer to limited human resources at a given time in this paper.

exogenously closed by states during the COVID-19 pandemic to study whether female analysts are more likely to be influenced by an increase in domestic responsibilities. Among financial analysts in the U.S., only around 10% are female in 2020.[2] On the one hand, female analysts may not spend more time on childcare than male analysts because they select a competitive industry and survive (Kumar (2010)). It is plausible to infer that female analysts are not like women in the general population regarding the effort on childcare. On the other hand, it is possible that female analysts spend more time and effort on childcare, even though they are successful in their careers. A nationwide survey in Hewlett (2002) suggests that high-achieving women also spend more time and effort on domestic responsibilities. In addition, studies find gender differences in childcare in competitive professions such as finance researchers (Barber et al. (2020)) or STEM scientists (Cui et al. (2021)). Therefore, it is interesting to empirically study whether female analysts are more likely to get distracted by domestic responsibilities compared to male analysts. It is also worth examining how female analysts allocate labor when facing an increase in domestic responsibilities.

The school closures caused by the COVID-19 pandemic in 2020 affected more than 55.1 million students in 124,000 schools in the U.S.[3] The large-scale and unexpected school closures led to a significant increase in the childcare demand at home (e.g., Power (2020)). Each state decided on school closures independently after the pandemic started. Hence, the school closures can be viewed as exogenous to people's labor market activities

[2]The fraction of female analysts is based on the 2020 sample in this paper. The percentage of female analysts fluctuates between 10% and 14% from 1993 to 2009, with an average of 12% in the sample of Fang and Huang (2017).

[3]Statistics from Map: Coronavirus and School Closures (2020, March 6), Education Week, Retrieved May 2020, see https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html.

and provide a unique opportunity to study how domestic duties influence attention at work of professional men and women differently.

The profession of sell-side equity analysts is a good setting to study the effect of domestic burdens on attention at work. First, sell-side analysts usually work for a long time and are required to have high attention to process new information and give timely responses (Bradshaw (2011), Bradshaw et al. (2017), and Brown et al. (2015)). Therefore, it is possible to capture and quantify the influence of limited attention on analysts' forecasts when they are overburdened by household responsibilities. Second, the profession is highly competitive. People who self-select into this industry are likely to be homogeneous in many aspects, such as education, risk aversion, and preference for competitiveness. Hence, it is implausible that observed differences in forecasting activities are from gender differences in preference or abilities. Male analysts constitute a valid control group in the investigation of the effect of an increase in domestic responsibilities on female analysts' forecast activities. Last, corporate earnings announcements and analysts' forecast releases have detailed timestamps in the data, making it possible to observe the change in forecasting behavior in the short window around the COVID-19 school closures.

Limited attention of analysts is most likely to have a negative impact on forecast timeliness. Driskill et al. (2020) find that limited attention caused by multiple simultaneous earnings announcements negatively influences analysts' forecast timeliness. They do not conduct analyses on forecast accuracy because analysts can improve accuracy by delaying forecasts (Cooper et al. (2001) and Clement and Tse (2003)).[4] In this paper, I first ana-

[4]Driskill et al. (2020) also mention that they do not examine forecast accuracy because they would like to avoid using benchmarks before earnings announcements when defining relative measures of forecast accuracy.

lyze in depth whether distractions of domestic responsibilities lead to less timely forecasts among female analysts because forecast timeliness is a perspective of forecast quality that is inevitably influenced by limited attention.

I conduct a difference-in-differences estimation by running a regression of the analyst forecast timeliness on a female dummy, a school closure dummy, and their interactions for a sample of earnings forecasts around the school closures caused by the COVID-19 pandemic, controlling for various firm and analyst characteristics, firm, broker and state (or analyst), and time fixed effects. Including analyst fixed effects helps rule out time-invariant analysts' characteristics such as their general capability and habits on forecast releases.

After the school closures, the probability of female analysts issuing timely forecasts within one day after earnings announcements decreases at a much larger magnitude than that of male analysts' in the first two quarters of 2020: the coefficient estimate of the interaction term between the female dummy and the school closure dummy is 6.7 percentage points (pp) and is statistically significant at the 1% level. The effect exists even after controlling for firm $\times$ quarter fixed effects, which effectively compares within analyst forecasts after the same firm's same earnings announcement. School closures do not have a significantly negative effect on male analysts' forecast timeliness when analyst fixed effects are controlled for.

Exploring the staggered beginning of school closures across states by using a sample of earnings forecasts in a shorter time window of March 2020, I find that female analysts are 12.2 pp less likely to issue timely forecasts after school closures, which accounts for 16.5% of the average probability to issue a timely forecast in the sample. Moreover, to rule out the influence of seasonality (e.g., Lo and Wu (2018)), I compare the timeliness of earnings forecasts issued after all states decided to close schools, i.e., from March 23rd, 2020 to the end of the sample in August 2020, with the timeliness of earnings forecasts issued in the same time period in 2019. I find similar results: female analysts' forecast timeliness decreases by 4.8 pp after school closures in 2020.

If the unequal division of labor between sexes in domestic work leads to the observed different effects of school closures on forecast timeliness between male and female analysts, I expect the phenomenon to be more salient in states with conservative gender attitudes because the gender imbalance in the allocation of housework is more salient in these states (Ruppanner and Maume (2016)), and financial analysts may conform to expectations of their social environment. I use the U.S. 2017 wave of the World Value Survey to calculate a measure of gender attitudes and divide states into liberal- or conservative- gender-attitude states with this measure. The results show that the negative effect of COVID-19 school closures on female analysts' forecast timeliness in states with conservative gender attitudes is about twice as large as that in states with liberal gender attitudes.

Since the time of COVID-19 school closures overlaps with a financial crash, I conduct a placebo test on whether there is any gender difference in analysts' forecast timeliness during financial crises. I find no robust gender difference in forecast timeliness during the 2001 or 2008 financial crises. Furthermore, I explore another school closure event during the 2009 H1N1 pandemic and find a significant reduction in female analysts' forecast timeliness after that school closure as well.

Analyses comparing the effects of school closures on forecast timeliness between male and female analysts estimate the average effect among all analysts with or without children. To better attribute the effect of school closures on forecast timeliness to an increase in childcare responsibilities, I manually collect information on whether analysts have children by checking their Facebook pages. With this novel data, I use triple difference estimation to identify that the increase in domestic responsibilities after school closures reduces the forecast timeliness of mothers by 15% to 20%. The finding rules out potential explanations of gender differences in risk aversion or overconfidence, because female analysts without non-adult children are not more influenced by the COVID-19 school closures, compared with male analysts.

In the next step, I examine how school closures influence female analysts' forecast accuracy with the same difference-in-difference estimation. School closures may have a significant negative effect on forecast accuracy as they do on forecast timeliness. However, it is possible for analysts to guarantee forecast accuracy by delaying the forecasts (Cooper et al. (2001) and Clement and Tse (2003)) or strategically allocate their efforts (Harford et al. (2019) and Chiu et al. (2021)). Forecast accuracy is the dominate trait of forecast quality that has a large impact on analysts' career (e.g., Mikhail et al. (1999), Bradshaw et al. (2017), and Brown et al. (2015)). It is plausible to infer that female analysts strive to issue accurate forecasts even when they are distracted by the abnormally high amount of domestic work.

The results show that school closures deteriorate forecast accuracy of female analysts but the effect is only statistically significant at the 10% level in the model controlling for firm $\times$ time fixed effects. If forecast accuracy is not compared within the same firm-quarter, the average effect of school closures on female analysts' forecast accuracy is not statistically significant. Hence, I take one step further and investigate how female analysts allocate their attention in the face of domestic responsibilities. Consistent with findings that analysts strategically allocate their efforts to firms that are more important to their careers (Harford et al. (2019) and Chiu et al. (2021)), female analysts allocate more effects to portfolio firms with relatively high institutional ownership and are able to mitigate the negative effect of school closures on forecast accuracy for these firms. More specifically, for firms without high institutional ownership, the forecast accuracy of female analysts decreases by 5.8 pp to 8.7 pp after school closures, compared to that of male analysts. Nevertheless, female analysts' forecasts on firms with high institutional ownership are 9 pp to 9.6 pp more accurate than those on firms with low institutional ownership.

In addition to forecast timeliness and accuracy, the pressure of domestic burdens after the COVID-19 school closures may also change the time of day when female analysts work. The literature has examined the seasonality of analysts' forecasts (Lo and Wu (2018) and Chang et al. (2017)), but little is known about factors that influence the exact time of day analysts issue earnings forecasts. I find that female analysts are more than 9 pp less likely to release forecasts during housework-intensive hours after the COVID-19 school closures while male analysts barely change their forecast release time. This analysis provides direct evidence that COVID-19-induced domestic responsibilities have more impact on professional women because the change of working time is unlikely to be caused by gender differences.

At last, I study the effect of the school closures on some other perspectives of analysts' forecasts and activities. Regarding forecast boldness, there is some evidence that female analysts' forecasts deviate more from the consensus of available analysts' forecasts after school closures, probably because they do not pay as much attention to the available forecasts as they did before the school closures. The effect of the school closures on the deviation from the analysts' own previous forecast is statistically insignificant and economically small. I also find some evidence that after school closures, female analysts are less likely to ask questions at conference calls that are held early in the morning or at noon. In addition, female analysts tend to ask shorter and fewer questions at earnings conference calls after the school closures.

This paper is the first to establish a causal link between the distraction of domestic burdens and financial markets and career outcomes in the financial industry. Previous literature documents that investors suffer from limited attention in the face of extraneous events (Hirshleifer et al. (2009)).[5] Even professional market participants such as fund managers and financial analysts fail to timely respond to new information when distracted (e.g., Kempf et al. (2017), and Schmidt (2019)). This paper explores an exogenous increase in the childcare demand to show that domestic responsibilities distract female analysts from issuing timely forecasts. It is important to understand how distractions of domestic work influence the forecast timeliness of financial analysts because analysts' timely reactions to new information have important implications for financial markets and analysts' career outcomes (Zhang (2008) and Chiu et al. (2021)).[6]

The paper closely relates to the literature on the gender gap in the finance industry and top positions in firms (e.g., Kumar (2010), Huang and Kisgen (2013), Fang and Huang (2017), and Niessen-Ruenzi and Ruenzi (2019)) and in labor markets in general (e.g.,

[5]Some other studies show that investors suffer from limited attention on Fridays (DellaVigna and Pollet (2009) and Louis and Sun (2010)) and when they are distracted by sensational news (Peress and Schmidt (2020)) or lottery events (Huang et al. (2019)).

[6]Chen et al. (2010), Livnat and Zhang (2012), and Huang et al. (2018) study analysts' roles of information interpretation or information discovery by investigating timely forecasts.

Niederle and Vesterlund (2007), Goldin (2014a))). It provides empirical evidence for the sexual division of labor theory in Becker (1985) in the setting of sell-side equity analysts: female analysts suffer more from limited attention and have to reduce labor force supply when facing an increase in domestic burdens. Furthermore, it sheds light on how professional women survive in competitive industries. When distracted by domestic responsibilities, female analysts allocate efforts to firms that weigh more in their careers and issue more accurate forecasts for these firms. This empirical finding provides a good example of how successful professional women mitigate the negative effect of domestic distractions.

Finally, this paper relates to the growing literature on the effect of COVID-19 on financial markets (e.g., Ding et al. (2020) and Baker et al. (2020)) and on social inequality (e.g., Alon et al. (2020), Brown and Ravallion (2020), Barber et al. (2020), and Collins et al. (2021)). Even though female analysts are skilled and competitive, they are still more likely to be influenced by domestic burdens after school closures than male analysts. It should be noted that lock-down measures unequally influence different groups.

1.2 Data and summary statistics of Chapter 1

1.2.1 Sample construction of Chapter 1

The earnings announcements and individual analysts' earnings forecasts are from the I/B/E/S database. The timestamps of earnings announcements and analyst forecasts must be available in order to measure the timeliness of forecasts. Therefore, the sample period starts from January 1999 when timestamps become widely covered in the I/B/E/S database, and ends in August 2020. Following Driskill et al. (2020) and Zhang (2008), I use the sample of the first forecast by each analyst for a firm's earnings in quarter t+1 issued after the firm's quarter t earnings announcement but before one day prior to its quarter t+1 earnings announcement. To be included in the sample, the earnings announcement dates for both quarter t and t+1 must be available. I merge the I/B/E/S data with CRSP and Compustat databases to obtain stock price and accounting information of the firm as of quarter t.

Following previous literature (e.g., DeHaan et al. (2015)), I exclude earnings announcements if the announcement date is more than 90 days after the fiscal quarter-end. I drop penny stocks with the stock price below $1 as of the fiscal end of quarter t. In addition, the first and the last coverage of an analyst following a firm and firms with fewer than two following analysts in the quarter are excluded from the sample. After these screening procedures, the sample includes 1,205,409 firm-quarter-analyst observations.

The main sample finally includes earnings announcements of the first two quarters in 2020 because primary analyses are around the COVID-19 school closures which started in March 2020. In this way, I construct a roughly symmetric window around the school closure events. This is sensible because a larger time window may include confounding events that influence the demand for domestic work and the gender difference in forecast timeliness.

A potential problem of the sample could be that for a given earnings announcement, analyst forecasts before school closures systematically proceed analyst forecasts after school closures. Earlier forecasts are, by definition, more timely and may tend to be more accurate (Keskek et al. (2014)). To avoid capturing this systematic effect of school closures on analyst forecasts, I exclude earnings announcements from the sample if earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures.

Figure 1.1 gives examples to demonstrate the exclusion of these observations. In Scenario 1, Firm A had an earnings announcement before Analyst 1's school closure date, and Analyst 1's forecast for Firm A was released after the school closure. This earnings announcement was also before Analyst 2's earnings forecast, but Analyst 2 issued a forecast before the school closure. If the analyst forecasts for Firm A were not excluded from the sample, Analyst 1's forecast would be regarded as an after-school-closure forecast while Analyst 2's forecast would be regarded as a before-school-closure forecast. In this case, before-school-closure forecasts are systematically more timely than after-school-closure forecasts. By contrast, the case demonstrated in Scenario 2 does not need to be excluded from the sample: both Firm B's earnings announcements and Analyst 3's forecast happened after Analyst 3's school closures, and both Firm B's earnings announcements and Analyst 4's forecast happened before Analyst 4's school closures. In this case, there is no systematic effect of school closures on forecast timeliness, and the staggered beginning of school closing across states creates the variation in the definition of the school closure indicator for each analyst forecast. I exclude the 11,247 observations involving earnings announcements before the school closures of a state and an analyst in that state issued forecasts after the school closures.[7]

The main sample includes 18,750 firm-quarter-analyst observations, with 2,201 firms

[7]Note that the exclusion of these observations aims to sensibly estimate the school closure effects. The main focus is the gender difference in the school closure effects, which should not be biased by including these observations. Table SA1 in the Supplementary Appendix shows that including observations with earnings announcements demonstrated in Figure 1.1 Scenario 1 does not influence the main results. However, the effect of school closures on forecast timeliness is significantly biased upward: the coefficient estimate of *School closure* is exaggerated to -20 pp, and the bias is even larger after controlling for time fixed effects.

and 1,880 analysts, out of which 201 are female analysts. Thereafter, summary statistics and discussions refer to the sample from January 2020 to August 2020 after the screening procedures as described above in this section, unless otherwise pointed out.

To measure forecast timeliness, I calculate the number of trading days between the earnings announcement date of firm i for quarter t and the date when analyst j releases earnings forecast for quarter t+1 of firm i in this sample. Following previous literature on analyst forecast timeliness (Zhang (2008), Driskill et al. (2020) and Chiu et al. (2021)), I define a dummy variable $Timely_{i,j,t}$, which is equal to one if analyst j issues the earnings forecast for quarter t+1 within one trading day (day 0 or day1) after the firm i's quarter t earnings announcement date, and zero otherwise.[8]

1.2.2 School closure

Data on the school closure time are manually collected online. The start of school closures is based on the timestamps of the media coverage on school closure decisions of the state or official documents issued by the governors because first, people started to arrange their work and life to adapt to the coming school closure at the time of announcement of school closures; second, many schools started to shorten the teaching time or close after the state announced the school closure decision and before the required latest closure dates. The map in Appendix 1.7 contains manually collected school closure dates, which range from March 7th to March 23rd. The darker the color of the state is, the earlier school closures

[8]The forecast timeliness is measured by a dummy variable to minimize the influence of extreme values because the distribution of the number of days between earnings announcements and analyst forecasts is highly skewed (Zhang (2008)). In my sample, the number of days between earnings announcements and analyst forecasts has a mean of 3.75, a median of 1, and a standard deviation of 10. Even the log form of the measure is highly positive-skewed. Table SA2 in the Supplementary Appendix shows baseline results using the log form of this continuous measure as a dependent variable. The gender difference in the effect of school closures on forecast timeliness is still economically large, i.e., 6.7% to 8.9%.

started. California and Kentucky are among the first states to announce school closure decisions.

School closure$_{i,j,t}$ is defined as a dummy variable equal to one, if schools are closed in the state where analyst j is located at the time of firm i's earnings announcement for quarter t, and zero otherwise.

1.2.3 Analysts' gender, location and family conditions

I/B/E/S only provides analysts' last names and the initial of their first names. In order to identify the gender of the analysts, I manually collect the full name and identify their gender based on their Linkedin profiles, official websites of the brokers, or media coverage. If I cannot identify the gender from the information online including their photos and the third-person pronoun "he" or "she" in the media coverage, I infer the gender from the analyst's first name. Analyst location data are obtained from the BrokerCheck website by FINRA.[9] I can determine the gender of analysts for 97.7% of the sample and the location for 91.7% of the sample.

Furthermore, I collect data on whether analysts have non-adult children by checking each analyst's Facebook page. Supplementary Appendix 3.6 describes the procedure of finding analysts' Facebook pages, checking whether they have children, and estimating the ages of their children. I find Facebook pages for 680 analysts. 262 of these analysts have children under 18 based on their Facebook. All variables are defined in Appendix 1.7.

[9]https://brokercheck.finra.org/. The website provides a time series of firms and locations where an analyst registers.

1.2.4 Summary statistics of Chapter 1

Table 1.1 reports statistics on variables used in the main analyses. Panel A shows that in the sample, 10% of the analysts are female and 64% of the earnings forecasts were released after the COVID-19 school closures. On average, an analyst follows around 18 firms in the quarter, works in a brokerage with 45 analysts, and has 23 quarters of firm-specific experience. *No. of followed firm's EA* is a factor that influences the level of an analyst's distraction (Driskill et al. (2020)): on average, an analyst has 0.82 additional firms that announce earnings forecasts on the earnings announcement date of firm i. [10]

Panel B of Table 1.1 shows the difference between female analysts and male analysts in the main sample of 2020. *t*-statistics are based on univariate regressions of the variables on the female dummy and standard errors are clustered by analyst and firm. For most variables, the difference between male and female analysts is economically small and statistically insignificant. The modest difference between gender is expected, given that only competitive women self-select into and survive in the financial analyst industry. Female analysts tend to issue slightly more timely forecasts than male analysts. On the contrary, male analysts issue more accurate forecasts than female analysts in the sample.[11] In addition, female analysts work in larger brokerage firms than male analysts, which is consistent with summary statistics in Fang and Huang (2017). I carefully control for these variables that are expected to affect analyst forecast performance in the analyses.

Figure 1.2 plots the probability of issuing timely forecasts among male and female ana-

[10]Table SA3 in Supplementary Appendix presents correlations between the variables used in the analysis. They show that multicollinearity should not be an issue in the regressions.

[11]There are mixed findings on the gender difference in forecast accuracy in the previous literature: Kumar (2010) shows that female analysts issue more accurate forecasts than male analysts while Fang and Huang (2017) find that connected male analysts issue more accurate forecasts than female analysts.

lysts over a 9-week event window surrounding the exogenous shock in childcare demands. It shows that the forecast timeliness is trending closely in parallel for male and female analysts in the 4 weeks before the school closures. Female analysts issue more timely forecasts than male analysts before school closures. School closures decrease forecast timeliness of both male and female analysts right in the week of school closure announcements, but the negative effect is visually larger for female analysts.

Extending the sample to previous years, Supplementary Appendix Table SA1 plots the evolution of forecast timeliness from 1999 to 2020. Male analysts are more likely to issue timely forecasts than female analysts before 2009, but female analysts' forecasts have become more timely than male analysts' forecasts since 2010. The significant change in the gender difference in forecast timeliness over time justifies the choice of a short time window when I analyze the effect of COVID-19 school closures.

1.3 Domestic distractions and analyst forecast timeliness

1.3.1 Forecast timeliness after the COVID-19 school closures

Forecast timeliness is an important perspective to assess the quality of analyst earnings forecasts. Investors care about the timeliness of analysts' forecasts, and timely earnings forecasts have a more significant price impact than delayed ones (Cooper et al. (2001)). Timely forecasts also play an important role in improving market efficiency, in the sense that they facilitate price discovery (Zhang (2008)). Forecast timeliness influences analysts' career outcomes as well: Chiu et al. (2021) find that analysts producing timely forecasts are more likely to be voted as an all-star analyst and less likely to be demoted to a smaller brokerage firm.

When financial analysts have limited attention, it is more difficult for them to issue timely forecasts because they cannot respond fast to new information. Driskill et al. (2020) show that analysts with limited attention issue less timely forecasts by studying the effect of concurrent firms' earnings announcements in the analysts' coverage portfolio on forecast timeliness. In this study, the increase in the childcare demand during school closures is an exogenous distraction for analysts and may reduce the timeliness of their forecasts.

Women spend more time on parenting and other domestic tasks than men (e.g., Bertrand et al. (2010)). According to Becker (1985), the optimal amount of effort allocated to an hour of activity is proportional to the effort intensity of the activity. The allocation of time that does not change effort intensities changes the effort per hour in all activities. When women spend more time on energy-consuming domestic activities such as childcare, they have not only less time left for market work but also less energy for each hour of market work. Therefore, I expect the exogenous increase in domestic work after COVID-19 school closures are more likely to distract female analysts rather than male analysts and decrease their forecast timeliness.

I test the effect of domestic responsibilities on the timeliness of analyst forecasts by exploring the exogenous school closure decisions during the COVID-19 pandemic in the following difference-in-differences model:

$$\begin{aligned} Timely_{i,j,t} =& \alpha + \beta_1 Female_j \times School\,closure_{i,j,t} + \beta_2 Female_j + \beta_3 School\,closure_{i,j,t} \\ &+ Controls + u_i + v_j + z_t + \varepsilon_{i,j,t}, \end{aligned} \tag{1.1}$$

where $Female_j$ is a dummy variable equal to one if the analyst is a female, and zero otherwise; $School\,closure_{i,j,t}$ indicates whether school closures start when analyst j issues earnings forecasts for firm i after the earnings announcement as of quarter t. The regression includes firm fixed effects, analyst fixed effects, and time fixed effects to control for time-invariant characteristics of firms and analysts, and the time trend.[12] Including analyst fixed effects takes care of any general capability, work habits, attitudes, education, and personality traits, etc. that may impact the likelihood to issue timely or non-timely forecasts. Standard errors clustered by analyst and firm.

Table 1.2 contains the regression results. In Column (1), the model compares the forecast timeliness of analysts after controlling for firm, broker, state, and time fixed effects. Female analysts' forecast timeliness decreases at a 4.3 pp larger magnitude than that of male analysts, and the gender difference is statistically significant at the 10% level. The COVID-19 school closures decrease forecast timeliness of male analysts by 6.4 percentage points (pp) and the effect is statistically significant at the 5% level. When schools are not closed in 2020, female analysts are 4.9 pp more likely to issue timely forecasts, compared with male analysts. Adding to the findings in Kumar (2010) that female analysts issue more accurate and bolder forecasts than male analysts, I show that they issue more timely forecasts in 2020 when schools are not closed.

The model in Column (2) additionally controls for analyst fixed effects and compares the forecast timeliness within an analyst. After controlling for time-invariant characteristics of analysts, the coefficient estimate of the interaction term of *Female* and *School closure* goes up to 6.7 pp, which is statistically significant at the 1% level. The difference is economically significant as well, given that it accounts for 9.05% of the average forecast timeliness in the sample (Table 1.1). On the contrary, the negative effect of the COVID-

[12] Time fixed effects control for the earnings announcement date of firm i in quarter t. Therefore, any calendar time effect such as the day of a week is controlled for.

19 school closures on forecast timeliness among male analysts decreases to half of the effect in the model without analyst fixed effects in Column (1) and becomes statistically insignificant.

The model in Column (3) controls for firm $\times$ quarter fixed effects. The model is very strict because it effectively compares within analyst forecasts after the same firm's same earnings announcement. The sample allows this comparison since there are earnings announcements and analysts' forecasts both happening before the school closure in one state and both happening after the school closure in another state (Scenario 2 demonstrated in Figure 1.1). Again, the negative effect of school closures on forecast timeliness is 6.2 pp larger among female analysts than male analysts within the same firm-quarter, which is statistically significant at the 1% level.

Several control variables significantly influence forecast timeliness. Consistent with the findings in Driskill et al. (2020), the number of followed firms' earnings announcements has a negative effect on forecast timeliness. Specifically, when the number of earnings announcements in the analysts' coverage portfolio increases by one unit, the probability to issue a timely forecast decreases by 1.7 pp. Analysts are more likely to issue timely forecasts for firms with higher institutional ownership, which means they cater to institutional clients and immediately respond to earnings announcements of firms with higher institutional ownership. When the analysts follow more firms or have more experience in issuing forecasts for the firm, they are more likely to issue timely forecasts.

By studying the effect within analysts and within firm-quarter, the above baseline analysis provides strong evidence that female analysts' forecast timeliness is significantly influenced by the increase in domestic burdens caused by the COVID-19 school closures. To further check the robustness of the results, I define the counterfactuals in different ways.

To start with, I use a shorter time window in March 2020 and conduct similar analyses. In this way, the model emphasizes the staggered feature in school closure decisions across states in March 2020. The number of observations in this sample significantly drops to 1698. Columns (1) and (2) in Table 1.3 contain the regression results. In line with previous findings, school closure reduces female analysts' forecast more than that of male analysts: the around 10 pp difference, which is statistically significant at the 10% level, accounts for 13.5% of the average probability to issue a timely forecast in the sample (Table 1.1). The effect of school closures on the forecast timeliness among male analysts (6.3 pp in Column (2) of Table 1.3) is not statistically significant at the 10% level. The estimated gender difference in this sample is larger than that in the sample from January 2020 to August 2020. The attenuation in the economic size of the school closure effect may be due to potential confounding factors in a larger time window. It is also possible that analysts are able to deploy strategies to deal with the increase in childcare demand over time, and therefore, the effect of school closures on forecast timeliness in March is mitigated in an extended window.

Analysts' forecasts before and after school closures are issued at different times of the year. Lo and Wu (2018) and Chang et al. (2017) find that analysts' forecasts are influenced by the seasonality. To take out the seasonality of the analysts' forecasts, I compare the earnings forecasts after the earnings announcements from March 23rd to August 31st in 2020 when most schools in all states are closed during the COVID-19 pandemic with those in the same time period in the previous year 2019. In other words, the sample is from March 23rd to August 31st in 2019 and 2020, and *School closure* is defined as equal to one if the earnings forecast is issued in the year 2020, and zero otherwise. Results in columns (3) and (4) of Table 1.3 confirm that school closures have a negative effect on female analysts' forecast timeliness.

1.3.2 The impact of gender attitude

The observed gender difference in the effect of the COVID-19 school closures on forecast timeliness may be due to reasons other than the gender inequality in housework allocation. For example, if female analysts spend a longer time in analyzing information to issue earnings forecasts during a pandemic or a recession caused by the pandemic because women are more risk-averse (e.g., Powell and Ansic (1997)) and less overconfident (e.g., Lenney (1977) and Barber and Odean (2001)), the findings in the previous section may be explained by the nature of gender differences rather than the unequal division of domestic work. However, the channel of gender differences in response to pandemics is not likely to exist because female analysts are more competitive and better educated than male analysts (Kumar (2010) and Fang and Huang (2017)). Studies have found that gender differences in risk aversion and overconfidence are much smaller after controlling for knowledge and self-selection (Dwyer et al. (2002) and Hardies et al. (2013)).

To further confirm the explanation of distractions of the childcare demand, I explore the cross-sectional difference in the division of household responsibilities across states. Social environment shapes people's values, beliefs, and behavior (e.g., Kumar et al. (2011)). The sexual division of labor at home is likely to be more imbalanced in states with conservative gender attitudes (Ruppanner and Maume (2016)), and analysts may conform to expectations of the local social environment.[13] Therefore, I expect the observed gender difference in the effects of the COVID-19 school closures on forecast timeliness is larger among states with conservative gender attitudes.

I use the U.S. 2017 wave of the World Value Survey to calculate a gender attitude index for each state as the average of three measures on gender attitude from questions about opinions on women in jobs, political positions, and education for all respondents from each state, following the way the World Value Survey calculates the gender attitude index for each country.[14] Supplementary Appendix Figure SA2 shows the cross-sectional variation of gender attitude across states in the U.S. I divide states into liberal- or conservative-gender-attitude states with this measure. $Liberal_j$ is a dummy variable equal to one, if the gender attitude index is larger or equal to the median in the sample, i.e., the gender attitude index of New York at 0.724, and zero otherwise. Table 1.1 shows that 82% of the analysts in the sample are located in states with liberal gender attitudes because more than half of the analysts are located in New York, where the gender attitude is relatively liberal.

Table 1.4 presents the regression results in sub-samples of states with liberal or conservative gender attitudes. The coefficient estimate of the interaction term between *Female* and *School closure* is statistically insignificant in states with liberal gender attitudes but is statistically significant at the 10% level and economically large (13 pp) in states with conservative gender attitudes in the model with firm, broker, state, and time fixed effects (columns (1) and (2)). In the model controlling for analyst, firm, and time fixed effects (columns (3) and (4)), the gender difference in the effect of the school closures on the

[13] Previous studies have used firms' local social environment as a proxy to examine CEOs' behavior, see, e.g., Hilary and Hui (2009) and Focke et al. (2017).

[14] I use the arithmetic mean of the measures across all respondents from the same states. Using weighted means with the sample weight from the survey does not materially change the state-level measure.

forecast timeliness increases to 6 pp and becomes statistically significant at the 5% level in states with liberal gender attitudes. The gender difference is much larger at 11.5 pp in states with conservative gender attitudes, which is statistically significant at the 10% level.

Indeed, school closures influence female analysts more in states with conservative gender attitudes. The results further confirm that the gender difference in the effect of school closures on forecast timeliness comes from the unequal allocation of domestic work between gender. Other channels such as gender differences in risk-aversion cannot explain the different findings in liberal and conservative states in terms of gender attitudes.

1.3.3 Placebo tests using financial crises

The time of COVID-19 school closures overlaps with a financial crash. Is it possible that female analysts' forecast timeliness is negatively influenced by the financial crash? As discussed previously, it is possible that female analysts are more risk-averse and less overconfident and thus, may be more likely to postpone the forecast release during financial crises. In this section, I conduct a placebo test on the gender difference in forecast timeliness during financial crises.

Based on the NBER definition of the financial crisis, there are two financial crises from 1999 to 2020 (restricted by the I/B/E/S sample): one from March 2001 to November 2001 and the other from December 2007 to June 2009. To have an approximately symmetric window around each financial crisis, I use the sample period from 2000 to 2002 and the sample period from 2007 to 2010, respectively. Table 1.5 presents the results. The financial crisis in 2001 does not have a significant effect on forecast timeliness while the more severe financial crisis in 2008 decreases the likelihood to issue timely forecasts by more than 20 pp. In contrast to the gender difference in the negative effect of the school closures on forecast timeliness, the negative effect of the 2008 financial crisis is not more salient among female analysts. If there is anything in gender difference, female analysts are even 1.8 pp more likely to issue timely forecasts during the 2008 financial crisis, but the effect becomes insignificant once the firm-quarter fixed effects and analyst fixed effects are controlled for.

1.3.4 Evidence from H1N1 school closures

Another massive school closure event in the U.S. happened during the H1N1 pandemic, commonly referred to as "swine flu", in 2009. However, it is hard to capture the effect of the school closure event in 2009 because the decisions on school closures were inconsistent and dispersed (Klaiman et al. (2011)), unlike the school closure decisions during the COVID-19 pandemic.[15] I try to capture the effect of school closures in two ways. First, I compare the forecast timeliness in 2009 with that in the previous and subsequent years 2008 and 2010. H1N1-related school closures happened at different times across the year 2009, i.e., both in spring when the pandemic started and in fall during the second wave. Therefore, comparing the forecast timeliness in 2009 with that in 2008 and 2010 may capture the aggregated effect of school closures in 2009, given that there is no massive school closure event in 2008 and 2010. In addition, I take advantage of the fact that New York continued school closures even after the CDC ceased recommending school closures, and other states opened schools (Klaiman et al. (2011)), comparing the difference in forecast timeliness between New York analysts and non-New York analysts in May and June 2009.

[15] The U.S. Centers for Disease Control and Prevention (CDC) recommended school closures on May 1st, 2009 but quickly revised its recommendation on May 5th, 2009 to not closing the school but keeping ill children home.

Table 1.6 contain the regression results. Female analysts are 2 pp less likely to issue timely forecasts in 2009 when school closures happened, compared with the forecasts in 2008 and 2010. In May and June 2009, in New York where many schools were still closed, the gender difference in the probability to issue timely forecast is 6.9 pp lower than that in states where schools were not ordered to close. The effect is statistically significant at the 5% level without control variables in the model (Column (3)) and is economically significant, amounting to 88% of the gender difference in forecast timeliness of analysts in states other than New York. The effect becomes statistically significant at the 10% level when control variables are added, but the economic level remains similar (Column (4)).

To summarize, female analysts are less likely to issue timely forecasts after unexpected school closures caused by pandemics, but there is no significant gender difference in forecast timeliness during financial crises. School closures increase the demand for domestic work and childcare, leading to less timely forecasts of female analysts. According to previous literature (Cooper et al. (2001), Zhang (2008), Chiu et al. (2021)), less timely forecasts are associated with smaller market impact and less favorable career outcomes, making it harder for female analysts to succeed in this competitive industry.

1.3.5 Child-rearing and effect of school closures on forecast timeliness

The analyses so far compare the effect of the COVID-19 school closures on the forecast timeliness of male and female analysts, independently of whether they have children or not.[16] The comparison of forecast timeliness in the sample pooling analysts with and without children may underestimate the treatment effect, potentially giving rise to attenu-

[16]Analysts are likely to be in the prime years of child-rearing, given that average age in the financial analyst industry is around 40 years old. See https://datausa.io/profile/soc/financial-analysts.

ation bias, because child-rearing duties are critical for the effect.

To further attribute the effect of the COVID-19 school closures on forecast timeliness to the distractions caused by school closures, I collect data on family conditions of analysts by checking their Facebook page. Supplementary Appendix 3.6 describes the detailed process of the data collection. I find Facebook pages for 680 analysts and 290 of these pages contain photos of the analysts' children.[17] I then estimate the children's ages based on the photos and the time of the posts. 262 out of the 290 analysts who have posted photos of their children have at least one child under 18. Analysts whose children are all adults, whose Facebook posts do not have photos of their children, or whose Facebook pages cannot be found, are used as the control group. Note that it is possible that some analysts who have children do not post them on Facebook. This adds noise in the measure and may even underestimate the treatment effect because some analysts in the control group may have children as well.

Figure 1.3 compares the coefficient estimates of *School closure* in the regression of *Timely* on *School closure* in sub-samples of male analysts with children, female analysts with children, and other male and female analysts, respectively. All regressions control for analyst fixed effects, and standard errors are clustered by analyst and firm. School closures have a negative impact on the forecast timeliness of all analysts, but the magnitude of the effect substantially differs across different groups of analysts. School closures decrease the forecast timeliness of female analysts with children by 14 pp and that of male analysts with children by only 2 pp. The effects of school closures on the forecast timeliness of other

[17] I identify whether the children in the photos are children of the analysts or, e.g., children of their friends or siblings, based on the texts and comments in the posts. Potential misattribution may add noise to the data, underestimating the treatment effect.

analysts in the sample have a modest gender difference, i.e., 4 pp for male analysts and 5 pp for female analysts. The decrease in forecast timeliness of female analysts with children amounts to 7 times the decrease in forecast timeliness of male analysts with children and around 3 times of the decrease in forecast timeliness of other male and female analysts.

Information on whether an analyst has a non-adult child refines the definition of the treatment and control groups. Analysts with children are in the treatment group whereas other analysts are in the control group. Moreover, analysts are subdivided based on their gender within each group because domestic burdens increased by school closures are expected to have a larger impact on female analysts.

To start with, I compare female analysts with children with other female analysts by running a regression of *Timely* on *School closure*, *Having children*, and their interaction term. *Having children* is a dummy variable equal to one if an analyst's Facebook page contains photos of her non-adult children, and zero otherwise. This sample consists of female analysts only, ruling out other explanations related to gender differences. Panel A of Table 1.7 contains the regression results. Column (1) presents the model controlling for analyst fixed effects. The result shows that the around 9 pp difference in the effects of school closures on female analysts with children and other female analysts is statistically significant at the 10% level. After including control variables and analyst, firm, and time fixed effects (Column (2)), female analysts with children are 13.1 pp less likely to issue timely forecasts after school closures than other female analysts, and the result is statistically significant at the 5% level. By contrast, in columns (3) and (4), I compare the forecast timeliness of male analysts with children and that of other male analysts but do not find any significant result.

The comparison within female analysts would be invalid to establish causality if there is a contemporaneous shock at the state-level, other than the COVID-19 school closures, that affects all analysts with children. To address this issue, another option to establish a counterfactual is to compare the gender difference within analysts with children. Panel B of Table 1.7 contains the regression results of *Timely* on *School closure*, *Female*, and their interaction term in the sub-samples of analysts with children or other analysts. The results show that the forecast timeliness of mothers decreases by 12.3 pp or 22.8 pp more after school closures, compared with that of fathers (columns (1) and (2)). By contrast, there is no gender difference in the effect of school closures on forecast timeliness in the sample of analysts who do not have non-adult children based on the Facebook data (columns (3) and (4)).

Finally, the setting allows conducting a triple difference or difference-in-difference-in-differences (DDD) analysis (e.g., Gruber (1994)), which uses higher-order contrast to draw causal inference (Angrist and Pischke (2008)). I conduct the triple difference estimation by adding interaction terms among *School closure*, *Having children*, and *Female* in the model of Equation 1.1. Panel C of Table 1.7 shows the results. The distraction of domestic burdens caused by school closures decreases mother analysts' forecast timeliness by 11.0–14.9 pp, which accounts for up to 20% of the average forecast timeliness in the sample. This effect estimated by the coefficient estimates of the triple interaction term is statistically significant at the 5% level in all model specifications.

Information from analysts' Facebook pages further confirms that analysts distracted by domestic burdens are less likely to issue timely forecasts. The data collected from Facebook may have limitations because it solely relies on public posts by analysts. Male analysts may be less likely to have Facebook pages or less likely to post photos of their children, compared with female analysts.[18] This would bias the results if male analysts who have posted photos of their children are less likely to be influenced by school closures than male analysts who have children but do not post them on Facebook. However, this is implausible because people who spend time taking care of their children are expected to be more likely to post photos of children on social web pages.

1.4 Domestic distractions, analyst forecast accuracy, and effort allocation

The findings presented in Section 1.3 suggest that analysts distracted by domestic work decrease forecast timeliness. Do domestic distractions influence forecast accuracy as well? Widely studied by the previous literature, forecast accuracy is the first-order concern in terms of forecast quality. However, compared with the effect of limited attention on forecast timeliness, whether and how school closures influence forecast accuracy are less clear. On the one hand, forecast accuracy may deteriorate when analysts suffer from limited attention after the school closures. On the other hand, forecast accuracy may represent analysts' capability to gather and interpret information and thus, is not influenced by limited attention to as large an extent as forecast timeliness. When distracted by household responsibilities, analysts have to delay the issuance of forecasts because they have less time for work, but they may not issue a forecast unless they think it is accurate enough. In this section, I empirically investigate whether and how forecast accuracy is influenced by school closures.

To measure forecast accuracy, I first calculate the forecast error as the absolute value

[18] Table 2 shows that slightly more female analysts are identified as having children. The reason is that more female analysts' Facebook pages are found (see Supplementary Appendix 3.6 for more details).

of the difference between the analyst earnings forecast and the actual earnings announced by the firm. The larger the forecast error is, the less accurate the forecast is. Following Clement and Tse (2005), I define *Forecast accuracy* as:

$$Forecast\,accuracy_{i,j,t} = \frac{Forecast\,error\,Max_{i,t} - Forecast\,error_{i,j,t}}{Forecast\,error\,Max_{i,t} - Forecast\,error\,Min_{i,t}}, \qquad (1.2)$$

where $Forecast\,error\,Min_{i,t}$ and $Forecast\,error\,Max_{i,t}$ are the minimum and maximum of the forecast errors (an absolute value) for all analysts following firm i in quarter t issued in the same calendar month. $Forecast\,accuracy_{i,j,t}$ varies from 0 to 1, and the larger the value is, the more accurate the analyst's forecast is, comparing within the forecasts for the same firm-quarter issued in the same month.

I run a regression of *Forecast accuracy* on the dummy variables *Female*, *School Closure*, and their interaction terms, controlling for firm and analyst characteristics and various fixed effects as in Table 1.2. Standard errors are clustered by analyst and firm.

Table 1.8 contains the regression results. I find some evidence that female analysts issue less accurate forecasts after school closures. The COVID-19 school closures decrease the relative measure of forecast accuracy by 2.2 pp to 5.1 pp, depending on the model specifications. The economic magnitude corresponds to 4% to 9% of the average forecast accuracy in the sample (0.54 pp in Table 1.1). However, the effect is only marginally statistically significant at the 10% level if firm $\times$ quarter fixed effects are controlled for.

Furthermore, if I compare forecast accuracy before and after school closures in March 2020 or that in 2019 and 2020 as in Table 1.3, Table SA4 in the Supplementary Appendix shows that the results are not statistically significant at the conventional level, either. Therefore, there is no strong and robust evidence that female analysts issue less accurate forecasts after the COVID-19 school closures.

In the next step, I explore how female analysts managed to mitigate the negative impact of domestic work on forecast accuracy. Harford et al. (2019) find that analysts strategically allocate more effort to firms that are important for their careers, e.g., firms with relatively large institutional ownership in their coverage portfolio. Hence, it is possible that after the COVID-19 school closures, female analysts allocate more efforts to issue a forecast for these firms to at least maintain the forecast accuracy of these forecasts. As a result, on average, school closures do not significantly deteriorate the forecast accuracy of female analysts.

To test the hypothesis of effort allocation under the pressure from domestic work, I measure the importance of a firm in an analyst portfolio based on its institutional ownership because firms with higher institutional ownership deliver more lucrative commission revenue for the broker firm (Frankel et al. (2006)). Moreover, analysts are dependent on institutional investors for performance ratings (Ljungqvist et al. (2007)), e.g., all-star analyst nomination. For each analyst-earnings announcement date, I rank the institutional ownership of firms and define a dummy variable *High institutional ownership* equal to one if the firm is in the top quartile of portfolio firms issuing forecasts on the same day in terms of institutional ownership, and zero otherwise.[19] I run a regression of *Forecast accuracy* on the dummy variables *Female*, *School Closure*, *High institutional ownership*, and their interaction terms with control variables and fixed effects as in Table 1.8.

Table 1.9 presents the regression results. The coefficients estimates of the interaction term between the female dummy and school closure dummy are negative and statistically

[19]The quartile cut-off follows Harford et al. (2019), and results remain similar if *High institutional ownership* is defined as in the top tertile or quantile.

significant in all model specifications. It means that for firms that are relatively less important for the analysts' career, female analysts' forecast accuracy reduces by 5.8 pp to 8.7 pp, i.e., more than 10% of the average forecast accuracy in the sample, after the school closures. By contrast, high institutional ownership mitigates the negative effect of school closures on female analysts' forecast accuracy by 9 pp to 9.6 pp. The effect is statistically significant at the 10% level in all models. The findings indicate that female analysts allocate more efforts to firms with higher institutional ownership after school closures, and therefore, guarantee forecast accuracy for these firms that are important for their careers.[20]

Another possibility is that analysts choose to delay the forecast releases in order to guarantee the forecast accuracy (Clement and Tse (2003), Guttman (2010), and Shroff et al. (2014)). If so, timely forecasts of female analysts are expected to be less accurate. However, regressions results of *Forecast accuracy* on a triple interaction term among *Female*, *School Closure*, *Timely* in Table SA5 do not support this conjecture.

To summarize, there is only weak and unrobust evidence that female analysts, on average, decrease forecast accuracy after the COVID-19 school closures since they strategically allocate their efforts and manage to maintain forecast accuracy for firms that are important for their career.

1.5 Domestic distraction and forecast release time

If female analysts get distracted by the increase in domestic burdens after the COVID-19 school closures, the time of day to release forecasts may be significantly influenced. For example, analysts may need to take care of the children and cook meals during the daytime

[20]Similar analysis on forecast timeliness also find that the decrease in female analysts' forecast timeliness after school closures is smaller for firms with high institutional ownership (see Supplementary Appendix Table SA6), but the mitigating effect is not statistically significant at the conventional level.

and therefore, have to issue forecasts at night when the children go to sleep. Analysts have busy daily schedules (Bradshaw et al. (2017)) and may strategically choose the time of day when they release earnings forecasts. However, very little is known about what influences the time of day when analysts issue forecasts.

This section investigates the effect of the COVID-19 school closures on the forecast release time. The forecast release time is obtained from the I/B/E/S database.[21] I transfer the data based on Eastern Standard Time zone to local time based on the state where the analyst locates.[22]

Figure 1.4 plots the distribution of the forecast release time of the day, separately, for male and female analysts before and after the school closures. The bright histogram draws the distribution of forecast release time before school closures whereas the dark histogram draws the distribution of forecast release time after the school closures. As expected, after school closures, the fraction of forecasts released by female analysts increases during most hour intervals at night (from 21:00 to 4:00 of the next day) but decreases during the day and in the evening. By contrast, the change in the forecast release time for male analysts after school closures is visually smaller, even though there is a similar pattern that more forecast releases happen at night rather than during the daytime.

In the next step, I formally test whether female analysts are less likely to release forecasts during the periods of a day when housework is intensive in regressions with control

[21] Based on the interpretation by the data provider, the variable announcement time (ANNTIMS) from IBES Detail History file is the time when a broker's estimate is being released to I/B/E/S. It may be obtained via research reports or via earnings feeds. The timestamp "00:00:00" may be missing values, so I exclude the observations (only 133) from the sample.

[22] I refer to Wikipedia page on the U.S. time zone: https://simple.wikipedia.org/wiki/List_of_U.S._states_and_territories_by_time_zone. Some states have more than one time zones and the time zone of the largest part of the territory in the state is used. For example, some counties near the southwestern and northwestern border of Indiana use Central Standard Time but I assume Indiana uses the Eastern Standard Time.

variables and fixed effects. I define *Housework-intensive time* as a dummy variable equal to one if analyst j releases the earnings forecast for firm i during the time period of a day when housework demands such as cooking and childcare are high, i.e., in the morning from 7:00 to 9:00, at noon from 12:00 to 14:00, and from 17:00 to 21:00 in the evening, and zero otherwise.

Based on the summary statistics in Table 1.1, 34% of the analyst forecasts in the sample are released during the housework-intensive. I run a regression of *Housework-intensive* on *Female*, *School closure*, and their interaction term, controlling for firm, broker and state (or analyst), and time fixed effects. I include analyst characteristics, the number of firms in the coverage, broker size, and analysts' experience in the firm, because these characteristics may influence the time of day an analyst releases forecasts. Table 1.10 contains the regression results. After school closures, female analysts are 9 pp less likely to release forecasts during housework-intensive hours. On the contrary, male analysts do not significantly shift the time of day when they release forecasts.

To have a closer look at how analysts shift their forecast releasing time, I run regressions of dummy variables indicating whether the forecast is released during the hour of the day on the school closure dummy in the sample of male analysts' forecasts and female analysts' forecasts, separately. The regressions control for analyst fixed effects to focus the within-analyst change in the forecast time, and the standard errors are clustered by analyst. Figure 1.5 contains the coefficient estimates of the school closure dummy for each time interval. The confidence intervals of coefficient estimates plotted are at the 90% level. Female analysts are less likely to release forecasts at noon from 12:00-14:00 and are more likely to release forecasts from 21:00-22:00 after school closures. By contrast, the change of likelihood to release forecasts during these time intervals for male analysts does not differ from zero. In general, I observe the pattern that the change in the release time for female analysts is economically larger than that for male analysts. However, the gender difference may not be statistically significant at the conventional level. The small number of female analysts leads to a large standard deviation of the coefficient estimates while the standard deviation of the coefficient estimates in the sample of male analysts is much smaller.

Taking advantage of the detailed time stamp of analysts' forecasts, I show that female analysts shift the forecast releases to hours when childcare activities and housework demand are less intensive. This result provides additional evidence that the COVID-19 school closures have a larger impact on female analysts' attention at work because women take more responsibilities for childcare.

1.6 Additional analyses of Chapter 1

1.6.1 Forecast boldness

Forecast boldness is another important perspective of the quality of analyst earnings forecasts. In this section, I investigate whether and how the forecast boldness is influenced by the school closures. It is possible that when distracted by domestic burdens, analysts may be more likely to herd and issue a forecast similar to that of other analysts or their previous forecasts. However, it is also possible that analysts may be less likely to pay attention to all available information including the forecasts by other analysts and issue a forecast deviating more from the consensus after school closures.

To define measures of forecast boldness, I first calculate the distance between a given forecast and the consensus of all forecasts for the firm-quarter (measured as the average of all available analyst earnings forecast values for the same firm-quarter) at the time of the analyst forecast release. Another measure is the distance between a given forecast and the previous forecast of the analyst for the firm-quarter. To get the consensus of the forecast and the analyst's previous forecast, I use a sample of all earnings forecasts 360 days before a firm's earnings announcement dates. I calculate variables *Distance from consensus* and *Distance from previous* with the following equation (Clement and Tse (2005)):

$$Distance_{i,j,t} = \frac{Absolute\,distance_{i,j,t} - Absolute\,distance\,Min_{i,t}}{Absolute\,distance\,Max_{i,t} - Absolute\,distance\,Min_{i,t}}, \tag{1.3}$$

where $Absolute\,distance_{i,j,t}$ is the absolute value of the difference between the analyst forecast value and the consensus of analyst forecasts or the previous forecast issued by the same analysts; $Absolute\,distance\,Min_{i,t}$ and $Absolute\,distance\,Max_{i,t}$ are the minimum and the maximum of $Absolute\,distance_{i,j,t}$ for firm i in quarter t. The boldness measures vary from 0 to 1, and the higher the score is, the bolder the analyst's forecast is, comparing within the forecasts for the same firm-quarter.

I run the same regressions as in the baseline analysis of Table 1.2 and present the result in the Supplementary Appendix Table SA7. Female analysts' forecasts deviate more from the consensus forecasts after school closures. The effect amounts to 4.9 pp-6.8 pp, which is statistically significant at the 5% level. Female analysts' forecasts deviate slightly more from their own previous forecasts as well, but the effect is not statistically significant. Female analysts issue forecasts that deviate more from the consensus but do not deviate more from their own previous forecasts, so a potential explanation could be that they do not pay as much attention to available forecasts by other analysts as they did before school closures.

1.6.2 Analysts' activities at earnings conference calls

At last, I investigate analysts' activities at earnings conference calls. If analysts are distracted by the COVID-19 school closures, their activities at the conference call may also be influenced and the effect is expected to be larger among female analysts. I conjecture that female analysts may be less likely to ask questions in conference calls after school closures. In addition, female analysts who participate in earnings conference calls may ask shorter and fewer questions.

I construct a sample consisting of conference call transcripts for earnings conference calls from January 2020 to August 2020. The conference call transcripts are obtained from Seeking Alpha. I extract the analysts' names from the transcripts and match them with the analysts that issue forecasts for the firm in the quarter based on the I/B/E/S database. Supplementary Appendix Section 3.6 contains the analyses and results in details.

I do not find a significant effect of the COVID-19 school closures on the participation of conference calls for either male or female analysts. Nevertheless, female analysts are less likely to ask questions during some time of the day after the COVID-19 school closures, more specifically, from 5:00 to 6:00 in the morning and from 11:00 to 12:00 at noon (Supplementary Appendix Figure SA3). Furthermore, conditional on participating in the conference, female analysts ask shorter and fewer questions after the COVID-19 school closures (Supplementary Appendix Table SA9).

1.7 Conclusion of Chapter 1

In this paper, I find strong and robust evidence that the COVID-19 school closures negatively influence the forecast timeliness of female analysts, especially in states where the general gender attitudes are conservative. Conducting a triple difference analysis with manually collected data, I estimate a 15 pp decrease in mother's forecast timeliness after the COVID-19 school closures. Female analysts shift the forecast release time to hours without intensive housework after the school closures. In addition, female analysts allocate their limited attention to firms that are more important for their careers and maintain forecast accuracy for these firms.

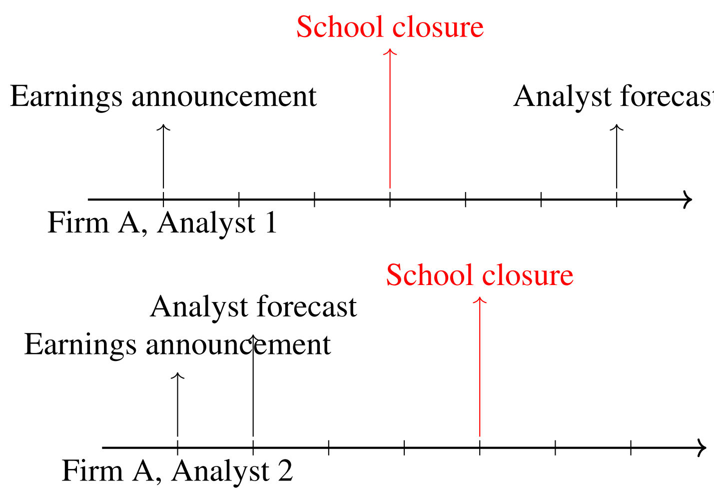
Even though female analysts are competitive women who choose and survive in this male-dominated industry, they are still more likely to be influenced by domestic responsibilities when the demand for childcare unexpectedly increases after the COVID-19 school closures. Consistent with the sexual division of labor theory by Becker (1985), the gender imbalance in childcare duties and domestic tasks may at least partially explain the notable unrepresentativeness of women. On the bright side, the findings imply that the gender gap in the job market may be able to get closed by alleviating the imbalance in housework allocation between gender or by providing better external childcare services. In addition, it is worth learning from female analysts' strategically allocating efforts in the face of domestic distractions.

To my knowledge, this paper is the first to link distractions of domestic work to analysts' forecasts and the labor market of the financial analyst industry. Even professional analysts are influenced by distractions of housework. It is likely that other financial market participants also suffer from limited attention due to distractions of domestic burdens, and the effect may have a large impact on financial markets. This study serves as a starting point for future research to quantify and investigate the effect of domestic duties on financial markets.

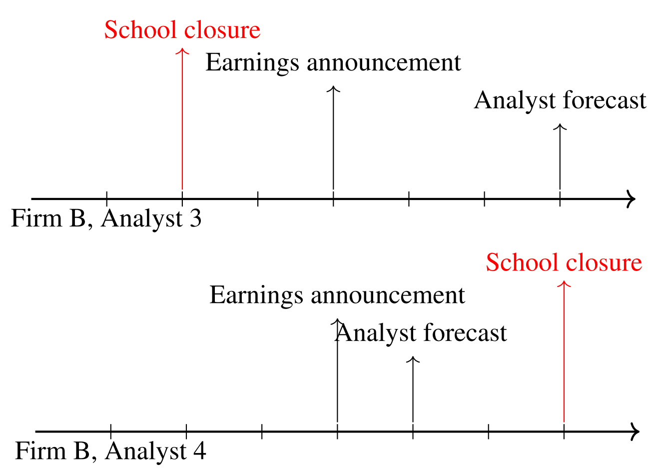
The findings also add to the increasing understanding of the social effects of the COVID-19 pandemic. COVID-19-induced measures such as school closures decrease forecast timeliness of female analysts, which influence information processing efficiency in financial markets. More importantly, it should be brought to the attention of policy-makers that these measures influence different groups in an unequal way. As found in this paper, even women in a competitive profession are more vulnerable to the COVID-19-related social effects.

Figure 1.1: Demonstration of the sample construction

This figure demonstrates the sample construction. Scenario 1 demonstrates earnings announcements excluded from the sample where earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures. Scenario 2 demonstrates earnings announcements not excluded from the sample where both earnings announcements and analyst's forecasts happened before or after the school closure.



Scenario 1



Scenario 2

Figure 1.2: Forecast timeliness of male and female analysts' earnings forecasts around the COVID-19 school closures

This figure plots the average probability to issue timely forecasts among male analysts and female analysts four weeks before and four weeks after the COVID-19 school closures.

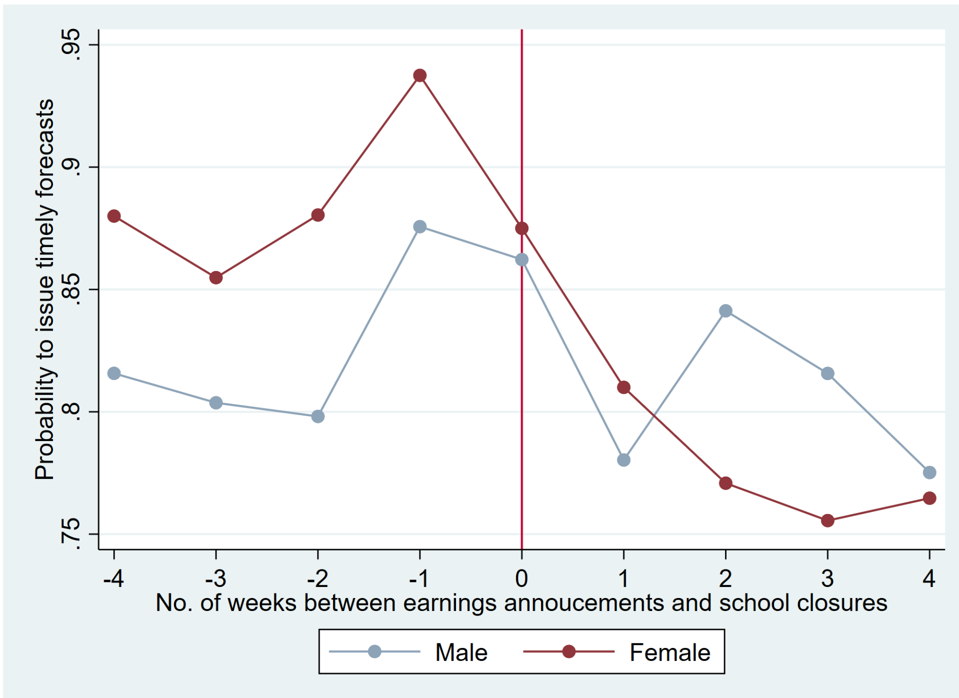


Figure 1.3: School closures effects on forecast timeliness among analysts

This figure plots the coefficient estimates of *School closure* in the regression of *Timely* on *School closure* in sub-samples of male analysts and female analysts with children based on the information from their Facebook, and male analysts and female analysts in the rest of the sample. The models control for analyst fixed effects. Standard errors are clustered by analyst and firm. The confidence intervals of the coefficient estimates are at the 90% level.

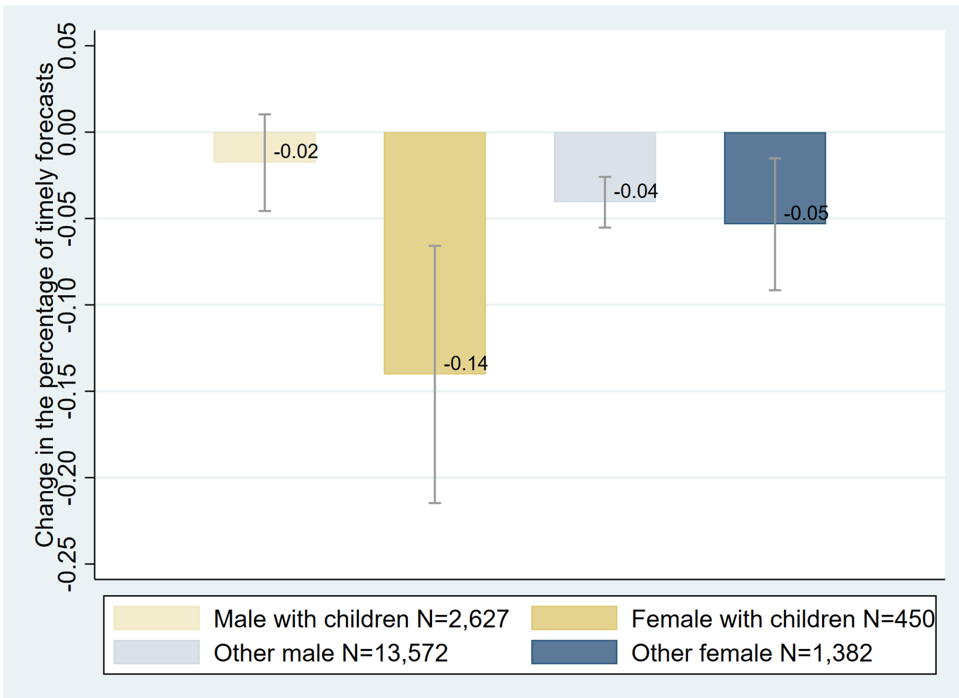


Figure 1.4: COVID-19 school closures and distribution of forecast release time

This figure plots the fraction of earnings forecasts released by male and female analysts during each time period of the day before and after the COVID-19 school closures. The bright histogram draws the distribution of forecast release time before school closures, and the dark histogram draws the distribution of forecast release time after school closures.

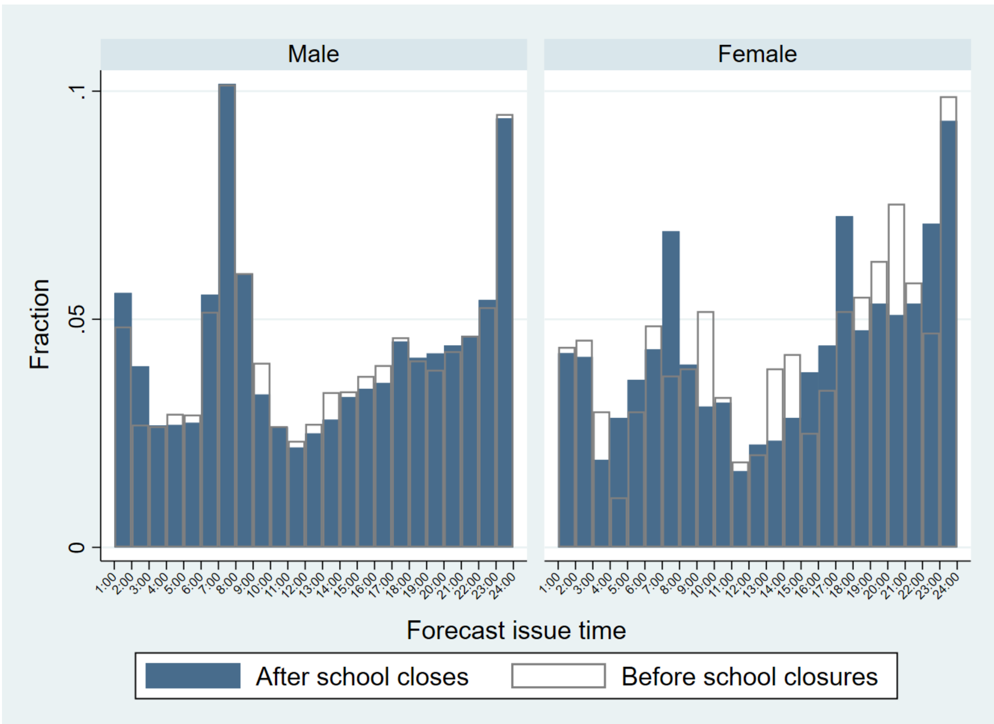


Figure 1.5: Effect of school closures on forecast release time among male and female analysts

This figure plots the coefficient estimates of *School closure* in the regressions of dummy variables indicating whether the forecast is released during the hour of the day on the dummy variable *School closure* in the sub-samples of male analysts' forecasts and female analysts' forecasts. The regressions control for analyst fixed effects, and the standard errors are clustered by analyst. The confidence intervals of the coefficient estimates are at the 90% level.

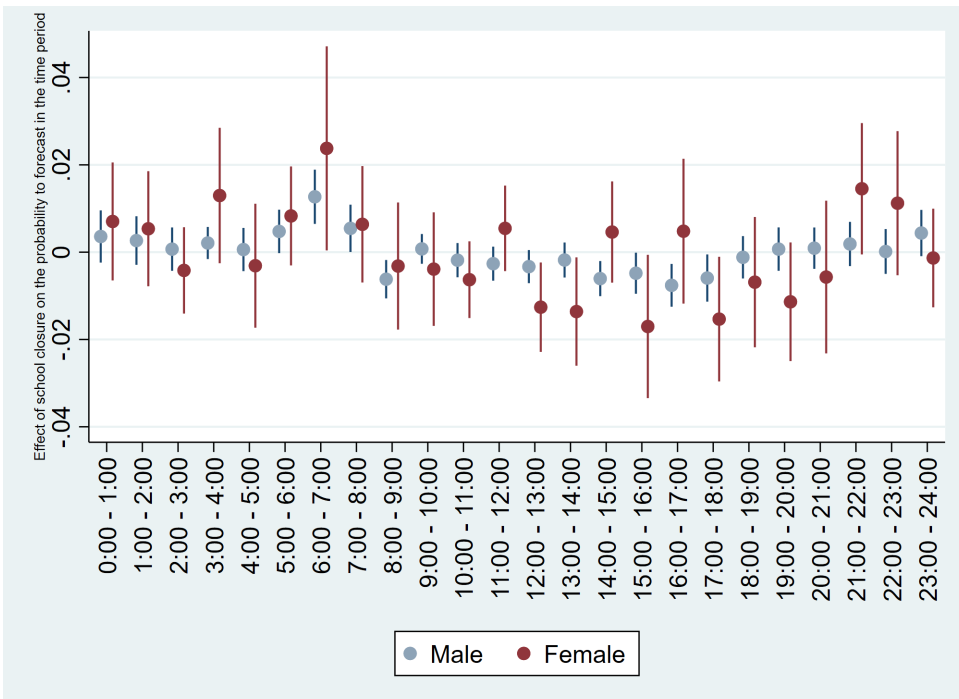


Table 1.1: Summary statistics of Chapter 1

This table contains summary statistics. Panel A contains the number of observations (Obs), mean, standard deviation (Std. Dev.), 25% percentile (P25), median, and 75% percentile (P75), for a sample of the first forecast by each analyst for a firm's earnings in quarter t+1 issued after the firm's quarter t earnings announcement but before one day prior to quarter t+1 earnings announcement from January 2020 to August 2020. Earnings announcements are excluded from the sample if earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures. Panel B contains the difference in the value of main variables and control variables for male and female analysts. t-statistics are based on univariate regressions of the variables on the female dummy, and standard errors are clustered by analyst and firm. Further variable definitions can be found in 1.7.

Panel A: Summary statistics of main variables

Variable	Obs	Mean	Std. Dev.	P25	Median	P75
Female	18701	0.10	0.30	0.00	0.00	0.00
School closed	18172	0.64	0.48	0.00	1.00	1.00
Timely	18701	0.74	0.44	0.00	1.00	1.00
Liberal	18701	0.82	0.38	0.00	1.00	1.00
Having children	18701	0.17	0.37	0.00	0.00	0.00
Forecast accuracy	15491	0.54	0.37	0.19	0.59	0.91
Housework-intensive time	18064	0.34	0.47	0.00	0.00	1.00
Distance from consensus	17853	0.45	0.35	0.12	0.40	0.77
Distance from previous	16156	0.46	0.36	0.14	0.42	0.78
No. of followed firms' EA	18701	0.82	1.21	0.00	0.00	1.00
No. of firms followed	18292	18.28	7.93	13.00	18.00	23.00
Broker size	18292	45.55	31.69	19.00	41.00	63.00
Experience in the firm	18584	22.85	23.28	6.00	15.00	33.00
Firm size	17389	14.72	2.70	13.44	14.98	16.52
Institutional ownership	18322	0.69	0.26	0.54	0.76	0.89
Book to market	16345	0.55	0.48	0.21	0.42	0.77
Bad earning news	18634	0.35	0.48	0.00	0.00	1.00
Special items	16384	0.65	0.48	0.00	1.00	1.00
Log number of following analysts	18641	2.54	0.60	2.08	2.56	3.00

Table 1.1: Summary statistics of Chapter 1 (continued)

Panel B: Comparison of main variables between gender

	Male		Female			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff	t-statistics
Timely	0.735	0.441	0.773	0.419	-0.038	-1.64
Liberal	0.824	0.381	0.877	0.328	-0.054	-1.45
Having children	0.158	0.365	0.229	0.421	-0.071	1.58
Housework-intensive time	0.334	0.472	0.363	0.481	-0.029	-1.53
Distance from consensus	0.451	0.354	0.467	0.361	-0.016	-1.29
Distance from previous	0.463	0.356	0.476	0.361	-0.013	-1.03
Forecast accuracy	0.545	0.371	0.515	0.374	0.030	2.37
No. of followed firms' EA	0.813	1.200	0.856	1.286	-0.043	-0.40
No. of companies followed	18.337	7.966	17.815	7.621	0.522	0.68
Broker size	44.854	31.334	51.702	34.019	-6.848	-2.11
Experience in the firm	22.993	23.360	21.632	22.546	1.360	0.88
Firm size	14.712	2.713	14.769	2.627	-0.057	-0.50
Institutional ownership	0.694	0.258	0.683	0.255	0.011	-0.08
Book to market	0.546	0.483	0.559	0.473	-0.013	-0.44
Bad earning news	0.343	0.475	0.362	0.481	-0.019	-1.02
Special items	0.658	0.474	0.596	0.491	0.062	3.19
Log number of following analysts	2.536	0.597	2.532	0.578	0.004	0.09

Table 1.2: Effect of COVID-19 school closures on forecast timeliness

This table contains the regression results of *Timely* on *Female*, *School closure* and their interaction term. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Timely	
	(1)	(2)	(3)
Female × School closure	-0.043*	-0.067***	-0.062***
	(-1.67)	(-2.66)	(-2.59)
School closure	-0.064**	-0.031	-0.036
	(-2.31)	(-1.01)	(-1.15)
Female	0.049**		
	(2.11)		
No. of followed firms' EA	-0.017***	-0.017***	-0.016***
	(-3.48)	(-4.11)	(-3.84)
Firm size	0.012	0.012*	
	(1.60)	(1.89)	
Institutional ownership	0.043*	0.046**	
	(1.75)	(2.04)	
Book to market	0.013	0.019	
	(0.41)	(0.66)	
Bad earning news	-0.010	-0.011	
	(-0.60)	(-0.73)	
Special items	0.019	0.007	
	(0.34)	(0.13)	
Log number of following analysts	0.074	0.032	
	(0.91)	(0.40)	
No. of firms followed	0.004***	0.003	0.003
	(5.57)	(1.07)	(1.00)
Broker size	0.001	-0.001	-0.000
	(0.75)	(-0.34)	(-0.22)
Experience in the firm	0.0005**	0.0004*	0.0004*
	(2.33)	(1.78)	(1.74)
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	15208	15378	15347
Adjusted R^2	0.292	0.428	0.429

Table 1.3: Effect of COVID-19 school closures on forecast timeliness – Other counterfactuals

This table contains the regression results of *Timely* on *Female*, *School closure* and their interaction term. Columns (1) and (2) run regressions in the sample of March 2020 and *School closure* is equal to one, if the state where the analyst is located has closed schools, and zero otherwise. Columns (3) and (4) run regressions in the sample from March 23rd to August 31st in 2019 and 2020 and *School closure* is equal to one, if the earnings forecast is issued in year 2020, and zero otherwise. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Counterfactual:	Across states in March 2020		2019 vs 2020	
Female × School closure	-0.093*	-0.122*	-0.039*	-0.048**
	(-1.86)	(-1.92)	(-1.67)	(-2.29)
School closure	-0.066*	-0.063		
	(-1.86)	(-1.26)		
Female	0.033		0.036**	
	(1.08)		(2.15)	
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Broker, State, Time	Firm, Analyst, Time
Observations	1698	1337	42675	43613
Adjusted R^2	0.357	0.398	0.282	0.418

Table 1.4: Gender attitudes and the effect of school closures on forecast timeliness

This table contains the regression results of *Timely* on *Female*, *School closure* and their interaction term in separate samples of states with conservative or liberal gender attitudes measured by the US 2017 wave of the World Value Survey. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Gender attitudes:	Liberal	Conservative	Liberal	Conservative
Female × School closure	-0.028	-0.130*	-0.060**	-0.115*
	(-1.02)	(-1.85)	(-2.12)	(-1.67)
School closure	-0.031	0.000	0.019	
	(-1.07)	(0.00)	(0.61)	
Female	0.037	0.081		
	(1.54)	(1.30)		
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Analyst, Time
Observations	12244	2448	12142	2418
Adjusted R^2	0.287	0.367	0.421	0.424

Table 1.5: Effect of financial crises on the forecast timeliness – a placebo test

This table contains the regression results of *Timely* on *Female*, *Financial crisis* and their interaction term. Columns (1) and (2) run regressions in the sample from 2000 to 2002 and *Financial crisis* is equal to one if the earnings forecast is issued from March 2001 to November 2001 based on the NBER financial crisis definition, and zero otherwise. Columns (3) and (4) run regressions in the sample from 2007 to 2010 and *Financial crisis* is equal to one if the earnings forecast is issued from December 2007 to June 2009 based on the NBER financial crisis definition, and zero otherwise. *Timely* is a dummy variable equal to one if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Financial crisis:	2001		2007-2009	
Female × Financial crisis	0.007	0.008	0.018**	0.013
	(0.64)	(0.71)	(2.22)	(1.54)
Financial crisis	-0.023	-0.011	-0.277***	-0.229***
	(-1.64)	(-0.75)	(-13.69)	(-12.72)
Female	0.005		-0.007	
	(0.61)		(-0.66)	
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm-quarter, Analyst, Time	Firm, Broker, State, Time	Firm-quarter, Analyst, Time
Observations	127681	152609	255772	288442
Adjusted R^2	0.198	0.308	0.243	0.331

Table 1.6: Effect of H1N1 school closures on the forecast timeliness

This table contains the regression results of *Timely* on *Female*, *H1N1 school closure* and their interaction term. Columns (1) and (2) run regressions in the sample from 2008 to 2010 and *School closure* is equal to one if the earnings forecast is issued in year 2020, and zero otherwise. Columns (3) and (4) run regressions in the sample of May and June 2020 and *School closure* is equal to one if the state where the analyst is located is New York, and zero otherwise. *Timely* is a dummy variable equal to one if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Counterfactual:	2009 vs 2008 and 2010		New York vs other states in May and June 2009	
Female × H1N1 school closure	-0.021**	-0.020**	-0.069**	-0.066*
	(-2.20)	(-2.15)	(-2.08)	(-1.95)
H1N1 school closure	0.079***	0.055***		
	(3.83)	(2.91)		
Female	0.008		0.078***	0.077***
	(0.72)		(2.84)	(2.76)
Control variables	Yes	Yes	No	Yes
Fixed effects	Firm, Broker, State, Time	Firm-quarter, Analyst, Time	Firm, Broker, State, Time	Firm, Broker, State, Time
Observations	190147	199488	8085	7563
Adjusted R^2	0.252	0.334	0.432	0.415

Table 1.7: Effect of COVID-19 school closures on parents' forecast timeliness

This table contains the regression results of *Timely* on *School closure*, *Female*, *Having Children* and their interaction terms. The information on whether an analyst has a non-adult child is manually collect from their Facebook pages. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
Panel A: Parent effect among female or male analysts				
	(1)	(2)	(3)	(4)
	Female		Male	
School closure × Having children	-0.087*	-0.131**	0.023	0.018
	(-1.78)	(-2.34)	(1.27)	(0.89)
School closure	-0.053**	-0.012	-0.041***	-0.062*
	(-2.32)	(-0.13)	(-4.55)	(-1.86)
Control variables	No	Yes	No	Yes
Fixed effects	Analyst	Firm, Analyst, Time	Analyst	Firm, Analyst, Time
Observations	1832	1240	16199	13969
Adjusted R^2	0.351	0.384	0.361	0.430
Panel B: Gender effect among parents or non-parents				
	(1)	(2)	(3)	(4)
	Parents		Other analysts	
School closure × Female	-0.123***	-0.228***	-0.013	-0.014
	(-2.61)	(-3.32)	(-0.53)	(-0.52)
School closure	-0.018	-0.132	-0.041***	-0.069*
	(-1.04)	(-1.41)	(-4.55)	(-1.90)
Control variables	No	Yes	No	Yes
Fixed effects	Analyst	Firm, Analyst, Time	Analyst	Firm, Analyst, Time
Observations	3077	2254	14954	12913
Adjusted R^2	0.291	0.416	0.370	0.435

Table 1.7: Effect of COVID-19 school closures on parents' forecast timeliness (continued)

Panel C: Triple difference analysis	(1)	(2)	(3)	(4)
School closure × Female Dummy × Having children	-0.110**	-0.138**	-0.149**	-0.133**
	(-2.08)	(-2.23)	(-2.47)	(-2.36)
School closure × Having children	0.023	0.025	0.021	0.022
	(1.27)	(1.32)	(1.06)	(1.24)
School closure × Female Dummy	-0.013	-0.000	-0.020	-0.003
	(-0.53)	(-0.01)	(-0.75)	(-0.14)
Female Dummy × Having children		0.064	0.000	0.000
		(1.18)	(0.00)	(0.00)
School closure	-0.041***	-0.087***	-0.043	-0.061**
	(-4.55)	(-3.05)	(-1.45)	(-2.05)
Having children		-0.007		
		(-0.41)		
Female Dummy		0.022		
		(0.82)		
Control variables	No	Yes	Yes	Yes
Fixed effects	Analyst	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	18031	15341	15609	17935
Adjusted R^2	0.360	0.294	0.429	0.446

Table 1.8: Effect of COVID-19 school closures on forecast accuracy

This table contains the regression results of *Forecast accuracy* on *Female*, *School closure* and their interaction term. *Forecast accuracy* measures the forecast accuracy of the forecast compared within all analysts forecasts issued in the same month for the same firm-quarter. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Forecast accuracy		
	(1)	(2)	(3)
Female Dummy× School closure	-0.022	-0.034	-0.051*
	(-0.84)	(-1.25)	(-1.85)
School closure	0.083	0.098	0.095
	(1.33)	(1.40)	(1.40)
Female Dummy	-0.002		
	(-0.08)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	14135	14217	15042
Adjusted R^2	0.020	0.043	0.028

Table 1.9: Forecast accuracy and effort allocation

This table contains the regression results of *Forecast accuracy* on *Female*, *School closure*, *High institutional ownership* and their interaction term. *Forecast accuracy* measures the forecast accuracy of the forecast compared within all analysts forecasts issued in the same month for the same firm-quarter. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Forecast accuracy	
	(1)	(2)	(3)
Female Dummy × School closure	-0.058*	-0.069**	-0.087***
	(-1.81)	(-2.05)	(-2.67)
Female Dummy × School closure × High inst. Ownership	0.090*	0.092*	0.096*
	(1.82)	(1.86)	(1.95)
School closure × High inst. Ownership	-0.034*	-0.029	-0.030
	(-1.80)	(-1.52)	(-1.33)
Female Dummy × High inst. Ownership	-0.062	-0.061	-0.063
	(-1.50)	(-1.45)	(-1.50)
High inst. Ownership	0.034**	0.033**	0.038**
	(2.18)	(2.09)	(2.01)
Female Dummy	0.019		
	(0.70)		
School closure	0.096	0.110	0.109
	(1.53)	(1.57)	(1.59)
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	14135	14217	15031
Adjusted R^2	0.021	0.043	0.028

Table 1.10: Effect of COVID-19 school closures on the forecast release time

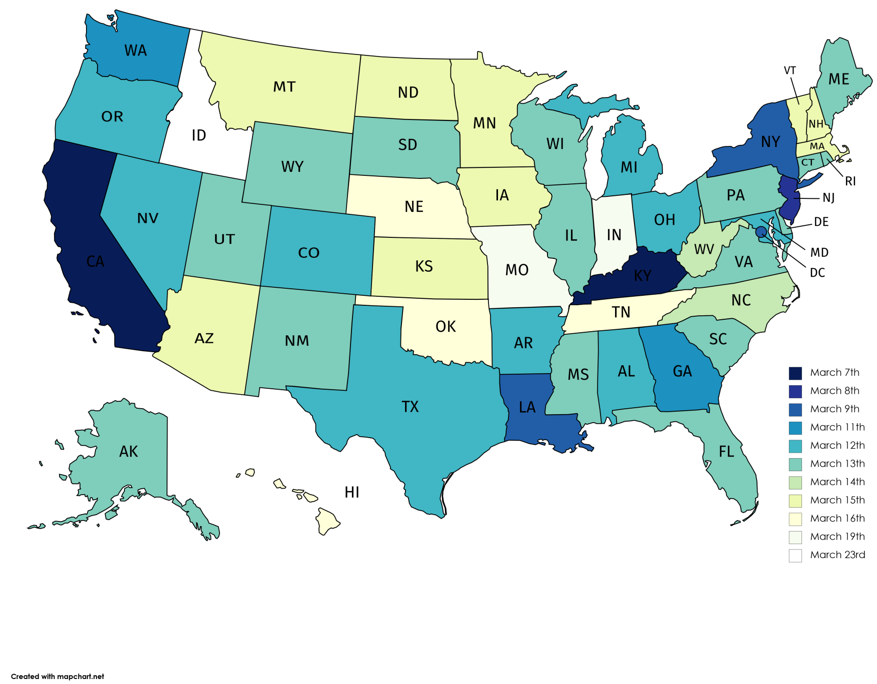
This table contains the regression results of *Housework-intensive time* on *Female*, *School closure* and their interaction term. *Housework-intensive time* is a dummy variable equal to one if housework demand is usually high during the hour intervals (in the mornings, at lunch, or in the evening), and zero otherwise. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Housework-intensive time		
	(1)	(2)	(3)
Female × School closure	-0.090***	-0.096***	-0.099***
	(-3.32)	(-3.49)	(-3.57)
School closure	-0.054	0.014	0.007
	(-0.97)	(0.27)	(0.14)
Female	0.085***		
	(3.32)		
No. of firms followed			-0.000
			(-0.14)
Broker size			0.001
			(0.64)
Experience in the firm			-0.000*
			(-1.65)
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Analyst, Time
Observations	17998	17858	17396
Adjusted R^2	0.113	0.196	0.195

Appendix

A1.1 COVID-19 School closure start dates in each state in the U.S.

This map contains the school closure dates manually collected based on the timestamps of the media coverage on school closure decisions across the states and official documents issued by the governors. The darker the color of the state is, the earlier school closures caused by the COVID-19 pandemic started.



A1.2 Variable description of Chapter 1

This table describes all variables used in the empirical analyses. Data sources are as follows:

1. IBES: I/B/E/S database
2. Online: Manually collected online
3. CRSP: CRSP stock price data
4. Compustat: Compustat quarterly financial statement data
5. Facebook: Manually collected from analysts' Facebook pages
6. TR: Thomson Reuters Institutional (13f) Holdings
7. WVS: U.S. 2017 wave of the World Value Survey
8. Call: Earnings conference transcripts from Seeking Alpha
9. MC: Manually constructed

Variable name	Description	Data Source
Bad earning news$_{i,t}$	Dummy variable equal to one, if firm i's realized earnings for quarter t are less than the analyst forecast consensus (the average of all available analyst earnings forecast values for the same firm-quarter) before quarter t's earnings announcement, and zero otherwise.	IBES, MC
Book to market$_{i,t}$	Firm i's book to market ratio at the fiscal end of quarter t	CRSP, Compustat
Broker size$_{j,t}$	The number of analysts working at the broker where analyst j works as of quarter t.	IBES, MC

Variable name	Description	Data Source
Distance from consensus$_{i,j,t}$	The distance between the analyst forecast value and the consensus of analyst forecasts (the average of all available analyst earnings forecast values for the same firm-quarter). The measure is in relative term adjusted as in Equation 1.3.	IBES, MC
Distance from previous$_{i,j,t}$	The distance between the analyst j's forecast value and the previous forecast issued by analyst j. The measure is in relative term adjusted as in Equation 1.3.	IBES, MC
Female$_j$	Dummy variable equal to one, if the analyst is female, and zero otherwise.	IBES, Online, MC
Financial crisis$_{i,j,t}$	Dummy variable equal to one, if there is a financial crisis following the NBER definition when analyst j issues earnings forecast for firm i after its earnings announcement for quarter t, and zero otherwise.	MC
Firm size$_{i,t}$	Log of firm i's market value (in thousand dollars) at the fiscal end of quarter t.	CRSP, MC
Forecast accuracy$_{i,j,t}$	Relative measure of the forecast accuracy calculated as in Equation 1.2.	IBES, MC
Forecast error$_{i,j,t}$	The absolute value of the difference between the analyst earnings forecast and the actual earning announced by the firm.	IBES, MC

Variable name	Description	Data Source
Forecast revision$_{i,j,t}$	The difference between the analyst j's current forecast and his or her previous forecast on stock i.	IBES, MC
H1N1 school closure$_{i,j,t}$	Dummy variable equal to one, if schools in the state where analyst j is located are assumed to be closed when she issues earnings forecast for firm i after its earnings announcement of quarter t. The H1N1 school closures are captured by either comparing 2009 with the previous and subsequent years or comparing New York analysts with non-New York analysts in May and June 2009.	Online, MC
Having children$_{j,t}$	Dummy variable equal to one if analyst j's Facebook page contains photos of her non-adult children, and zero otherwise.	Facebook, MC
High institutional ownership	Dummy variable equal to one if the firm is in the top quartile of portfolio firms issuing forecasts on the same day in terms of institutional ownership, and zero otherwise.	IBES, TR, MC
Housework-intensive time$_{i,j,t}$	Dummy variable equal to one, if analyst j releases the earnings forecast for firm i during the time period of a day when housework demand is high, i.e., in the morning from 7:00 to 9:00, at noon from 12:00 to 14:00, and from 17:00 to 21:00 in the evening, and zero otherwise.	IBES, MC

Variable name	Description	Data Source
Institutional ownership$_{i,t}$	Firm i's institutional ownership in the percentage of total market value at the fiscal end of quarter t.	TR
Log number of following analysts$_{i,t}$	Log of the number of analysts who follow firm i as of the earnings announcement for quarter t.	IBES, MC
Liberal$_{j,t}$	Dummy variable equal to one, if the gender attitude index is larger or equal to the median in the sample, i.e., the gender attitude index of New York at 0.724, and zero otherwise.	WVS, MC
No. of firms followed$_{i,j,t}$	The number of firms for which analyst j issues an earnings forecast in quarter t.	IBES, MC
No. of industries followed$_{j,t}$	The number of industries analyst j covers in year t.	IBES, MC
No. of followed firms' EA$_{i,j,t}$	The number of followed firms' earnings announcements on the day when analyst j issues earnings forecast for firm i after its earnings announcement of quarter t.	IBES, MC
Participate$_{i,j,t}$	Dummy variable equal to one, if the analyst appears in conference call transcripts and the I/B/E/S database, and zero if analysts only appear in the I/B/E/S database.	IBES,Call, MC
Question count$_{i,j,t}$	The number of questions asked by analyst j at the firm i's conference call of quarter t.	Call, MC

Variable name	Description	Data Source
School closure$_{i,j,t}$	Dummy variable equal to one, if schools are closed in the state where analyst j is located at the time of firm i's earnings announcement for quarter t, and zero otherwise.	IBES, Online, MC
Sentence count$_{i,j,t}$	The number of sentences in the speech of analyst j at the firm i's conference call of quarter t.	Call, MC
Special items$_{i,t}$	Dummy variable equal to one, if the special items reported by firm i are positive in quarter t, and zero otherwise.	Compustat
Timely$_{i,j,t}$	Dummy variable equal to one, if analyst j issues the earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm i's quarter t earnings announcement date.	IBES, MC
Word count$_{i,j,t}$	The number of words in the speech of analyst j at the firm i's conference call of quarter t.	Call, MC

CHAPTER 2

Counter-stereotypical Female Role Models and Women's Occupational Choices

Coauthors: Vidhi Chhaochharia and Alexandra Niessen-Ruenzi

2.1 Introduction of Chapter 2

Over the last 30 years, the gap between men and women in terms of education and labor market outcomes has markedly narrowed (Goldin (2014b)). Despite this "grand convergence", women are still underrepresented in lucrative and competitive professions, such as STEM, business, and finance, which in turn perpetuates the gender pay gap. Women might be avoiding male-dominated fields due to their preferences (e.g., Niederle and Vesterlund (2007) and Booth and Nolen (2012)), or biases against women (e.g., Goldin and Rouse (2000), and Reuben et al. (2014)). It is also possible that a lack of appropriate female role models that would otherwise nudge women into more lucrative occupations enlarges the gender gap in competitive industries. Previous studies find evidence that working mothers (Olivetti et al. (2020)) and successful female figures in the same industry (e.g., Bell et al. (2018) and Jannati (2020)) encourage women to participate in the labor market and perform well in their respective industries. These successful professional women may be perceived as female role models which help mitigate gender stereotypes arising from traditional gender norms. However, while female role models have been shown to raise women's self-confidence and willingness to compete (Schier (2020)), their long-term impact on labor market choices remains unexplored, probably due to the lack of data.

In this study, to the best of our knowledge, we are the first to create a systematic measure of counter-stereotypical female role models based on a long time series of public opinion surveys and investigate its relation to occupational choices, fertility choices, and labor market outcomes for women in the US. Using Gallup surveys from 1951 to 2014, we collect all responses to the question "What woman that you have heard or read about, living today in any part of the WORLD, do you admire the MOST?". The question is in open-end format, i.e., survey respondents must come up spontaneously with the name of a woman they admire. We then categorize the responses into stereotypical or counter-stereotypical role models depending on whether a woman, who has been named as admired, is in a male-dominated or in a female-dominated occupation, respectively. For example, admired women in counter-stereotypical roles are politicians, scientists, or astronauts, while admired women in stereotypical roles are famous wives, nurses, or movie stars. We then create an aggregate measure of counter-stereotypical role models based on the fraction of respondents in a given state, who admire these women. We observe that, over time, counter-stereotypical female role models become more popular than stereotypical female role models.

Counter-stereotypical female role models challenge gender identities that are usually derived from traditional gender norms (Olsson and Martiny (2018)). Gender norms are shared by the majority of people in a society and shape individual gender role beliefs, i.e., expectations of what behavior is appropriate for men and women based on their distribution in different roles (Eagly et al. (2000)). In an identity framework as defined by Akerlof and Kranton (2000), people fit themselves into different social categories according to what they think society expects from them. People are exposed to gender norms from an early age through their social environment and the media that usually depicts stereotypical gender roles (Wood (1994) and Signorielli (1990)). For example, being a nurse would be a gender-stereotypical occupation for women, while being in a managerial position would not.[1]

Given the widespread exposure to stereotypical gender roles, it is not surprising that women's gender role beliefs are strongly influenced by gender stereotypes (e.g., Solow and Kirkwood (2002), Cadsby et al. (2013), Hicks et al. (2015) and Bordalo et al. (2019)). Bertrand (2017) points out that the negation of gender stereotypes may help undo whatever role they have on holding women back in their career choices. Counter-stereotypical female role models, for example, a male nurse or a female manager, are such negations of gender stereotypes as they pose deviations from what is typically expected from a woman. Whether and to what extent counter-stereotypical female role models are related to women's labor market choices, as well as their educational and fertility choices, is the core question in this paper.

We first examine whether female survey respondents, who admire counter-stereotypical female role models, are more likely to be employed and work in managerial positions. Specifically, we run regressions of respondents' labor market outcomes on whether they admire counter-stereotypical female role models after controlling for various demographic characteristics such as age, ethnicity, state of residence, year, and education. State fixed effects take out a large proportion of social factors that do not vary over time such as religion and culture.

We find that admiring a counter-stereotypical female role model is associated with a

[1] Similarly, Casey and Dustmann (2010) find that identity with home and host countries relates to immigrants' and their children's labour market outcomes.

3.3–9.1 percentage points (pp) higher probability that a woman is employed, and with a 5.7–11.2 pp higher probability of full-time employment. Furthermore, women who admire counter-stereotypical female role models are 1.5 pp more likely to become an executive, which corresponds to around 20% of the average probability of becoming an executive in the sample. We do not find a relation between counter-stereotypical female role models and men's labor market outcomes.

In the next step, we create an aggregate state-year level measure of counter-stereotypical female role models and match it to survey data from the Current Population Survey (CPS) based on CPS survey respondents' state of residence. This allows us to look at a more detailed set of labor, occupation, and education-related variables. We match the role model variable as of the year in which a CPS survey respondent was 20 years old, i.e., her formative years in which role model effects should be strongest and career choices are more likely to be made (Olsson and Martiny (2018)). Our empirical strategy follows Fernández and Fogli (2009) and explores the idiosyncratic variation in female role models of age cohorts from different states. We add state$\times$year fixed effects to take out heterogeneity across states such as, e.g., local economic conditions.

In line with our findings from the Gallup survey, our analysis using CPS data also shows that the gender gap in labor market participation is lower if counter-stereotypical female role models are more popular. The presence of counter-stereotypical female role models is also associated with a larger fraction of women working in male-dominated industries, male-dominated occupations, STEM industries, and managerial positions. For example, the admiration of counter-stereotypical female role models is associated with a 12.4% reduction of the gender gap in the probability of becoming a manager.

CPS data also allow us to examine fertility and educational choices. We find that women in states with more people admiring counter-stereotypical female role models are older when they have their first child. In addition, they are more likely to seek degrees of higher education, such as a Bachelor's degree or a post-graduate degree.

We find that the difference in career choices between women in states with high vs. low admiration of counter-stereotypical female role models is also associated with the gender pay gap. Specifically, the gender pay gap is significantly lower in states where counter-stereotypical female role models are more popular.

Finally, we examine the relation between our state-level counter-stereotypical female role mode variable and state-level gender norms. We find that counter-stereotypical female role models stem from both, states with liberal gender norms and states with conservative gender norms. Thus, they are not simply the result of more progressive gender norms in general. Furthermore, while state-level gender norms are quite persistent over time (Bertrand et al. (2020), the strength of our state-level role model variable varies over states across time. Its correlation with state-level gender norms is positive and is statistically significant, but only ranges around 0.2. These results suggest that the state-level counter-stereotypical role model variable does not simply capture gender norms. Rather, it is a separate construct related to women's choices and may be considered as a starting point for subsequent changes in gender norms, which move much more slowly over time. In line with this view, we find that our results are robust to including state-level measures of gender norms.

Our paper contributes to the literature on how role models help to reduce gender stereotypes. For example, Bettinger and Long (2005a) suggest that female role models are important for women's educational choices. Additionally, Schier (2020) and Drupp et al. (2020) show that female and male role models increase women's willingness to compete. Sonnert et al. (2007) show that if the percentage of female faculty in the science and engineering departments of US universities increases by 10%, the number of female majors in physical sciences, engineering and biological sciences increases by 1.2%. If parents of daughters are exposed to female leaders, they have higher aspirations for their daughters as well. Research on mandatory quotas promoting women to leadership positions in local communities (e.g., Beaman et al. (2012)) also shows that the admiration of counter-stereotypical role models leads to girls reporting higher educational aspirations for themselves.

This paper differs from previous studies on role model effects by developing a direct measure of counter-stereotypical female role models over a long period of time. The role models are named by survey respondents themselves and are not artificially imposed on them as needs to be done in laboratory experiments. Furthermore, the long time series allows us to document changes in the relative importance of stereotypical vs. counter-stereotypical female role models over more than fifty years and study how women's fertility, educational, and labor market choices vary with the relative importance of counter-stereotypical vs. stereotypical female role models.

2.2 Data of Chapter 2

2.2.1 Measuring counter-stereotypical female role models

Our measure of counter-stereotypical female role models is derived from Gallup surveys. These US-based surveys provide chronicled reactions to major events and measure public opinion towards political, social, and economic issues from as early as 1941.[2] Starting in 1951, Gallup asked respondents "What woman that you have heard or read about, living today in any part of the WORLD, do you admire the MOST?". This question has been repeatedly asked in subsequent years without changing the wording of the question too much. Thus, we can collect answers to this question for a long time period and portray how answers changed over almost half a century.

Specifically, using 46 repeated cross-sectional Gallup surveys from 1951 to 2014, we create a systematic measure of female role models over time. In addition to collecting survey respondents' answers to the question on which woman they admire the most, we also collect their state of residence and all other relevant demographic information.[3]

Different from other surveys that ask people about their attitude towards gender, Gallup specifically asks respondents about women who they admire. Respondents are supposed to answer the question in open text format so that their answer is based on their spontaneous association with a woman they consider admirable. Figure 2.1 shows the number of admired women per survey year and the number of counter-stereotypical female role models that were mentioned in this year. We find that the minimum and maximum number of admired women over the sample period in a given year ranges from 11 (2003) to 78 (1969), respectively. The number of counter-stereotypical female role models ranges from 5 (1951) to 21 (1969). The average number of (counter-stereotypical) female role models in our sample period is (10.7) 27.8.

Supplementary Supplementary Appendix SA11 shows a sample survey from Decem-

[2]Gallup data are obtained from the Roper center for public research.

[3]Supplementary Supplementary Appendix SA10 lists all surveys included in our sample, out of which 8 surveys (highlighted) also include all demographic variables like education, age, religion, political party, city size, number of children in a household, employment status, marital status, and occupation.

ber 7-12, 1961 and the list of women that survey respondents named. In 1961, survey respondents came up with 66 different women, for example, Jackie Kennedy, Queen Elizabeth, or Marilyn Monroe. These women are likely to serve as female role models to survey respondents. According to the literature, for a person to serve as a role model, she needs to be perceived as likable, and her behavior has to be socially rewarded (Bandura (1986)). In addition, role models are particularly effective if they are of the same gender as the observer (Olsson and Martiny (2018)). Since Gallup specifically asks about admired women, the precondition that the role model is perceived as likable should be fulfilled. Also, the behavior of these admired women should usually be rewarded by society because they are perceived by respondents as admirable. In addition, female role models should be more strongly related to female survey respondents' labor and employment outcomes, because they they share the same gender.

In our paper, we define counter-stereotypical female role models as admired women in counter-stereotypical gender roles. The traditional role of women in societies can be traced back to agricultural practices of plough versus shift cultivation (Boserup (2007)). In plough societies, characterized by strong physical demands of cultivation, women usually stayed at home to take care of the family and raise children. Linking the past to the present, Alesina et al. (2013) show that in plough societies, women were less likely to participate in the labor force or politics. These cultural gender norms have persisted through time. Numbers from the Bureau of Labor Statistics as of 2019 suggest that healthcare (78%), child care and social services (84%), and education (68%) are still female-dominated professions, while mining and manufacturing industries have less than 30%

female participation.[4]

To define our counter-stereotypical female role model variable, we first construct a list of all 247 admired women that appear in any of the 46 Gallup surveys and divide them into the following 14 categories according to their primary occupation or role in their Wikipedia biography: politician, athlete, entertainer, writer or journalist, famous wife, religious person, scientist, family or friends, activist, famous mother, famous daughter, astronaut, nurse, and businesswoman.

Next, we compare the fraction of men and women in a given occupation during the sample period and define *Counter-stereotypical female role models* as women in male-dominated occupations.[5] These are politicians, writers or journalists, businesswomen, astronauts, scientists, athletes, or activists. We classify admired women as being in stereotypical female roles if they are famous wives, famous mothers, famous daughters, nurses, religious persons, family members or friends, as well as entertainment figures.[6] Table 2.1 shows the 20 most admired women in the counter-stereotypical female role model category and the stereotypical female role model category, respectively.

Among the counter-stereotypical female role models, female politicians are most frequently mentioned, including Hillary Clinton, Margaret Thatcher, and Indira Gandhi. Writers like Helen Keller and journalists like Barbara Walters who are well known for their intellectual work also appear on the list of counter-stereotypical female role models.

[4] https://www.bls.gov/spotlight/2011/women/data.htm#ces_industry

[5] Supplementary Appendix SA12 shows the fraction of women in each of our 14 occupations and the sources used for classification.

[6] While women are underrepresented in the entertainment industry (see Supplementary Appendix SA12), we still sort admired women in entertainment to the stereotypical role model category, because the literature has shown that the media usually portrays both, women and men, in stereotyped ways (Wood (1994) and Signorielli (1990)).

Stereotypical female role models include women famous for their husbands (e.g., Jackie Kennedy, or Eleanor Roosevelt) and women working in stereotypical female professions like entertainment, i.e., movie stars or singers.

To account for the fact that women's roles may have changed over time, we also collect historical information about each woman appearing as most admired in Gallup survey responses from their Wikipedia biographies. For example, Hillary Clinton was known as a famous wife first, i.e. First Lady of the United States, while she later ran for office herself and became a famous politician. In Table 2.1, we add an asterisk to all women who change their roles from stereotypical to counter-stereotypical, and vice versa. Overall, we find a role change for 8.96% of women in our sample. While this should mostly add noise to our analysis, we exclude these women in a later robustness check.

2.2.2 Labor market information from the Current Population Survey (CPS)

CPS data are obtained from the Integrated Public Use Microdata Series (IPUMS) which provides harmonized microdata from the CPS. The CPS is a nationally representative household survey run monthly in the US. It also includes extensive demographic and labor market variables. Moreover, the CPS includes the Annual Social and Economic Supplement (ASEC), which collects detailed information on individuals' annual income each year in March.

We use data from all CPS respondents between 25 and 65 years of age indicating that they are eligible for employment.[7] The time period ranges from 1962 to 2018.

To measure survey respondents' employment status we create two dummy variables:

[7] Students, people in the armed forces, and retired people are excluded from the sample as we focus on employment outcomes.

(1) *Employed* is equal to one if a respondent is currently employed, and zero otherwise; (2) *Not in labor* is a dummy variable equal to one if a respondent is not in the labor force, i.e. neither employed nor looking for a job, and zero otherwise.

ASEC provides data on each respondent's total pre-tax personal income or losses from all sources based on the previous calendar year (INCTOT). We use log (INCTOT) to measure a survey respondent's personal income. When computing the gender pay gap, we only include people who are employed or are currently searching for a job. We calculate the average personal income (log INCTOT) among male and female employees and take the difference to measure the *Gender pay gap*. We then run regressions of *Personal income* on the *Female respondent* dummy and the gender pay gap is captured by the coefficient estimate of *Female respondent*.

The CPS also provides extensive data on occupational choices of survey respondents. Occupation (OCC) in CPS reports respondents' primary occupation, and industry (IND) reports the type of industry in which the respondent performs her primary occupation. From these variables, we create measures for male-dominated industries and male-dominated occupations by calculating the percentage of male respondents reporting to work in a given industry or occupation, i.e., the number of male employees in a given industry or occupation divided by the total number of employees in the industry or occupation. Next, we define male-dominated industries (occupations) as a dummy variable that equals one if the fraction of male survey respondents currently employed in a given industry (occupation) is above 50%, and zero otherwise.

We additionally create a measure of job hierarchy by exploring the definition of the 2010 occupation codes. We define a dummy variable, Manager, which is equal to one if a survey respondent works in a management occupation (i.e., occupation 2010 code falls into the range of 10 to 430), and zero otherwise.

To capture whether female respondents work in a STEM field, we follow Adams and Kirchmaier (2016) and develop two variables, STEM intensity and STEM industry, respectively. *STEM intensity* is defined as the proportion of employees in STEM occupations in each industry (Adams and Kirchmaier (2016)). *STEM industry* is a dummy variable equal to one if a respondent works in an industry with an above-median STEM intensity.

Lastly, we create measures of the nature of the tasks belonging to a given occupation. We follow Autor et al. (2006) and Autor and Dorn (2013) and use the 1990 occupation codes to create these measures. Specifically, for each occupation, we measure how much the occupation involves abstract tasks, routine tasks, and manual tasks and assign a score ranging from 0 to 10. Abstract tasks are “abstract, creative, problem-solving, and coordination tasks performed by highly-educated workers”, and occupations involving finance and technology are usually assigned a high score of abstract tasks. Routine tasks follow precise and well-defined procedures. Occupations like machine operator and clerical worker usually score high in the category of routine tasks. Manual tasks involve physical dexterity like in the transportation and construction sector. The index of routine task-intensity (*RTI*) for each occupation is calculated as:

$$RTI_k = ln\left(T_k^{Routine}\right) - ln\left(T_k^{Manual}\right) - ln\left(T_k^{Abstract}\right), \tag{2.1}$$

where $T_k^{Routine}$, T_k^{Manual}, $T_k^{Abstract}$ are the routine, manual and abstract task inputs in each occupation code k.[8]

2.2.3 Measuring gender norms

Following the previous literature ((Fortin (2015), Bertrand et al. (2020)) and Fernández (2007)), we calculate state-level gender norms from the General Social Survey (GSS) for the time period from 1972 to 2018. To make answers comparable across questions, we standardize the scales and calculate to which degree respondents agree or disagree to the following statements: (1) It is much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family; (2) A preschool child is likely to suffer if his or her mother works; (3) If your party nominated a woman for President, would you vote for her if she were qualified for the job?; (4) Most men are better suited emotionally for politics than are most women; (5) A working mother can establish just as warm and secure a relationship with her children as a mother who does not work.

In addition, we take the weighted average across all respondents in a certain state and year (using the sample weights provided by GSS variable (WTSSALL), and aggregate answers across the five questions to get an overall measure of GSS gender norms, *Liberal gender norms (GSS)*. The variable is constructed in a way such that larger values reflect more liberal gender norms. For years without GSS survey, we fill missing values with the value of the previous year, because gender norms within a state can be considered as sufficiently stable over time (Bertrand et al. (2020)).

[8] Following Autor and Dorn (2013), we use the score of the 5th percentile in manual tasks and abstract tasks for the five percent of observations with the lowest manual and abstract task score. Results (not reported) do not change if we use the raw manual and abstract task score.

2.2.4 Empirical methodology of Chapter 2

When using Gallup data, we run regressions at the respondent-year level, adjusted for sample weights. All variables are included contemporaneously, since Gallup surveys are repeated cross-sectional surveys and do not allow following the same individual over time. Therefore, we can only link survey respondents' most admired woman and their labor market choices contemporaneously. This means that we can only show correlations rather than a causal relationship as long as we conduct our analysis with Gallup survey data only. In addition, Gallup does not always ask respondents about their employment status, occupation, and demographic characteristics. Therefore, some variables are missing for certain survey years. However, Gallup data allow us to directly link the role model variable to employment outcomes of the same individual, which we consider the major advantage of using this database.

To circumvent some of the limitations when using Gallup data, we also collect data from the Current Population Survey (CPS) and link it to a state-year level version of the Gallup counter-stereotypical female role model variable (*counter-stereotypical female role models CPS*) to investigate the impact of these role models on women's occupational choices. Aggregating the female role model measure from Gallup to the state-year level also allows us to lag it and to explore the idiosyncratic variation in female role models across cohorts. It comes at the cost of losing the direct link between a given individual's most admired woman and her occupational choices.

To match Gallup and CPS survey data, we first create a state-year level measure of counter-stereotypical female role models derived from the Gallup survey. This measure, *counter-stereotypical female role models CPS*, is a weighted-average of our dummy variable "Counter-stereotypical female role model" based on all respondents in a given state and year in the Gallup surveys.[9]

In the next step, we merge the counter-stereotypical female role model measure, *counter-stereotypical female role models CPS*, at the state-year level with the CPS sample. To isolate the influence of cultural variables from economic variables, we attribute the female role model variable to a given survey respondent at the time when she was 20 years old. That is, a 40-year-old survey respondent living in Nevada in 2010 would be matched to Nevada's role model score in 1990. Note that this assumes that the survey respondent did not move across states over the past 20 years.[10] This matching procedure allows us to create cohorts based on respondents' exposure to counter-stereotypical female role models in their formative years, when they were just about to enter the job market. A similar methodology is used in several studies on peer effects (e.g., Hanushek et al. (2002) and Lavy and Schlosser (2011)).[11]

Counter-stereotypical female role models should have a particularly strong impact on individuals' career choices if they are observed in their formative years. This is especially true for girls, where a number of studies have found a positive correlation between working mothers and labor supply of daughters (Farré and Vella (2013)). Strong role models in the form of high school peers' mothers can also affect adolescent girls' choices to work and

[9] We use the sampling weights provided by Gallup. For more details on the weights of Gallup surveys, see Farber et al. (2018) and Kuziemko and Washington (2018).

[10] According to the American Community Survey collected by the US census, the state-to-state migration has been very low over time. For details in the state-to-state migration flows, see https://www.census.gov/data/tables/time-series/demo/geographic-mobility/state-to-state-migration.html.

[11] In alternative matching approaches and to account for the fact that fertility and educational choices may be made earlier in life, we link the counter-stereotypical female role model variable of the year in which respondents were 10 or 15 years old and match it with CPS data based on the state in which a given respondent lives.

have children (Olivetti et al. (2020)). Gender role models and social identity also affect choices of going to college and to complete high school (Bifulco et al. (2011), Gould et al. (2011)). Even though the female role model measures are not directly obtained from survey respondents in the CPS sample, admired counter-stereotypical female role models in the respondent's state when she was 20 years old should influence her perception of what a woman can - and is supposed to - achieve in her life.

Our cohort structure allows us to include state $\times$ time fixed effects, which take care of concurrent economic and social conditions, as well as changing gender norms in a given state that may otherwise contribute to changes in labor market outcomes for women (Bertrand (2011)). Lagging the female role model measure and exploiting the cohort structure of the data should thus at least mitigate reverse causality concerns, which clearly exist if we conduct the analysis with Gallup survey data only.

The counter-stereotypical female role model score in each state varies significantly over time. In Supplementary Appendix SA13, we rank states according to their *counter-stereotypical female role model CPS* values in years 1951, 1982, and 2014. There is much variation in this ranking and it is not always the same set of states ranking high on *counter-stereotypical female role models CPS*. For example, in 1951, survey respondents in Oklahoma, Oregon, and Kentucky were most likely to admire counter-stereotypical female role models. In 1982, the top three states were Vermont, Connecticut, and Wisconsin. Oklahoma ranked highest in terms of admiring counter-stereotypical female role models in 1951 but ranked second to last in 1982. Supplementary Appendix SA14 shows further statistical tests. States that scored high on admiring counter-stereotypical female role models in the last year do not necessarily score high in the subsequent year as well. This result stands in contrast to studies on state-level gender norms, which have been shown to be fairly persistent over time (Bertrand et al. (2020)) and are a first indication that our counter-stereotypical role model variable is not simply capturing gender norms.

2.2.5 Summary statistics of Chapter 2

The fraction of survey respondents admiring counter-stereotypical vs. stereotypical female role models has changed strongly over time. The long time series of Gallup surveys allows us to capture these changes. Figure 2.2 plots the percentage of respondents who admire women in counter-stereotypical roles (e.g., politicians, writers or scientists) and the percentage of respondents who admire women in gender stereotypical roles (e.g., famous wives or entertainment figures), by year of the Gallup survey. Over time, counter-stereotypical female role models become increasingly popular: the percentage of people who admire stereotypical female role models falls from above 80% in 1950 to around 30% in 2014 while the percentage of people who admire counter-stereotypical female role models increases from below 20% to around 50%. Counter-stereotypical female role models became more popular than stereotypical female role models in the 1980s.

Table 2.2 shows summary statistics of the demographic variables from the Gallup surveys (Panel A) and the CPS sample matched with the counter-stereotypical female role model measure from Gallup surveys (Panel B). There is a slightly higher proportion of female respondents in the Gallup survey (56.1%) compared to the final CPS sample (51.4%). A smaller percentage of people (72.2%) are employed in the Gallup survey, while 77% of the respondents are employed in the final CPS sample, which may be due to the different time periods (CPS from 1962 to 2018 and the Gallup surveys from 1951 to 2014 with gaps). All variables used in this paper are described in detail in Supplementary Supplementary Appendix SA15.

2.3 Counter-stereotypical female role models - Evidence from Gallup survey respondents

2.3.1 Who admires counter-stereotypical female role models?

We first examine whether admiring a counter-stereotypical female role model is correlated with survey respondents' demographic characteristics. Table 2.3 presents results from regressions at the respondent-year level, adjusted for sample weights. The dependent variable is equal to one if a Gallup survey respondent indicates that she admires a counter-stereotypical female role model, and zero otherwise. As independent variables, we include survey respondents' gender, her age in years, and squared age to account for potential non-linearities in the age variable (e.g., Goldin (2014b)). We also include a dummy variable indicating whether the respondent holds a bachelor degree, a dummy variable equal to one if a survey respondent's race is white Caucasian, and a dummy variable equal to one if a survey respondent's religion is Christian. Furthermore, we include a dummy variable equal to one if a survey respondent indicates her political orientation to be Democrat, and a dummy if she has children below 18 years of age. Finally, we include a dummy capturing whether a survey respondent is married and a dummy indicating whether she works in an advanced occupation, defined as a business executive, manager executive or official, manufacturer's representative, or runs her own business. All regressions include state fixed effects to account for geographical differences in gender norms, with Bible Belt states being generally more conservative than states at the East and West coasts. We also include year fixed effects in all regressions to control for year-specific events that generated large media coverage and may otherwise drive our measure of counter-stereotypical female role models like, for example, Sally Ride as the first American woman in space in 1983. Robust standard errors are used to adjust for heteroscedasticity.

Results in column (1) of Table 2.3 show that female survey respondents are generally less likely to admire counter-stereotypical female role models than men. This is not surprising, because counter-stereotypical female role models by definition violate prescriptive stereotypes on women's role in society and may be a perceived threat to women's identity. In addition, survey respondents' age is positively related to admiring a counter-stereotypical female role model.

In column (2), we add survey respondents' education, race and religion to the regression equation. We find that more educated survey respondents are more likely to admire counter-stereotypical female role models. Since most of the counter-stereotypical female role models in our sample are white-caucasian, we would expect that white-caucasian survey respondents are more likely to admire these role models due to in-group favoritism, i.e. people systematically adopting more favorable opinions about members of their own group and lower opinions about members who are outside of their group (e.g., Hewstone et al. (2002) and Ben-Ner et al. (2009)). This is indeed what we find. Furthermore, as Christian faith promotes stereotypical female role models such as being a good mother and housewife, we expect survey respondents with Christian faith to be less likely to admire counter-stereotypical female role models. Our results support this conjecture.

Finally in column (3), we examine whether having children, being married, being democrat, or working in an advanced occupation is linked to admiring counter-stereotypical female role models. These variables are not available for all survey respondents and drastically reduce the sample size. We do not find a significant impact of these variables on admiring counter-stereotypical female role models, which may also be the result of poor statistical power.

2.3.2 Counter-stereotypical female role models and female labor supply

In the next step, we examine whether Gallup survey respondents' labor supply is related to admiring counter-stereotypical female role models. We conjecture that counter-stereotypical female role models at least partly offset prescriptive gender stereotypes, according to which women in general and mothers in particular are expected to stay home and take care of their family rather than participating in the labor force.

In Table 2.4, we estimate regressions at the respondent level. The dependent variable in columns (1) to (4) is a dummy variable equal to one if a survey respondent is employed, and zero otherwise. In columns (5) to (8), the dependent variable is a dummy equal to one for survey respondents in full-time employment, and zero otherwise. Both variables are based on survey respondents' answers and are thus self-reported.

Our main independent variable, counter-stereotypical female role model, is equal to one if a survey respondent indicates that she admires a female activist, astronaut, businesswoman, politician, writer, or journalist, and zero otherwise. We include survey respondents' age, squared age, ethnicity, religion, and family status (being married and/or having children below 18 years of age) as additional control variables. In addition, we include education-, state-, and year fixed effects. Roust standard errors are used to adjust for heteroscedasticity. Regressions are run separately for sub-samples of female and male survey respondents. It is possible that female role models reflect some unobserved preferences or experiences of respondents that also influence labor market outcomes. If so, we expect female role models to have similar effects on labor market outcomes of men and women. If female role models shape identity norms of women and reduce negative gender stereotypes, we expect that female role models are significantly related only to women's labor market outcomes but not to men's.

Results in column (1) are estimated without fixed effects and the regression only includes the measure for counter-stereotypical female role models. We find that female survey respondents admiring counter-stereotypical female role models are significantly more likely to be employed. Specifically, we find that admiring counter-stereotypical female role models is associated with an increase in the likelihood of being employed by 8.6 percentage points (pp), which corresponds to 15% of the baseline female labor market participation rate in our sample.

In column (2) we include state, year, and education fixed effects with additional demographic controls to the baseline specification and find that admiring counter-stereotypical female role models is still associated with a higher likelihood of women to be employed. The economic effect still amounts to 7.4% of the baseline female labor market participation rate. Note that, since the Gallup surveys have missing demographic information, our sample size decreases markedly when we include individual demographic controls.

As for male respondents, results in column (3) show a significant, but economically weak relation between counter-stereotypical female role models and male respondents' labor supply. Specifically, admiring counter-stereotypical female role models is associated with a 2.7 pp higher employment probability for male survey respondents, which is much smaller than the 8.6 pp higher employment probability for female survey respondents. The inclusion of additional demographic controls in column (4) further shrinks the coefficient and renders it statistically insignificant. The results are consistent with findings in several papers that female role models have a stronger impact on women than men (Carrell et al. (2010) and Meier et al. (2019)).

In columns (5)-(8) we refine the dependent variable to only capture full-time employment. Results in column (5) show a statistically and economically large coefficient on the counter-stereotypical female role model variable. Specifically, admiring counter-stereotypical female role models is associated with an 11.2 pp higher likelihood of women working full-time. Results in column (6) are based on a specification including state, year, and education fixed effects, as well as demographic controls. We again find a positive and statistically significant relation between the counter-stereotypical female role model variable and women's labor supply, i.e. a larger fraction of female survey respondents in full-time employment. Again, the effect on male survey respondents is much smaller and insignificant in economic terms. Thus, counter-stereotypical female role models seem especially important for women in terms of their labor supply decisions.

Counter-stereotypical female role models may also affect women's career choices when it comes to managerial positions where prescriptive gender stereotypes might be particularly strong. Based on the occupation categories in Gallup, we define a dummy variable *Advanced occupation* equal to one if a survey respondent reports occupations that belong to the business, executive, managerial, executive or official sector, as well as running their own business, and zero otherwise. We also define a second dummy variable, Executive, which is equal to one if a survey respondent reports to be a business executive or managerial executive.

Table 2.5 shows regression results of the relation between counter-stereotypical female role models and survey respondents' occupational choices. No matter whether we include the full set of control variables, or just examine the raw relationship between our main independent and dependent variable, we find that counter-stereotypical female role models are related to a higher propensity of female survey respondents to work in advanced (columns (1) and (2)) or executive (columns (5) and (6)) positions. In column (2), we find that admiring counter-stereotypical female role models is associated with a 2.1 pp increase in the probability of being in an advanced occupation (34% of the average probability of being in an advanced occupation in the female sample). We also find large effect sizes for women in executive positions. Specifically, admiring counter-stereotypical female role models is associated with a 2 pp increase in the probability of becoming an executive, which accounts for more than 30% of the average probability of being an executive in the female sample. Again, we only find small and mostly insignificant effects in the subsample of male survey respondents.[12]

Some admired women in our sample have changed their roles over time from counter-stereotypical to stereotypical, and vice versa (see Table 2.1). While this should mainly add noise to our results, we re-run our regressions from Tables 2.4 and 2.5 and exclude these women from the counter-stereotypical role model variable. Supplementary Supplementary Appendix SA16 shows that our results are robust to this variation in the role model variable.

[12]In unreported results, we examine whether the relation between counter-stereotypical female role models and female survey respondents' labor market choices are stronger if they are both coming from the same state, because the role model may be more visible to respondents in the same state. We do not find this to be the case.

2.4 Counter-stereotypical female role models - Evidence from CPS survey respondents

The data structure of the Gallup surveys only allows for cross-sectional regressions. Therefore, we now link our measure of counter-stereotypical female role models to CPS data. Specifically, we create a state-level measure of counter-stereotypical female role models ranging from 1962 to 2018 and merge it to CPS survey respondents' state. This variable has a different interpretation than the one used in the previous section, as it is aggregated across individuals. Thus, we do not look at individual counter-stereotypical role models and their relation to the same individuals' labor market choices, but examine differences between individuals living in states where the fraction of survey respondents who admire counter-stereotypical female role models is higher or lower. In this regard, our measure may rather reflect the starting point of subsequent changes in gender norms, a question that we examine more formally in the next section.

Even though there is evidence that role models can be effective at any point in a person's lifespan (Eagly and Wood (2011)), preadolescence and early adulthood seem to be the most sensitive years in which counter-stereotypical role models are very effective (Olsson and Martiny (2018)). On the one hand, and in contrast to early childhood, cognitive development already allows observers to generalize counter-stereotypical behavior to other domains, while at the other hand gender stereotypes and gender-roles are not fixed to the same extend as in adulthood.

To make sure that our analysis captures the most formative years in adolescence when it comes to role model effects, we allocate each CPS survey respondent the counter-stereotypical female role model variable of her state at the time when she was twenty years of age. This way, we capture the role model effect in survey respondents' formative years when career choices are made and when the impact of a female role model on occupational choices is arguably stronger than later in life (Olivetti et al. (2020)). Since the lagged counter-stereotypical role model variables are aggregated at the state level, they should capture the preferences and beliefs commonly held about women's role in the state while the CPS person was a young adolescent. Given the different time lags conditional on respondent's current age, only the preferences and beliefs embodied in the role model variable should be relevant to female respondents' work decisions, while past economic and institutional conditions should cancel out.[13]

In the following, we run regressions of labor outcome variables on our counter-stereotypical female role measure and its interaction with a female dummy variable. Each CPS respondent is allocated the fraction of GPS respondents who admired counter-stereotypical female role model variable when the CPS respondent was twenty years of age. All regressions include either state, year or state $\times$ year fixed effects and demographic controls. State $\times$ year fixed effects take care of time-varying economic conditions and gender norms at the state level, which may otherwise influence both, the counter-stereotypical female role measure and the gender gap in labor market outcomes. It is important to note though that we can only control for state level gender norms in the year in which labor market outcomes are measured, but not in the year when a respondent was 20 years old. Bertrand et al. (2020) provide evidence that state-level gender norms are persistent over time. Therefore, we are confident that the inclusion of state $\times$ year fixed effects at least

[13] Alternatively, each survey respondent is allocated the counter-stereotypical female role model variable when she was ten or fifteen years of age. Results from this alternative approach are reported below each table.

partially controls also for gender norms in earlier years, while acknowledging that we would ideally explicitly control for them. Standard errors are clustered by state.

2.4.1 Female labor supply

We start by investigating the relation between counter-stereotypical female role models and the gender gap in employment and labor force participation. In columns (1) to (3) of Table 2.6, the dependent variable is Employment, a dummy variable equal to one if a survey respondent is employed. In columns (4) to (6), the dependent variable is equal to one if a survey respondent is neither participating in the labor force, nor looking for a job, and zero otherwise.

In column (1) we include state and year effects individually and find that CPS respondents in states where counter-stereotypical female role models were strongly admired when they were twenty face smaller gender gaps in labor supply today. Specifically, the gender gap in employment is 12.2 pp smaller, and the gender gap in not participating in the labor force at all is 12.3 pp smaller. Our results are robust if we match the counter-stereotypical female role model variable of respondents' state when they were 15 and 10 years old (see lower panel of Table 2.6). In economic terms, a one standard deviation (0.2) increase in the counter-stereotypical female role model variable reduces the gender gap in employment by 10.95%. Furthermore, we find that female respondents are significantly less likely to be employed than male respondents. We also find that the baseline relation between counter-stereotypical female role models and employment is significantly negative, i.e., men are less likely to be employed in states where counter-stereotypical female role models are more popular. This result is in line with the view that our aggregated role model variable at the state-level captures early changes towards more liberal gender norms, which have been shown to result in a shift towards more housework and less labor market participation for men (Bertrand et al. (2020), Moriconi and Rodriguez-Planas (2021)).

Our results remain basically unchanged if we include demographic control variables in the regression (column (2)). Similar to our analysis of Gallup survey respondents' labor supply, we find that older, more educated, and white-caucasian survey respondents are more likely to be employed, while being married and having children has a negative impact on employment.

In column (3), we include demographic controls and state $\times$ year fixed effects. Inclusion of state $\times$ year fixed effects allows us controlling for time varying unobserved heterogeneity at the state level, for example, local economic factors or political and social attitudes. We again find that admiring counter-stereotypical women is significantly related to the gender gap in employment. The effect is similar to the magnitude reported for column (1) and corresponds to 11.24%.

The positive relation between the admiration of counter-stereotypical female role models and female labor supply is further corroborated in columns (4)-(6), where we show that admiring counter-stereotypical female role models has a significantly negative correlation with the gender gap in being out of the labor force. Specifically, admiring counter-stereotypical female role models (a one standard deviation change) is associated with a 10.5% decrease in the gender gap of not participating in the job market.

2.4.2 Women's occupational choices

Although women occupy half of the labor force, there still continues to be a gender gap in STEM fields. One of the reasons that has been discussed in the literature is a lack of role models that young girls and women can aspire to. Carrell et al. (2010) find that STEM female teachers are more likely to inspire female students to take STEM classes in college. In fact these influences have a long term effect on women's career choices (Lim and Meer (2020)). In addition, as documented by Hwang et al. (2018), there are very few women in managerial positions.[14] Therefore, the most salient effect of counter-stereotypical female role models on women's occupational choices may be observed in STEM fields, male-dominated professions and in managerial positions as the lack of female role models in these fields might be a deterrent to women entering these occupations.

Following Adams and Kirchmaier (2016), we create an industry STEM classification and examine the association between counter-stereotypical role models and the likelihood of working in STEM industries. [15] Table 2.7 presents regression results on the relation between counter-stereotypical role models and the likelihood of women working in STEM industries. The dependent variable in columns (1) and (2) is a dummy variable equal to one if a respondent works in an industry with above median STEM intensity, and zero otherwise. Alternatively, we use the STEM intensity of the industry itself as dependent variable (columns (3) and (4)).

[14] 21% of the Russell 4000 firms in the US do not have any woman on their board.

[15] Adams and Kirchmaier (2016) define STEM intensity as industries where a large share of employees are in STEM occupations. To that end they match industries to a list of occupations that require education in science, technology, engineering, and mathematics disciplines from O*NET (2015) (https://www.onetonline.org/).They then calculate the percentage of the number of employees in each industry working in a STEM occupation. The top 5 sectors by share of STEM employees are labeled as STEM sectors.

We find that female respondents in states where counter-stereotypical role models are popular are significantly more likely to enter STEM industries. Specifically, a one-standard deviation increase in the counter-stereotypical role model variable is associated with a 4.8% to 5.5% reduction of the gender gap in the likelihood to work in a STEM field. We find a similar association between counter-stereotypical role models and women in STEM intensive industries (columns (3) and (4)).[16]

In the next step, we examine the association between the admiration of counter-stereotypical female role models and the likelihood of women to enter male-dominated occupations and seeking managerial positions. We define male-dominated industries (occupations) as those with more than 50% male employees based on the average share of men in an industry/occupation across all states and years in the data.[17]

Results in columns (1) and (2) of Table 2.8 show that exposure to counter-stereotypical female role models is associated with more women in male-dominated industries. For example, in column (2), a one standard deviation increase in our counter-stereotypical female role model variable is associated with a 1.5% increase of the likelihood for women to work in a male-dominated industry, after controlling for state$\times$year fixed effects. We find a similar relation between the counter-stereotypical female role model variable and the gender gap in male-dominated occupations (column (4)). Here, a one standard deviation increase in the counter-stereotypical role model variable is associated with a 2.5% larger probability of women working in a male-dominated occupation, relative to their male counterparts.

[16] As shown in the bottom of Table 2.7, our results hold, but become weaker in statistical terms, if we match the state-level counter-stereotypical role model variable of the year in which a respondent was 10 or 15 years of age, respectively.

[17] Results (not reported) are robust to alternative cut-off definitions of male-dominated industries (occupations) such as 75% and 90%.

In the next step, we examine whether counter-stereotypical female role models are related to the gender gap in managerial positions. Results in Table 2.8, columns (5) and (6)), show that a one standard deviation increase of the counter-stereotypical female role model variable is associated with a 12.4% reduction of the gender gap in the likelihood to work in a managerial position.

We also dig deeper into the type of tasks associated with certain occupations and examine whether counter-stereotypical female role models encourage women to take over more abstract tasks. Autor and Price (2013) show that the task composition for male and female employees has changed over time. In 1960, female employees were more likely to perform routine tasks than male employees, but they have taken over more non-routine tasks over the last few decades. Black and Spitz-Oener (2010) also show that, over time, female employees experienced strong increases in non-routine tasks, requiring higher cognitive skills. We conjecture that counter-stereotypical role models support this development and inspire more women to take over non-routine and more abstract tasks at work.

We follow Autor and Dorn (2013) and create a routine task index (RTI) based on the nature of tasks in all industries (see Section 2.2.2).[18] Figure 2.3 shows how RTI develops by gender and over time. On average, we find that women are less likely to enter occupations characterized by abstract tasks (Panel A) rather than routine tasks (Panel B). Panel C shows that men are more likely to work in jobs involving a high amount of manual tasks. The aggregated routine task index (RTI) in Panel D shows a pronounced decline in the routine task share of female survey respondents over time, while it remains low and quite stable over time for male survey respondents.

[18]While Autor and Dorn (2013) use these measures to explain the polarization of US employment and the growth of low skill service occupations, we focus on gender differences in occupational task types.

Results in Supplementary Supplementary Appendix SA17 show that counter-stereotypical female role models indeed are positively and significantly related to female survey respondents' choice of occupations with more abstract tasks, while they have a negative association with women's choice of routine tasks. A one standard deviation increase of the counter-stereotypical female role model variable is associated with a reduction of the gender gap in the manual task score by 2.1%.

2.4.3 Women's fertility and educational choices

So far, our focus has been the association between counter-stereotypical role models and employment choices. In this section, we focus on women's decision when to have a baby and whether to aspire for higher education.

Earlier research shows that being employed reduces the likelihood of becoming pregnant Budig (2003). In fact, for decades, highly educated women have been delaying parenthood.[19] Delaying motherhood is associated with a wage premium (Miller (2011)) and highly educated women, who delay motherhood, experience a smaller wage penalty (Buckles (2008)).

As shown in Tables 2.6 and 2.8, exposure to counter-stereotypical female role models is associated with more labor supply and a higher likelihood of being in a managerial position for women. We therefore hypothesize that women in states where more counter-stereotypical female role models are admired are also more likely to delay childbirth and to focus more on their education.

Table 2.9 column (1) examines the association between the admiration of counter-stereotypical role models and women's age when having their first child. We find that ex-

[19] https://www.nytimes.com/2021/06/16/us/declining-birthrate-motherhood.html

posure to counter-stereotypical role models is associated with a delay in childbirth. Specifically, a one standard deviation increase of the counter-stereotypical role model variable is associated with a 12.1% increase in women's age at the time when their first child is born. The average age at which women have their first child in our sample is 27. Thus, in absolute terms, this translates to a three years increase in women's age at the birth of the first child.

Next we study the association between admiring counter-stereotypical female role models and achieving higher educational degrees. Beaman et al. (2012) find that female leadership encourages adolescent girls to aspire for higher education. In the same vein, exposure to counter-stereotypical role models should also be correlated with higher educational attainment for women. In our sample, 23% of women have a college degree and 7% have a post-graduate degree.

In line with our conjecture, results in column (2) of Table 2.9 show that exposure to counter-stereotypical female role models is associated with more women pursuing a college degree. We find that a one standard deviation increase of women's exposure to counter-stereotypical role models is associated with a 5.3% increase of the fraction of women obtaining a college degree. A similar relation is also shown in column (3), where we find that women in states where counter-stereotypical female role models are popular more frequently gather a postgraduate degree (i.e., Master's level or higher degrees).

Exposure to female role models early in life can have long lasting effects. Therefore, we additionally explore the association between counter-stereotypical role models and fertility and education choices when the respondent was 10 or 15 years old. Our results (presented in the lower part of the table) are very similar.

2.4.4 Counter-stereotypical female role models and the gender pay gap

Our results suggest that the presence of counter-stereotypical female role models is associated with women being more likely to enter male-dominated industries, seek out higher ranked positions and move into jobs involving more abstract tasks. Since these occupations and positions are generally associated with a higher pay scale, we should also find a positive impact on women's earnings and, eventually, the gender pay gap should decrease.

In Table 2.10, we show results from panel regressions including state $\times$ year fixed effects with log income of a CPS respondent as the dependent variable. We find that admiring counter-stereotypical female role models is associated with smaller gender pay gaps. Specifically, a one standard deviation increase of the counter-stereotypical female role model variable reduces the gender pay gap by 9.89% (see column (4) of Table 2.10).

2.5 Counter-stereotypical female role models and gender norms

Results in the previous section suggest that women in states where more people admire counter-stereotypical female role models are more likely to be (full-time) employed and work in male-dominated industries such as STEM. This finding could be the result of changing gender norms, as a higher state level value of the counter-stereotypical role model variable may capture more positive attitudes towards women doing counter-stereotypical activities and thus lower social sanctions if women engage in these activities.

To differentiate between counter-stereotypical role models and gender norms, we first examine whether counter-stereotypical role models in our sample are more likely to stem from states with more liberal gender norms, and thus can be considered the result of more liberal gender norms, or whether they arise randomly across states. We collect information on place of birth of each role model in our sample and classify all states in the US as either gender liberal or gender conservative based on survey data from the General Social Survey (GSS). Specifically, we use the average *liberal gender attitude (GSS)* within a state across the sample period and then rank states as gender liberal if the measure is higher than the median, and gender conservative otherwise.[20] We find that 73 (46.5%) of the counter-stereotypical female role models in our sample are born in a state with liberal gender norms, while 84 (53.5%) of counter-stereotypical female role models are born in a state with conservative gender norms. Thus, counter-stereotypical female role models do not mostly stem from states with liberal gender norms. In contrast, slightly more counter-stereotypical role models stem from states with more conservative gender norms. This suggests that our counter-stereotypical role model variable is not just a reflection of gender norms in a given state.

Following Bertrand et al. (2020), we additionally create two rank-based measures of the state-level counter-stereotypical female role variable, one for the earlier time period of the sample (1951–1985), and one for the later time period (1986–2014). The Spearman rank correlation between the "early" and "late" state-level ranks of the role model variable is 0.1107. Further, the correlations between the overall (early + late) state-level ranks of the role model variable and the individual "early" and "late" variables are 0.6474 and 0.5789, respectively. In comparison, Bertrand et al. (2020) report that the Spearman rank correlation between their "early" and "late" gender norm measure is 0.75, while correla-

[20]Even though we only observe GSS gender norms for the time period of 1974 to 2018, Bertrand et al. (2020) show that the relative ranking of states in terms of gender norms has remained quite constant over time with a correlation of 0.92. We therefore assume that gender norms were quite similar in a given state at the time when a counter-stereotypical role model was born. Results (not reported) are similar if we use *liberal gender attitude (GSS)* of a state in the earliest year of the sample.

tions between the overall gender norm and the "early" and "late" measures are 0.92 and 0.93, respectively. This suggests that they are capturing stable rank differences in gender norms across states, while counter-stereotypical role models are not persistently found in one state compared to the other and seem to arise independently from existing gender norms in a given state.

To further examine the relation between counter-stereotypical role models and gender norms, we compute pair-wise correlations between these two variables over time. Table 2.11 presents the results. We find that our state-level measure of counter-stereotypical female role models is positively correlated with all state-level measures of GSS gender norms. The correlations are all statistically significant at the 1% level. However, correlations are rather low and range between 0.11 to 0.31. This again supports the view that counter-stereotypical female role models are not just capturing gender norms. Rather, we think that they work in addition to, and maybe earlier than gender norms, which are slow moving and more persistent over time. Specifically, counter-stereotypical female role models aggregated at the state-level may capture the starting point for subsequent changes in gender norms.

In the next step, we re-run all regressions from the previous section, but additionally include a GSS state-level measure of liberal gender norms and its interaction with the female dummy variable. This specification allows us to examine the relative impact of the state-level counter-stereotypical female role model variable and state-level gender norms on women's educational, labor market, and fertility choices. Results are reported in Table 2.12.

We find that our main result on the relation between counter-stereotypical female role models and women's employment status (Panel A), their likelihood to work in STEM (Panel B) or in male-dominated fields (Panel C), as well as their fertility and educational choices (Panel D) is still positive and statistically significant. Effect sizes are smaller for women's employment status, while they are comparable for choices regarding STEM fields or male-dominated occupations. More liberal gender norms are also positively related to women's employment and occupational choices, while they are not related to the decision to work in STEM fields or women's fertility choices. This result is in line with previous literature showing that female role models are particularly important for encouraging more women to work in STEM fields (Bettinger and Long (2005b), Herrmann et al. (2016), González-Pérez et al. (2020)).

Finally, we examine whether selective migration is a concern in our analysis. It could be the case that states with more counter-stereotypical female role models 20 years ago have attracted more career-oriented women who make systematically different labor market choices than their less career-oriented counterparts. For survey years 1980, 1985, 1995, 2005, and 2015, our data includes a variable indicating whether a survey respondent has migrated within the last five years. This allows us to run sub-sample analyses for these years based on a sample that only includes respondents who did not migrate over the past five years and compare them to all survey respondents in these survey years. Results are reported in Supplementary Supplementary Appendix SA18. While some of our results in this restricted sample become weaker, we do not observe that they are different between the full sample of respondents compared to the sub-sample of respondents who have not migrated in the past five years.

Taken together, our results are consistent with the view that counter-stereotypical role models challenge gender stereotypes and impact women's choices in addition to gender norms. The positive view of a counter-stereotypical role model, which is expressed by the fact that Gallup respondents are explicitly asked whom they admire, may overrule the impact of conservative gender norms and their associated gender stereotypes on women's choices. This is also suggested by Feldmann et al. (2020), who show that concrete examples of female role models in a family serve as a stronger influence than more abstract gender norms shared in a society, particularly when implied norms of role models and gender norms clash.

What is the mechanism through which counter-stereotypical female role models change gender norms? If a higher prevalence of counter-stereotypical female role models is associated with more women working full-time, being highly educated, and working in managerial positions, observing more women in these positions will change people's perception about which roles in society are supposed to be taken by men or by women. As a result, traditional gender stereotypes may disappear and gender identities will change. Since gender norms change very slowly over time (Bertrand et al. (2020)), our sample period may not be long enough to formally examine these changes, but we find, for example, that the correlation between the counter-stereotypical female role model variable and respondents' labor market participation in the state when she was twenty years is 31.1% and statistically significant at the 1% level. This at least suggests that respondents in these states were already exposed to several counter-stereotypical working women in their adolescence and thus made different labor market choices later on in their life.

2.6 Conclusion of Chapter 2

This paper examines whether counter-stereotypical female role models are correlated with women's labor supply, occupational choices, and educational and fertility choices. We find that admiring counter-stereotypical female role models is associated with more women seeking full-time employment, working in male-dominated occupations such as STEM, and taking over managerial positions. Women in states with higher popularity of counter-stereotypical female role models are also more likely to seek higher education and to have their first child later in life. Finally. the gender pay gap is smaller in these states.

While our analysis controls for various potentially co-founding variables, the nature of our data does not allow for a clean natural experiment that would, for example, exogenously shock the admiration of counter-stereotypical female role models to establish causality. We believe that the uniquely long time series of data collected from the Gallup surveys still offers novel insights into the development of women's career choices and the admiration of counter-stereotypical female role models over more than half a century.

Counter-stereotypical female role models vary across states and are less stable over time than gender norms. They influence women's choices in addition to gender norms and may be considered as a starting point for future changes of state-level gender norms if the fraction of people admiring counter-stereotypical female role models in a state increases. As a result, at some point, female role models in politics, science, or related fields may not be counter-stereotypical anymore and reflect the new normal.

Figure 2.1: Number of (counter-stereotypical) female role models per survey year

This figure plots the number of different female role models and the number of different counter-stereotypical female role models named by respondents, respectively, by year of the Gallup survey.

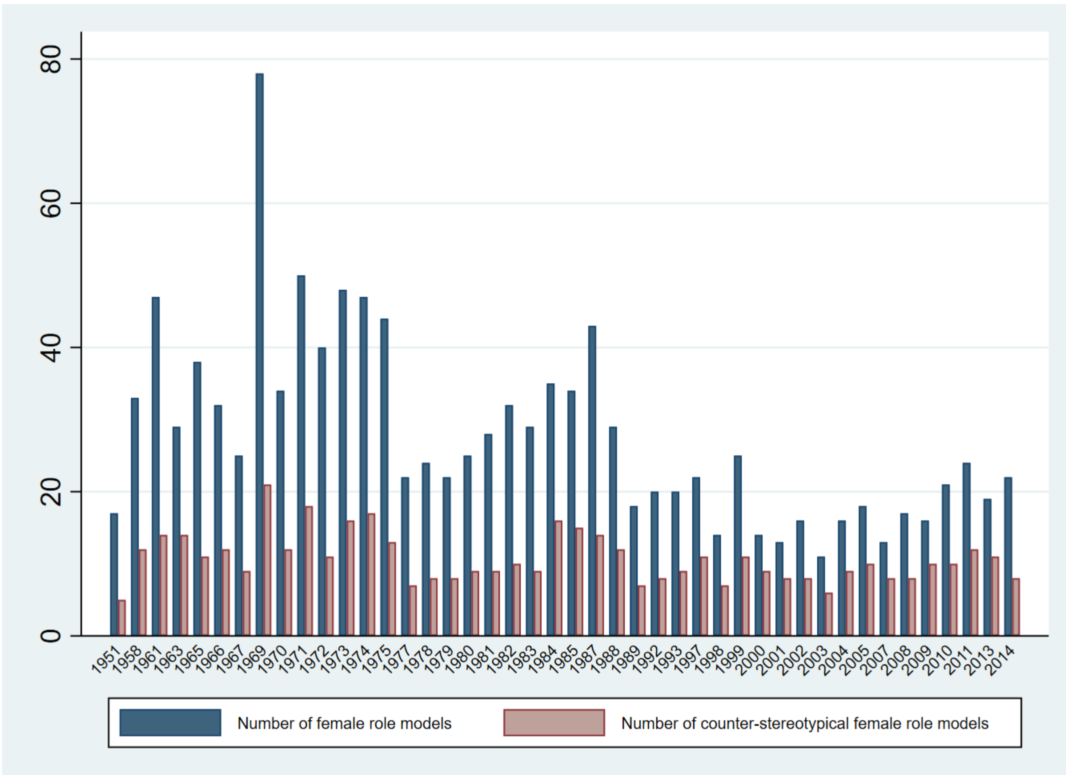


Figure 2.2: Most admired women over time

This figure plots the percentage of respondents who admire counter-stereotypical female role models (activists, astronauts, athletes, businesswomen, politicians, scientists and writers or journalists) and stereotypical female role models (wives, mothers, daughters, nurses, religious individuals, family and friends, and entertainment figures), respectively, by the year of the Gallup survey.

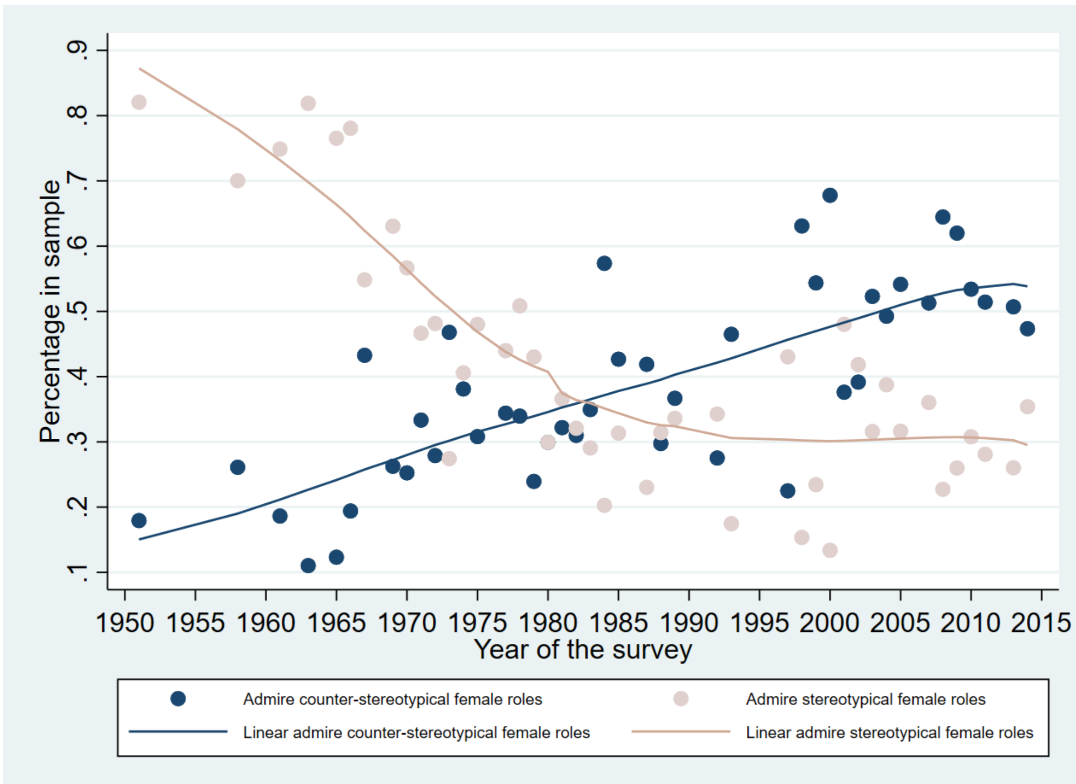
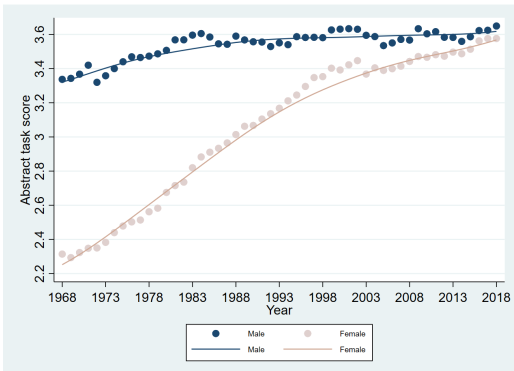
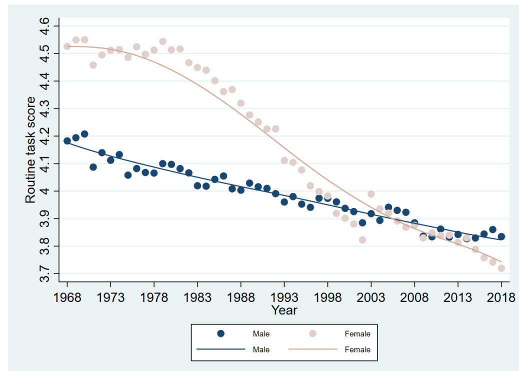


Figure 2.3: Occupation characteristics by gender over time

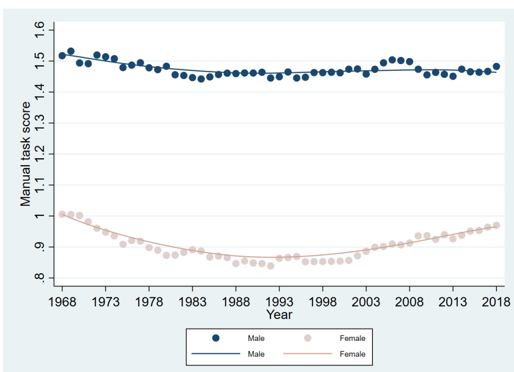
This figure plots the abstract, routine, and manual task measures and, at the aggregate level, the routine task index (RTI) from Autor and Dorn (2013) in the CPS by gender over time. The y-axis represents the weighted average of abstract, routine, manual task measures and RTI. The x-axis shows the year of the survey.



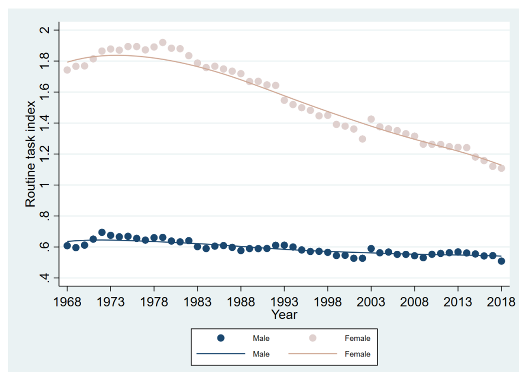
Panel A: Abstract task score



Panel B: Routine task score



Panel C: Manual task score



Panel D: Routine task index

Table 2.1: Top 20 most admired women and their categorization

This table lists the 20 most admired women in counter-stereotypical roles and in stereotypical roles, respectively. We collect each women's main occupation or role from Wikipedia and compare the fraction of men and women in this occupation or role over the sample period. If an occupation or role is male (female) dominated, we classify this role as counter-stereotypical (stereotypical). The list includes all women who are named by Gallup respondents as most admired. The sample ranges from 1951 to 2014. The sorting is based on the frequency of mentioning by Gallup respondents in the whole sample period. Asterisks denote women whose roles have changed over time from stereotypical to counter-stereotypical, or vice versa.

Counter-stereotypical female role models		Stereotypical female role models	
Name	Category	Name	Category
Hillary Clinton*	Politician	Jackie Kennedy	Famous wife
Margaret Thatcher	Politician	Eleanor Roosevelt	Famous wife
Elizabeth I or Elizabeth II	Politician	Oprah Winfrey*	Entertainer
Golda Meir	Politician	Mamie Eisenhower	Famous wife
Helen Keller	Writer or Journalist	Lady Bird Johnson	Famous wife
Condoleezza Rice	Politician	Pat Nixon	Famous wife
Indira Ghandi	Politician	Betty Ford	Famous wife
Sarah Palin	Politician	Rose Kennedy	Famous wife
Margaret Chase Smith	Politician	Nancy Reagan	Famous wife
Clare Boothe Luce	Politician	Barbara Bush	Famous wife
Pearl Buck	Writer or Journalist	Laura Bush	Famous wife
Barbara Walters	Writer or Journalist	Rosalynn Carter	Famous wife
Shirley Chisholm	Politician	Lady Diana	Famous wife
Geraldine Ferraro	Politician	Coretta King	Famous wife
Barbara Jordan	Politician	Ethel Kennedy*	Famous wife
Sandra Day Oconnor	Politician	Madame Chiang Kai Shek	Famous wife
Madeleine Albright	Politician	Michelle Obama	Famous wife
Elizabeth Dole	Politician	Grace Kelly	Entertainer
Corazon Aquino	Politician	Sister Kenny	Nurse
Maya Angelou	Writer or Journalist	Anita Bryant*	Entertainer

Table 2.2: Summary statistics

This table presents summary statistics, including the number of observations (N), the weighted mean, the weighted standard deviation (Weighted SD), minimum (Min), and maximum (Max) of the demographic variables from the Gallup surveys (Panel A) and the CPS sample matched with the most admired female role measure from Gallup surveys (Panel B). Weights are provided by the Gallup surveys (after 1966) and by the CPS. All variables are defined in Supplementary Supplementary Appendix SA15.

Panel A: Gallup survey sample					
	N	Weighted Mean	SD	min	max
Female respondent	30,344	0.561	0.496	0	1
Employed	7,995	0.722	0.448	0	1
Full time work	7,995	0.594	0.491	0	1
White-caucasian	30,205	0.851	0.356	0	1
Age	30,347	40.162	12.915	18	65
Children	15,872	0.601	0.490	0	1
Christian	24,117	0.836	0.371	0	1
Married	9,938	0.665	0.472	0	1
Bachelor	30,159	0.227	0.419	0	1
Advanced occupation	7,373	0.281	0.449	0	1
Executive	7,373	0.072	0.258	0	1
Panel B: CPS sample					
	N	Weighted Mean	SD	min	max
Female respondent	4,295,842	0.514	0.500	0	1
Counter-str. CPS	3,334,594	0.347	0.200	0	1
Employed	4,295,842	0.770	0.421	0	1
Not in labor force	4,295,842	0.188	0.391	0	1
White-caucasian	4,295,842	0.842	0.365	0	1
Age	4,295,842	42.619	11.213	25	65
Children	4,295,842	0.587	0.492	0	1
Log income	3,871,018	9.588	1.531	0.693	14.365
Married	4,295,842	0.694	0.461	0	1
Bachelor	4,295,839	0.168	0.374	0	1
Male-dominated industry	4,034,144	0.462	0.499	0	1
Male-dominated occupation	4,034,144	0.490	0.500	0	1
Manager	4,295,842	0.092	0.289	0	1
Abstract task	3,332,859	3.325	2.420	0	9.002
Routine task	3,332,859	4.034	2.368	1.186	8.642
Manual task	3,332,859	1.233	1.321	0	10
RTI	3,332,859	1.000	1.901	-2.411	6.672
STEM industry	1,837,714	0.347	0.476	0	1
STEM intensity	1,837,714	9.342	5.328	3.889	21.800
Age at first childbirth	1,355,072	26.912	6.058	13	65
Bachelor	2,228,805	0.227	0.419	0	1
Post-graduate	2,228,806	0.070	0.255	0	1

Table 2.3: Who admires counter-stereotypical female role models?

This table contains weighted regression results of a dummy variable indicating whether the respondent admired counter-stereotypical female role models on survey respondents' demographic characteristics. The dependent variable is a dummy variable equal to one if the respondent admires a counter-stereotypical female role model, and zero otherwise. Counter-stereotypical female role models are defined as activists, astronauts, athletes, businesswomen, politicians, scientists, and writers or journalists. State fixed effects and survey year fixed effects are included in all regressions. All variables are defined in Supplementary Supplementary Appendix SA15. Robust standard errors are used to adjust for heteroscedasticity. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Counter-stereotypical female role model		
	(1)	(2)	(3)
Female respondent	-0.071***	-0.059***	-0.091***
	(-10.47)	(-7.84)	(-4.44)
Age	0.004**	0.002	-0.001
	(2.40)	(1.46)	(-0.19)
Age squared	-0.000	-0.000	0.000
	(-0.86)	(-0.27)	(0.53)
Bachelor degree		0.137***	0.094***
		(13.61)	(4.18)
White-caucasian		0.045***	-0.028
		(3.82)	(-0.90)
Christian		-0.054***	-0.057*
		(-4.32)	(-1.80)
Children			-0.008
			(-0.30)
Married			0.035
			(1.50)
Advanced occupation			-0.040
			(-1.53)
Democrat			0.009
			(0.62)
State fixed effects	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes
Observations	29,752	23,819	3,213
Adjusted R^2	0.098	0.100	0.070

Table 2.4: Counter-stereotypical female role models and labor supply (Gallup sample)

This table contains weighted regression results of employment status on our measure of counter-stereotypical female role models and further demographic control variables. The sample contains Gallup survey respondents from age 18 to age 65. The dependent variable is Employed, a dummy variable indicating whether the respondent is employed (columns (1) to (4)) or full-time employed (columns (5) to (8)). Counter-stereotypical female role models are defined as activists, astronauts, athletes, businesswomen, politicians, scientists, and writers or journalists. Columns (1), (2), (5), and (6) present regression results from a sub-sample of only female respondents while columns (3), (4), (7), and (8) present regression results from a sub-sample of only male respondents. All variables are defined in Supplementary Supplementary Appendix SA15. Robust standard errors are used to adjust for heteroscedasticity. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Employed				Full-time Employed			
Sample:	Female		Male		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Counter-stereotypical female role model	0.086***	0.043**	0.024*	0.012	0.108***	0.057***	0.035**	-0.000
	(4.78)	(2.06)	(1.78)	(0.82)	(5.72)	(2.66)	(2.09)	(-0.00)
Age		0.025***		0.014***		0.038***		0.034***
		(4.54)		(2.75)		(6.76)		(6.05)
Age squared		-0.000***		-0.000***		-0.001***		-0.000***
		(-5.36)		(-3.22)		(-7.53)		(-6.40)
White-Caucasian				0.063**		-0.030		0.046*
				(2.46)		(-0.89)		(1.65)
Christian		-0.005		0.012		0.026		0.016
		(-0.16)		(0.64)		(0.79)		(0.72)
Children		-0.133***		-0.011		-0.143***		-0.011
		(-5.48)		(-0.61)		(-5.57)		(-0.52)
Married		-0.130***		0.049**		-0.128***		0.097***
		(-6.11)		(2.45)		(-5.48)		(4.24)
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Education fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Dependent variable mean	0.582	0.583	0.875	0.877	0.395	0.398	0.798	0.792
Counter-stereotypical female mean	0.328	0.336	0.479	0.427	0.351	0.328	0.479	0.428
Observations	4,322	3,183	3,476	3,055	4,093	3,160	3,476	3,055
Adjusted R^2	0.007	0.103	0.001	0.076	0.011	0.122	0.002	0.126

Table 2.5: Counter-stereotypical female role models and occupational choices (Gallup sample)

This table contains weighted regression results of survey respondents' occupational choices on our measure of counter-stereotypical female role models. The sub-samples contain only female or male Gallup survey respondents from age 18 to age 65, respectively. In columns (1) to (4), the dependent variable is Advanced occupation, a dummy variable indicating whether the respondent's occupation falls into the one of the following categories: business executive, manager executive or official, manufacturer's representative, or own business. In columns (5) to (8), the dependent variable is Executive, indicating whether the respondent is a business executive or managerial executive. Counter-stereotypical female role models are defined as activists, astronauts, athletes, businesswomen, politicians, scientists, and writers or journalists. Columns (1), (2), (5), and (6) present regression results for the sub-sample of female survey respondents while columns (3), (4), (7), and (8) present regression results for the sub-sample of male survey respondents. All variables are defined in Supplementary Supplementary Appendix SA15. Robust standard errors are used to adjust for heteroscedasticity. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Advanced occupation				Executive			
Sample:	Female		Male		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Counter-stereotypical female role model	0.025**	0.021*	0.001	-0.026	0.020**	0.020*	0.003	-0.011
	(2.50)	(1.71)	(0.06)	(-1.56)	(2.18)	(1.84)	(0.27)	(-0.85)
Age		0.002		0.008*		0.004		0.005
		(0.79)		(1.89)		(1.64)		(1.37)
Age squared		-0.000		-0.000*		-0.000*		-0.000
		(-0.92)		(-1.77)		(-1.74)		(-1.29)
White-Caucasian		0.026**		0.049**		0.017		0.039**
		(1.96)		(2.16)		(1.55)		(2.23)
Christian		-0.033		-0.010		-0.018		0.001
		(-1.30)		(-0.38)		(-0.89)		(0.06)
Children		-0.015		-0.007		-0.019		-0.004
		(-0.96)		(-0.34)		(-1.33)		(-0.24)
Married		0.007		0.027		0.006		0.024
		(0.60)		(1.31)		(0.54)		(1.43)
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Education fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Dependent variable mean	0.070	0.062	0.140	0.151	0.061	0.048	0.103	0.104
Counter-stereotypical female mean	0.281	0.321	0.363	0.419	0.281	0.321	0.363	0.419
Observations	4,263	2,542	3,110	2,192	4,263	2,542	3,034	2,192
Adjusted R^2	0.002	0.037	-0.000	0.043	0.001	0.050	-0.000	0.034

Table 2.6: Counter-stereotypical female role models and labor supply (CPS sample)

This table contains weighted regression results of CPS survey respondents' employment status on the interaction term between gender and our measure of *Counter-stereotypical female role model CPS* for a respondents' state and year when she was twenty years old (ten or fifteen years old in the lower part of the table). The sample contains respondents in the CPS ASEC surveys (1962 to 2018) from age 25 to age 65. In columns (1) to (3), the dependent variable is Employed, a dummy variable equal to one if the respondent is currently employed, and zero otherwise. In columns (4) to (6), the dependent variable is Not in labor force, a dummy variable equal to one if the respondent is neither employed nor looking for a job, and zero otherwise. All variables are defined in Supplementary Supplementary Appendix SA15. Standard errors are clustered by state and time. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Employed			Not in labor force		
	(1)	(2)	(3)	(4)	(5)	(6)
Counter-str. CPS × Female respondent	0.121***	0.122***	0.122***	-0.118***	-0.123***	-0.123***
	(4.05)	(4.00)	(4.00)	(-3.94)	(-4.01)	(-4.01)
Female respondent	-0.221***	-0.217***	-0.217***	0.236***	0.234***	0.234***
	(-11.51)	(-11.40)	(-11.41)	(12.13)	(12.10)	(12.10)
Counter-str. CPS	-0.078***	-0.058***	-0.058***	0.062***	0.057***	0.058***
	(-4.55)	(-4.02)	(-3.90)	(3.79)	(3.88)	(3.82)
Age		0.012***	0.012***		-0.010***	-0.010***
		(8.37)	(8.48)		(-6.50)	(-6.59)
Age squared		-0.000***	-0.000***		0.000***	0.000***
		(-6.41)	(-6.48)		(5.20)	(5.27)
Bachelor degree		0.079***	0.080***		-0.053***	-0.053***
		(16.50)	(16.70)		(-12.98)	(-13.20)
White-Caucasian		0.040***	0.040***		-0.017***	-0.016***
		(6.83)	(6.75)		(-3.54)	(-3.46)
Married		-0.006	-0.006		0.036***	0.036***
		(-1.43)	(-1.41)		(9.04)	(9.02)
Children		-0.033***	-0.033***		0.033***	0.033***
		(-7.73)	(-7.76)		(8.56)	(8.58)
State fixed effects	Yes	Yes	No	Yes	Yes	No
Year fixed effects	Yes	Yes	No	Yes	Yes	No
State × Year fixed effects	No	No	Yes	No	No	Yes
Observations	3,334,593	3,334,593	3,334,593	3,334,593	3,819,859	3,819,859
Adjusted R^2	0.070	0.081	0.082	0.097	0.106	0.108
Coefficient estimates of the interaction term with alternative Counter-str. CPS matching age						
Match as of age 15	0.082***	0.082***	0.082***	-0.082***	-0.086***	-0.086***
	(3.24)	(3.19)	(3.19)	(-3.25)	(-3.34)	(-3.34)
Match as of age 10	0.042**	0.041**	0.041**	-0.040**	-0.044**	-0.044**
	(2.34)	(2.28)	(2.28)	(-2.14)	(-2.32)	(-2.32)

Table 2.7: Women working in STEM fields

This table contains weighted regression results of CPS respondents' personal income on the interaction term between gender and our measure of *Counter-stereotypical female role model CPS* for a respondents' state and year when she was twenty years old. The sample contains all currently employed individuals in the CPS ASEC surveys from age 25 to age 65. The dependent variables are STEM industry, which is a dummy variable equal to one if a respondent works in an industry with an above-median STEM intensity, or STEM intensity of the industry the respondent works in (Adams and Kirchmaier (2016)). *Counter-str. CPS* is the fraction of Gallup survey respondents in a CPS respondents' state who admired counter-stereotypical female role models in the year when the CPS respondent was twenty years old (ten or fifteen years old in the lower part of the table). All variables are defined in Supplementary Supplementary Appendix SA15. Standard errors are clustered by state and time. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	STEM industry		STEM intensity	
	(1)	(2)	(3)	(4)
Counter-str. CPS× Female respondent	0.030***	0.025***	0.238***	0.166**
	(3.48)	(2.88)	(3.04)	(2.06)
Female	-0.109***	-0.105***	-1.039***	-1.011***
	(-13.29)	(-12.69)	(-14.01)	(-13.45)
Counter-str. CPS	-0.014**	-0.012**	-0.044	-0.049
	(-2.57)	(-2.62)	(-0.72)	(-0.99)
Age		0.003***		0.051***
		(3.87)		(10.88)
Age squared		-0.000***		-0.001***
		(-4.32)		(-12.03)
White-Caucasian		0.025***		0.145**
		(4.06)		(2.35)
Married		0.019***		0.132***
		(7.85)		(5.65)
Bachelor degree		0.057***		1.087***
		(5.81)		(9.09)
Children		-0.009***		-0.132***
		(-4.32)		(-6.06)
State fixed effects	Yes	No	Yes	No
Year fixed effects	Yes	No	Yes	No
State × Year fixed effects	No	Yes	No	Yes
Observations	2,091,384	2,091,383	2,091,384	2,091,383
Adjusted R^2	0.019	0.023	0.014	0.022
Coefficient estimates of the interaction term with alternative matching age				
Match as of age 15	0.031***	0.025***	0.216**	0.141
	(3.55)	(2.87)	(2.68)	(1.62)
Match as of age 10	0.022**	0.017	0.190*	0.113
	(2.14)	(1.67)	(1.86)	(1.09)

Table 2.8: Women in male-dominated industries or managerial positions (CPS sample)

This table contains weighted regression results of occupational choices on the interaction term between gender and our measure of *Counter-stereotypical female role model CPS* for a respondents' state and year when she was twenty years old (ten or fifteen years old in the lower part of the table). The sample contains all currently employed individuals in the CPS ASEC surveys (1962 to 2018) from age 25 to age 65. The dependent variables are Male-dominated industry, a dummy variable equal to one if a respondent is currently employed in an industry with more than 50% male employees, Male-dominated occupation, a dummy variable equal to one if a respondent is currently employed in an occupation with more than 50% male employees, or Manager, a dummy variable equal to one if a respondent is in a management occupation. All variables are defined in Supplementary Supplementary Appendix SA15. Standard errors are clustered by state and time. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Male-dominated industry		Male-dominated occupation		Manager	
	(1)	(2)	(3)	(4)	(5)	(6)
Counter-str. CPS × Female respondent	0.027***	0.030***	0.066***	0.068***	0.047***	0.036***
	(4.59)	(5.26)	(5.29)	(5.69)	(4.51)	(4.04)
Female respondent	-0.407***	-0.404***	-0.544***	-0.543***	-0.062***	-0.058***
	(-53.42)	(-52.93)	(-91.25)	(-90.44)	(-16.11)	(-15.67)
Counter-str. CPS	-0.027***	-0.017***	-0.044***	-0.032***	-0.052***	-0.014**
	(-4.33)	(-3.91)	(-4.84)	(-4.78)	(-4.46)	(-2.46)
Age		0.009***		0.011***		0.009***
		(10.47)		(16.37)		(24.08)
Age squared		-0.000***		-0.000***		-0.000***
		(-10.74)		(-15.70)		(-19.56)
Bachelor degree		-0.089***		-0.070***		0.097***
		(-8.40)		(-12.01)		(46.57)
White-Caucasian		0.053***		0.020***		0.043***
		(9.05)		(8.21)		(14.52)
Married		0.020***		0.016***		0.021***
		(6.50)		(4.88)		(17.29)
Children		-0.001		-0.003*		-0.000
		(-0.60)		(-1.70)		(-0.17)
State fixed effects	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	No	Yes	No	Yes	No
State × Year fixed effects	No	Yes	No	Yes	No	Yes
Observations	2,091,383	2,091,383	2,091,383	2,091,383	2,122,773	2,122,773
Adjusted R^2	0.171	0.181	0.283	0.288	0.032	0.038
Coefficient estimates of the interaction term with alternative Counter-str. CPS matching age						
Match as of age 15	0.011*	0.014**	0.050***	0.053***	0.041***	0.031***
	(1.86)	(2.23)	(3.98)	(4.27)	(4.63)	(4.23)
Match as of age 10	0.003	0.007	0.052***	0.055***	0.039***	0.029***
	(0.33)	(0.77)	(4.06)	(4.26)	(4.17)	(3.86)

Table 2.9: Fertility choices and educational choices

This table contains weighted regression results of fertility and educational choices on the interaction term between gender and our measure of *Counter-stereotypical female role model CPS* for a respondents' state and year when she was twenty years old (ten or fifteen years old in the lower part of the table). The sample contains all currently employed individuals in the CPS ASEC surveys (1962 to 2018) from age 25 to age 65. The dependent variables are the age of the respondent when the first child in the household was born, Bachelor, a dummy variable equal to one if a respondent has a bachelor's degree, or Post-graduate, a dummy variable equal to one if a respondent has a master's degree or above. All variables are defined in Supplementary Supplementary Appendix SA15. Standard errors are clustered by state and time. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Age at first childbirth	Bachelor	Post-graduate
	(1)	(2)	(3)
Counter-str. CPS× Female respondent	0.606***	0.061***	0.027***
	(5.18)	(5.93)	(7.13)
Female	-1.969***	0.001	-0.002
	(-34.60)	(0.39)	(-1.10)
Counter-str. CPS	-0.172**	-0.021***	-0.010***
	(-2.64)	(-4.28)	(-3.65)
Age	0.174***	0.004***	0.004***
	(7.56)	(6.23)	(9.44)
Age squared	0.002***	-0.000***	-0.000***
	(6.61)	(-11.05)	(-6.42)
White-Caucasian	0.455***	0.005	-0.006
	(3.05)	(0.25)	(-1.45)
Married	0.959***	0.070***	0.030***
	(28.27)	(36.64)	(26.39)
Bachelor degree	2.808***		
	(22.03)		
Children		-0.050***	-0.014***
		(-6.67)	(-5.59)
State × Year fixed effects	Yes	Yes	Yes
Observations	1355071	2228805	2228806
Adjusted R^2	0.370	0.128	0.041
Coefficient estimates of the interaction term with alternative Counter-str. CPS matching age			
Match as of age 15	0.607***	0.063***	0.025***
	(4.88)	(5.43)	(5.17)
Match as of age 10	0.457***	0.066***	0.027***
	(2.94)	(4.19)	(4.67)

Table 2.10: Counter-stereotypical female role models and the gender pay gap

This table contains weighted regression results of CPS respondents' personal income on the interaction term between gender and our measure of *Counter-stereotypical female role model CPS* for a respondents' state and year when she was twenty years old (ten or fifteen years old in the lower part of the table). The sample contains all currently employed individuals in the CPS ASEC surveys (1962 to 2018) from age 25 to age 65. The dependent variable is the log of personal income. All variables are defined in Supplementary Supplementary Appendix SA15. Standard errors are clustered by state and time. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Log income			
	(1)	(2)	(3)	(4)
Counter-str. CPS$\times$ Female respondent	0.371***	0.314***	0.370***	0.313***
	(5.49)	(5.24)	(5.52)	(5.25)
Female respondent	-0.651***	-0.634***	-0.651***	-0.633***
	(-20.01)	(-20.37)	(-20.06)	(-20.40)
Counter-str. CPS	-0.373***	-0.152***	-0.377***	-0.146***
	(-5.73)	(-5.33)	(-5.90)	(-5.30)
Age		0.055***		0.056***
		(22.98)		(23.22)
Age squared		-0.001***		-0.001***
		(-19.47)		(-19.61)
Bachelor degree		0.565***		0.566***
		(33.50)		(33.38)
White-Caucasian		0.138***		0.137***
		(6.72)		(6.52)
Married		0.077***		0.077***
		(10.38)		(10.34)
Children		0.004		0.005
		(0.49)		(0.71)
State fixed effects	Yes	Yes	No	No
Year fixed effects	Yes	Yes	No	No
State $\times$ Year fixed effects	No	No	Yes	Yes
Observations	2,195,091	2,195,091	2,195,091	2,195,091
Adjusted R^2	0.274	0.331	0.275	0.332
Coefficient estimates of the interaction term with alternative matching age				
Match as of age 15	0.317***	0.264***	0.317***	0.263***
	(5.02)	(4.80)	(5.04)	(4.81)
Match as of age 10	0.276***	0.225***	0.277***	0.224***
	(4.77)	(4.59)	(4.80)	(4.59)

Table 2.11: Correlations between counter-stereotypical female role model variable and gender norms

This table contains pair-wise correlations between GSS variables measuring gender norms and our counter-stereotypical female role model variable for different leads and lags. All variables are defined in detail in Supplementary Supplementary Appendix SA15. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

GSS variable	Lag 10	Lag 5	Lag 1	Concurrent	Lead 1	Lead 5	Lead 10
Female family	0.2534***	0.1616***	0.2809***	0.1939***	0.2433***	0.2389***	0.1252***
Female children	0.1979***	0.1737***	0.2115***	0.1760***	0.2404***	0.2314***	0.1576***
Female president	0.1744***	0.1610***	0.2501***	0.1753***	0.1472***	0.1737***	0.1588***
Female politics	0.1922***	0.2108***	0.3121***	0.2011***	0.1528***	0.2069***	0.1621***
Working mother	0.1201***	0.1107***	0.1885***	0.1307***	0.1844***	0.1738***	0.1464***
GSS average gender attitudes	0.1559***	0.1784***	0.2626***	0.1774***	0.1514***	0.2531***	0.2299***

Table 2.12: Counter-stereotypical female role models and gender norms

This table contains weighted regression results from our baseline analyses using CPS survey data and additionally includes state-level gender norms measured by GSS survey data, as well as its interaction with *Female respondent*. The sample includes respondents from age 25 to age 65 in the CPS ASEC surveys. *GSS gender attitude* is the standardized average of state-year level measures for five gender-related GSS questions (FEFAM, FEPRESCH, FEPRES, FEPOL, and FECHLD). *Counter-str. CPS* is the fraction of Gallup survey respondents in a CPS respondents' state who admired counter-stereotypical female role models in the year when the CPS respondent was twenty years old. All variables are defined in Supplementary Supplementary Appendix SA15. Standard errors are clustered by state and time. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Employment status - Results from Table 2.6						
Dependent variable	Employed			Not in labor force		
	(1)	(2)	(3)	(4)	(5)	(6)
Counter-str. CPS × Female	0.031***	0.032***	0.032***	-0.028**	-0.034***	-0.033***
	(2.78)	(2.75)	(2.74)	(-2.45)	(-2.83)	(-2.81)
Female	-0.177***	-0.173***	-0.173***	0.192***	0.191***	0.191***
	(-17.41)	(-17.37)	(-17.39)	(18.27)	(18.34)	(18.34)
Counter-str. CPS	-0.029***	-0.009	-0.009	0.014*	0.008	0.009
	(-3.66)	(-1.65)	(-1.60)	(1.76)	(1.51)	(1.50)
Liberal gender attitude (GSS) × Female	0.056***	0.054***	0.054***	-0.055***	-0.054***	-0.054***
	(6.07)	(5.98)	(5.99)	(-5.96)	(-5.93)	(-5.94)
Liberal gender attitude (GSS)	-0.029***	-0.028***		0.028***	0.028***	
	(-5.95)	(-5.85)		(5.98)	(5.99)	
Control variables	No	Yes	Yes	No	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Year fixed effects	Yes	Yes	No	Yes	Yes	No
State × Year fixed effects	No	No	Yes	No	No	Yes
Observations	2,974,608	2,974,608	2,974,608	2,974,608	2,974,608	2,974,608
Adjusted R^2	0.058	0.069	0.070	0.080	0.090	0.091

Table 2.12: Counter-stereotypical female role models and gender norms (continued)

Panel B: STEM industry - Results from Table 2.7				
Dependent variable	STEM industry		STEM intensity	
	(1)	(2)	(3)	(4)
Counter-str. CPS× Female respondent	0.033***	0.028***	0.271***	0.208***
	(3.74)	(3.30)	(3.62)	(2.80)
Female	-0.108***	-0.105***	-1.038***	-1.011***
	(-13.64)	(-13.03)	(-14.21)	(-13.66)
Counter-str. CPS	-0.016***	-0.013***	-0.058	-0.064
	(-2.81)	(-2.94)	(-0.96)	(-1.31)
Female × Liberal gender attitude (GSS)	-0.011**	-0.012***	-0.112***	-0.133***
	(-2.56)	(-2.82)	(-3.09)	(-3.50)
Liberal gender attitude (GSS)	0.007***		0.075***	
	(3.46)		(3.69)	
Control variables	No	Yes	No	Yes
State fixed effects	Yes	No	Yes	No
Year fixed effects	Yes	No	Yes	No
State × Year fixed effects	No	Yes	No	Yes
Observations	1,911,318	1,911,318	1,911,318	1,911,318
Adjusted R^2	0.018	0.022	0.013	0.021

Panel C: Occupational choices - Results in Table 2.8						
Dependent variable	Male-dominated industry		Male-dominated occupation		Manager	
	(1)	(2)	(3)	(4)	(5)	(6)
Counter-str. CPS × Female	0.022***	0.025***	0.045***	0.047***	0.041***	0.032***
	(3.62)	(4.21)	(5.52)	(6.13)	(4.22)	(3.78)
Female	-0.405***	-0.402***	-0.537***	-0.536***	-0.061***	-0.056***
	(-54.39)	(-53.99)	(-113.32)	(-111.06)	(-16.96)	(-16.30)
Counter-str. CPS	-0.026***	-0.016***	-0.036***	-0.024***	-0.050***	-0.012**
	(-4.08)	(-3.45)	(-4.80)	(-4.73)	(-4.26)	(-2.09)
Liberal gender attitude (GSS) × Female	0.007***	0.008***	0.026***	0.027***	0.008***	0.006**
	(2.72)	(3.15)	(6.14)	(6.34)	(3.09)	(2.22)
Liberal gender attitude (GSS)	-0.001		-0.013***		-0.004**	
	(-0.81)		(-5.69)		(-2.57)	
Control variables	No	Yes	No	Yes	No	Yes
State fixed effects	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	No	Yes	No	Yes	No
State × Year fixed effects	No	Yes	No	Yes	No	Yes
Observations	1,911,318	1,911,318	1,911,318	1,911,318	1,911,318	1,911,318
Adjusted R^2	0.162	0.170	0.277	0.281	0.007	0.030

Table 2.12: Counter-stereotypical female role models and gender norms (continued)

Panel D: Fertility and educational choices - Results from Table 2.9			
Dependent variable	Age at first childbirth	Bachelor	Post-graduate
	(1)	(2)	(3)
Counter-str. CPS× Female	0.584***	0.055***	0.025***
	(4.79)	(5.50)	(6.61)
Female	-1.949***	0.003	-0.002
	(-33.10)	(0.72)	(-0.86)
Counter-str. CPS	-0.146**	-0.018***	-0.008***
	(-2.22)	(-3.66)	(-3.06)
Female × Liberal gender attitude (GSS)	-0.003	0.017***	0.008***
	(-0.16)	(9.87)	(6.37)
State × Year fixed effects	Yes	Yes	Yes
Observations	1,229,919	2,037,791	2,037,791
Adjusted R^2	0.366	0.122	0.040

Panel E: Gender pay gap - Results from Table 2.10				
Dependent variable	Log income			
	(1)	(2)	(3)	(4)
Counter-str. CPS × Female	0.270***	0.220***	0.271***	0.220***
	(5.40)	(5.08)	(5.41)	(5.09)
Female	-0.612***	-0.596***	-0.612***	-0.597***
	(-22.56)	(-22.83)	(-22.58)	(-22.84)
Counter-str. CPS	-0.322***	-0.102***	-0.326***	-0.100***
	(-5.71)	(-5.32)	(-5.83)	(-5.13)
Liberal gender attitude (GSS) × Female	0.105***	0.092***	0.105***	0.092***
	(6.45)	(5.87)	(6.48)	(5.92)
Liberal gender attitude (GSS)	-0.042***	-0.033***		
	(-5.25)	(-4.12)		
Control variables	No	Yes	No	Yes
State fixed effects	Yes	Yes	No	No
Year fixed effects	Yes	Yes	No	No
State × Year fixed effects	No	No	Yes	Yes
Observations	1,980,802	1,980,802	1,980,802	1,980,802
Adjusted R^2	0.215	0.278	0.215	0.279

CHAPTER 3

Stock Repurchasing Bias of Mutual Funds

Coauthors: Alexandra Niessen-Ruenzi and Terrance Odean

3.1 Introduction of Chapter 3

The investment behavior of mutual fund managers is important to the financial well-being and wealth of many households. According to the Investment Company Institute, 59 million households in the US owned mutual funds in 2021; the median mutual fund-owning household had $126,700 in funds; and 60% of mutual fund assets were actively managed.[1] Decisions made in delegated portfolio management obviously affect a large number of individual investors and it is, therefore, important to understand how these decisions are made. Not surprisingly, there is a large literature investigating research questions on whether fund managers suffer from behavior biases.

Fund managers have more expertise and experience than retail investors and more opportunity to learn about and correct trading biases. Thus their trading behavior is likely to be influenced by biases to a lesser degree than that of retail investors.[2] Consistent with this observation, Barber and Odean (2007) find that attention has a larger effect on retail investors' decisions about which stocks to buy than on fund managers' decisions. Similarly, retail investors have been shown to be subject to the disposition effect (e.g.,

[1]For a detailed view on the Investment Company Institute's annual statistics on households' mutual fund holdings, see https://www.ici.org/system/files/2021-05/2021_factbook.pdf.

[2]For example, Dhar and Zhu (2006) and Graham et al. (2009) find that investor sophistication and competence influence behavioral biases in trading.

Shefrin and Statman (1985) and Odean (1998)), while evidence of the disposition effect among institutional investors is mixed (Frazzini (2006), O'Connell and Teo (2009) and Cici (2012)). However, fund managers have been shown to suffer from behavioral biases that are related to emotional familiarity (e.g., home bias in Pool et al. (2012)) and personal characteristics (e.g., overconfidence in Puetz and Ruenzi (2011)). Thus, whether fund managers are subject to behavioral biases may depend on the type of the bias.

In this paper, we show that fund managers are less likely to repurchase stocks that they have previously sold for a loss and that this trading pattern does not enhance performance. There are several, not mutually exclusive, psychological mechanisms that could lead to this behavior. The simplest is operant conditioning; managers don't buy stocks that previously resulted in losses (punishments) and buy stocks that resulted in gains (rewards). Managers may also be influenced by anticipated regret. Loewenstein (2000) argues that anticipated emotions predict economic decision making. Managers may anticipate that they will feel strong regret if they repurchase a previous loser and incur another loss. In other words, they anticipate feeling worse if they have a bad outcome from repeating behavior which–ex-post–appears to have been previously been a mistake. Finally, managers may avoid repurchasing prior losers in order to maintain a positive image with others. They may anticipate that team members, management, and/or investors who observe their behavior will think less of them if they appear to repeat a previous mistake.

We analyze the repurchase behavior of fund managers with the quarterly holdings of active U.S. mutual funds from 1980 to 2019 from the Thomson Reuters dataset. For each mutual fund-stock combination at a quarter end, we define previous winner and loser stocks, respectively, as stocks a mutual fund previously sold for a gain or a loss when the fund completely sells the stocks. We then examine whether the probability that a stock is repurchased by the same fund depends on whether it was sold for a gain or a loss by a fund. We control for various fund characteristics such as fund size, fund age, fund performance, and the fund's trading activity. We also include stock, fund, and time fixed effects, fund$\times$time fixed effects, and in separate regressions, stock$\times$time fixed effects.

Our main result is that mutual fund managers are significantly less likely to repurchase a stock if they sold it for a loss in the past. That is, repurchasing decisions are biased away from stocks previously sold for a loss. The result is economically significant: the probability of repurchasing a past loser stock is about 17% lower than that of repurchasing a past winner stock. By including stock$\times$time fixed effects, we show that the repurchase decision is influenced by each fund's prior experience with a stock not simply the time varying attractiveness of a stock to all funds.

As is common in the mutual fund literature, we investigate fund managers' investment decisions based on quarterly holdings (see, e.g., Frazzini (2006) and Cici (2012) and Lou (2012)). One drawback of quarterly holdings data is that realized returns are measured with noise, because the exact date of a trade can not be identified. Therefore, we replicate our main result with a second database of daily trades of ANcerno institutional clients from 1990 to 2010. Again, we include fund$\times$time fixed effects together with stock fixed effects or stock$\times$time fixed effects to control for fund and stock characteristics. As in the quarterly data analysis, we find that fund managers are less likely to repurchase stocks that they previously sold for a loss rather than a gain. Because the Thomson Reuters quarterly holdings data contains a more representative sample and enables us to identify individual funds in order to merge with other control variables, we use the quarterly holdings for our additional analyses.

We further investigate the gender difference in the repurchasing bias. We show that funds with female managers in the management are associated with less repurchasing bias. Female fund managers are not more emotional than male fund managers and are not more likely to bias against past loser stocks. In the contrary, we find evidence that female fund managers are slightly less likely to suffer from the repurchasing bias.

Repurchasing bias is influenced by fund flows. For stocks sold during a period in which a fund had outflows, there is less of a bias against repurchasing losers. This could be because the manager feels less personal responsibility for sales made for a loss during periods when when the fund was forced to sell.

Consistent with the conjecture that the repurchasing bias is caused by personal trading experiences, we find that mutual fund managers who change funds are less likely to purchase stocks they sold for a loss at their previous fund. Also, after a fund manager leaves a fund, the new manager continues to avoid repurchasing stocks the previous manager sold for a loss. However, the bias is much weaker than for a manager's own sales. This behavior is consistent with the conjecture that managers don't want to be observed repeating apparent mistakes, even the mistakes of their predecessors.

An alternative reason why fund managers may avoid repurchasing prior losers is that they have superior information about the future underperformance of these stocks. To examine this possibility, we compare the subsequent performance of repurchased losers stocks to repurchased winners and to the fund itself. Repurchased losers outperform repurchased winners and the fund itself in the quarter following repurchase. Hence, avoiding repurchasing losers does not enhance portfolio performance.

Our paper contributes to the literature on biased investment decisions of individual and institutional investors. The previous literature has shown that behavioral biases such as home bias (Ivković and Weisbenner (2005), Seasholes and Zhu (2010), Pool et al. (2012) and Lin and Viswanathan (2016)), and overconfidence (Odean (1999) and Puetz and Ruenzi (2011)) are present among both individual investors and mutual fund managers. Our paper establishes that the repurchase bias, which was previously documented for retail investors Strahilevitz et al. (2011) is also present among mutual fund managers. Positive emotions from repurchasing stocks previous winners may add to retail investors' utility. However, in delegated portfolio management, managers should not make trades that increase their personal utility if those trades do not enhance their investors' returns.

Our findings also relate to the broader literature on how personal experiences influence economic decision-making. For example, Malmendier and Nagel (2011) and Malmendier and Nagel (2016) show that households' financial decisions are influenced by their experienced inflations or stock market returns. In addition, political environment affects future financial decisions of individuals (Laudenbach et al. (2019), and Strahilevitz et al. (2011)). We show that even though mutual fund managers are sophisticated investors, their investment decisions are also significantly influenced by their own experiences and emotions. Mutual fund trading behavior deserves scrutiny because it has a significant impact investor welfare and the capital markets.

3.2 Data and summary statistics of Chapter 3

3.2.1 Data and sample selection of Chapter 3

Quarterly mutual fund holding data

We obtain quarterly stock holdings data of U.S. mutual funds from 1980 to 2019 from the Thomson Reuters Mutual Fund Holdings Database. We then merge the stock holdings data with the CRSP Survivorship-Bias-Free Mutual Fund Database using MFLINKS by Wermers (2000). The CRSP Mutual Fund Database contains data on fund characteristics such as total net assets (TNA), monthly returns, expense ratios, and first offer dates. We further merge the data with the Morningstar Direct database using TICKER and CUSIP as fund identifiers since the Morningstar database provides more accurate information on fund managers (Massa et al. (2010)). We aggregate all share classes of the same fund to avoid multiple counting.

We include all actively-managed, open-end U.S. domestic equity funds in the sample. As stock repurchasing bias is only relevant for actively managed funds, we exclude ETFs, index funds, and funds with an expense ratio below 0.1% p.a. We also exclude funds with total net assets in the bottom 5% of all observations to make sure that reported stock holdings do not change because of complete liquidation of the fund.

Next, we merge the mutual fund data with stock information from CRSP using the report date (RDATE) and the stock identifiers (CUSIP and PERMNO) in the stock holdings. Following Daniel et al. (1997) and Wermers (1999), we only include ordinary common stocks traded on NYSE, AMEX or NASDAQ and exclude ADRs, preferred stock, and depository units.

We define the sale of a stock as clearing the entire position. According to Alexander et al. (2006), selling to zero usually represents value-based sales while selling partial positions may be caused by liquidity restrictions or portfolio rebalancing. Thus, to capture deliberate trades of fund managers that are significant enough to be associated with repurchasing bias, we focus on stocks that have been previously completely sold. For each stock sold by a fund, we track it for one year to see whether the stock is repurchased by the same fund.

Our main sample consists of 11,200,456 fund-stock-quarter observations, including 5,725 distinct funds.

Daily institutional trading data

To more precisely calculate previous trading returns, we construct an alternative sample by exploring institutional trading data (usually referred to as ANcerno data) from Abel Noser Solutions, a brokerage firm that provides consulting services to institutional clients. Hu et al. (2018) provide background information on the ANcerno data and estimate that the data cover approximately 12% of the CRSP trading volume.[3] The data cover daily trades of institutions including both money managers (e.g., Lazard Asset Management and Fidelity) and pension funds (e.g., the YMCA retirement fund). ANcerno institutional trading data enables us to measure more precisely whether a fund manager sold a stock for a gain or a loss. We obtain the following information for each transaction between 1999 to 2010 from the ANcerno database: the stock identifier, the transaction date, the institution identifier, the fund identifier within each institution, the trade date, the transaction direction (a purchase or a sale), the trading volume, and the transaction price per share. We create an identifier for each fund in each institution. The identity of the institution or the fund is unknown but we can observe the trading behavior of a certain fund over time, which serves the purpose of our main analysis.

We exclude all trades by institutions with the identifier (clientcode) equal to zero be-

[3]Previous studies using ANcerno data include, e.g., Goldstein et al. (2009) and Puckett and Yan (2011).

cause this indicates ANcerno cannot reliably track a fund. We also discard intraday buys and sells of the same stock because intraday time stamps in ANcerno are incomplete (e.g., Anand et al. (2013) and Chakrabarty et al. (2017)). We further exclude trades with a trading price below 1 cent. We then merge ANcerno trading data with CRSP daily stock data and only include ordinary common stocks.[4] As in our analysis based on quarterly data, we investigate whether a stock is repurchased by the same fund within one year after a fund completely sells the stock. Since we need to be able to see whether the stock is repurchased within one year after the sale, all funds that are present in the sample for less than a year are excluded. We then calculate the returns for each sale based on the actual purchase and selling prices rather than estimating these prices from quarterly data. Finally, we create a sample at the quarterly frequency to make the repurchasing activities comparable to the main sample.

Our ANcerno sample consists of 3,363,321 fund-stock-quarter observations, including 971,070 complete sales by 4,602 funds. Even though ANcerno institutional trading data enables us to estimate the returns from previous sales using the actual trading prices, the anonymity and the incomplete coverage of funds limit our analyses. Therefore, we use the ANcerno sample to show that our baseline result is robust and that it is not influenced by the potentially noisy estimation of returns using quarterly holdings. We use the more representative CRSP mutual fund and Thomson quarterly holdings databases to conduct all further analyses.

[4] Chakrabarty et al. (2017) exclude trades in which there is a stock dividend distribution and a stock split between the purchase and the sale of a stock. Excluding these observations or adjusting the stock splits and dividend distributions using CRSP cumulative factors does not change our results (not reported).

3.2.2 Construction of main variables of Chapter 3

Definition of repurchasing bias

For each stock completely sold by a fund, we check whether it re-appears in reported stock holdings of the fund in the next four quarters, i.e., within one year after the sale, following Strahilevitz et al. (2011).[5] Our main dependent variable, $\text{Repurchase}_{i,j,q}$, is equal to one for the first of the four quarters following the sale in which a stock re-appears in the stock holdings report of the fund. For each quarter in which the stock does not reappear in the stock holdings and has not yet reappeared, the repurchase dummy is set to zero.[6] Quarters subsequent to the stock reappearing in the stock holdings are not included in the sample. We also exclude delisted stocks from the sample as they are no longer available for repurchase. We measure the repurchasing behavior of funds in the same way in the ANcerno sample. The only difference is that we can observe the repurchasing behavior within the same quarter of the sale in the ANcerno sample. If a stock is completely sold in the ANcerno database and then repurchased in the same quarter, we include the quarter of the sale in our regression and set our repurchase dummy equal to one. If a stock is sold in a given quarter but not repurchased in the same quarter, we also include the quarter of the sale in our regression and set our repurchase dummy equal to zero. We denote the repurchase dummy in the ANcerno sample as $\text{Repurchase}^{ANcerno}$.

Appendix B provides an overview of the top 20 funds that purchase previously sold stocks most frequently (Panel A) and of the top 20 stocks that are repurchased for the most

[5]All quarters after the sale of a stock are in the sample. The one-year horizon ensures that the same managers are likely to be in charge of a fund and that managers are likely to remember the sale. However, our results also hold for varying time periods after the sale (see Supplementary Appendix SA21).

[6]Note that this approach makes sure that our results are not driven by a potential disposition effect of fund managers because a larger number of winners sold would result in a larger number of observations with a repurchase dummy equal to zero if the stocks are not repurchased.

times (Panel B) in our main sample.

Definition of winner and loser stocks

Our main sample is comprised of quarterly stock holdings of funds which are widely used by previous mutual fund literature. Previous studies, e.g., Frazzini (2006) and Cici (2012) and Lou (2012), have defined a clear way to measure trading performance of funds on each stock using the quarterly stock holding data. Following these papers, we assume mutual funds trade stocks on each report date. To estimate the average purchase price and measure whether a fund sells a stock for a gain or a loss in a given quarter, we use two alternative approaches.

First, we follow Frazzini (2006) and define a loser dummy, LoserFIFO, by comparing the price on the report date when the stock no longer appears in the reported mutual fund holdings with the weighted average purchase price based on the first-in-first-out (FIFO) principle. LoserFIFO equals one if the sale price is lower than the average purchase price of the stock, and equals zero if the sale price is lower than the average purchase price.

Second, we use the trade-value-weighted average of all purchase prices before the report date when the stock no longer appears in the mutual fund holdings to approximate whether the previous sale was for a gain or a loss so the measure is not influenced by the sequence of stock purchases. We define a loser dummy, LoserAVG, which is equal to one if the sale price is lower than the trade-value-weighted average of all purchase prices before the sale.[7]

In Supplementary Appendix SA19, we calculate the purchase price of stocks based on low-in-first-out—i.e., we assume the lowest priced purchases are sold first—and high-in-first-out as in Cici (2012). Alternatively, we apply the last-in-first-out principle to calculate the purchase price. Our results are robust to these alterations. In addition, we show that our results are robust if we define winner and loser stocks based on market-adjusted returns (see Supplementary Appendix SA20), and if we vary the number of quarters after a sale that we include in the analysis (see Supplementary Appendix SA21).

The quarterly mutual fund holdings data only provide a snapshot of stock holdings each quarter. Thus, a fund may purchase and sell stocks on any day between report dates. The potentially noisy measures of previous gains and losses should not systematically bias our results and may even make it harder for us to observe the effect of previous trading experiences on repurchasing behavior. As a robustness check, we use ANcerno daily trading data and calculate the returns based on the actual trade prices. Again, we calculate two purchase price measures one based on the first-in-first-out (FIFO) principle and the other on the trade-value-weighted average of all purchases before the sale. LoserFIFO^{ANcerno} (LoserAVG^{ANcerno}) equals one if the sale price is lower than the average (trade-value weighted average) purchase price of the stock, and equals zero otherwise.

All variables used in this paper are described in detail in Appendix 3.6.

[7]The following example illustrates how our two measures, LoserFIFO and LoserAVG, are computed. Assume a fund purchases a stock at a volume of 100, 200, and 100 at a price of \$2, \$3, and \$1, in quarter 1, quarter 2, and quarter 3, and the fund sells the stock at a volume of 200 and 200 in quarter 4 and quarter 5. The sale in quarter 5 is a complete sale so it is included in the sample. The average purchase price is \$2 ($\frac{100\times3+100\times1}{100+100}$) based on the FIFO principle and \$2.25 ($\frac{100\times2+200\times3+100\times1}{100+200+100}$) based on the trade-value-weighted average of all purchase prices before the sale. If the selling price as of quarter 5 is \$2.1, LoserFIFO is equal to zero because \$2.1>\$2 and LoserAVG is equal to one because \$2.1<\$2.25.

3.2.3 Summary statistics of Chapter 3

Panel A of Table 3.1 reports summary statistics of variables used in our analysis. We find that stocks in the main sample are repurchased by the same fund within one year with a probability of 5.3% on average and the repurchasing probability is slightly lower in the ANcerno sample (4.7%). According to the LoserFIFO (LoserAVG) measure, 49.3% (58.7%) of the stocks in our main sample are sold for a loss. In the ANcerno sample, 50.9% (51.4%) of the sales are at a loss, based on the measure LoserFIFO^{ANcerno} (LoserAVG^{ANcerno}).

In Panel B of Table 3.1, we partition stocks previously sold based on whether funds selling these stocks repurchase them. We then conduct mean comparisons of stock and fund characteristics among both groups.[8] For both datasets, LoserFIFO and LoserAVG are smaller for repurchased stocks than for stocks that are not repurchased. Thus, funds are less likely to repurchase a stock if it was previously sold for a loss.

In Panel C of Table 3.1 we partition stocks previously sold based on whether these stocks were sold for a gain or a loss according to the LoserFIFO measure and, as in Panel B, conduct a mean comparison.[9] The probability of being repurchased is between 1.1% (in the main sample) and 0.7% (in the ANcerno sample) lower if a stock was previously sold for a loss rather than for a gain. This corresponds to a 20.8% and 14.9% higher repurchase probability, respectively, relative to the baseline repurchase probability in each sample.

[8] Specifically, we run a regression of the variable under consideration on the repurchase dummy. The coefficient of the repurchase dummy represents the difference in variables between both groups. We report t-statistics clustered by fund and time in column (4).

[9] Results (not reported) are virtually identical if we use the LoserAVG measure instead.

3.3 Repurchasing behavior of mutual fund managers

Figure 3.1 depicts the average return from a stock's complete sale conditional on whether this stock is subsequently repurchased. Stocks repurchased tend to have been sold for higher returns than stocks not repurchased. Using the first-in-first-out principle, the return difference between repurchased stocks and stocks that are not repurchased is 3.62%, while using the value-weighted average principle, the return difference is 4.23%. Both differences are statistically significant at the 1% level.

3.3.1 Baseline Results of Chapter 3

To test our hypothesis that stocks previously sold for a loss are less likely to be repurchased than stocks previously sold for a gain, we calculate the proportion of winner stocks repurchased (PWR) and the proportion of loser stocks repurchased (PLR) and test the differences against zero based on *t*-tests.[10] The proportions are calculated to measure the aggregated tendency of repurchasing previous winner stocks or loser stocks by all funds in the main sample. This serves as a first step to quantify the difference in the propensity to repurchase previous winner stocks and previous loser stocks, and is similar to the ratio comparations in papers studying the disposition effect (Odean (1998) and Dhar and Zhu (2006)). PWR and PLR are defined as:

$$PWR = \frac{NWR}{ORW}, \tag{3.1}$$

[10]Following Strahilevitz et al. (2011), we calculate standard errors based on the assumption that realized repurchases are independent observations as $\sqrt{\frac{NWR+NLR}{ORW+ORL} \times \left(1 - \frac{NWR+NLR}{ORW+ORL}\right) \times \left(\frac{1}{NWR} + \frac{1}{NLR}\right)}$.

$$PLR = \frac{NLR}{ORL}, \tag{3.2}$$

where NWR (NLR) is the number of winners (losers) completely sold by a fund and then repurchased in one of the four quarters after the sale. ORW (ORL) is the number of opportunities to repurchase previous winners (losers), where an opportunity is each quarter in one year subsequent to the sale of a stock until the stock is repurchased by the fund. NWR (NLR) and ORW (ORL) are aggregated across all funds over the sample period.

Table 3.2 shows average differences between PWR and PLR. Results in column (1) are based on the first-in-first-out principle, while results in column (2) are based on the average purchase price. The difference between PWR and PLR is 1.1% or 1.2% and statistically significant at the 1% level.

The differences that we document between PWR and PLR for fund managers (i.e., 1.2%) are smaller than those found by Strahilevitz et al. (2011) for retail investors, which range from 2.0% to 4.8%. Thus the ratio of 1.255 (0.059/0.047) of PWR to PLR is lower for fund managers compared to a range of PWR to PLR of 1.360 to 2.356 for retail investors. Hence, the repurchasing bias of mutual fund managers, while statistically and economically significant, is lower in magnitude than that of individual investors.

To control for fund characteristics that may correlate with repurchasing behavior and realization of gains or losses on stocks, we estimate the following linear probability model with fixed effects and time-varying fund characteristics as control variables:

$$
\begin{aligned}
Repurchase_{i,j,q} =& \alpha + \beta_1 LoserDummy_{i,j,q} + \beta_2 FundSize_{i,q} + \beta_3 FundAge_{i,q} \\
&+ \beta_4 TurnoverRatio_{i,q} + \beta_5 ExpenseRatio_{i,q} + \beta_6 \\
&ReturnVolatility_{i,q} + \beta_7 PerformanceRank_{i,q} + u_j + w_i + v_q + \varepsilon_{i,j,q},
\end{aligned}
\tag{3.3}
$$

where i, j, q indicate funds, stocks, and the quarter of the (potential) repurchase within four quarters after the sale, respectively. The dependent variable, Repurchase$_{i,j,q}$, is an indicator for whether stock j sold completely by fund i is repurchased in quarter q within one year after the sale. Loser$_{i,j,q}$ denotes our two measures of loser stocks, LoserFIFO$_{i,j,q}$ or $LoserAVG_{i,j,q}$, as defined in Section 3.2.2. u_j, w_i, and v_q represent stock fixed effects, fund fixed effects, and time fixed effects, respectively.

We include various fund characteristics as control variables. Fund size and fund age are included, because repurchasing activity may generally be higher for large funds with more stocks in their portfolios. We also control for a fund's turnover ratio, since turnover may be positively correlated with repurchasing activity. A fund's expense ratio is included as another proxy for its trading activity and active management in general. Finally, we include a fund's performance rank in its investment objective and the fund return volatility, as these variables may influence the fund manager's repurchasing decisions due to tournament or window dressing incentives (Brown et al. (1996), Kempf and Ruenzi (2008), Agarwal et al. (2014)).

All models include stock, fund, and time fixed effects to control for unobserved fund trading patterns, stock characteristics, and potential time trends in repurchasing behavior. Fund fixed effects take out time-invariant fund characteristics such as their investment styles and investment abilities. We assume that the repurchasing behavior is independent across funds but not within funds and thus, cluster standard errors by fund.[11] Estimation results are presented in Table 3.3.

In columns (1) and (4), we estimate the baseline effect without any additional control variables, while in columns (2) and (5), we control for fund characteristics. We include fund×time fixed effects in columns (3) and (6). Across all specifications, we find that mutual fund managers are significantly less likely to repurchase stocks that they previously sold for a loss. The impact of the loser dummy on the probability of a stock to be repurchased is negative and statistically significant at the 1% level in all model specifications. The effect is also economically meaningful: depending on the loser measure and the model specification, the estimates show that the probability of being repurchased is 0.8 pp to 0.9 pp lower for previous losers than for previous winners. Relative to a stock's mean repurchase probability of 5.3% (see Panel A of Table 3.1), this difference corresponds to a 17% lower probability for a loser stock to be repurchased.

Coefficient estimates of most control variables on fund characteristics are also in line with expectations. We find that larger funds are significantly more likely to repurchase stocks. More active funds also tend to repurchase more stocks: the higher the turnover ratio of a fund, the more likely a fund repurchases a stock. Results also show that a higher fund ranking in the investment objective has a negative impact on the likelihood to repurchase a stock previously sold. Note that including fund×time fixed effects accounts for all time-varying fund characteristics including the management structure (i.e., single vs. team managed). We conjecture that behavioral biases can be present in both team and

[11] Our results remain robust if the standard errors are clustered by both fund and time.

single managed funds, as teams may, e.g., share a common reference point for regret. In fact, we find that our main result obtains in both subsamples of team- and single-managed funds (see Supplementary Appendix SA22).

3.3.2 Evidence from daily transaction data

The measures of gains and losses based on mutual fund quarterly holdings are not estimated from actual trading prices. This may introduce noise into our classification of previous winner and loser stocks. In addition, mutual funds may have incentives to improve reported returns at quarter ends (Carhart et al. (2002)) and thus, trading performance based on the quarter-end data may be biased. Nevertheless, quarterly data are commonly used in the mutual fund literature for measuring fund trading behavior and performance (e.g., Frazzini (2006), Cici (2012), and Lou (2012)). And the noise introduced by using quarterly data should make it harder for us to confirm our hypothesis. As a robustness check, we use ANcerno daily institutional trading data to more accurately calculate whether stocks were sold for gains or for losses. We estimate the regression model in Equation 3.3 with the dependent variable Repurchase^{ANcerno} and independent variables LoserFIFO^{ANcerno} and LoserAVG^{ANcerno}, as defined in Section 3.2.2. Since the identity of funds is unknown in this sample, it is not possible to include measurable fund characteristics as control variables. However, we include various combinations of fixed effects (fund$\times$time fixed effects and stock$\times$time fixed effects) to control for any time-varying fund and stock characteristics. Standard errors are clustered by fund.

Table 3.4 contains the regression results. The regressions in Columns (1) and (3) include fund fixed effects, stock fixed effects and time fixed effects. Columns (2) and (4) additionally include fund$\times$time fixed effects. The results show that mutual funds are 0.8 pp or 0.9 pp less likely to repurchase previous loser stocks compared to previous winner stocks. The negative effect of being a previous loser on the repurchasing probability is statistically significant at the 1% level and accounts for around 20% of the baseline repurchasing probability (see Panel A of Table 3.1). If we compare the repurchasing probabilities of stocks sold by the same fund in a given quarter after the sale, by including fund$\times$time fixed effects, we find that mutual funds are still 0.3 pp or 0.5 pp less likely to repurchase this stock when the stock was sold for a loss. These results confirm that the potential noise in measuring trading returns with quarterly holdings data does not bias our baseline findings.

3.3.3 Magnitudes of losses and gains

We examine whether the magnitude of losses and gains influences repurchasing bias. Specifically, we run regressions with the same set of fixed effects as in Equation 3.3 with dummy variables for different return intervals and plot the corresponding estimated repurchasing probabilities in Figure 3.2. The baseline interval (i.e., intercept) is a return between -0.05 and 0.05 percentage points (pp); the remaining intervals are less than -0.75, -0.75 to -0.65, ..., -0.15 to -0.05 and 0.05 to 0.15, ..., 0.65 to 0.75, and greater than 0.75.

The figure shows that the probability of repurchasing a stock is highly dependent on the returns realized when the stock was sold. The probability of repurchase is approximately linear in returns of losses and of gains less than 15 pp. Regardless of whether we use the FIFO or AVG measure to approximate returns, the effect of previous trading returns on repurchasing a stock becomes positive when the returns move from the negative domain to the positive domain. There is a kink in the slope of repurchase probability over returns at the return interval around zero. However, a stock's likelihood of being repurchased declines in the magnitude of losses but does not increase further for gains over 15 pp. The pattern is consistent with findings of loss-aversion in the reference-dependent model (Tversky and Kahneman (1991)): losses and negative experiences have a greater impact on preferences than gains and positive experiences.

3.3.4 Stock$\times$time fixed effect and taxes

In Table 3.5, we estimate the models reported in Table 3.3, additionally including stock$\times$time fixed effects. These models, compare the repurchase rates of the same stock in the same quarter conditional on whether a fund sold the stock for a gain or a loss in the last year. This specification restricts inferences to stocks repurchased in the same quarter both by funds that sold the stock for a gain in the previous year and funds that sold it for a loss in the previous year. The magnitudes of gains and losses in these situations tend to be small and thus gains and losses could easily be misclassified due to estimation errors. To avoid misclassifications, we restrict this analysis to gains above 0.15 and losses below -0.15. After adding stock$\times$time fixed effects, the coefficient estimates of the loser dummies are still negative and statistically significant at the 1% level though lower in magnitude. Thus, even for the same stock in the same time period, the probability to be repurchased is dependent on whether the stock was previously sold by a mutual fund for a gain or a loss.

While many investors own mutual funds in tax-advantaged retirement accounts, some investors will be concerned about the capital gains tax implications of a mutual fund's trades. Stocks repurchased within 30 days of being sold for a loss, cannot be claimed as a capital loss for tax purchases. For this reason, some fund managers may avoid repurchasing stocks sold for a loss within 30 days of the sale. To test whether these tax considerations explain our results, in a robustness test, we exclude the first quarter after the sale in our analysis. Supplementary Appendix SA23 shows that our main result is not affected if we account for these tax considerations. Generally, capital gains tax considerations should increase fund managers' motivation to sell stocks for a loss and then repurchase these stocks after at least 30 days if they only sell them for tax reasons. Selling stocks for a gain and then repurchasing these stocks within one year would not make tax sense from an investors' point of view, given that short-term capital gains distributions are typically taxed at substantially higher rates than long-term capital gains distributions (Sialm and Zhang (2020)). Thus, mutual funds would reduce the tax burdens of their shareholders by deferring the realization of capital gains, rather than selling stocks for a gain and then repurchasing these stocks in the short run.

3.3.5 Gender difference in the repurchasing bias

In this section, we investigate whether fund manager gender influences the repurchasing bias. It is ex-ante not clear. On the one hand, female managers may be more likely to suffer from the repurchasing bias because women are found to be more emotional and compassionate than man (e.g., Brownmiller (1984) and Farr (1984)). On the other hand, female fund managers need to have superior skills and traits to survive in a male-dominated industry and therefore, they are as likely as male analysts, or even less likely, to suffer from behavioral biases.

We collect data on fund managers' gender based on their first name and define a dummy variable, Female manager$_{i,j,q}$, which is equal to one if there is a female fund manager in the fund management. We run the same regressions as in Table 3.3 and add an interaction term between Loser$_{i,j,q}$ and Female manager$_{i,j,q}$.

Table 3.6 contains the regression results. The coefficient estimates of the interaction terms between Loser and Female manager are negative and statistically significant at the 5% level in the models with stock, fund and time fixed effects. Female analysts are 0.3 pp more likely to repurchase previous loser stocks, which accounts for around 30% of the baseline repurchasing bias. The effect becomes statistically insignificant after adding control variables at the fund level, but the economic level still amounts to 0.2 pp.

Female fund managers are not more emotional than male fund managers and are not more likely to bias against past loser stocks. In the contrary, we find evidence that female fund managers are slightly less likely to suffer from the repurchasing bias.

3.3.6 Price changes since being sold

Strahilevitz et al. (2011) find that retail investors are less likely to repurchase previous winners that have gone up in price since they were sold. Retail repurchases of previous losers are not affected by post-sale returns. To test whether mutual fund managers display similar behavior, we define a dummy variable, Price up$_{i,j,q}$, which is an indicator of whether the price of a stock at the sale is lower than the price of this stock in quarter q. To facilitate a comparison with Strahilevitz et al. (2011)'s result, we define a winner dummy (= 1 - loser) and re-run our main regression with the winner dummy and an interaction term of the winner dummy and Price up$_{i,j,q}$.

Results are presented in Table 3.7. The coefficient on Winner is positive and significant. Thus confirming our baseline results, prior winners are more likely to be repurchased than prior losers. The positive coefficient on Price up, indicates that–for both prior losers and winners–mutual fund managers prefer to repurchase stocks that have gone up since they were sold. This is inconsistent with the behavior of retail investors but consistent with prior findings that fund managers trade on momentum (Grinblatt et al. (1995)). The coefficient on the interaction term Winner$\times$Price up is negative, but lower in magnitude than the coefficient for Price up. This indicates that the importance of post-sale returns is less for Winners than Losers. Put differently, fund managers are least likely to repurchase Losers that have continued to have negative returns after being sold. These results are robust in the sample of ANcerno trading data (see Supplementary Appendix SA24).

3.3.7 Do fund flows influence the repurchasing bias?

Previous literature documents that fund flows influence trading and performance of mutual funds (e.g., Edelen (1999) and Alexander et al. (2006)). Fund managers may have less emotional investment in sales made during a period of outflows (and many other sales). If so, the repurchasing bias will be less for stocks sold during outflows. In contrast, fund managers have more freedom in purchase decisions during periods of inflows and may, as a result, demonstrate stronger repurchasing bias.

In order to examine the effect of fund flows on repurchasing bias, we define two dummy variables. Outflow at sale$_{i,j,q}$ is a dummy variable equal to one if a fund experiences outflows when selling a stock, and zero otherwise. Inflow at purchase$_{i,j,q}$ is a dummy variable equal to one if a fund experiences inflows when making a repurchasing decision, and zero otherwise. We expect that repurchasing bias is smaller if the stock was sold when the fund has net outflows and larger if the repurchasing decision regarding this stock is made when funds need to purchase stocks because of net inflows.

We run the same regressions as in Table 3.3 and add an interaction term between $\text{Loser}_{i,j,q}$ and Outflow at $\text{sale}_{i,j,q}$ (Inflow at $\text{purchase}_{i,j,q}$). Table 3.8 contains the regression results. Consistent with our conjecture, results in Panel A show a less pronounced repurchasing bias after sales at outflows and results in Panel B show a more salient repurchasing bias when funds encounter inflows. The coefficients of the interaction term between $\text{Loser}_{i,j,q}$ and Outflow at $\text{sale}_{i,j,q}$ are positive and statistically significant at the 1% level. Outflows at sale decrease the tendency to avoid previous losers by 20% to 33%, depending on the model specification. By contrast, the coefficients on the interaction term between $\text{Loser}_{i,j,q}$ and Inflow at $\text{purchase}_{i,j,q}$ are negative and statistically significant at the 1% level. Buying pressure from additional inflows thus increases the tendency to avoid previous losers by around 30%.

Among papers examining mutual fund managers' investment behavior, Cici (2012) show that fund managers are more likely to disproportionately sell winners when their fund encounters outflows. While funds tend to demonstrate stronger selling bias (i.e., the disposition effect) when funds encounter outflows, their tendency to avoid repurchasing previous losers is stronger when funds encounter inflows.

3.4 Do fund manager changes influence repurchasing bias?

If a fund's repurchasing bias is due to the fund manager's positive or negative trading experience from selling stocks for a gain or a loss, we would expect a diminished repurchasing bias after a manager change. Furthermore, fund managers who change funds may have a negative association with stocks they sold for a loss at their previous fund and thus avoid purchasing those stocks at the new fund.

To test these hypotheses, we restrict the sample to single managed funds in the following analyses. This allows us to clearly determine the quarter in which a fund's management changes completely. We first examine whether fund manager changes reduce repurchasing bias in a given fund. We define a dummy variable, Manager change$_{i,j,q}$, which is equal to one if a stock was sold before the funds' manager was replaced, but the repurchase decision is made after the new fund manager has taken over. We then re-run our baseline linear probability model from Table 3.3 but additionally include an interaction term between the loser dummy and a dummy variable reflecting a manager change.

Results are presented in Table 3.9. We find that new fund managers are significantly less like to repurchase any previously sold stock than incumbent managers. As a result, repurchasing bias reduces significantly. The coefficient estimates of the interaction term are negative and statistically significant at the 5% level, i.e., new fund managers are 0.3 pp more likely to repurchase previous losers sold by their predecessors than fund managers who remain in charge of the same fund. The increase is about one-third of the baseline repurchasing bias, according to which fund managers are 0.9 pp less likely to repurchase previous losers rather than previous winners.

Nevertheless, previous loser stocks are still 6 pp (0.009-0.003) less likely to be repurchased than previous winner stocks after a manager change. Thus, if new managers decide to repurchase stocks that were previously sold, they are less likely to buy stocks sold for a loss. One possible explanation for this lingering repurchase bias is that the new managers does not want to be observed repeating the (ex-post) mistakes of his predecessor.

In the next step, we analyze whether fund managers who have changed funds are less likely to repurchase stocks they sold for a loss at a previous fund. In this analysis, the sample consists of repurchasing activities and opportunities at the new fund to repurchase stocks previously sold by a fund manager in the fund she managed before. Thus, the repurchase dummy is now defined at the fund manager level.

To account for the fact that single fund managers may be responsible for several funds at the same time and thus sell the same stock through different funds, we calculate previous returns of stocks sold as the average return of the stock across all funds managed by the same single manager. We then run a regression of the repurchasing dummy on the loser dummy and manager fixed effects, time fixed effects, or manager$\times$time fixed effects, after a fund manager has left all funds where she sold a particular stock. The average repurchase rate is 0.9 pp in this sample (untabulated), which is lower than the average repurchase rate 5.3 pp in the main sample. After changing the funds they manage, fund managers are, in general, less likely to repurchase stocks they sold at a previous fund. We, however, focus on the difference in repurchase rates of previous winner and loser stocks relative to the average repurchase rate, in order to measure repurchasing bias.

Fund managers are still 0.3 pp less likely to repurchase previous losers than previous winners, even if they have already left all funds where they sold this particular stock, as shown in Panel A of Table 3.10. All coefficient estimates are statistically significant at the 1% level. The effect amounts to 33% of the average repurchase probability (0.3/0.9). Results are very similar if we restrict the sample to cases where one manager manages only one fund when she sold a particular stock (Panel B of Table 3.10). These results support the view that the repurchasing bias we document is indeed caused by negative (positive) trading experience from previously selling the stock for a loss (gain).

A potential explanation for the repurchasing bias is that mutual funds cater to fund investors' preferences when avoiding previous loser stocks due to clientele effects (Chen et al. (2008), Agarwal et al. (2019) and Clifford et al. (2020)). Since we find that fund managers still have repurchasing bias on stocks they sold in a previous fund (i.e., a fund with different clientele), it is implausible that repurchasing bias is solely driven by fund investors' preferences.

3.5 Is fund managers' repurchasing bias driven by superior information?

In the previous sections, we document that mutual fund managers are less likely to repurchase stocks that they previously sold for a loss (and more likely to repurchase stocks sold for a gain). It is possible that this behavior is driven by superior information rather than behavioral biases. For example, suppose that a fund manager believes that a stock held by the mutual fund for a gain is over-valued and about to drop in price. She could sell this stock and, possibly, buy it back later at a lower price. If her information is superior, the stock will underperform the mutual fund after it is sold and outperform after it is repurchased. To test whether this information-based pattern leads to our results we examine whether, indeed, managers repurchase winner stocks that dropped in price after they were sold. We also look at whether repurchased winners subsequently outperform the fund. For brevity, we only report the results by calculating stock returns based on the first-in-first-out principle since results are very similar if we use the average purchase price instead. In order to construct and compare calender time portfolios of repurchased winners, repurchased losers, and funds, the sample in this section includes funds that repurchase both previous winner stocks and loser stocks in the same quarter.

Table 3.11 shows the performance of repurchased winners, repurchased losers, and funds that sell and repurchase these stocks between sale and repurchase. We form portfolios with repurchased winner stocks and repurchased loser stocks in each mutual fund portfolio in the months between the previous sale and the repurchase of the stock. We first compute the trade-value-weighted average monthly returns of the repurchased winners or repurchased losers in the fund portfolio in these months. Then we calculate the returns of calendar time portfolios as the equal-weighted average across funds. Fund performance is calculated by equally weighting the returns and risk-adjusted returns of the mutual funds selling and repurchasing stocks in the same month.

Repurchased winners outperform mutual funds that make the selling and repurchasing decisions by about 8 pp per year during the period after the sale and before the repurchase, no matter whether we use the raw portfolio returns or portfolio alphas under CAPM, Fama-French-three-factor, and Carhart-four-factor models.[12] The differences are statistically significant at the 1% level. This is not consistent with the information advantage explanation in which managers sell winners that they anticipate to repurchase at a lower price. By contrast, previous loser stocks underperform the funds after the sale and before the repurchase. Between the sale and repurchase, repurchase winners outperform repurchased losers by around 10 pp per year. We are not claiming that the fund managers make poor selling decisions–that claim would require a different analysis. Rather we show that managers do not appear to be implementing a successful strategy of selling stocks in anticipation of a drop in price and subsequently repurchasing them.

[12]The risk factors to compute monthly alphas are obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We also examine the performance of repurchased winner stocks after the repurchase. Table 3.12 shows calendar time portfolio returns and risk-adjusted returns of previous winner stocks, previous loser stocks, funds that sell and repurchase these stocks, and other stocks purchased by the funds in the quarter after the repurchase. We form portfolios with repurchased winner stocks and repurchased loser stocks in each mutual fund portfolio in the quarter after the repurchase if the stock is still in the fund's portfolio. The portfolio returns of the repurchased winners or repurchased losers are calculated as the trade-value-weighted average of monthly returns across stocks which we then equally-weighted across all funds. The portfolio of new purchases consists of other stocks purchased by the fund in the same time period (excluding repurchased stocks). The portfolio is also trade-value-weighted across stocks in a fund and then equally-weighted across funds.

Repurchased winner stocks subsequently underperform repurchased loser stocks by around 4 pp per year, but the difference is statistically significant at the 10% level only if the Carhart four factor alpha is used as the performance measure. The returns of repurchased winners are also lower than returns of funds that sell and repurchase these stocks and stocks that are newly purchased, but the differences are not statistically significant. Given that repurchased loser stocks outperform the fund and the repurchased winner stocks after the repurchase, we conclude that the tendency to repurchase previous winners rather than previous losers is not due to information advantage.

3.6 Conclusion of Chapter 3

This paper provides the first evidence that mutual fund managers are biased against repurchasing stocks that they previously sold for a loss rather than for a gain. The results are robust in samples based on both mutual fund quarterly holding data and ANcerno daily institutional trading data. We conjecture that this behavior is driven by fund managers avoiding repeating behavior that previously led to a bad outcome. Even if fund managers leave the fund where they sold a particular stock for a loss, they are still less likely to repurchase this stock when managing a new fund.

We do not find that mutual fund managers are biased towards repurchasing past winner stocks because of superior information. Repurchased stocks do not underperform the fund between being sold and repurchased. And repurchased winners do not outperform repurchased losers (or the fund) after the repurchase.

Repurchasing bias is an emotion-based bias that leads managers to avoid stocks previously sold for a loss. Our results show that emotion-based biases are strong enough to impact the behavior of sophisticated investors such as mutual fund managers.

Figure 3.1: Average returns of stocks that are (not) repurchased

This figure plots average returns at the time of sale of stocks that are sold and repurchased (yellow bars), or sold but not repurchased (blue bars). A stock is defined as repurchased if it has been sold completely and then is repurchased by the same fund within one year. Returns are computed by either the first-in-first-out principle (FIFO), or by using the trade-value-weighted average of all purchase prices of a stock (AVG).

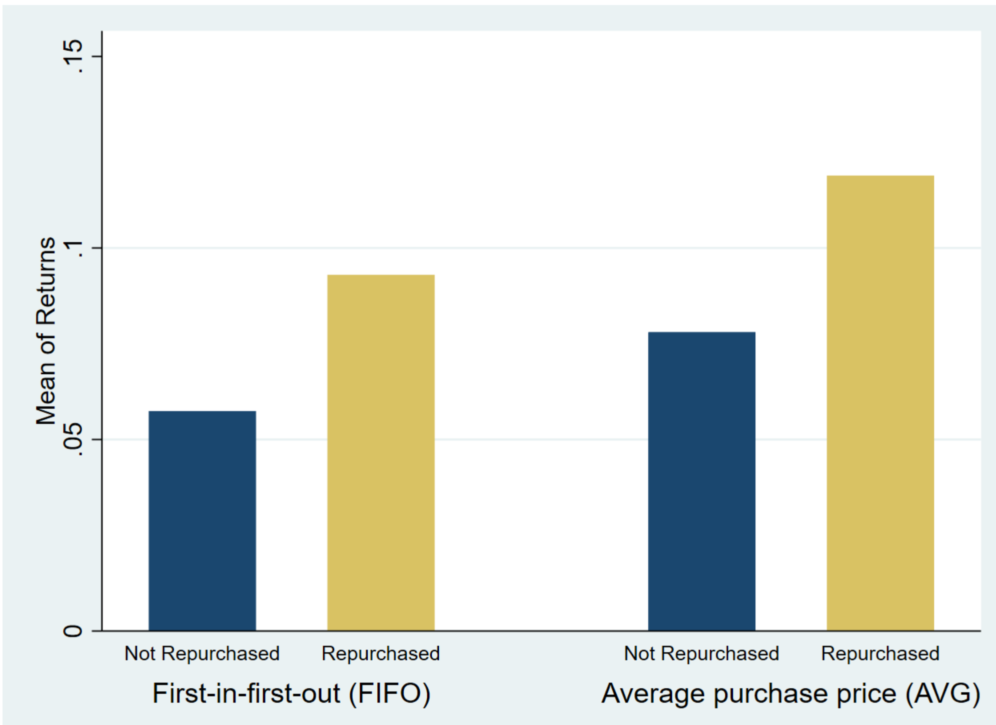
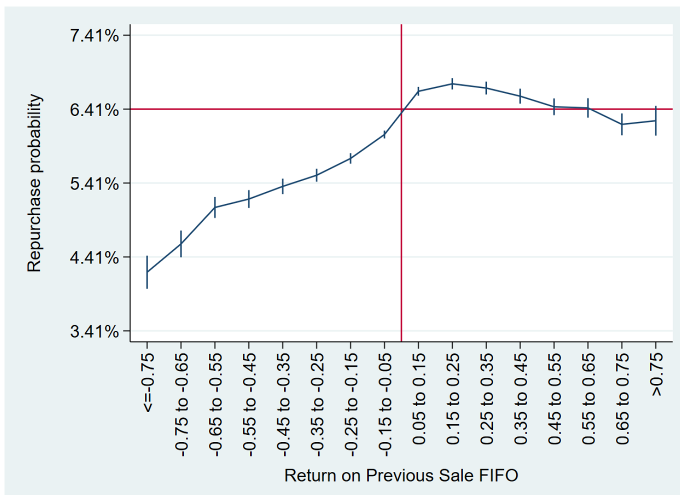


Figure 3.2: Repurchasing probability conditional on past stock returns

This figure plots the probability that a stock is repurchased for different intervals of past stock returns. The probability to repurchase a stock is estimated from a linear probability model with stock, fund, and time fixed effects. Return intervals are in percentage points. The red vertical line indicates the probability to repurchase a stock that was previously sold at a zero return. Returns are computed by either the first-in-first-out principle (FIFO), or by using the trade-value-weighted average of all purchase prices of a stock (AVG). Blue vertical lines indicate 95% confidence intervals. The standard errors are clustered by fund.



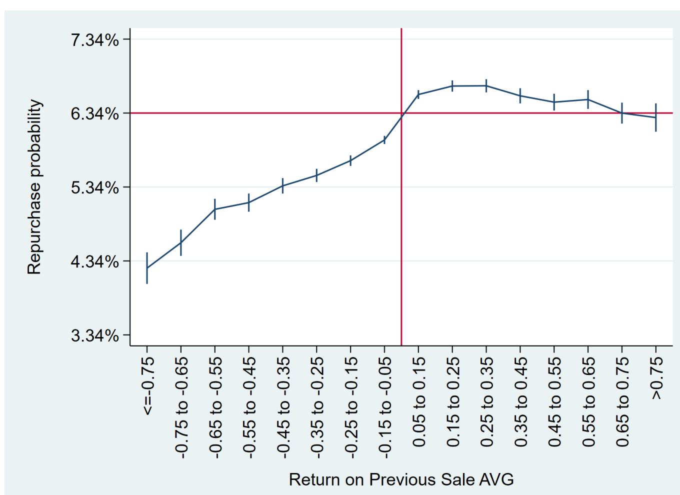


Table 3.1: Summary statistics of Chapter 3 and univariate differences

Panel A of this table shows descriptive statistics of all variables in our sample of stocks sold completely at least once by a U.S actively managed equity fund. The sample runs from January 1980 to December 2019. The number of observations, means, medians, and standard deviations (Std. Dev.) are reported in columns (1) to (4). A detailed description of all variables is provided in Appendix 3.6. Panel B shows the mean comparison of stocks repurchased, stocks not repurchased, and of characteristics of the funds repurchasing or not repurchasing these stocks. Panel C shows the mean comparison of stocks previously sold for a gain, stocks previously sold for a loss (defined by LoserFIFO), and of characteristics of the funds previously selling winner or loser stocks. Significance based on a regression of the variable on Repurchase (Panel B) or LoserFIFO (Panel C) is reported in column (4). The standard errors are clustered by fund and time.

Panel A: Descriptive statistics				
	Observations (1)	Mean (2)	Median (3)	Std. Dev. (4)
Variables on the stock-fund-quarter level				
Repurchase	11,200,456	0.053	0	0.224
Repurchase^{ANcerno}	3,363,321	0.047	0	0.211
LoserFIFO	10,859,007	0.493	1	0.500
LoserAVG	10,864,057	0.487	1	0.500
LoserFIFO^{ANcerno}	3,363,321	0.509	0	0.500
LoserAVG^{ANcerno}	3,363,321	0.514	0	0.500
Variables on the fund-quarter level				
Fund size	224,539	5.548	5.480	1.789
Fund age	231,972	14.310	10.833	12.667
Turnover Rrtio	222,084	0.887	0.630	1.227
Expense ratio	225,243	0.013	0.012	0.005
Return volatility	220,277	0.163	0.144	0.136
Performance rank	234,213	0.523	0.532	0.283

Table 3.1: Summary statistics of Chapter 3 and univariate differences (continued)

Panel B: Repurchased VS Not repurchased				
	Repurchased	Not repurchased	Difference	*t*-statistic
	(1)	(2)	(3)	(4)
LoserFIFO	0.442	0.496	-0.054	-7.61
LoserAVG	0.432	0.490	-0.058	-8.26
LoserFIFO^{ANcerno}	0.467	0.511	-0.044	-14.68
LoserAVG^{ANcerno}	0.465	0.516	-0.051	-16.73
Fund size	5.862	5.714	0.148	4.98
Fund age	13.337	13.636	-0.298	-1.42
Turnover ratio	1.498	1.225	0.273	4.69
Expense ratio	0.012	0.013	-0.001	-2.41
Return volatility	0.163	0.170	-0.007	-3.39
Performance ranking	0.514	0.521	-0.007	-1.81

Panel C: Previous winners VS previous losers				
	Previously sold for gain	Previously sold for loss	Difference	*t*-statistic
	(1)	(2)	(3)	(4)
Repurchase	0.059	0.048	0.011	7.94
Repurchase^{ANcerno}	0.044	0.037	0.007	15.43
Fund size	5.802	5.684	0.118	6.02
Fund age	14.049	13.360	0.690	5.93
Turnover ratio	1.211	1.261	-0.050	-3.67
Expense ratio	0.012	0.013	-0.001	-4.69
Return Volatility	0.155	0.185	-0.030	-7.17
Performance Ranking	0.532	0.509	0.022	4.81

Table 3.2: Univariate tests of repurchasing bias

This table presents the difference between the proportion of winners repurchased (PWR) and the proportion of losers repurchased (PLR) aggregated over the sample period. PWR (PLR) is the ratio between NWR (NLR) and ORW (OLR). NWR (NLR) and ORW (OLR) reflect the number of winners (losers) repurchased, and the number of opportunities to repurchase winners (losers). All variables are defined in detail in Appendix 3.6. In column (1), winner stocks are defined based on the first-in-first-out principle (FIFO). In column (2), winner stocks are defined using the trade-value-weighted average of all purchase prices of a stock (AVG). We assume that realized repurchases are independent observations when computing standard errors.

	FIFO (1)	AVG (2)
No. of winners repurchased (NWR)	322,877	328,960
Opportunities to repurchase winners (ORW)	5,503,345	5,577,453
Proportion of winners repurchased (PWR)	0.059	0.059
No. of losers repurchased (NLR)	256,088	250,319
Opportunities to repurchase losers (ORL)	5,355,662	5,286,604
Proportion of losers repurchased (PLR)	0.048	0.047
Diff (PWR-PLR)	0.011	0.012
t-stat (PWR=PLR)	(18.26)	(19.52)

Table 3.3: Repurchasing bias in a multivariate regression framework

This table contains results of linear probability regressions. The dependent variable is Repurchase, a dummy variable equal to one if a stock is repurchased by the same fund within one year after it was sold, and zero otherwise. The main independent variable, Loser, is equal to one if a stock was sold for a loss, and zero otherwise. The loser dummy is based on the difference between selling price and average purchase price. The average purchase price is calculated either following the first-in-first-out principle (columns (1) to (3)), or by taking the trade-value-weighted average of all purchase prices before the sale (columns (4) to (6)). All variables are defined in detail in Appendix 3.6. Columns (1), (2), (4) and (5) include stock, fund, and time fixed effects. Columns (3) and (6) include stock and fund×time fixed effects. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)			Average purchase price (AVG)		
	(1)	(2)	(3)	(4)	(5)	(6)
Loser	-0.008***	-0.008***	-0.009***	-0.009***	-0.009***	-0.009***
	(-24.31)	(-22.75)	(-31.15)	(-25.63)	(-23.96)	(-32.31)
Fund size		0.003***			0.003***	
		(3.87)			(3.85)	
Fund age		-0.000			-0.000	
		(-0.08)			(-0.07)	
Turnover ratio		0.009***			0.009***	
		(9.59)			(9.59)	
Expense ratio		-0.038			-0.039	
		(-0.14)			(-0.14)	
Return volatility		-0.000			-0.000	
		(-0.17)			(-0.19)	
Performance rank		-0.003**			-0.003**	
		(-2.42)			(-2.45)	
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	No	Yes	Yes	No
Fund×Time FE	No	No	Yes	No	No	Yes
Observations	10,858,603	9,019,700	10,844,552	10,863,653	9,023,951	10,849,601
Adjusted R^2	0.036	0.038	0.104	0.036	0.038	0.104

Table 3.4: Repurchasing bias - Evidence from ANcerno daily trading data

This table contains results of linear probability regressions in the ANcerno sample. We include all sales that clear the current positions accumulated from purchases and observe whether the stock is purchased again by the same fund in one year after the sale. The dependent variable is Repurchase^{ANcerno}, a dummy variable equal to one if a stock is repurchased by the same fund in a given quarter within one year after it was sold, and zero otherwise. The main independent variable, Loser^{ANcerno}, is equal to one if a stock was sold for a loss, and zero otherwise. The loser dummy is based on the difference between selling price and average purchase price. The exact trading prices from the ANcerno trading data are used. The average purchase price is calculated either following the first-in-first-out principle (columns (1) to (3)), or by taking the trade-value-weighted average of all purchase prices before the sale (columns (4) to (6)). All variables are defined in detail in Appendix 3.6. t-statistics are provided in parentheses. Standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)		Average purchase price (AVG)	
	(1)	(2)	(3)	(4)
Loser^{ANcerno}	-0.003***	-0.003***	-0.005***	-0.005***
	(-7.16)	(-7.97)	(-10.23)	(-12.53)
Fund FE	Yes	No	Yes	No
Stock FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No
Fund$\times$Time FE	No	Yes	No	Yes
Observations	3,363,301	3,361,128	3,363,301	3,361,128
Adjusted R^2	0.065	0.104	0.065	0.104

Table 3.5: Repurchasing bias controlling for time-varying stock characteristics

This table contains the results of a linear probability model with stock×time fixed effects. The sample is restricted to previous gains above 0.15 and previous losses below -0.15. The dependent variable is Repurchase, a dummy variable equal to one if a stock is repurchased by the same fund within one year after it was sold, and zero otherwise. The main independent variable, Loser, is equal to one if a stock was sold for a loss, and zero otherwise. The loser dummy is based on the difference between selling price and average purchase price. The average purchase price is calculated either following the first-in-first-out principle (columns (1) to (3)), or by taking the trade-value-weighted average of all purchase prices before the sale (columns (4) to (6)). All variables are described in detail in Appendix 3.6. In columns (1), (2), (4) and (5), fund and stock×time fixed effects are included. Columns (3) and (6) include fund×time and stock×time fixed effects. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)			Average purchase price (AVG)		
	(1)	(2)	(3)	(4)	(5)	(6)
Loser	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.002***
	(-3.49)	(-3.79)	(-4.93)	(-4.50)	(-4.88)	(-5.98)
Fund size		0.003***			0.003***	
		(3.59)			(3.54)	
Fund age		-0.000			-0.000	
		(-0.65)			(-0.79)	
Turnover ratio		0.009***			0.009***	
		(9.41)			(9.38)	
Expense ratio		-0.075			-0.069	
		(-0.29)			(-0.26)	
Return volatility		0.000			0.000	
		(0.07)			(0.15)	
Performance rank		-0.002*			-0.002*	
		(-1.90)			(-1.93)	
Fund fixed effects	Yes	Yes	No	Yes	Yes	No
Stock×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund×Time FE	No	No	Yes	No	No	Yes
Observations	6,502,795	5,427,280	6,486,139	6,367,633	5,312,333	6,350,764
Adjusted R^2	0.066	0.068	0.133	0.066	0.068	0.133

Table 3.6: Repurchasing bias and fund manager gender

This table contains results of linear probability regressions. The dependent variable is Repurchase, a dummy variable equal to one if a stock is repurchased by the same fund within one year after it was sold, and zero otherwise. The main independent variable, Loser, is equal to one if a stock was sold for a loss, and zero otherwise. The loser dummy is based on the difference between selling price and average purchase price. The average purchase price is calculated either following the first-in-first-out principle (columns (1) to (2)), or by taking the trade-value-weighted average of all purchase prices before the sale (columns (3) to (4)). Female manager indicates whether there is any female manager in the fund management. All variables are defined in detail in Appendix 3.6. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)		Average purchase price (AVG)	
	(1)	(2)	(3)	(4)
Loser × Female manager	0.003**	0.002	0.003**	0.002
	(2.23)	(1.62)	(2.21)	(1.60)
Loser	-0.010***	-0.010***	-0.010***	-0.010***
	(-15.37)	(-14.74)	(-15.97)	(-15.31)
Female manager	0.004*	0.005***	0.004*	0.005***
	(1.84)	(2.62)	(1.84)	(2.63)
Fund size		0.003***		0.003***
		(4.02)		(4.01)
Fund age		-0.000		-0.000
		(-1.26)		(-1.27)
Turnover ratio		0.013***		0.013***
		(8.57)		(8.59)
Expense ratio		-0.574		-0.572
		(-1.31)		(-1.31)
Return volatility		0.001		0.001
		(0.35)		(0.35)
Performance rank		-0.003*		-0.003*
		(-1.82)		(-1.82)
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	3,760,980	3,511,906	3,761,739	3,512,577
Adjusted R^2	0.033	0.033	0.033	0.033

Table 3.7: Repurchasing bias conditional on subsequent price changes

This table contains the results of linear probability regressions. The dependent variable is Repurchase, a dummy variable equal to one if a stock is repurchased by the same fund within one year after it was sold, and zero otherwise. Price up is equal to one if the price of a stock has increased since it was sold, and zero otherwise. Winner is equal to one if a stock was sold for a gain, and zero otherwise, i.e., 1-Loser. The winner dummy is based on the difference between selling price and average purchase price. The average purchase price is calculated either following the first-in-first-out principle (FIFO) or by taking the trade-value-weighted average of all purchase prices before the sale (AVG). All variables are defined in detail in Appendix 3.6. Columns (1), (2), (4) and (5) include stock, fund, and time fixed effects. Columns (3) and (6) include stock and fund×time fixed effects. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)			Average purchase price (AVG)		
	(1)	(2)	(3)	(4)	(5)	(6)
Winner× Price up	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-23.38)	(-22.17)	(-25.79)	(-22.31)	(-21.05)	(-24.48)
Winner	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(38.33)	(37.27)	(46.44)	(38.67)	(37.56)	(46.43)
Price up	0.019***	0.020***	0.020***	0.019***	0.020***	0.020***
	(38.96)	(37.08)	(41.18)	(39.20)	(37.30)	(41.51)
Fund size		0.003***			0.003***	
		(3.82)			(3.79)	
Fund age		0.000			0.000	
		(0.01)			(0.01)	
Turnover ratio		0.009***			0.009***	
		(9.45)			(9.45)	
Expense ratio		-0.038			-0.039	
		(-0.14)			(-0.14)	
Return volatility		-0.000			-0.000	
		(-0.12)			(-0.14)	
Performance rank		-0.003**			-0.003***	
		(-2.56)			(-2.58)	
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	No	Yes	Yes	No
Fund×Time FE	No	No	Yes	No	No	Yes
Observations	10,063,617	8,440,503	10,049,015	10,068,082	8,444,335	10,053,479
Adjusted R^2	0.037	0.039	0.106	0.037	0.039	0.106

Table 3.8: Repurchasing bias conditional on fund flows

This table contains the results of linear probability regressions. The dependent variable is Repurchase, a dummy variable equal to one if a stock is repurchased by the same fund within one year after it was sold, and zero otherwise. Outflow at sale is a dummy variable equal to one if fund flows in the quarter of selling the stock is negative. Inflow at purchase is a dummy variable equal to one if fund flows in the quarter of repurchsing the stock is positive. Loser is equal to one if a stock was sold for a loss, and zero otherwise. The loser dummy is defined either following the first-in-first-out principle (FIFO) or by taking the trade-value-weighted average of all purchase prices before the sale (AVG). *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)			Average purchase price (AVG)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Flows at the time of sale						
Loser× Outflow at sale	0.003***	0.003***	0.002***	0.002***	0.003***	0.002***
	(3.34)	(4.17)	(4.32)	(3.12)	(3.85)	(3.85)
Loser	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-15.65)	(-16.28)	(-22.77)	(-16.04)	(-16.68)	(-23.39)
Outflow sale	-0.002*	-0.000	0.002***	-0.002*	-0.000	0.002***
	(-1.90)	(-0.36)	(4.95)	(-1.95)	(-0.45)	(4.75)
Observations	9,374,640	8,745,614	9,363,920	9,378,660	8,749,424	9,367,937
Adjusted R^2	0.037	0.039	0.105	0.037	0.039	0.105
Panel B: Flows at the time of repurchase						
Loser× Inflow at purchase	-0.003***	-0.003***	-0.002***	-0.003***	-0.003***	-0.002***
	(-3.92)	(-4.31)	(-4.32)	(-3.84)	(-4.12)	(-4.21)
Loser	-0.007***	-0.007***	-0.008***	-0.007***	-0.008***	-0.008***
	(-16.47)	(-18.10)	(-22.77)	(-17.75)	(-19.58)	(-23.63)
Inflow at purchase	0.001	0.001		0.001	0.001	
	(1.49)	(0.81)		(1.50)	(0.86)	
Observations	9,533,327	8,975,303	9,521,879	9,537,744	8,979,529	9,526,289
Adjusted R^2	0.037	0.038	0.104	0.038	0.038	0.104
Fund controls	No	Yes	No	No	Yes	No
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	No	Yes	Yes	No
Fund×Time FE	No	No	Yes	No	No	Yes

Table 3.9: Fund manager changes between sale and repurchase

This table contains the results of linear probability regressions. The sample is restricted to single-managed funds. The dependent variable is Repurchase, a dummy variable equal to one if a stock is repurchased by the same fund within one year after it was sold, and zero otherwise. Manager change is equal to one if the fund manager of a fund changes between the sale and the repurchase decision of a stock, and zero otherwise. Loser is equal to one if a stock was sold for a loss, and zero otherwise. The loser dummy is based on the difference between selling price and average purchase price. The average purchase price is calculated either following the first-in-first-out principle (FIFO) or by taking the trade-value-weighted average of all purchase prices before the sale (AVG). All variables are defined in detail in Appendix 3.6. All models include stock, fund, and time fixed effects. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)		Average purchase price (AVG)	
	(1)	(2)	(3)	(4)
Loser $\times$ Manager change	0.003**	0.003**	0.003**	0.003**
	(2.19)	(2.29)	(2.20)	(2.27)
Manager change	-0.010***	-0.010***	-0.010***	-0.010***
	(-8.38)	(-7.59)	(-8.25)	(-7.52)
Loser	-0.009***	-0.009***	-0.010***	-0.010***
	(-17.89)	(-17.26)	(-18.26)	(-17.80)
Control variables	No	Yes	No	Yes
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	2,997,498	2,756,139	2,999,082	2,757,529
Adjusted R^2	0.033	0.034	0.033	0.034

Table 3.10: Repurchasing bias at the fund manager level

This table presents results from linear probability regressions at the fund manager level. The sample is restricted to single-managed funds and cases where fund managers switch to another fund after selling a stock, but before making a repurchase decision. In Panel A, loser stocks are defined based on the average return of a stock across all funds through which a manager previously sold the stock. Panel B includes only cases where a fund manager was in charge of just one single-managed fund when they sold the stock. Columns (1) and (3) include manager and time fixed effects, and columns (2) and (4) include manager×time fixed effects. *t*-statistics are provided in parentheses. Standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)		Average purchase price (AVG)	
	(1)	(2)	(3)	(4)
Panel A: Single-managed funds				
Loser	-0.0034***	-0.0031***	-0.0036***	-0.0034***
	(-4.74)	(-4.93)	(-4.73)	(-4.97)
Observations	153,870	153,613	153,925	153,667
Adjusted R^2	0.075	0.174	0.075	0.174
Panel B: Single-managed funds and only managers in charge of one fund				
Loser	-0.0031***	-0.0028***	-0.0032***	-0.0030***
	(-4.38)	(-4.44)	(-4.29)	(-4.42)
Observations	138,790	138,513	138,842	138,564
Adjusted R^2	0.085	0.179	0.085	0.179
Manager FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Manager×Time FE	No	Yes	No	Yes

Table 3.11: How do winner and loser stocks perform between sale and repurchase?

This table contains calendar time portfolio returns and risk-adjusted returns between sale and repurchase of stocks sold for a gain or a loss and repurchased and funds that sell and repurchase these stocks. The sample includes funds that repurchase both previous winner stocks and loser stocks in the same quarter. Repurchased winners (losers) are stocks that are repurchased within one year after the sale with a gain (loss). Winner and loser stocks are defined based on the first-in-first-out principle. We form portfolios with repurchased winner stocks and repurchased loser stocks in each mutual fund portfolio in the months between the previous sale and the repurchase of the stock. Monthly returns of the repurchased winners or repurchased losers in the fund portfolio are weighted by the fund's dollar holdings. We compute calendar time portfolios of repurchased winners and repurchased losers by taking the equal-weighted average across funds. The fund portfolio performance is calculated by equal-weighting the returns and risk-adjusted returns of the mutual funds selling and repurchasing the repurchased stocks. We compare performance during the same time period between the portfolio of repurchased winners (losers) and funds. The difference is tested against zero. Returns are expressed in annual percentages.

	Return (1)	CAPMα (2)	FF3α (3)	Carhart4α (4)
Winner	20.36%	8.80%	8.64%	8.55%
Loser	8.85%	-3.96%	-4.99%	-0.80%
Fund	11.30%	0.45%	0.54%	0.20%
Winner-Fund	9.06%	8.36%	8.10%	8.35%
t-statistics	(8.99)	(8.52)	(8.20)	(8.47)
Loser-Fund	-2.45%	-4.40%	-5.52%	-1.00%
t-statistics	(-1.21)	(-2.31)	(-2.90)	(-0.64)
Winners-Losers	11.50%	12.76%	13.62%	9.35%
t-statistic	(6.30)	(7.17)	(7.60)	(6.73)

Table 3.12: Performance of repurchased winner and loser stocks after the repurchase

This table contains calendar time portfolio returns and risk-adjusted returns in the quarter after the repurchase of previous winner stocks, previous loser stocks, funds that sell and repurchase these stocks, and other stocks purchased by the funds. Winner and loser stocks are defined based on the first-in-first-out principle. We form portfolios with repurchased winner stocks and repurchased loser stocks in each mutual fund portfolio in the quarter after the repurchase if the stock is still in the fund's portfolio. Monthly returns of the repurchased winners or repurchased losers in the fund portfolio are weighted by the fund's dollar holdings. We compute calendar time portfolios of repurchased winners and repurchased losers by taking the equal-weighted average across funds. The fund portfolio performance is calculated by equal-weighting the returns and risk-adjusted returns of the mutual funds selling and repurchasing the repurchased stocks. The new purchase portfolio consists of other stocks purchased by the funds (not repurchased stocks). The portfolio is also trade-value-weighted across stocks in a fund and equal-weighted across funds. We compare performance during the same time period between the portfolio of repurchased winners (losers), funds, and other stocks purchased by the funds. The difference is tested against zero. Returns are expressed in annual percentages.

	Return (1)	CAPMα (2)	FF3α (3)	Carhart4α (4)
Winner	11.40%	-0.38%	-0.80%	-0.57%
Loser	15.91%	3.42%	2.39%	4.31%
New purchase	11.79%	-0.43%	-0.93%	-0.62%
Fund	12.08%	1.03%	0.96%	0.64%
Winner-Fund	-0.68%	-1.41%	-1.76%	-1.21%
t-statistics	(-0.38)	(-0.79)	(-1.00)	(-0.68)
Loser-Fund	3.83%	2.39%	1.43%	3.67%
t-statistics	(1.67)	(1.06)	(0.65)	(1.74)
Winner-New purchase	-0.39%	0.05%	0.13%	0.05%
t-statistics	(-0.22)	(0.03)	(0.07)	(0.03)
Loser-New purchase	4.12%	3.85%	3.32%	4.93%
t-statistics	(1.73)	(1.62)	(1.41)	(2.13)
Winner-Loser	-4.51%	-3.80%	-3.19%	-4.88%
t-statistics	(-1.56)	(-1.32)	(-1.12)	(-1.73)
New purchase-Fund	-0.29%	-1.46%	-1.89%	-1.26%
t-statistics	(-0.21)	(-1.07)	(-1.41)	(-0.95)

Appendix

A3.1 Variable description of Chapter 3

This table contains a description of all variables used in our empirical analyses. Data sources are as follows:

1. TR Holdings: Thomson Reuters Mutual Funds Holdings Database
2. ANcerno: ANcerno Institutional Trading Database
3. CRSP Stock: CRSP U.S. Stock Database
4. CRSP Fund: CRSP Survivorship-Bias-Free Mutual Fund Database
5. MS Fund: Morningstar Direct
6. FF: Data Library on Kenneth French's website
7. MC: Variable is manually constructed by the authors.

Variable name	Description	Data source
CAPMα	The intercept from 36-month rolling regressions of excess fund returns on the market excess return (the S&P 500 return minus the risk-free rate).	CRSP Fund, CRSP stock, FF, MC
Carhart4α	The intercept from fund-by-fund 36-month rolling regressions of excess fund returns on the market excess return (the S&P 500 return minus the risk-free rate), SMB (small-minus-big) factor, HML (high-minus-low) factor, and momemtum factor (Carhart (1997)).	CRSP Fund, CRSP stock, FF, MC
Expense ratio$_{i,q}$	Annual expense ratio of a fund.	CRSP Fund

Variable name	Description	Data source
Fund age$_{i,q}$	Fund age in quarter q.	CRSP Fund
FF3α	The intercept from fund-by-fund 36-month rolling regressions of excess fund returns on the market excess return (the S&P 500 return minus the risk-free rate), SMB (small-minus-big) factor, and HML (high-minus-low) factor (Fama and French (1993)).	CRSP Fund, CRSP stock, FF, MC
Fund size$_{i,q}$	Logarithm of the total net assets of fund i in million dollars in quarter q.	CRSP Fund
Inflow at purchase$_{i,q}$	Dummy variable equal to one if fund flows in the quarter of repurchsing the stock is positive, and zero otherwise.	CRSP Fund
Manager change$_{i,j,q}$	Dummy variable equal to one if stock j was sold by fund i before a manager change and a repurchase decision is made after the manager change in fund i, and zero otherwise.	MS Fund, TR Holdings, MC
NWR (NLR)	No. of winners (losers) repurchased accumulated across the sample.	CRSP Stock, TR Holdings, MC

Variable name	Description	Data source
$\text{Loser}_{i,j,q}$	Dummy variable equal to one if the stock j was sold by fund i for a loss before quarter q, and zero otherwise. It compares the selling price of the stock and the average purchase price. The average purchase price is calculated either following the first-in-first-out (FIFO) principle or taking the trade-value-weighted average of all purchase prices before the sale (AVG). In Supplementary Appendix SA19, the average purchase price is calculated based on the low-in-first-out, high-in-first-out and last-in-first-out principles, or based on the returns of a stock in the last holding period.	CRSP Stock, TR Holdings, MC
$\text{Loser}_{i,j,q}^{ANcerno}$	Dummy variable equal to one if the stock j was sold by fund i for a loss before quarter q, and zero otherwise. It compares the selling price of the stock and the average purchase price. The average purchase price is calculated either following the first-in-first-out (FIFO) principle or taking the trade-value-weighted average of all purchase prices before the sale (AVG). The returns for each sale are based on the exact purchasing and selling price from the ANcerno trading data.	ANcerno, MC

Variable name	Description	Data source
ORW (ORL)	No. of opportunities to repurchase winners (losers) accumulated across the sample.	CRSP Stock, TR Holdings, MC
Outflow at sale$_{i,q}$	Dummy variable equal to one if fund flows in the quarter of selling the stock is negative, and zero otherwise.	CRSP Fund
Performance rank$_{i,q}$	Rank of annual returns of all funds within the same CRSP objective code. First, annual accumulated monthly returns of all funds belonging to the same investment objective are ranked. In the next step, we scale the rank by the total number of funds in the investment objective. The performance rank ranges from 0 to 1.	CRSP Fund
Price up$_{i,j,q}$	Dummy variable equal to one if the price of stock j has increased in quarter q compared to the price when it was completely sold by fund i, and zero otherwise.	CRSP Stock, TR Holdings, MC
Return volatility$_{i,q}$	Annualized standard deviation of monthly fund returns in the preceding 12 months (e.g., Sirri and Tufano (1998)).	CRSP Fund
Turnover ratio$_{i,q}$	Fund i's annual turnover ratio.	CRSP Fund

Variable name	Description	Data source
Price up$_{i,j,q}^{ANcerno}$	Dummy variable equal to one if the price of stock j has increased in quarter q compared to the price when it was completely sold by fund i, and zero otherwise. The selling and repurchasing prices of a repurchased stock are based on the exact selling and purchasing price from the ANcerno trading data.	ANcerno, MC
PWR (PLR)	Proportion of winners (losers) repurchased accumulated across the sample.	CRSP Stock, TR Holdings, MC
Repurchase$_{i,j,q}$	Dummy variable equal to one if stock j sold by fund i is repurchased in quarter q within one year after the sale, and zero otherwise.	TR Holdings, MC
Repurchase$_{i,j,q}^{ANcerno}$	Dummy variable equal to one if stock j sold by fund i is repurchased in quarter q within one year after the sale, and zero otherwise. The difference from the main sample is that we can observe the repurchasing behavior in the same quarter of the sale in the ANcerno sample.	ANcerno, MC
Return	Annualized return of a portfolio.	CRSP Fund, CRSP stock

A3.2 Funds and stocks with highest repurchasing activity

This table lists the top 20 funds that repurchase most stocks (Panel A) and the top 20 stocks that are most frequently repurchased (Panel B). In Panel A, No. of repurchases is the number of times that a fund repurchases stocks within one year after the sale (of the fund's entire position in the stock), and No. of sales is the number of sales of a fund across the whole sample period from 1980 to 2019. Repurchase rate is equal to No. of repurchases divided by No. of sales. In Panel B, No. of repurchases is the number of times a stock is repurchased and No. of sales is the number of sales of a stock across the whole sample period from 1980 to 2019. Repurchase rate is equal to No. of repurchases divided by No. of sales.

Panel A: Funds with highest repurchasing activity			
Fund name	No. of repurchases	No. of sales	Repurchase rate
Invesco Exchange Fund	41	50	82.0%
Credit Suisse Warburg Pincus Value II Fund	28	54	51.9%
Union Investors Value Momentum	7	15	46.7%
Smith Barney Utility Portfolio	30	74	40.5%
Riverfront Long-Term Growth & Income Fund	8	20	40.0%
Brown Capital Management Small Company Fund	40	101	39.6%
Alliancebernstein Retirement Strategy	867	2204	39.3%
Smith Barney Appreciation Fund	66	175	37.7%
Wilmington Multi-Manager Small-Cap Fund	723	1932	37.4%
Jackson National Growth Fund	164	439	37.4%
Wasatch Strategic Income Fund	21	58	36.2%
AXA Franklin Small Cap Value Core Portfolio	1673	4630	36.1%
Hartford LargeCap Growth Fund	26	73	35.6%
U.S. All American Equity	50	144	34.7%
Lexington Corporate Leaders Trust Fund	12	35	34.3%
Gamerica Capital Fund	29	85	34.1%
Lifetime Achievement Fund	4	12	33.3%
Frankiln Small Cap Value Portfolio	6	18	33.3%
Marsico Focus Portfolio	10	30	33.3%
Colonial Natural Resources Fund	5	15	33.3%

A3.2 Funds and stocks with highest repurchasing activity cont'd

Panel B: Stocks most frequently repurchased

Stock name	No. of repurchases	No. of sales	Repurchase rate
Intel Corp.	2117	16925	12.5%
Pfizer Inc.	1752	14186	12.4%
Microsoft Corp.	1647	12141	13.6%
Cisco Systems Inc.	1636	13027	12.6%
Oracle Systems Corp.	1627	14087	11.5%
International Business Machs Corp.	1596	15597	10.2%
Qualcomm Inc.	1559	13034	12.0%
Texas Instruments Inc.	1540	14907	10.3%
Gilead Sciences Inc.	1429	10831	13.2%
Amgen Inc.	1420	13527	10.5%
General Electric Co.	1388	13310	10.4%
Johnson & Johnson	1365	14011	9.7%
Apple Computer Inc.	1300	11700	11.1%
Procter & Gamble Co.	1271	12361	10.3%
Hewlett Packard Co.	1266	15057	8.4%
Applied Materials Inc.	1264	14587	8.7%
Halliburton Company	1257	14522	8.7%
E M C Corp.	1218	13132	9.3%
Disney Walt Productions	1205	13719	8.8%
Goldman Sachs Group Inc.	1192	10560	11.3%

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Supplementary Appendix: Locked-in at Home: Female Analysts' Attention at Work during the COVID-19 Pandemic

Facebook data collection process

This Supplementary Appendix section describes the details on how the analysts' Facebook pages are searched for and how the information on whether an analyst has children is collected.

To find an analyst's Facebook page, we follow the steps as follows:

1. Search for the analyst on LinkedIn or TipRanks based on the analysts' full name, company name, and the city where she works to get a photo of the analyst;

2. If her photo is not available on the above two websites, google the analyst's the analysts' full name and company name for a photo of the person (e.g., a photo at an interview on TV);

3. Search for the analyst's full name on Facebook and compare photos of the analysts with the same name against the profile photos on LinkedIn or TipRanks or photos from Step 2;

4. If there is no match of photos, google "Facebook"+"analyst full name"+"analyst location" and check whether there is a matched Facebook page;

5. If there is no match, google "Facebook"+"analyst full name"+"the company the analyst currently works in (from LinkedIn)" and check whether there is a matched Facebook page

6. If there is no match, google "Facebook"+"analyst full name"+"the universities the analyst attended (from LinkedIn)" and check whether there is a matched Facebook page;

7. If there is still no match, assume there is no public Facebook page of the analyst;

8. To ensure the accuracy of photo matching, two individuals independently collect analysts' Facebook pages following the above steps. If there is any inconsistency, i.e., one person finds the link while the other does not (around 10% of links collected in the first round) or different Facebook links are collected (only less than 1% of links collected in the first round), a third person makes the judgment on whether the Facebook page (or which Facebook page) should be used.

After getting an analyst's Facebook page, we check the posted photos to identify whether she has children. The children in the photo may not be the person's children but e.g., her nephews or nieces. The identity of the children is distinguished based on the texts and comments in the posts.

If the analyst has children, we also estimate the children's ages. If the analyst has posted photos of the children's birth or birthday celebrations, it is possible to accurately identify the children's age. Otherwise, we estimate whether a child's age is among the following age groups: younger than 3, 3 to 5, 5 to 10, 10 to 15, 15 to 18, or older than 18, based on the photos of the children and the time when these photos were posted.

As shown in the table below, we finally find Facebook pages for 682 analysts, 262 out of which have non-adult children.

	No Facebook	Facebook found	% Facebook found	Have children	% Children	Non-adult children	% Non-adult children
Male	1,089	590	35.14%	255	43.22%	228	38.64%
Female	109	92	45.77%	35	38.04%	34	36.96%
Total	1,198	682	36.28%	290	42.52%	262	38.42%

Previous studies show that in the general population, women are more likely to use Facebook (Acquisti and Gross (2006)) and share personal topics such as families (Wang et al. (2013)). Among financial analysts, women are also more likely to have Facebook pages than men (45.77% vs 35.14%). However, women are not more likely to post photos of their children (38.04% vs 43.22%). It is also possible that female analysts are less likely to have children, compared with male analysts because this is a very competitive profession, and having a child is more costly for women.

Analysts' activities at earnings conference calls

In this Supplementary Appendix section, I present the detailed analyses and results on analysts' activities at earnings conference calls.

I construct a sample consisting of conference call transcripts for earnings conference calls from January 2020 to August 2020. The conference call transcripts are obtained from Seeking Alpha. I extract the analysts' names from the transcripts and match them with the analysts that issue forecasts for the firm in the quarter based on the I/B/E/S database. The sample uses 7,064 conference transcripts and contains 29,369 observations on firm-analyst-call date level with 3174 distinct firms, 1701 analysts of which 186 are female. Panel A in Table SA8 contains the summary statistics of variables in the sample. Similar to the main sample, 10% of analysts who participate in the conference calls are female. On average, an analyst who participates in a conference call asks 2.68 questions, using 163.35 words and 12.58 sentences.

Table SA9 contains the regression results of the question length or the question number in earnings conference calls on *Female*, *School closure* and their interaction terms. All regressions control for No. of followed firms' EA to measure the distraction of concurrent earnings announcements (Driskill et al. (2020)), Forecast revision from consensus (Mayew (2008)), and firm and analyst characteristics. The COVID-19 school closures have negative effects on the question length and the question number of female analysts at the earnings conference calls while the effect on those of male analysts is not significant. Female analysts use 9 fewer words (5.5% of the sample average in Table SA8), 0.648 fewer sentences (5.15% of the sample average in Table SA8), and ask 0.150 fewer questions (5.6% of the sample average in Table SA8) at earning conference calls after the COVID-19 school closures. The effect is statistically significant at the 1% level in models controlling for firm, broker, state, and time fixed effects (Column (1), Column (3), and Column (5)) and is still statistically significant at the at least 10% after controlling for analyst fixed effects (Column (2), Column (4), and Column (6)).

Furthermore, taking one step back and considering the probability to participate in earnings conference calls, I expect female analysts are less likely to ask questions after the school closure. In a similar vein, Driskill et al. (2020) finds that analysts distracted by multiple concurrent earnings announcements in their coverage portfolio are less likely to ask questions at earnings conference calls. In order to determine the probability of participating in an earnings conference call, I make assumptions on the analysts that potentially participate in the earnings conference call. Following Mayew (2008), I define a pool of analysts that potentially ask questions at conference calls as analysts that issue a forecast for the firm in the quarter in the I/B/E/S database. Participate is a dummy variable equal to one if analysts appear in conference call transcripts and the I/B/E/S database, and zero if analysts only appear in the I/B/E/S database. As shown in Panel B of Table SA8, 46% of analysts who follow a firm in the quarter participate in the firm's earnings conference call, asking questions and therefore, appearing in the respective conference transcript.

At the aggregated level in the whole sample, I do not find a significant effect of the COVID-19 school closures on the participation of conference calls. I conjecture that the effect may vary for conference calls happening at different times of the day. I extract the time of the conference call from conference transcripts and transfer the time to the local time of the state where the analyst is located. I obtain the time of the conference calls for 76% of the sample. Based on the local time, I define a dummy variable for each hour interval. Then I run regressions of *Participate* on a dummy variable indicating whether the earnings conference call is held during the hour of the day, the female dummy, the school closure dummy, and their interaction terms, controlling for analyst and time (earnings conference call date) fixed effects and clustering the standard errors by analyst. Figure SA3 plots the coefficient estimates of the interaction terms between the hour interval, *Female*, and *School closure* for each hour intervals. It seems that the COVID-19 school closures have a larger negative effect on the probability for a female analyst to participate in earnings conference calls during most times of the day. However, the effect is only statically significant at the 10% level for conferences held in the morning from 5:00 to 6:00 or at noon from 11:00 to 12:00.

Figure SA1: Timeliness of male and female analysts' earnings forecasts from 1999 to 2020

This figure plots the average of the dummy variable Timely among male analysts and female analysts over the years from 1999 to 2020.

Figure SA2: Gender equality index for each state from the World Value Survey

This map contains the gender attitude index for each state from the U.S. 2017 wave of the World Value Survey. The survey asks about respondents' gender attitudes on women regarding jobs, political positions, and education. The gender attitude index for each state is calculated by taking the average of these three measures among respondents from the state. The darker the color of the state is, the more conservative gender attitudes in the state are.

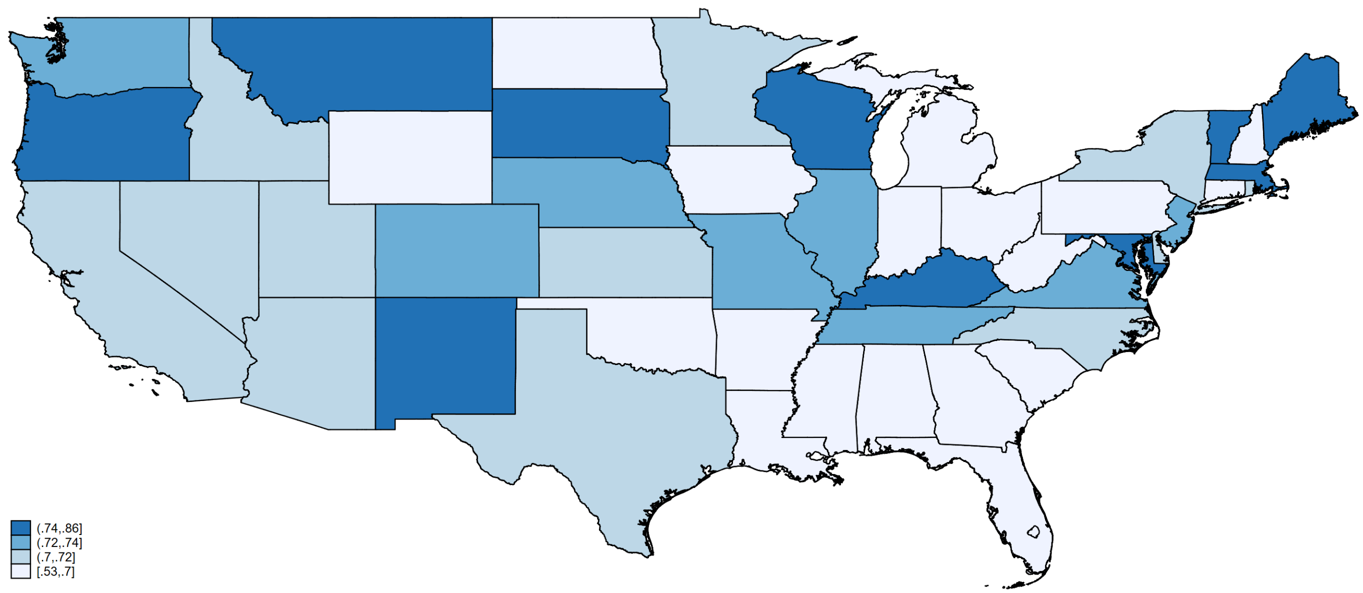

Figure SA3: Effect of school closures on forecast issue time among male and female analysts

This figure plots the coefficient estimates of the triple-interaction terms in the regressions of *Participate* on a dummy variable indicating whether the earnings conference call is held during the hour of the day, the dummy variable *Female*, the dummy variable *School closure*, and their interaction terms. The regressions control for analyst and time (earnings conference call date) fixed effects, and the standard errors are clustered by analyst. The confidence intervals of the coefficient estimates are at the 90% level.

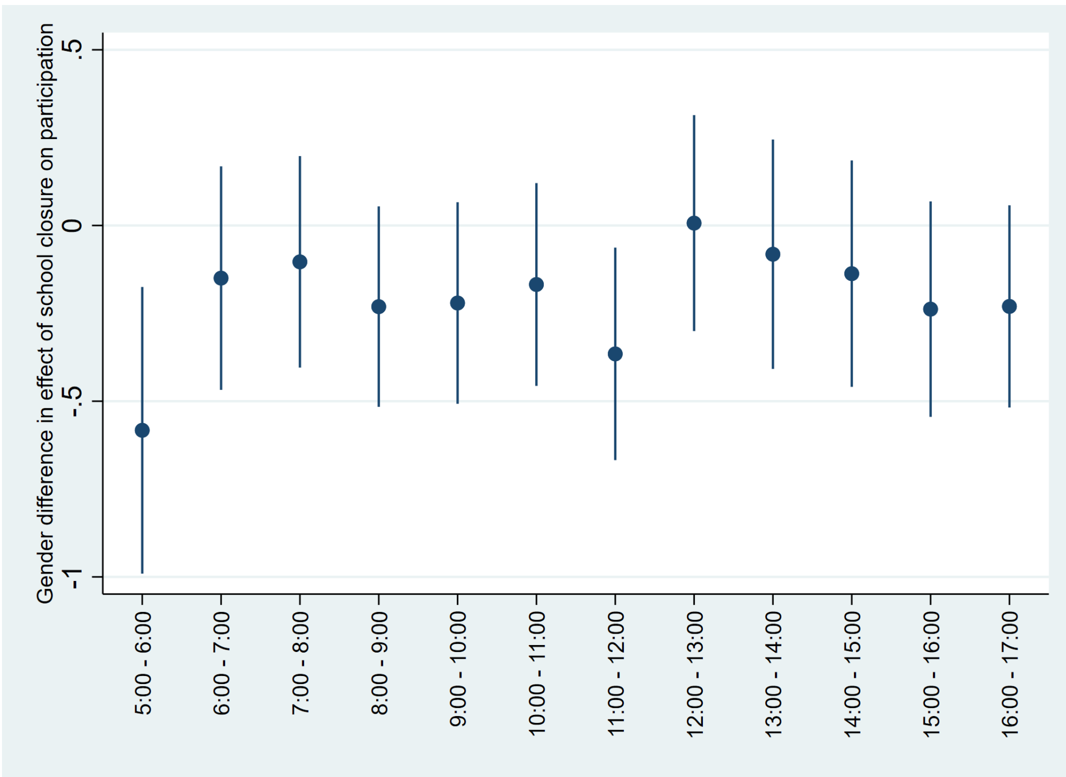

Table SA1: Robustness check in the sample not excluding earnings announcements before school closures with analysts' forecasts after school closures

This table contains the regression results of *Timely* on *Female*, *Financial crisis* and their interaction term in the sample of earnings announcements from January 2020 to August 2020. Earnings announcements are not excluded from the sample if earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Female × School closure	-0.070***	-0.053***	-0.059***	-0.054***
	(-3.07)	(-2.61)	(-2.95)	(-2.71)
School closure	-0.221***	-0.179***	-0.653***	-0.593***
	(-18.87)	(-17.29)	(-41.14)	(-34.78)
Female	0.064***		0.062***	
	(3.46)		(3.57)	
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State	Firm, Analyst	Firm, Broker, State, Time	Firm, Analyst, Time
Observations	24858	25370	24858	25370
Adjusted R^2	0.312	0.435	0.392	0.499

Table SA2: Continuous measure of forecast timeliness

This table contains the regression results of the continuous measure of forecast timeliness on *Female*, *School closure* and their interaction term. The continuous measure of forecast timeliness is the Log form of the number of days between earnings announcements and analyst forecasts. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Timely	
	(1)	(2)	(3)
Female × School closure	0.067	0.089*	0.081*
	(1.28)	(1.82)	(1.65)
School closure	0.129**	0.096	0.109*
	(2.49)	(1.53)	(1.71)
Female	-0.076**		
	(-1.99)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	15208	15378	15347
Adjusted R^2	0.292	0.428	0.429

Table SA3: Correlations of Chapter 2

This table shows pairwise correlation coefficients between all variables used in the analysis. A detailed description of all variables is provided in Appendix 1.7. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Female Dummy	1.000															
(2) School close	0.010	1.000														
(3) Timely	0.026***	-0.119***	1.000													
(4) Distance from consensus	0.013*	0.003	0.054***	1.000												
(5) Distance from previous	0.011	0.022***	-0.022***	0.482***	1.000											
(6) Forecast accuracy	-0.024***	0.039***	-0.001	-0.197***	-0.100***	1.000										
(7) No. of followed firms' EA	0.011	-0.004	-0.080***	-0.013*	0.016**	-0.018**	1.000									
(8) No. of firms followed	-0.020***	0.019**	0.064***	0.012	0.010	-0.014*	0.324***	1.000								
(9) Broker size	0.065***	0.044***	0.062***	0.027***	-0.003	-0.002	0.017**	0.146***	1.000							
(10) Experience in the firm	-0.018**	0.050***	0.030***	-0.007	0.004	0.017**	0.068***	0.082***	0.045***	1.000						
(11) Firm size	0.006	-0.037***	0.081***	-0.001	-0.003	0.038***	-0.021***	-0.034***	0.104***	0.145***	1.000					
(12) Institutional ownership	0.001	0.184***	-0.076***	-0.016**	-0.012	-0.013*	-0.021***	0.006	-0.011	-0.022***	-0.769***	1.000				
(13) Book to market	0.008	0.051***	-0.127***	-0.014*	0.002	0.010	0.140***	0.069***	-0.004	0.031***	-0.107***	0.115***	1.000			
(14) Bad earning news	0.012*	0.024***	-0.054***	0.013*	0.009	0.009	0.061***	0.015**	-0.045***	-0.036***	-0.052***	0.024***	0.080***	1.000		
(15) Special items	-0.040***	-0.044***	-0.003	-0.004	-0.007	-0.005	-0.076***	-0.029***	0.036***	0.060***	-0.024***	0.031***	-0.060***	-0.115***	1.000	
(16) Log number of following analysts	-0.002	0.121***	0.081***	-0.043***	-0.024***	0.029***	-0.057***	0.004	0.146***	0.178***	0.398***	-0.043***	-0.091***	-0.098***	0.040***	1.000

Table SA4: Effect of COVID-19 school closures on forecast accuracy – Other counterfactuals

This table contains the regression results of *Forecast accuracy* on *Female*, *School closure* and their interaction term. Columns (1) and (2) run regressions in the sample of March 2020 and *School closure* is equal to one, if the state where the analyst is located has closed schools, and zero otherwise. Columns (3) and (4) run regressions in the sample from March 23rd to August 31st in 2019 and 2020 and *School closure* is equal to one, if the earnings forecast is issued in year 2020, and zero otherwise. *Forecast accuracy* measures the forecast accuracy of the forecast compared within all analysts forecasts issued in the same month for the same firm-quarter. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Forecast accuracy			
	(1)	(2)	(3)	(4)
Counterfactual:	Across states in March 2020		2019 vs 2020	
Female Dummy × School closure	-0.054	-0.044	-0.019	-0.012
	(-0.63)	(-0.45)	(-0.97)	(-0.60)
School closure	0.155**	0.190**		
	(2.18)	(2.00)		
Female Dummy	0.015		-0.021**	
	(0.21)		(-2.14)	
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Broker, State, Time	Firm, Analyst, Time
Observations	1577	1199	31280	31765

Table SA5: Trade-off between forecast accuracy and timeliness

This table contains the regression results of *Forecast accuracy* on *Timely Female*, *School closure* and their interaction terms. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Forecast accuracy	
	(1)	(2)	(3)
Female Dummy × School closure × Timely	0.030	0.054	0.055
	(0.40)	(0.67)	(0.69)
Female Dummy × School closure	-0.052	-0.079	-0.098
	(-0.69)	(-0.98)	(-1.23)
School closure	0.091	0.109	0.111
	(1.37)	(1.49)	(1.55)
Female Dummy	0.032		
	(0.45)		
Timely	0.016	0.014	0.018
	(0.88)	(0.67)	(0.86)
Female Dummy × Timely	-0.042	-0.021	-0.026
	(-0.60)	(-0.29)	(-0.37)
School closure × Timely	-0.007	-0.012	-0.018
	(-0.31)	(-0.53)	(-0.74)
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	14135	14217	15042
Adjusted R^2	0.020	0.043	0.027

Table SA6: Forecast timeliness and effort allocation

This table contains the regression results of *Timely* on *Female*, *School closure*, *High institutional ownership* and their interaction term. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Timely	
	(1)	(2)	(3)
Female Dummy × School closure	-0.052*	-0.082***	-0.082***
	(-1.77)	(-2.89)	(-3.07)
Female Dummy × School closure × High inst. Ownership	0.019	0.032	0.049
	(0.48)	(0.86)	(1.27)
School closure × High inst. Ownership	0.004	0.009	0.010
	(0.27)	(0.62)	(0.56)
Female Dummy × High inst. Ownership	-0.061**	-0.073***	-0.081***
	(-2.03)	(-2.68)	(-2.89)
High inst. Ownership	0.034**	0.033**	0.038**
	(2.18)	(2.09)	(2.01)
Female Dummy	0.073***		
	(2.77)		
School closure	-0.066**	-0.035	-0.041
	(-2.32)	(-1.12)	(-1.24)
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	15208	15378	15347
Adjusted R^2	0.292	0.428	0.429

Table SA7: Effect of COVID-19 school closures on the forecast boldness

This table contains the regression results of forecast boldness measures on *Female*, *School closure* and their interaction term. *Distance from consensus* measures the deviation of the forecast from the consensus of analyst forecasts. *Distance from previous* measures the deviation of the forecast from the same analyst's previous forecast. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Boldness measured by distance from consensus forecast			
Dependent variable:		Distance from consensus	
	(1)	(2)	(3)
Female Dummy × School closure	0.049*	0.065**	0.068***
	(1.95)	(2.47)	(2.72)
School closure	0.029	0.032	0.038
	(0.51)	(0.53)	(0.64)
Female Dummy	-0.025		
	(-1.28)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	14876	15009	17114
Adjusted R^2	0.041	0.105	0.086

Panel B: Boldness measured by distance from previous forecast			
Dependent variable:		Distance from previous	
	(1)	(2)	(3)
Female Dummy × School closure	0.036	0.023	0.012
	(1.40)	(0.85)	(0.46)
School closure	-0.011	0.045	0.017
	(-0.15)	(0.56)	(0.23)
Female Dummy	-0.011		
	(-0.47)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	13535	13603	15485
Adjusted R^2	0.024	0.100	0.075

Table SA8: Summary statistics for the sample of earnings conference calls

This table contains summary statistics, including the number of observations (Obs), mean, standard deviation (Std. Dev.), 25% percentile (P25), median, and 75% percentile (P75), for the earnings conference calls from January 2020 to August 2020. Panel A contains summary statistics for the sample of I/B/E/S analysts participating in the earnings conference calls and Panel B contains summary statistics for the sample of I/B/E/S analysts following the firms in the quarter of the earnings conference call, i.e., analysts participating or potentially participating in the conference call. Further variable definitions can be found in 1.7.

Variable	Obs	Mean	Std. Dev.	P25	Median	P75
Panel A: Analysts participating the conference call						
Word count	29369	163.35	98.06	100.00	146.00	203.00
Sentence count	29369	12.58	7.38	8.00	11.00	16.00
Question count	29369	2.68	1.74	2.00	2.00	3.00
Female Dummy	29369	0.10	0.30	0.00	0.00	0.00
School closure	29369	0.52	0.50	0.00	1.00	1.00
No. of followed firms' EA	29314	0.91	1.38	0.00	0.00	1.00
Forecast revision from consensus	28044	-0.04	0.29	-0.08	-0.01	0.03
No. of firms followed	29238	17.50	7.64	13.00	17.00	22.00
Broker size	29360	48.78	32.53	21.00	49.00	68.00
Experience in the firm	29255	22.24	22.24	6.00	15.00	32.00
Firm size	29223	15.18	1.89	13.98	15.20	16.41
Institutional ownership	29205	0.09	0.09	0.05	0.06	0.10
Book to market	28871	0.61	0.87	0.15	0.33	0.69
Bad earning news	29077	0.34	0.48	0.00	0.00	1.00
Special items	28866	0.66	0.47	0.00	1.00	1.00
Log number of following analysts	29099	2.48	0.59	2.08	2.56	2.89
Panel B: Analysts participating or potentially participating the conference call						
Participate	63396	0.46	0.50	0.00	0.00	1.00
Female Dummy	63396	0.10	0.30	0.00	0.00	0.00
School closure	63396	0.54	0.50	0.00	1.00	1.00

Table SA9: Effect of COVID-19 school closures on analysts' activities at the earnings conference calls

This table contains the regression results of question length or question numbers in earnings conference calls on *Female*, *School closure* and their interaction terms in the sample of I/B/E/S analysts participating in the earnings conference calls from January 2020 to August 2020. Control variables include *No. of followed firms' EA*, *Forecast revision from consensus*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. Further variable definitions can be found in 1.7. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Word count		Sentence count		Question count	
Female Dummy × School closure	-9.154***	-6.614**	-0.648***	-0.410*	-0.150***	-0.105**
	(-2.92)	(-2.27)	(-2.66)	(-1.84)	(-2.79)	(-2.13)
School closure	8.822	-1.429	0.168	-0.224	0.114	0.036
	(0.88)	(-0.16)	(0.20)	(-0.30)	(0.56)	(0.20)
Female Dummy	-5.928		-0.261		0.049	
	(-1.38)		(-0.88)		(0.69)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Broker, State, Time	Firm, Analyst, Time
Observations	27275	27183	27275	27183	27275	27183
Adjusted R^2	0.390	0.581	0.421	0.562	0.481	0.580

Supplementary Appendix: Counter-stereotypical Female Role Models and Women's Occupational Choices

Table SA10: Gallup surveys used in our analysis

This table lists all Gallup surveys used in the analysis. The Gallup surveys are included if the state, year, and the most admired woman are available. The shadowed surveys contain all control variables in Table 2.3.

Surveys	Year
Gallup Poll # 1951-0483: Politics/Life [USAIPO1951-0483]	1951
Gallup Poll # 608 [USAIPO1958-0608]	1958
Gallup Poll # 1958-0593: Price Increases/Presidential Election/Television/Automobiles [USAIPO1958-0593]	1958
Gallup Poll # 1961-0653: 1964 Presidential Election [USAIPO1961-0653]	1961
Gallup Poll # 681 [USAIPO1963-0681]	1963
Gallup Poll # 721 [USAIPO1965-0721]	1965
Gallup Poll # 1966-0738: World Power/Most Admired People/Finances/Politics [USAIPO1966-0738]	1966
Gallup Poll # 1967-0755: Economy/Presidential Election/Vietnam/Most Admired People [USAIPO1967-0755]	1967
Gallup Poll # 1969-0793: Vietnam/Most Admired People [USAIPO1969-0793]	1969
Gallup Poll # 773 [USAIPO1969-0773]	1969
Gallup Poll # 820 [USAIPO1970-0820]	1970
Gallup Poll # 842 [USAIPO1971-0842]	1971
Gallup Poll # 861 [USAIPO1972-0861]	1972
Gallup Poll # 1973-0885: Middle East/Most Admired People [USAIPO1973-0885]	1973
Gallup Poll # 920 [USAIPO1974-0920]	1974
Gallup Poll # 942 [USAIPO1975-0942]	1975
Gallup Poll # 990 [USAIPO1977-0990]	1977
Gallup Poll # 1117G [USAIPO1978-1117G]	1978
Gallup Poll # 1979-1144G: The Year 1980 [USAIPO1979-1144G]	1979
Gallup Poll # 1980-1166G: Religion [USAIPO1980-1166G]	1980
Gallup Poll # 1186G [USAIPO1981-1186G]	1981
Gallup Poll # 1206G [USAIPO1982-1206G]	1982
Gallup Poll # 1228G [USAIPO1983-1228G]	1983
Gallup Poll # 1246G [USAIPO1984-1246G]	1984
Gallup Ad-Hoc Telephone Survey # 1985-841: Reagan/Death Penalty/Homosexuality [USAIPOSPAI1985-841]	1985
Gallup Poll # 1987-1272G: Reagan/1988 Presidential Election/Political Party/Finances/Federal Spending [USAIPO1987-1272G]	1987
Gallup Poll # 1296G [USAIPO1988-1296G]	1988
Gallup News Service Survey #1989-89141-W1: Eastern Europe/Racial Relations [USAIPOGNS1989-89141-W1]	1989
Gallup News Service Survey: December, 1992 - Wave 1 [USAIPOGNS1992-322036]	1992
Gallup/CNN/USA Today Poll # 1993-422025: Most Admired/Congressional Elections/Cuba Embargo/Gun Control [USAIPOCNUS1993-422025]	1993
Gallup/CNN/USA Today Poll: Al Gore [USAIPOCNUS1997-9709021]	1997
Gallup News Service Poll # 1998-9812057: Economy/Government [USAIPOGNS1998-9812057]	1998
Gallup/CNN/USA Today Poll # 1999-9912046: 2000 Election/Religion [USAIPOCNUS1999-9912046]	1999
Gallup/CNN/USA Today Poll: Election Wrap-up Poll [USAIPOCNUS2000-56]	2000
Gallup/CNN/USA Today Poll: Admirable Leaders/Economy/Terrorism/Religion [USAIPOCNUS2001-46]	2001
Gallup/CNN/USA Today Poll: Most Admirable People/Iraq/2004 Presidential Election [USAIPOCNUS2002-50]	2002
Gallup/CNN/USA Today Poll: 2004 Presidential Election/US Military/Medicare and Prescription Drug Benefits [USAIPOCNUS2003-52]	2003
Gallup/CNN/USA Today Poll: Economy/Politics/Terrorism/Taxes/Social Security/Iraq/Holidays/Sports [USAIPOCNUS2004-46]	2004
Gallup/CNN/USA Today Poll # 2005-62: Finances/Economy/Muslim and Islamic World [USAIPOCNUS2005-62]	2005
USA Today/Gallup Poll # 2007-42: December Wave I–2008 Presidential Primary [USAIPOUSA2007-42]	2007
USA Today/Gallup Poll # 2008-47: December Wave 1–Economy/Stock Market/Automobile Industry [USAIPOUSA2008-47]	2008
USA Today/Gallup Poll: December Wave 1 [USAIPOUSA2009-22]	2009
Gallup/USA Today Poll: December Wave 1 [USAIPOUSA2010-22]	2010
USA Today/Gallup Poll: December Wave 1–2012 Presidential Election [USAIPOUSA2011-22]	2011
Gallup News Service Poll: GPSS Lifestyle–Consumerism/Religion [USAIPOGNS2013-21]	2013
Gallup News Service Poll: Honesty and Ethical Standards in Different Fields [USAIPOGNS2014-15]	2014

Table SA11: Survey example from the 1961 Gallup poll

This table presents the question "Who is your most admired women?" and the aggregated answers that were collected from the Gallup Poll # 1961-0653: 1964 Presidential Election.

27a. What woman that you have heard or read about, living today in any part of the WORLD, do you admire the MOST?

.... Cols. 35–36 ...... See code .....

Question 27: What woman that you have heard or read about, living today in any part of the WORLD , do you admire the MOST?

01. Jackie Kennedy
02. Elonor Roosevelt
03. Mamie Eisenhower
04. Queen Elizabeth
05. Clare Booth Luce
06. Helen Keller
07. Madame Chiang Kai-shek
08. Pat Nixen
09. Senator Margaret Chase Smith
10. Dinah Shore
11. Princess Grace
12. Princess Margaret
13. Madame Pandit Nehru
14. Queen Elzabeth
15. Marion Anderson
16. Helen Hayes
17. Loretta Young
18. Pearl Buck
19. Debbie Reynolds
20. Marilyn Monroe
21 Dale Evans
22. Virginia Price
23. Maragret Church
24. Stritch
25. My Wife
26. Mrs. Truman
27. Arlene Frances
28. Pauline Frederick
29. Sister Coe
30. Kathryn Coleman
31. Onneta Hobby
32. Golda Meyer
33. Ingrid Bergman
34. Duthess of Windsor
35. Genevieve Blatz
36. Mrs. Khruschev
37. Sophie Tucker
38. Elsa Maxwell
39. F.J. Lewis
40. Mrs. Winston Churchill
41. Mrs. Priest
42. Queen Mother of England
43. Elizabeth Tayler
44. My Mother
45. Lillian Smith
46. Doris Day
47. Mrs. Holmes (Congresswoman)
48. Judge Sarah Hughes
49. Joan Crawford
50. Ida Lupino
51. Elaine Farrel
52. Dorothy Schiff
53. Katherine Marshall
54. Betty Grable
55. Alice Roosevelt Longworth
56. Lena Horne
57. Mary Pickford
58. Lucille Ball
59. Mrs. King
60. Frances Perkins
61. Marlene Dietrick
62. Irene Dunne
63. Ethal Barrymore
64. Mabalia Jackson
65. Althea Gibson
66. Dorothy Malone
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00. No answer, blank.
XX. Miscellaneous others
VV. Don$t Know

Table SA12: Fraction of women in different occupations and roles

This table presents the fraction of women in each of the 14 occupations and roles used to classify admired women in stereotypical and counter-stereotypical roles, respectively. We include statistics covering the longest sample period possible. Column (1) lists each occupation and role, and column (2) indicates whether a given role is classified as counter-stereotypical. Column (3) shows the fraction of women in a given occupation or role, and column (4) shows the time period to which the numbers in column (3) refer. Column (5) shows the source of the corresponding statistics.

Occupation/ Role (1)	Counter-stereotypical (yes/no) (2)	Fraction of women (3)	Time period (4)	Source (5)
Politician	yes	17.1%	1979-2015	Institute for Women's Policy Research
Athletes	yes	29.0%	1964-2016	IOC; olympic.org
Entertainment	no	31.0%	2008-2016	Women and Hollywood
Writer or journalist	yes	39.2%	1999-2013	American Society of News Editors via Washington Post
Famous wife	no	100.0%		by definition
Scientist	yes	24.8%	1993-2010	National Science Foundation
Family or friends	no	100.0%		by definition
Activist	yes	male dominated	2000	DiGrazia (1995)
Religious person	no	60%	2014	Pew Research Center
Famous mother	no	100.0%		by definition
Famous daughter	no	100.0%		by definition
Astronaut	yes	16.2%	1965-2013	NASA Astronaut Factbook, via statista.com
Nurse	no	85.0%	2000-2017	Census
Businesswoman	yes	13.9%	1995-2016	Pew Research Center

Table SA13: Rank of states based on counter-stereotypical female role model score

This table contains the rank of states based on *Counter-stereotypical female role model CPS*, the measure of admiring counter-stereotypical female role models for the state and year, in years 1951, 1982, and 2014.

1951					
Rank	State	Score	Rank	State	Score
1	Oklahoma	1.00	21	North Carolina	0.14
2	Oregon	0.50	22	Illinois	0.14
3	Kentucky	0.50	23	New Mexico	0.13
4	Tennessee	0.43	24	Colorado	0.13
5	Maine	0.40	25	Ohio	0.11
6	Mississippi	0.38	26	Nebraska	0.11
7	Utah	0.33	27	Vermont	0.11
8	Michigan	0.30	28	Arkansas	0.10
9	Indiana	0.27	29	Iowa	0.10
10	Kansas	0.25	30	Alabama	0.10
11	Louisiana	0.25	31	Georgia	0.10
12	New Jersey	0.25	32	Virginia	0.09
13	Pennsylvania	0.23	33	Maryland	0.08
14	Minnesota	0.20	34	Missouri	0.05
15	Massachusetts	0.20	35	Washington	0.00
16	California	0.19	36	South Dakota	0.00
17	Texas	0.18	37	Connecticut	0.00
18	New York	0.18	38	Florida	0.00
19	Wisconsin	0.17	39	Idaho	0.00
20	South Carolina	0.17	40	West Virginia	0.00

1982					
Rank	State	Score	Rank	State	Score
1	Vermont	1.00	21	Maine	0.33
2	Connecticut	1.00	22	Colorado	0.32
3	Wisconsin	0.71	23	Florida	0.32
4	New Hampshire	0.67	24	California	0.31
5	Nevada	0.50	25	New York	0.30
6	Massachusetts	0.50	26	Ohio	0.29
7	District of Columbia	0.50	27	Pennsylvania	0.28
8	Washington	0.45	28	New Mexico	0.27
9	Iowa	0.43	29	Idaho	0.27
10	Hawaii	0.43	30	South Dakota	0.25
11	Utah	0.43	31	Arizona	0.24
12	Missouri	0.41	32	Montana	0.22
13	Mississippi	0.39	33	Oregon	0.22
14	Illinois	0.39	34	Virginia	0.21
15	Texas	0.39	35	Indiana	0.21
16	Nebraska	0.38	36	Georgia	0.21
17	Maryland	0.38	37	Minnesota	0.20
18	New Jersey	0.37	38	Kentucky	0.19
19	Michigan	0.33	39	Tennessee	0.19
20	Louisiana	0.33	40	Alabama	0.17
			41	South Carolina	0.15
			42	West Virginia	0.14
			43	Kansas	0.14
			44	North Carolina	0.09
			45	Arkansas	0.00
			46	Oklahoma	0.00
			47	Rhode Island	0.00

2014					
Rank	State	Score	Rank	State	Score
1	New Hampshire	1.00	21	Oregon	0.50
2	Vermont	1.00	22	Colorado	0.50
3	South Dakota	1.00	23	Arkansas	0.50
4	Wyoming	1.00	24	Florida	0.49
5	Indiana	0.95	25	Wisconsin	0.46
6	Minnesota	0.91	26	Massachusetts	0.45
7	Maine	0.89	27	Pennsylvania	0.44
8	Kentucky	0.86	28	Alabama	0.43
9	Tennessee	0.79	29	Kansas	0.41
10	Oklahoma	0.77	30	South Carolina	0.39
11	Virginia	0.75	31	District of Columbia	0.35
12	Idaho	0.75	32	Ohio	0.28
13	Iowa	0.69	33	Michigan	0.28
14	Texas	0.69	34	West Virginia	0.25
15	North Carolina	0.67	35	Montana	0.25
16	Washington	0.65	36	California	0.25
17	New Jersey	0.57	37	Utah	0.24
18	Georgia	0.55	38	Delaware	0.24
19	New York	0.54	39	Missouri	0.23
20	Arizona	0.52	40	Louisiana	0.22
			41	Rhode Island	0.21
			42	Illinois	0.20
			43	Maryland	0.16
			44	Connecticut	0.12
			45	Nevada	0.00
			46	New Mexico	0.00
			47	Nebraska	0.00
			48	Alaska	0.00
			49	Mississippi	0.00

Table SA14: Frequency distributions of the counter-stereotypical female role model score of a state in year $t-1$ and t

Cell frequencies from a 2×2 classification of states based on the rank-ordered counter-stereotypical female role model in year $t-1$ and t are reported. The counter-stereotypical female role model (Counter-str. CPS) is calculated every year for each state as the average of the dummy variable indicating whether the respondent admires counter-stereotypical female role models from the Gallup survey. We classify states as high- or low- counter-stereotypical female role model states if their Counter-str. CPS is, respectively, above or below the cross-sectional median for that year. The χ^2 statistic is calculated under the null hypothesis that median cut-offs of Counter-str. CPS at t and Counter-str. CPS at $t-1$ are independent from each other, i.e., each cell comprises 25% of the observations.

	Counter-str. CPS at t	
Counter-str. CPS at $t-1$	Low	High
Low	24.70%	24.06%
High	24.73%	26.52%
Pearson χ^2 = 0.8133 Pr = 0.367		

Table SA15: Variable description

This table contains a description of all variables used in our empirical analyses. Data sources are as follows:

1. Gallup: Gallup surveys obtained from Roper center for public research
2. GSS: General Social Survey
3. CPS: Current Population Survey Annual Social and Economic Supplement obtained from Integrated Public Use Microdata Series.
4. DD: Data obtained from David Dorn's website https://www.ddorn.net/data.htm (Autor and Dorn (2013)).
5. MC: Variable is manually constructed by the authors.

Variable name	Description	Data source
Abstract	A score ranging from 0 to 10 indicating how much the occupation involves abstract tasks. Abstract tasks are "'abstract' creative, problem-solving, and coordination tasks performed by highly-educated workers" (p.6, Autor and Dorn (2013)). Occupations such as finance, technology, and managers are assigned a high score of abstract tasks.	CPS, DD
Advanced occupation	Dummy variable equal to one if the respondent's occupation falls into the following categories: business executive, manager executive or official, manufacturer's representative, and runs own business.	Gallup, MC

Table SA15: Variable description (continued)

Variable name	Description	Data source
Age	Age of the respondent.	Gallup, CPS
Bachelor	Dummy variable equal to one the the respondent has a bachelor degree, and zero otherwise.	Gallup, CPS, MC
Children	Dummy variable equal to one if the household has at least one child under 18 or 21 (depending on the survey questions), and zero otherwise.	Gallup, CPS, MC
Christian	Dummy variable equal to one if the respondent is a christian, and zero otherwise.	Gallup, MC
Counter-stereotypical female role model	Dummy variable equal to one if the Gallup respondent's most admired woman falls into one of the following categories: activist, astronaut, athlete, businesswomen, politician, scientist, writer or journalist, and zero otherwise.	Gallup, MC
Counter-stereotypical female role model CPS	Measuring the female role model in each state and year by taking the average of the dummy variable *Counter-stereotypical female role model* indicating whether the respondent admires counter-stereotypical female role models from the Gallup survey based on the states the respondent is in.	Gallup, CPS, MC

Table SA15: Variable description (continued)

Variable name	Description	Data source
Education	Categorical variable measuring different levels of education: less than high school, high school graduate, training, bachelor degree, and post-graduate.	Gallup, CPS, MC
Employed	Dummy variable equal to one if the respondent is currently employed, and zero otherwise.	Gallup, CPS, MC
Executive	Dummy variable equal to one if the respondent's occupation is business executive or managerial executive.	Gallup, MC
Female children	Standardized scales to which degree the respondents agree with the following statement: a preschool child is likely to suffer if his or her mother works	GSS
Female family	Standardized scales to which degree the respondents agree with the following statement: it is much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family	GSS

Table SA15: Variable description (continued)

Variable name	Description	Data source
Female president	Standardized scales to which degree the respondents agree with the following statement: if your party nominated a woman for President,would you vote for her if she were qualified for the job?	GSS
Female politics	Standardized scales to which degree the respondents agree with the following statement: most men are better suited emotionally for politics than are most women.	GSS
Female respondent	Dummy variable equal to one if the respondent is female, and zero otherwise.	Gallup, CPS
Full time work	Dummy variable equal to one if the respondent is currently employed as full time worker, and zero otherwise.	Gallup, MC
Liberal gender attitude (GSS)	The average of state-year level measures for five gender-related questions.	GSS, MC
High income	Dummy variable indicating the high-income households with an annual income above $ 50,000, and zero otherwise.	Gallup, MC
Log income	Log form of the respondent's total pre-tax personal income from all sources for the previous calendar year.	CPS, MC

Table SA15: Variable description (continued)

Variable name	Description	Data source
Manual	A score ranging from 0 to 10 indicating how much the occupation involves routine tasks. Manual tasks involve physical dexterity and flexible interpersonal communication, e.g., transport, mining, and construction (Autor and Dorn (2013)).	CPS, DD
Married	Dummy variable indicating the marital status of the respondent, and zero otherwise.	Gallup, CPS, MC
Not in labor force	Dummy variable equal to one if the respondent is not currently in labor force, i.e., not employed or searching for a job, and zero otherwise.	CPS, MC
Routine	A score ranging from 0 to 10 indicating how much the occupation involves routine tasks. Routine tasks follow precise and well-defined procedures and occupations such as machine operator and clerical work are scored high as routine tasks (Autor and Dorn (2013)).	CPS, DD

Table SA15: Variable description (continued)

Variable name	Description	Data source
RTI	Routine task-intensity (*RTI*) for each occupation following Autor and Dorn (2013), calculated as: $$RTI_k = ln\left(T_k^{Routine}\right) - ln\left(T_k^{Manual}\right) - ln\left(T_k^{Abstract}\right),$$ where $T_k^{Routine}$, T_k^{Manual}, $T_k^{Abstract}$ are the routine, manual and abstract task measures in each occupation k. The score of the 5^{th} percentile in manual tasks and abstract tasks are used for the five percent of observations with the lowest manual and abstract task score.	CPS, DD, MC
STEM industry	A dummy variable equal to one if a respondent works in an industry with an above-median STEM intensity, and zero otherwise.	Gallup, CPS, MC

Table SA15: Variable description (continued)

Variable name	Description	Data source
STEM intensity	Are industries where a large share of employees are in STEM occupations. To create this variable Adams and Kirchmaier (2016) match industries to a list of occupations that require education in science, technology, engineering, and mathematics disciplines from O*NET (2015) (https://www.onetonline.org/).They then calculate the percentage of the number of employees in each industry working in a STEM occupation. The top 5 sectors by share of STEM employees are labeled as STEM sectors.	CPS
White-caucasian	Dummy variable equal to one if the respondent is white-caucasian in race, and zero otherwise.	Gallup, CPS, MC
Working mother	Standardized scales to which degree the respondents agree with the following statements: a working mother can establish just as warm and secure a relationship with her children as a mother who does not work.	GSS

Table SA16: Excluding admired women who change their role over time (Gallup sample)

This table contains weighted regression results of employment status or occupational choices on our measure of counter-stereotypical female role models and further demographic control variables. The sample contains female Gallup survey respondents from age 18 to age 65. Female role models whose roles have changed from counter-stereotypical to stereotypical or from stereotypical to counter-stereotypical are excluded from the sample. All variables are described in detail in Appendix SA15. Robust standard errors are used to adjust for heteroscedasticity. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Labor market participation				
Dependent variable:	Employed		Full-time Employed	
	(1) Female	(2) Male	(3) Female	(4) Male
Counter-stereotypical female role model	0.041*	0.004	0.053**	-0.008
	(1.88)	(0.23)	(2.37)	(-0.47)
Control variables	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Education fixed effects	Yes	Yes	Yes	Yes
Observations	2,780	2,734	2,780	2,734
Adjusted R^2	0.112	0.077	0.129	0.131

Panel B: Occupational choices				
Dependent variable:	Advanced occupation		Executive	
	(1) Female	(2) Male	(3) Female	(4) Male
Counter-stereotypical female role model	0.023*	-0.027	0.019*	-0.009
	(1.91)	(-1.49)	(1.94)	(-0.61)
Control variables	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Education fixed effects	Yes	Yes	Yes	Yes
Observations	2,098	1,843	2,098	1,843
Adjusted R^2	0.022	0.047	0.022	0.035

Table SA17: Counter-stereotypical female role models and occupation type (CPS sample)

This table contains weighted regression results of occupation category on the interaction term between gender and the *Counter-stereotypical female role model* variable at a respondents' state when she was twenty years old (ten or fifteen years in the bottom part of the table). The sample contains all currently employed individuals in the CPS ASEC surveys (1962 to 2018) from age 25 to age 65. The dependent variable is defined as in Autor and Dorn (2013): Abstract (0-10) measures to what extend an occupation involves abstract, creative, problem-solving, and coordination tasks; Manual (0-10) measures to what extend an occupation involves manual tasks such as physical dexterity and flexible interpersonal communication; Routine (0-10) measures to what extend an occupation involves routine tasks; Routine task intensity (RTI) is calculated as

$$RTI_k = Ln(Routine_k) - Ln(Abstract_k) - Ln(Manual_k).$$

All variables are described in detail in Appendix SA15. Standard errors are clustered by state. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Abstract		Routine		Manual		RTI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Counter-str. CPS × Female respondent	0.433***	0.227***	-0.410***	-0.340***	0.030	0.062**	-0.364***	-0.299***
	(6.04)	(4.84)	(-7.33)	(-6.89)	(1.21)	(2.56)	(-7.55)	(-7.26)
Female respondent	-0.370***	-0.304***	0.175***	0.167***	-0.586***	-0.597***	0.955***	0.941***
	(-14.14)	(-15.96)	(7.21)	(7.29)	(-39.01)	(-41.04)	(63.64)	(64.59)
Counter-str. CPS	-0.345***	-0.105***	0.295***	0.166***	0.013	-0.024	0.202***	0.129***
	(-4.56)	(-3.06)	(6.52)	(5.64)	(0.65)	(-1.42)	(6.43)	(5.99)
Age		0.060***		-0.007**		0.009***		-0.039***
		(18.66)		(-2.34)		(5.34)		(-14.36)
Age squared		-0.001***		-0.000		-0.000***		0.000***
		(-17.30)		(-0.06)		(-5.92)		(13.37)
Bachelor degree		1.978***		-0.825***		-0.374***		-0.606***
		(66.66)		(-25.16)		(-58.53)		(-40.80)
White-Caucasian		0.385***		-0.030		-0.057**		-0.096***
		(6.68)		(-0.53)		(-2.26)		(-3.99)
Married		0.333***		0.036***		-0.039***		-0.053***
		(21.60)		(4.12)		(-5.55)		(-10.04)
Children		-0.075***		-0.007		0.050***		-0.048***
		(-3.73)		(-1.11)		(9.37)		(-8.89)
State fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
State × Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,193,089	1,193,089	1,193,089	1,193,089	1,193,089	1,193,089	1,193,089	1,193,089
Adjusted R^2	0.149	0.190	0.029	0.036	0.068	0.082	0.072	0.076
Coefficient estimates of the interaction term with alternative Counter-str. CPS matching age								
Match as of age 15	0.404***	0.210***	-0.350***	-0.285***	0.003	0.033	-0.298***	-0.237***
	(5.25)	(4.25)	(-5.42)	(-4.98)	(0.13)	(1.35)	(-5.21)	(-4.90)
Match as of age 10	0.416***	0.226***	-0.355***	-0.288***	-0.019	0.010	-0.261***	-0.199***
	(4.66)	(4.49)	(-4.82)	(-4.61)	(-0.65)	(0.36)	(-4.16)	(-3.91)

Table SA18: Robustness: Selective migration

This table contains weighted regression results as in our baseline analyses using CPS survey data. The sample period is restricted to years 1980, 1985, 1995, 2005, and 2015 based on the availability of the variable "migrate5" which indicates whether a respondent migrated within the last five years. The coefficient estimates of the interaction term between *Counter-str. CPS* and *Female* are reported in the sample with (Panel A) and without (Panel B) respondents who have migrated in the last five years. *Counter-str. CPS* is the fraction of Gallup survey respondents in a CPS respondents' state who admired counter-stereotypical female role models in the year when the CPS respondent was twenty years old. All variables are described in detail in Appendix SA15. Standard errors are clustered by state. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Employment status - Results from Table 2.6						
Dependent variable	Employed			Not in labor force		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample with all respondents	0.056***	0.056***	0.056***	-0.055	-0.061***	-0.060***
	(4.47)	(4.45)	(4.40)	(-1.78)	(-4.86)	(-4.81)
Observations	365,967	365,967	365,967	365,967	365,967	365,967
Adjusted R^2	0.059	0.072	0.073	0.081	0.093	0.094
Sample excluding migrated respondents	0.058***	0.058***	0.057***	-0.058	-0.063***	-0.063***
	(4.52)	(4.45)	(4.41)	(-1.73)	(-4.82)	(-4.77)
Observations	345,625	345,625	345,625	345,625	345,625	345,625
Adjusted R^2	0.057	0.069	0.070	0.079	0.089	0.090
Control variables	No	Yes	Yes	No	Yes	Yes
State fixed effects	Yes	Yes	No	Yes	Yes	No
Year fixed effects	Yes	Yes	No	Yes	Yes	No
State $\times$ Year fixed effects	No	No	Yes	No	No	Yes

Table SA18: Robustness: Selective migration (continued)

Panel B: STEM industry - Results from Table 2.7				
Dependent variable	STEM industry		STEM intensity	
	(1)	(2)	(3)	(4)
Sample with all respondents	0.017	0.013	0.113	0.042
	(1.26)	(0.98)	(0.78)	(0.29)
Observations	208,722	208,722	208,722	208,722
Adjusted R^2	0.018	0.022	0.014	0.022
Sample excluding migrated respondents	0.016	0.011	0.104	0.029
	(1.18)	(0.85)	(0.72)	(0.20)
Observations	198,817	198,817	198,817	198,817
Adjusted R^2	0.019	0.022	0.014	0.022
Control variables	No	Yes	No	Yes
State fixed effects	Yes	No	Yes	No
Year fixed effects	Yes	No	Yes	No
State $\times$ Year fixed effects	No	Yes	No	Yes

Table SA18: Robustness: Selective migration (continued)

Panel C: Occupational choices - Results in Table 2.8						
Dependent variable	Male-dominated industry		Male-dominated occupation		Manager	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample with all respondents	0.022	0.027**	0.053***	0.057***	0.061***	0.049***
	(1.68)	(2.10)	(3.96)	(4.23)	(4.91)	(4.50)
Observations	237,208	237,208	237,208	237,208	237,208	237,208
Adjusted R^2	0.166	0.174	0.284	0.289	0.008	0.031
Sample excluding migrated respondents	0.021	0.027**	0.051**	0.055***	0.055**	0.043***
	(1.62)	(2.11)	(3.89)	(4.01)	(3.76)	(3.78)
Observations	225,301	225,301	225,301	225,301	225,301	225,301
Adjusted R^2	0.167	0.176	0.285	0.290	0.008	0.031
Control variables	No	Yes	No	Yes	No	Yes
State fixed effects	Yes	No	Yes	No	Yes	No
Year fixed effects	Yes	No	Yes	No	Yes	No
State × Year fixed effects	No	Yes	No	Yes	No	Yes

Table SA18: Robustness: Selective migration (continued)

Panel D: Fertility and educational choices - Results from Table 2.9			
Dependent variable	Age at first childbirth	Bachelor	Post-graduate
	(1)	(2)	(3)
Sample with all respondents	0.552***	0.076***	0.026***
	(3.10)	(4.74)	(3.94)
Observations	153,930	251,751	251,751
Adjusted R^2	0.365	0.127	0.041
State × Year fixed effects	Yes	Yes	Yes
Sample excluding migrated respondents	0.557***	0.078***	0.028***
	(3.21)	(4.58)	(3.84)
Observations	146,790	238,656	238,656
Adjusted R^2	0.365	0.119	0.039
State × Year fixed effects	Yes	Yes	Yes

Panel E: Gender pay gap - Results from Table 2.10				
Dependent variable	Log income			
	(1)	(2)	(3)	(4)
Sample with all respondents	0.353***	0.296***	0.354**	0.296***
	(5.30)	(5.27)	(3.40)	(5.27)
Observations	244,370	244,370	244,370	244,370
Adjusted R^2	0.224	0.280	0.225	0.281
Sample excluding migrated respondents	0.349***	0.290***	0.350**	0.290***
	(5.15)	(5.11)	(3.27)	(5.11)
Observations	231,953	231,953	231,953	231,953
Adjusted R^2	0.219	0.277	0.220	0.278
Control variables	No	Yes	No	Yes
State fixed effects	Yes	Yes	No	No
Year fixed effects	Yes	Yes	No	No
State × Year fixed effects	No	No	Yes	Yes

Table SA19: Robustness checks with alternative winner measures

In this table, we calculate the purchase price of stocks with low-in-first-out and high-in-first-out principles following Cici (2012) and compare the purchase price with the selling price to determine whether the stock was sold for a gain or a loss. We further use the last-in-first-out principle to calculate the purchase price. We additionally use the last holding period return of a stock to measure the previous trading experience: a stock is defined to be a previous winner if the last holding period return of the stock by the fund is positive. We rerun regressions with baseline results in Table 2 and Table 3. A detailed description of all variables is contained in Appendix 3.6. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Univariate tests of repurchasing bias

	(1) Low-in-first-out	(2) High-in-first-out	(3) Last-in-first-out	(4) Last holding period return
No. of winners repurchased	325,474	321,441	318,489	299,085
Opportunities to repurchase winners	5,501,914	5,470,670	5,403,444	5,132,109
Proportion of winners repurchased (PWR)	0.059	0.059	0.059	0.058
No. of Losers Repurchased	249,483	249,827	247,944	278,234
Opportunities to repurchase losers	5,282,478	5,254,783	5,239,202	5,672,276
Proportion of losers repurchased (PLR)	0.047	0.048	0.047	0.049
Diff (PWR-PLR)	0.012	0.011	0.012	0.009
t-stats (PWR=PLR)	(19.95)	(18.72)	(19.32)	(15.57)

Repurchasing bias in a multivariate regression framework

	Low in first out			High in first out			Last in first out			Last holding period winner		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Loser	-0.009***	-0.009***	-0.009***	-0.008***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.007***	-0.007***	-0.007***
	(-25.62)	(-24.01)	(-32.71)	(-25.27)	(-23.61)	(-31.85)	(-25.65)	(-23.94)	(-32.18)	(-20.02)	(-19.81)	(-25.83)
Fund size		0.003***			0.003***			0.003***			0.003***	
		(3.82)			(3.79)			(3.79)			(3.80)	
Fund age		-0.000			-0.000			-0.000			-0.000	
		(-0.05)			(-0.04)			(-0.04)			(-0.03)	
Turnover ratio		0.009***			0.009***			0.009***			0.009***	
		(9.58)			(9.54)			(9.52)			(9.57)	
Expense ratio		-0.039			-0.035			-0.038			-0.030	
		(-0.14)			(-0.13)			(-0.14)			(-0.11)	
Return volatility		-0.000			-0.000			-0.000			-0.000	
		(-0.18)			(-0.21)			(-0.25)			(-0.06)	
Performance rank		-0.003**			-0.003**			-0.003**			-0.003**	
		(-2.40)			(-2.40)			(-2.37)			(-2.36)	
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Fund×Time FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	10,783,985	8,959,950	10,769,862	10,725,048	8,908,746	10,710,888	10,642,237	8,840,161	10,627,981	10,804,038	9,002,789	10,790,054
Adjusted R^2	0.036	0.038	0.104	0.036	0.038	0.104	0.036	0.038	0.104	0.036	0.038	0.104

Table SA20: Repurchasing bias with market-based loser measures

This table presents results from the same regression model used in Table 3.3. The dependent variable is Repurchase, a dummy variable equal to one if the stock sold is repurchased by the fund in the quarter within one year after the sale, and zero otherwise. Loser equals one if the returns from the previous stock sale were lower than the S&P 500 return, and zero otherwise. The average purchasing price is calculated either following first in first out principle (FIFO) or taking value-weighted average of all purchase prices (AVG) before the sale. Control variables include fund characteristics (Fund size, Fund age, Turnover ratio, Expense ratio, Return volatility, Fund Ranking), which are all defined in Appendix 3.6. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out			Average purchase price		
	(1)	(2)	(3)	(4)	(5)	(6)
Loser	-0.008***	-0.008***	-0.008***	-0.009***	-0.009***	-0.009***
	(-24.00)	(-22.53)	(-30.76)	(-25.35)	(-23.77)	(-31.85)
Fund size		0.003***			0.003***	
		(3.85)			(3.83)	
Fund age		-0.000			-0.000	
		(-0.04)			(-0.04)	
Turnover ratio		0.009***			0.009***	
		(9.66)			(9.66)	
Expense ratio		-0.044			-0.044	
		(-0.16)			(-0.16)	
Return volatility		-0.000			-0.000	
		(-0.16)			(-0.17)	
Performance rank		-0.003**			-0.003**	
		(-2.42)			(-2.43)	
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	No	Yes	Yes	No
Fund×Time FE	No	No	Yes	No	No	Yes
Observations	11,008,777	9,127,074	10,994,803	11,011,673	9,129,732	10,997,701
Adjusted R^2	0.036	0.038	0.104	0.036	0.038	0.104

Table SA21: Repurchasing bias with different time periods after the sale

This table contains results of linear probability regressions. The dependent variable is Repurchase, a dummy variable equal to one if a stock is repurchased by the same fund within one quarter (Panel A), two quarters (Panel B), or three quarters (Panel C) after it was sold, and zero otherwise. All variables are defined in detail in Appendix 3.6. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)			Average purchase price (AVG)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Repurchasing bias one quarter after the sale						
Loser	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
	(-22.61)	(-21.19)	(-26.45)	(-23.33)	(-21.82)	(-27.16)
Observations	3109354	2603704	3090019	3110823	2604958	3091505
Adjusted R^2	0.072	0.075	0.171	0.072	0.075	0.171
Panel B: Repurchasing bias two quarters after the sale						
Loser	-0.012***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***
	(-25.24)	(-23.48)	(-30.96)	(-26.21)	(-24.39)	(-31.84)
Observations	5912102	4939614	5895598	5914857	4941958	5898364
Adjusted R^2	0.047	0.049	0.130	0.047	0.049	0.130
Panel C: Repurchasing bias three quarters after the sale						
Loser	-0.010***	-0.010***	-0.010***	-0.010***	-0.011***	-0.011***
	(-24.86)	(-23.48)	(-31.49)	(-25.93)	(-24.59)	(-32.47)
Observations	8463426	7054164	8448671	8467364	7057501	8452614
Adjusted R^2	0.040	0.043	0.117	0.040	0.043	0.117
Control variables	No	Yes	No	No	Yes	No
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	No	Yes	Yes	No
Fund×Time FE	No	No	Yes	No	No	Yes

Table SA22: Repurchasing bias in team- and single-managed funds

This table contains results of the same linear probability regressions as in Table 3.3 in the subsample of team- and single-managed funds, respectively. All variables are described in detail in Appendix 3.6. *t*-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	LoserFIFO		LoserAVG	
	Team	Single	Team	Single
	(1)	(2)	(3)	(4)
Loser	-0.009***	-0.009***	-0.009***	-0.009***
	(-16.38)	(-17.98)	(-17.16)	(-18.73)
Fund size	0.005***	0.002*	0.005***	0.002*
	(3.60)	(1.81)	(3.57)	(1.78)
Fund age	-0.000	-0.000	-0.000	-0.000
	(-0.35)	(-0.64)	(-0.34)	(-0.63)
Turnover ratio	0.012***	0.006***	0.012***	0.006***
	(7.92)	(4.53)	(7.92)	(4.53)
Expense ratio	0.010	-0.412	0.010	-0.418
	(0.02)	(-1.18)	(0.02)	(-1.20)
Return volatility	-0.010	0.003	-0.010	0.003
	(-1.37)	(1.25)	(-1.38)	(1.25)
Performance rank	-0.005***	-0.001	-0.006***	-0.001
	(-3.37)	(-0.76)	(-3.38)	(-0.78)
Stock FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	5,204,449	2,952,639	5,206,777	2,954,203
Adjusted R^2	0.043	0.035	0.043	0.035

Table SA23: Does the tax saving wash-sale rule matter?

This table contains results of the same linear probability regressions as in Table 3.3. Observations within the first quarter after a stock is sold have been excluded from the sample. All variables are described in detail in Appendix 3.6. t-statistics are provided in parentheses. The standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	LoserFIFO			LoserAVG		
	(1)	(2)	(3)	(4)	(5)	(6)
Loser	-0.006***	-0.007***	-0.007***	-0.007***	-0.007***	-0.008***
	(-21.25)	(-19.74)	(-27.20)	(-22.34)	(-20.82)	(-28.50)
Fund size		0.003***			0.003***	
		(3.66)			(3.63)	
Fund age		-0.000			-0.000	
		(-0.01)			(-0.01)	
Turnover ratio		0.008***			0.008***	
		(8.62)			(8.62)	
Expense ratio		0.017			0.017	
		(0.09)			(0.08)	
Return volatility		0.001			0.001	
		(0.32)			(0.29)	
Performance rank		-0.002*			-0.002*	
		(-1.73)			(-1.74)	
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	No	Yes	Yes	No
Fund×Time FE	No	No	Yes	No	No	Yes
Observations	7,747,847	6,414,852	7,733,000	7,751,439	6,417,857	7,736,595
Adjusted R^2	0.030	0.032	0.082	0.030	0.032	0.082

Table SA24: Repurchasing bias conditional on subsequent price changes - Evidence from ANcerno daily trading data

This table contains results of linear probability regressions in the ANcerno sample. We include all sales that clear the current positions accumulated from purchases and observe whether the stock is purchased again by the same fund in one year after the sale. The dependent variable is Repurchase^{ANcerno}, a dummy variable equal to one if a stock is repurchased by the same fund in a given quarter within one year after it was sold, and zero otherwise. Winner^{ANcerno} is equal to one if a stock was sold for a gain, and zero otherwise, i.e., 1-Loser^{ANcerno}. The winner dummy is based on the difference between selling price and average purchase price. The exact trading prices from the ANcerno trading data are used. The average purchase price is calculated either following the first-in-first-out principle (columns (1) to (3)), or by taking the trade-value-weighted average of all purchase prices before the sale (columns (4) to (6)). Price up^{ANcerno} is equal to one if the price of a stock is higher than the price of repurchase (trading price from ANcerno) when a stock is repurchased or the stock price as of the date the fund makes a repurchasing decision when a stock is not repurchased. t-statistics are provided in parentheses. Standard errors are clustered by fund. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-in-first-out (FIFO)			Average purchase price (AVG)		
	(1)	(2)	(3)	(4)	(5)	(6)
Winner^{ANcerno} × Price up^{ANcerno}	-0.008***	-0.009***	-0.007***	-0.008***	-0.007***	-0.006***
	(-9.50)	(-9.57)	(-7.92)	(-9.02)	(-7.90)	(-6.59)
Winner^{ANcerno}	0.013***	0.010***	0.005***	0.014***	0.011***	0.005***
	(20.12)	(14.41)	(7.67)	(21.16)	(16.72)	(8.03)
Price up^{ANcerno}	0.016***	0.013***	0.009***	0.016***	0.012***	0.009***
	(22.22)	(16.89)	(12.30)	(22.25)	(16.35)	(11.75)
Fund×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	No	Yes	No
Stock×Time FE	No	No	Yes	No	No	Yes
Observations	2,582,426	2,582,378	2,555,648	2,582,426	2,582,378	2,555,648
Adjusted R^2	0.077	0.108	0.236	0.077	0.108	0.236

Short CV - Mengqiao Du

Education

09/2017-Present	Ph.D. Candidate	University of Mannheim
12/2021-03/2022	Visiting scholar	UC Berkeley
09/2019-12/2019	Visiting scholar	University of Miami
09/2015-09/2017	M.Sc.	University of Mannheim
07/ 2011-08/2011	Summer Exchange	Hong Kong Baptist University
09/2010-06/2014	B.Sc.	University of International Business and Economics

Work Experience

08/2017-Present	Research and Teaching Fellow	University of Mannheim
01/2016-08/2017	University of Mannheim	Research Assistant
07/2014-06/2015	SIEMENS Ltd. China	Commercial Trainee
01/2013-03/2013	KPMG China	Audit Intern

Awards and Scholarships

08/2020-12/2020	DAAD research project funding
09/2019-12/2019	DAAD short-term research stay funding
08/2018	Julius Paul Stiegler Gedächtnis Stiftung
06/2018	DAAD IPID4all Mobility Funding
06/2017	DAAD Graduation Scholarship
2012-2014	UIBE Comprehensive Scholarship (Top 10%)
09/2010	Freshman Scholarship (Top 5%)

Professional Certificates, Language and Computer Skills

ACCA (Association of Chartered Certified Accountants)

Chinese (Native), English (Proficient), German (Upper-intermediate)

Stata, Python, Java, SPSS, Latex