When Gender Disparities Meet Financial Technology in Financial Advisory

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Abstract

Can financial technology level the playing field for female financial advisors? In the setting of copy trading on a social trading platform, we find that female lead traders attract more investors than male lead traders, controlling for performance, risk, trader characteristics, and country and time fixed effects. This finding is more pronounced among traders engaging in high-risk trading, or in countries with more women participating in the labor force. In the dynamic relation of investor flow responding to traders' performance, we find a more convex relation between performance and flow for female lead traders, in that female traders attract more investors with good performance and lose fewer investors with poor performance than male traders. Using Baidu AI face detection, we find that older and less attractive female lead traders attract more investors. Our findings indicate that investors on the social trading platform trust female lead traders more.

Keywords: Gender Disparities, Fintech, Copy Trading, Financial Advisory, AI Face Detection

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1. Introduction

Gender differences in the financial sector attract considerable attention. Finance is a large and highly compensated industry that consistently ranks among the bottom industries in terms of gender equality. The persistence of this pattern over time runs counter to more general labor market trends (Goldin 2006). Consequently, concerns about the lack of diversity and discrimination in the financial industry have become an important policy issue.[1] Financial advisers have among the largest gender earning gaps across occupations.[2] The emerging financial technology could alter this pattern because it could lower the barriers in gender-incongruent industries for women and offer flexibility to balance work and family responsibilities (Goldin 2020).

The barrier for women in the financial advisory industry exists for many reasons. Hiring discrimination may exist against women, and female advisors may face discriminatory treatment (Egan, Matvos, and Seru 2022). Women may choose less competitive professions (Polachek 1981, Niederle and Vesterlund 2007, Sutter and Gätzle-Rützler 2019). Women face more career interruptions (Bertrand et al. 2010). An important question is whether investors have gender biases, which cannot be easily addressed with corrective policies. Existing evidence provides an affirmative answer. Gurun, Stoffman, and Yonker (2021) show the importance of the relationship between financial advisors and their clients. Female advisors might face more difficulties in establishing and maintaining such relationships since the investors are mostly male. Niessen-Ruenzi and Ruenzi (2019) find that mutual fund investors have biases against female managers. Ewens and Townsend (2020) show that early-stage investors have gender biases against female entrepreneurs. We study this question in an alternative setting where technology could change the landscape of the financial advisory industry.

The rise of network platforms has transformed many industries, such as transportation, media, and tourism. This paper explores the social trading platforms that typically provide their members with

[1] Former FDIC chairwoman Sheila Bair (2017) writes that the glass ceiling in finance is "barely cracked" for women.

[2] For example, see, Day and Rosenthal (2008). Recent survey evidence found that nearly 88% of female financial service professionals believe that gender discrimination exists within the financial services industry (Tuttle 2014).

online brokerage and social networking services. In particular, these platforms allow their traders to directly copy the investment choices of other traders ("lead traders") and reward the leaders for being copied, an arrangement called "copy trading." The incentive structure of lead traders and copiers resembles traditional financial advisors and their clients, with possibly better incentive alignment because of the same held positions by design.[3] However, important differences in the social trading platforms could have implications for female leaders. First, the relatively flat organization structure on the social trading platforms can level the playing field for women, in contrast to traditional financial advisory or mutual fund industries, where the widespread "machoism" could put women at a disadvantage. Second, all lead traders on social trading platforms have access to the same pool of investors, whereas female managers could have less favorable investor pools than male managers in the traditional financial advisory industry. Third, the relationship between financial advisors and clients is transient in social trading platforms, as the copiers can easily terminate the copy trading arrangement with a leader. Since the relationship between financial advisors and clients usually favors male advisors, the smaller role of the relationship in social trading could benefit female leaders. These differences also highlight the cleaner setting for examining investors' gender biases in social trading because copy trading volume reflects investors' beliefs about the ability rather than the institutional background that could favor one gender over the other.

Our data is from the social trading platform eToro between 2015 and 2019. We chose the start date when female lead traders start to emerge on the platform eToro.[4] Female lead traders account for around 10% of all lead traders and join the platform later than male traders. The number of lead traders grows exponentially during this period, and the growth rate is comparable between the genders. Similar to the underrepresentation by women in the financial industry, women also participate less on social trading platforms, which could result from self-selection in employment opportunities or more difficulty for women to attract copiers.

[3] Financial advisors and their clients could have conflicts of interest which contribute to the high cost of advice and poor performance of advisors. Additionally, Linnainmaa, Melzer, and Previtero (2021) find that financial advisors have misguided beliefs.
[4] As one of the largest of these, eToro as of 2021 has more than 20 million users from nearly 140 countries.

To gauge investors' attitudes towards following female lead traders, we compare the gender differences in the number of copiers and the speed of gaining copiers. We find that female lead traders have more copiers and gain copiers faster than male lead traders, controlling for performance, risk, trader characteristics, and country and time fixed effects. The lead traders on eToro have different levels of riskiness based on their traded asset types and use of leverage. We find that female lead traders have significantly more copiers within the group of lead traders of higher risk levels. These findings indicate that the investors consider female lead traders favorably in our setting.

We next explore cross-country variations. Our sample includes traders from over 100 countries with varied developments toward gender equality in the labor force. Women face hurdles in entering the labor force that could arise from family responsibilities and innate prejudices. Technological development could help work-life balance for women to care for the family, but may not effectively reduce prejudices. We conduct subsample analysis across countries based on the index of female labor force participation rate (FLFPR) from the United Nations Development Program (UNDP) Global Inequality Indices. Among the lead traders from high (low) FLFPR countries, female lead traders have more (fewer) copiers and gain copiers faster (slower) than their male counterparts. Technology-induced job flexibility could help women from low FLFPR countries enter the social trading platforms, but their success on the trading platform is still influenced by gender biases within each country. Our findings are thereby consistent with the narrative that women from low FLFPR countries face high hurdles to achieve gender equality in the labor markets.

Our findings indicate that the investors do not hold prejudice, an irrational bias (Becker 1971), or statistical discrimination (Phelps 1972) against female lead traders in our sample, especially in high FLFPR countries. Previous studies show that investors tend to follow traders with similar cultural backgrounds, thus leading to local biases. In high FLFPR countries, investors might be more receptive to female lead traders since these countries have made progress in gender equality. As a result, female lead traders from high FLFPR countries gain more copiers than their male counterparts on social trading platforms.

Several reasons could explain investors' gender preferences in choosing lead traders in copy trading. Investors could have unfavorable views about women's ability to make investment decisions. The literature on mutual funds shows that female managers attract lower flows than male managers (Atkinson, Baird, and Frye 2003, Niessen-Ruenzi and Ruenzi 2019). Women are also more risk-averse than men in financial decision-making (Sunden and Surette 1998), possibly less appealing to investors. On the other hand, Barber and Odean (2001) document that men are more overconfident about their investment ability and trade more aggressively than women. This could give investors qualms in a relatively less regulated and riskier environment, such as social trading platforms. Our finding is consistent with this explanation in that female leader traders attract even more copiers than male lead traders when the risks of copied trades are high.

As explained in Barber and Odean (2001), the gender differences in confidence are greatest for tasks perceived to be in the masculine domain, such as trading. To further understand the nature of gender-based biases, we further explore the variations in the characteristics among female lead traders. A large body of literature in economics and psychology suggests that people are often rewarded for their attractiveness, and previous studies document a significant beauty premium in the labor market (Hamermesh and Biddle 1998). However, facial attractiveness could work differently for men and women in the labor markets (Frieze, Olson, and Russell 1991, Ruffle and Shtudiner 2015, Li, Lin, Lu, and Veenstra 2020). Beauty premium for women could also depend on the job types, as attractive women may suffer a beauty penalty for managerial positions as opposed to clerical positions (Heilman and Saruwatari 1979, Frieze, Olson, and Russell 1991).[5]

We examine the effect of facial attractiveness and the age of lead traders on the number of their copiers.[6] While female lead traders have more copiers than male lead traders, beauty has a different effect

[5] Heilman and Saruwatari (1979) explain, "Attractive males were seen as more masculine than unattractive males. Unattractive women were also seen as more masculine than attractive women. The attractive males and unattractive females were rated as more motivated, unemotional, and decisive than their same-sex counterparts. Since these are thought to be desirable qualities for a manager, it is not surprising that these candidates were the most preferred for the managerial job."

[6] We utilize Baidu AI face detecting techniques via picture recognition to infer traders' facial attractiveness, as well as corroboration for gender in our empirical analysis.

between male and female lead traders – beauty is positive for men but negative for women. Age is positive for both men and women, but has a much larger effect for women.[7] We also find the beauty penalty is stronger in high FLFPR countries.[8] These findings are consistent with the notion that investors are attracted to female lead traders who possess perceived experience and confidence in financial decision making. In other words, the copiers would choose lead traders who are confident but not overconfident.

We further examine how investors react to trading profits and losses differently based on the gender of lead trader. Based on the dynamic relation between lead trader's performance and change in the number of copiers, we find that female lead traders attract more copiers for their good performance and lose fewer copier for their bad performance than male counterparts. This finding suggests a mechanism for female lead traders having a larger number of copiers than male counterparts. Additionally, this finding provides further support that investors caution against male overconfidence. Gervais and Odean (2001) propose that overconfidence can result from self-serving attribution bias. Traders could infer their own abilities from their successes and failures. Taken together with the findings in psychology, men have a stronger tendency to overweight their successes and underweight their failures and thus become more overconfident. Therefore, copiers may have more positive attitudes toward profits and less punitive toward losses made by female lead traders.

Our paper is related to several strands of literature. First, our paper contributes to the literature on gender disparity in the financial industry. Women face various hurdles. Hiring discrimination may exist against women, and female advisors may face discriminatory treatment (Egan, Matvos, and Seru 2022). Women may choose less competitive professions (Polachek 1981, Niederle and Vesterlund 2007, Sutter and Gätzle-Rützler 2015). Women face more career interruptions (Bertrand et al. 2010). Gurun, Stoffman, and Yonker (2021) show the importance of the relationship between financial advisors and

[7] Bai, Ma, Mullally and Solomon (2019) find that relatively older fund managers perform better and display more confident behavior, and survey respondents judge relatively older managers as appearing more confident in photographs.
[8] Li, Lin, Lu, and Veenstra (2020) find that beauty penalty is stronger in U.S. than in China. They attribute the differences in gender and beauty biases to culture and the legal environment.

their clients. Female advisors might face more difficulties in establishing and maintaining such relationships since the investors are mostly male.

Second, our paper studies an important question whether investors have gender biases, which cannot be easily addressed with corrective policies. Niessen-Ruenzi and Ruenzi (2019) find that mutual fund investors have biases against female managers. Ewens and Townsend (2020) show that early-stage investors have gender biases against female entrepreneurs. In a study of mutual fund managers, Atkinson, Baird, and Frye (2003) find that the net asset flows into funds managed by females are lower than for males, especially for the managers' initial years. Our paper adds to these existing pieces of evidence with an investigation in the fintech-enabled setting of copy trading and provides a different answer.

Third, our paper relates to gender differences in overconfidence in financial decision-making. A widespread view is that men are more over-confident than women in financial decision-making, including trading decisions (Barber and Odean 2001) and corporate financial and investment decisions (Huang and Kisgen 2013, Bernile, Bhagwat, and Yonker 2018). Overconfidence of lead traders is an important concern for copiers in copy-trading, as Barber and Odean (2001) explain that overconfidence is a severe problem for stock trading since it is a difficult task with low predictability and noisy feedback. Therefore, men will generally be more overconfident about their ability to make financial decisions than women. Additionally, the lack of clear and unambiguous feedback increases gender differences in self-confidence, which makes men more confident than women.

2. Data

2.1 Sample Selection

As the world's largest social investment network, eToro has pioneered the concept of Copy Trading, which enables you to automatically copy traders of your choosing, replicating what they do in your own accounts. The Copy Trading system is one of the key reasons the platform is considered among the leaders of the social trading revolution. Choose the traders you want to copy, decide on the amount you wish to invest, and copy trades in real-time automatically.[9] Copied trades are typically executed in less than a second from the instant the lead traders execute their own trades. Copy trading allows investors to choose traders around the world.

The platform introduces stocks and some investment choices in 2013 and introduces crypto in 2014. Thus, the point about treating 2015 as an early stage of the platform trading which the platform begin to receive attention is justified.

There is no additional charge for copying another trader or traders, and just the spreads on the trading and/or transaction fees where applicable. The traders on eToro can be copied if their profiles are public. Importantly, only users approved to participate on eToro's Popular Investor Program are eligible to receive monthly earnings. The Popular Investor (PI), when copied by other investors, will earn a predetermined percentage of their annual assets under management (AUM), which are paid out monthly. The AUM is the total amount other investors have allocated to copy a trader.

There were more than 360,000 users, including 2247 traders who have at least 2 copiers on eToro copy trading platform. Our basis sample consists of eToro trading history file, the merged number of copiers file for the period from May 2016 to March 2019. On top of the specific information, we also observe a rich set of trader attributes including usernames, first and last name, country of origin and the trader's photo (if any). These trader attributes are verified by the platform. Not all traders posted photos of their own faces. Gender is not identified for those traders who post photos of scenery, pets, etc. We note that nonhuman photos represent a small proportion of our sample. To prevent discriminatory behaviors and privacy breaches, the platform does not collect demographic information such as age and gender from its traders. Despite this precautionary step, copiers are likely to infer the gender identity of traders from either their names or profile photos. We make a similar inference of the trader's gender through the

[9] There are several limitations for trade copying: the minimum amount to invest in a trader is $200; the maximum number of traders you can copy simultaneously is 100; the maximum amount you can invest in one trader is $2,000,000; the minimum amount for a copied trade is $1.

application of machine-learning approaches on the names and photos found on traders' profiles. For payment purposes, the platform requires all popular investors to use real and verifiable names on their profiles.

Several studies demonstrated the possibility of inferring gender identity from first names (e.g., Gallagher and Chen 2008). In particular, Tang et al. (2011) constructed a comprehensive list of first names with annotated gender probabilities based on data from the public Facebook profile pages of 1.67 million users. Using the name-gender probability estimates, we matched the trader's name in our sample to that in the list and inferred the trader's gender by both Baidu AI face detection technology and manual identification. Furthermore, a large proportion of traders in our dataset come from traders with full names and profile photos.

Compared to names, photos convey more direct and salient information about one's gender. Advances in computer vision and machine learning have produced mature techniques for the automatic extraction of facial features such as pupil-to-nose vertical distance, chin ratio, eyebrow thickness, and hair for gender prediction (e.g., Gao and Ai 2009; Gutta et al. 1998; Yang et al. 2006). We employed Baidu AI face-detecting technology that makes use of a facial recognition package to perform gender, beauty, and age classification on the profile photos of traders in our dataset.[10]

Combining the two approaches described above, we are able to infer the gender identity of traders for 1,550 traders, which represents nearly 80% of all the traders who had at least two copiers in the dataset. To check the overall accuracy level of our labels, we cross-validate the inferred gender of traders under the two approaches and observe an agreement rate of 96.45%. Observations with mismatched genders from the two approaches are omitted from our analysis. Given the high agreement in the predicted gender across independent sources of information (i.e., names and photos), we believe our name-photo validated approach yielded highly accurate trader attribute labels.

[10] To validate user photos, we downloaded nearly 40,000 users' avatars, including both copiers and traders. We finally detected more than 30,000 avatars by both Baidu AI and manual identification.

In Table I, we list the variables used in our analysis. Table II reports statistics for these variables.

3. Empirical Results

3.1. Female Lead Traders and Number of Copiers

Our first research question is whether gender disparity exists among lead traders in copy trading. We use the monthly number of copiers to proxy for a copied trader's popularity and regress this proxy on gender, controlling for the trader's performance, risk profile, the number of months as a lead trader on the platform, and personal characteristics such as age and beauty. We also report the results using the returns of the previous six months for trader performance and use 12-month performance for a robustness check. Specifically, we estimate the following regression models:

$$\begin{aligned} \textit{Number of Copiers}_{i,t} &= \beta_0+\beta_1 \cdot \textit{Female}_i+\beta_2 \cdot \textit{Performance}_{i,t} + \textit{other control variables} \\ &\quad + \textit{month and country Fixed Effects} + \varepsilon_{i,t}\,, \qquad (1) \end{aligned}$$

where female is an indicator variable set to one for female traders and zero for male traders. Age and beauty of the traders are recognized from the traders' photos by Baidu AI.

In Table III column (1), we report the regression results comparing the number of traders following female and male lead traders. In the whole sample, we find female traders have significantly more copiers, controlling for past performance, risk profile, trader characteristics, and country and month fixed effects. The estimates for other control variables in Table III have expected signs. Traders with better past performance, lower risk scores, and more experience on the platform have more copiers. Regarding personal characteristics, traders whose facial images appear more attractive or older have more copiers. We include year-month and country fixed effects in the regression, so the variations come from the differences between traders in the same sample period and from the same country. These findings indicate that the female lead traders have more copiers in our sample.

To understand why female traders attract more copiers, we further explore the traders' facial features that could influence copiers' perception of the lead traders. We apply the Baidu AI face detection method to the traders' profile photos to obtain their age and facial attractiveness. These characteristics relate to the beauty premium and the age premium in labor markets.

In Table III column (2), we run the regression in equation (1) with additional interaction terms between the female trader dummy variable and facial attractiveness (beauty) and age variables. While female lead traders have more copiers than male lead traders, beauty has a stronger effect on male than female lead traders. The effect of age is significantly positive for female lead traders, yet insignificant for male lead traders. These findings suggest that the age premium is stronger and the beauty premium is weaker for female lead traders than male lead traders.

3.2. Trading Risk Level

The lead traders on eToro have different levels of riskiness based on their traded asset types, such as cryptocurrencies, and the use of leverage. If the copiers choose female lead traders because of their cautiousness, this should be more pronounced when the trading involves a higher level of risks.

In Table IV, we separate the lead traders based on their level of riskiness. In column (1), we find that female lead traders have significantly more copiers in the subsample of lead traders of high-risk level, and the difference is insignificant in the subsample of low-risk level. We further compare the effects of age and beauty in column (2). The effect of age is similar to the finding in the whole sample. The effect of beauty becomes more striking for the high-risk traders, where copiers perceive female attractiveness negatively and male attractiveness positively. Psychological studies find that male facial attractiveness is often associated with masculinity, whereas female facial attractiveness is associated with femininity. So, facial attractiveness could have the opposite perception between male and female lead traders.

These findings indicate that the female lead traders attract more copiers when trading involves a higher level of risks, consistent with the notion that when choosing a stranger to follow in risky investments, copiers are likely choose an experienced female lead trader.

3.2. Female Labor Force Participation

Cultural background can influence how copiers perceive female lead traders. To explore cross-country variations, we examine subsamples with the lead traders from high (low) FLFPR countries. Women may still face prejudice in low FLFPR countries and are underrepresented in the labor force. We expect that female lead traders face a higher hurdle in attracting copiers in countries of low FLFPR.

In Table V column (1), we indeed find that female lead traders have fewer copiers than their male counterparts in low FLFPR counties. In contrast, female lead traders in high FLFPR countries attract more copiers. Turning to age and beauty in column (2), we find that female facial attractiveness has opposite effects in the two subsamples of countries. Female beauty has little effect in high FLFPR countries and a significant positive effect in low FLFPR countries.

These findings are consistent with the notion that when investors are more used to women in the workforce, they tend to choose female lead traders in the setting of social trading.

3.3. Female Traders and Net Flow

We further examine the dynamic relation between the lead trader's performance and the change in the number of copiers. This analysis resembles the flow-performance relationship in the mutual fund literature. We also include the nonlinear terms in performance to account for the convex relation between flow and performance in that more inflows follow good performance than outflows follow poor performance. We use the performance from the previous six months in our main analysis and the 12-month performance in the robustness check. We use zero as the cutoff for good and poor performance in the reported results and the median as a cutoff in the robustness check. Specifically, we estimate the following regression models:

$$Net\ Flow_{i,t} = \beta_0 + \beta_1 \cdot Female_i + \beta_2 \cdot Performance_{i,t} + \beta_3 \cdot Performance_{i,t} * (Performance_{i,t} < 0)$$

$$+\beta_4 \cdot Female * Performance_{i,t} + \beta_5 \cdot Female * Performance_{i,t} * (Performance_{i,t} < 0)$$

$$+other\ control\ variables + month\ and\ country\ Fixed\ Effects + \varepsilon_{i,t}, \quad (2)$$

In Table VI, we report the regression results for the whole sample. In columns (1) and (2), we find that female lead traders attract more copiers for their good performance and lose fewer copiers for their poor performance than their male counterparts. The gender differences in flow sensitivity to performance are both statistically and economically significant, with 158% (=0.197/ 0.125) higher in sensitivity to good performance and 245% (=-0.277/-0.113) lower in sensitivity to poor performance. The estimates for the performance terms show a significant convex performance-flow relation. The estimate for the female dummy variable is significantly negative, indicating that female traders lose more copiers than male traders when they are inactive.

Table VII reports the results from the subsample analysis based on trader risk scores. We find stronger flow sensitivity for female traders in the high-risk trader subsample than in the low-risk trader subsample. The sensitivity differences are especially pronounced for trading losses.

Table VIII reports the results from the subsample analysis based on the trader country FLFPR. We find significant flow sensitivity for female traders in the high-FLFPR subsample but insignificant in the low-FLFPR subsample.

These findings are consistent with the earlier findings that female traders have more copiers in these subsamples. The dynamic relation between the flow and performance demonstrates the channels for female lead traders having a larger number of copiers than their male counterparts.

Our findings also provide support that investors caution against male overconfidence. Gervais and Odean (2001) propose that overconfidence can result from self-serving attribution bias. Traders could infer their own abilities from their successes and failures. Taken together with the findings in psychology, men have a stronger tendency to overweight their successes and underweight their failures and thus become more overconfident. Therefore, copiers may have more positive attitudes toward profits and less punitive toward losses made by female lead traders.

4. Conclusion

Gender disparity among financial advisers is a significant and persistent issue for the finance industry. Emerging financial technology could alter this pattern because it could induce a flat organizational structure and flexibility for women to enter this profession. A potential barrier for women in the financial advisory industry is that investors might have gender biases. We study this question in a setting where technology could change the landscape of the financial advisory industry. This paper explores copy trading on social trading platforms that allow traders to copy the investment choices of other traders directly. Copy trading can offer a cleaner setting for examining investors' gender biases again financial advisors absent the institutional background that could favor one gender over the other.

Using the data from the social trading platform eToro between 2015 and 2019, we find that female lead traders have more copiers than male lead traders, controlling for performance, risk, trader characteristics, and country and time fixed effects. This finding is more pronounced among traders engaging in high-risk trading, or in countries women participate more in the labor force. In the dynamic relation of how copiers respond to traders' performance, we find a more convex relation between performance and flow for female traders in that female traders gain more copiers with good performance and lose fewer copiers with poor performance than male traders.

Our findings are consistent with the previous studies that men are more overconfident about their investment ability and trade more aggressively than women, which could give investors qualms in a relatively less regulated and riskier environment such as social trading platforms. Our finding is consistent with this explanation in that female leader traders attract even more copiers than male lead traders when the risks of copied trades are high. We further find that facial attractiveness helps male lead traders but hurts female lead traders, which is consistent with the notion that investors are attracted to female lead traders who appear confident.

Overall, our paper demonstrates that financial technology could level the playing field for women in financial advisory profession because the technology changes the organizational structure and lower the entry barrier for women, and investors are less concerned about overconfidence from female advisors.

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Table I

Variable Definitions

Variable	Definition
$Female_i$	Female is a dummy variable for whether or not gender of the trader i is female
$Perf_{it-1}$	The mean monthly return over the past six months of the trader i at month t-1
$Copiers_{it}$	The number of copiers for trader i at month t
$Net\ flow_{it}$	The monthly changes in the number of copiers for trader i at month t
$Beauty_i$	The score is calculated by Baidu AI Face Detection for each user from 1 to 100, where 100 is the most beautiful
Age_i	The age of trader is detected by Baidu AI Face Detection
$Risk_{it}$	The monthly risk score is calculated using a special formula by eToro which includes the total allocation of the user's portfolio, the leverage they are using, the overall volatility of the markets they trade and the correlation between them. The score is calculated for each user from 1 to 10, where 1 is the lowest possible risk and 10 is the highest possible risk.
MSA_{it}	The number of months since activation for trader i at month t

Table II

Descriptive Statistics

This table shows average trader characteristics for all observations in our main regression in Table III. All variables are in decimals unless indicated otherwise. The respective number of trader-month observations is displayed. All variables are defined in detail in Table I.

Variable	mean	sd	p10	p25	p50	p75	p90	p95
Netflow	1.08	34.77	-7.49	-0.87	0.00	0.00	3.15	21.19
Copiers	90.59	344.19	0.00	0.87	2.93	27.48	147.50	372.35
Perf	0.06	0.52	-0.45	-0.17	0.01	0.17	0.53	0.94
Risk	4.55	1.63	3.00	3.00	4.00	6.00	7.00	7.00
Female	0.09	0.29	0.00	0.00	0.00	0.00	0.00	1.00
Beauty	45.31	13.74	26.37	34.92	46.46	55.02	62.93	66.81
Age	34.82	7.04	26.00	30.00	34.00	39.00	44.00	47.00
Msa	35.12	22.69	10.00	17.00	30.00	50.00	67.00	76.00

Table III

Trader Gender and Number of Copiers

This table shows the regression estimates of the number of copiers, regressed on a female trader dummy and trader characteristics. All variables are defined in Table I. All regressions include month and country fixed effects. We report the results from the whole sample. The second and third columns report the results of subsamples of low and high one-month lagged trader risk scores. The fourth and fifth columns report the results of subsamples of low and high-FLFPR countries. The robust standard errors are in parentheses.

	(1)	(2)
Female	0.059**	0.118***
	(0.029)	(0.032)
Female*Beauty		-0.041**
		(0.021)
Female*Age		0.144***
		(0.022)
Beauty	0.105***	0.108***
	(0.008)	(0.008)
Age	0.020***	0.005
	(0.007)	(0.008)
Perf	0.120***	0.121***
	(0.012)	(0.012)
Risk	-0.084***	-0.082***
	(0.005)	(0.005)
Msa	0.002***	0.003***
	(0.000)	(0.000)
Year-month FE	Yes	Yes
Country FE	Yes	Yes
N	17,692	17,692
Adj. R^2	0.126	0.128

Table IV

Trader Gender and Number of Copiers: Trader Risk-Taking Levels

This table shows the regression estimates of the number of copiers, regressed on a female trader dummy and trader characteristics. All variables are defined in Table I. All regressions include month and country fixed effects. We report the results from subsamples of traders taking low and high levels of risks based on one-month lagged trader risk scores. The robust standard errors are in parentheses.

	Low Trader Risk Score		High Trader Risk Score	
	(1)	(2)	(1)	(2)
Female	0.036	0.076**	0.188***	0.504***
	(0.035)	(0.035)	(0.045)	(0.090)
Female*Beauty		-0.012		-0.087***
		(0.028)		(0.021)
Female*Age		0.159***		0.352***
		(0.026)		(0.063)
Beauty	0.118***	0.120***	0.030***	0.035***
	(0.010)	(0.011)	(0.009)	(0.010)
Age	0.021**	0.004	0.031***	0.009
	(0.010)	(0.010)	(0.008)	(0.007)
Perf	0.208***	0.210***	0.050***	0.045***
	(0.021)	(0.021)	(0.011)	(0.010)
Risk	-0.060***	-0.057***	-0.066***	-0.063***
	(0.010)	(0.010)	(0.011)	(0.011)
Msa	0.003***	0.003***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Year-month FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	13,129	13,129	4,561	4,561
Adj. R^2	0.134	0.135	0.141	0.168

Table V

Trader Gender and Number of Copiers: Female Labor Force Participation Rate

This table shows the regression estimates of the number of copiers, regressed on a female trader dummy and trader characteristics. All variables are defined in Table I. All regressions include month and country fixed effects. We report the results from subsamples of low and high-FLFPR countries. The robust standard errors are in parentheses.

	Low female LFPR Countries		High female LFPR Countries	
	(1)	(2)	(1)	(2)
Female	-0.123***	-0.032	0.126***	0.183***
	(0.021)	(0.023)	(0.041)	(0.042)
Female*Beauty		0.052**		-0.123***
		(0.026)		(0.030)
Female*Age		0.166***		0.110***
		(0.028)		(0.028)
Beauty	0.062***	0.058***	0.126***	0.133***
	(0.012)	(0.013)	(0.011)	(0.011)
Age	-0.059***	-0.078***	0.054***	0.041***
	(0.010)	(0.011)	(0.010)	(0.010)
Perf	0.025***	0.025***	0.185***	0.185***
	(0.006)	(0.006)	(0.018)	(0.018)
Risk	-0.084***	-0.082***	-0.083***	-0.081***
	(0.007)	(0.007)	(0.006)	(0.006)
Msa	0.001	0.001	0.003***	0.003***
	(0.001)	(0.001)	(0.000)	(0.001)
Year-month FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	6,555	6,555	11,137	11,137
Adj. R^2	0.139	0.141	0.128	0.129

Table VI

Trader Gender and Net Flow

This table shows the regression estimates of net flow, regressed on a female trader dummy and trader characteristics. All variables are defined in Table I. All regressions include month and country fixed effects. The results are based on the whole sample. The robust standard errors are in parentheses.

	(1)	(2)
Female	-0.083***	-0.165***
	(0.032)	(0.037)
Perf	0.134***	0.125***
	(0.012)	(0.012)
Female*Perf	0.095**	0.197***
	(0.044)	(0.074)
Female*Perf_loss		-0.277***
		(0.094)
Perf_loss	-0.145***	-0.113***
	(0.021)	(0.021)
Beauty	0.007	0.007
	(0.008)	(0.008)
Risk	-0.043***	-0.042***
	(0.005)	(0.005)
Age	-0.009	-0.006
	(0.008)	(0.008)
Msa	-0.001***	-0.001***
	(0.000)	(0.000)
Year-month FE	Yes	Yes
Country FE	Yes	Yes
N	19,940	19,940
Adj. R^2	0.030	0.030

Table VII

Trader Gender and Net Flow: Trader Risk-Taking Levels

This table shows the regression estimates of net flow, regressed on a female trader dummy and trader characteristics. All variables are defined in Table I. All regressions include month and country fixed effects. We report the results from subsamples of traders taking low and high levels of risks based on one-month lagged trader risk scores. The robust standard errors are in parentheses.

	Low Trader Risk Score		High Trader Risk Score	
	(1)	(2)	(1)	(2)
Female	-0.070*	-0.142***	-0.075	-0.307***
	(0.037)	(0.043)	(0.062)	(0.071)
Perf	0.278***	0.266***	0.049***	0.038***
	(0.026)	(0.027)	(0.010)	(0.010)
Female*Perf	0.026	0.143	0.082	0.235**
	(0.066)	(0.109)	(0.064)	(0.110)
Female*Perf_loss		-0.327**		-0.435***
		(0.134)		(0.149)
Perf_loss	-0.138***	-0.089**	-0.080***	-0.040**
	(0.039)	(0.040)	(0.019)	(0.016)
Beauty	0.006	0.007	-0.001	0.001
	(0.011)	(0.011)	(0.007)	(0.007)
Risk	-0.065***	-0.064***	0.012	0.016**
	(0.010)	(0.010)	(0.008)	(0.008)
Age	-0.008	-0.005	-0.011	-0.006
	(0.010)	(0.011)	(0.008)	(0.008)
Msa	-0.001***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Year-month FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	14,586	14,586	5,352	5,352
Adj. R^2	0.043	0.043	0.070	0.082

Table VIII

Trader Gender and Net Flow: Female Labor Force Participation Rate

This table shows the regression estimates of net flow, regressed on a female trader dummy and trader characteristics. All variables are defined in Table I. All regressions include month and country fixed effects. We report the results from subsamples of low and high-FLFPR countries. The robust standard errors are in parentheses.

	Low female LFPR Countries		High female LFPR Countries	
	(1)	(2)	(1)	(2)
Female	-0.028	-0.042	-0.105**	-0.255***
	(0.040)	(0.049)	(0.042)	(0.052)
Perf	0.077***	0.076***	0.174***	0.160***
	(0.013)	(0.014)	(0.019)	(0.019)
Female*Perf	0.039	0.055	0.167**	0.372***
	(0.026)	(0.039)	(0.077)	(0.126)
Female*Perf_loss		-0.045		-0.531***
		(0.066)		(0.155)
Perf_loss	-0.063**	-0.056**	-0.208***	-0.158***
	(0.025)	(0.027)	(0.032)	(0.030)
Beauty	0.001	0.002	0.011	0.011
	(0.013)	(0.013)	(0.011)	(0.011)
Risk	-0.036***	-0.035***	-0.048***	-0.046***
	(0.007)	(0.007)	(0.007)	(0.007)
Age	-0.007	-0.007	-0.009	-0.005
	(0.011)	(0.011)	(0.010)	(0.010)
Msa	-0.002***	-0.002***	-0.001**	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Year-month FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	7,361	7,361	12,579	12,579
Adj. R^2	0.019	0.019	0.038	0.040

Figure I

This figure shows the relationship between the average number of copiers following the lead traders and the number of months since activation for each trader. We fit a cubic polynomial with the year-month fixed effect for female and male lead traders separately. The 95% confidence interval of the fitted curve is calculated with the fitted curve.

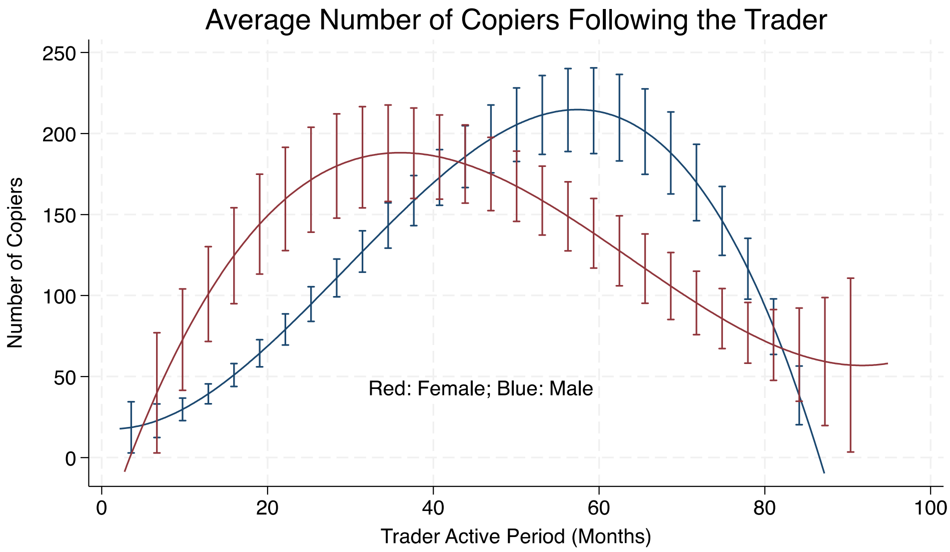

Figure II

This figure shows the relationship between the average lead trader performance and the number of months since activation for each trader. We fit a cubic polynomial with the year-month fixed effect for female and male lead traders separately. The 95% confidence interval of the fitted curve is calculated with the fitted curve.