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Why Do Female Traders Outperform? Evidence from the Japanese Retail FX Market

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Abstract: Using account-level daily data provided by SBI FXTRADE Co., Ltd. from 2021 to 2023, I find that female traders outperform male traders in the retail foreign exchange (FX) market across two profitability metrics: a likelihood of gaining positive profit per day and daily profit relative to order amounts. For instance, women have approximately a 5%-point higher probability of achieving positive profit and about 0.01%-point higher profit-to-order ratios than men. The gender gap in those profitability measures remains robust across different levels of personal assets. In the estimation by income bracket, a significant gender difference is observed except for the highest income tier. Three empirical facts help explain this gender gap. First, limit orders are positively associated with profitability, whereas stop orders are negatively associated. Women tend to use more limit and fewer stop orders than men, contributing to superior performance. Second, the decline in profitability associated with increased trading experience is larger for men than for women. This fact suggest that women exhibit a less substantial overconfidence bias than men. Third, the likelihood of exiting the market declines with successful trading experience, and this decline is more pronounced among women, suggesting a more effective self-selection process favoring skilled female traders.

Keywords: Foreign exchange; Retail trading; Behavioral bias; Female traders; Learning

JEL Classification: F31; G40

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1. Introduction

The retail foreign exchange (FX) market has continued to expand and now holds significant prominence as an investment option for individual investors, alongside equities and commodities. A key attraction for individual participants is the potential for substantial profits from high leverage, albeit at the cost of heightened risk. Given the inherently high-risk nature of FX trading, investors need to possess sufficient knowledge before participating. Nonetheless, the relatively low transaction costs and the possibility of initiating trades with modest capital have led to broad participation among retail investors.

This study is conducted in collaboration with SBI FXTRADE Co., Ltd. (SBI FXT), with the primary objective of analyzing the profitability of FX traders. The dataset used comprises account-level, daily aggregated data provided by SBI FXT, covering the period from the beginning of 2021 to the end of 2023. This paper's central focus is examining gender differences in trading performance. As detailed in the subsequent section, our analysis reveals that female traders outperform their male counterparts regarding profitability.

This paper empirically demonstrates three key factors contributing to this outcome: (i) women tend to employ trading strategies that are more conducive to profitability; (ii) women exhibit lower levels of overconfidence bias in FX trading, and (iii) self-selection mechanisms among female traders operate more effectively in this market. While numerous studies have examined gender differences in behavioral biases and profitability using individual trading data from equity markets,[1] relatively few have explored these issues within the retail FX market. Focusing on this under-researched domain, our study contributes to the literature on behavioral biases in investment decisions in retail FX trading.

I identify three main factors explaining differential profitability among retail FX investors. First, the share of limit and stop orders is positively and negatively associated with profitability, respectively. Notably, female traders tend to exhibit a higher share of limit orders. In FX trading, limit orders are typically used to profit from exchange rate fluctuations within a range by buying at lower and selling at higher prices. In contrast, stop orders capture returns from relatively larger exchange rate trends, such as buying during upward and selling during downward trends. Accordingly, trading strategies that seek to gain from range-bound fluctuations rather than trend-following strategies appear more successful in the highly volatile FX market. The results suggest that female traders are more inclined to adopt such a range-trading strategy.

Second, the analysis reveals a negative association between trading

[1] See Barbe and Odean (2001), Hibbert et al. (2018) and Hsu and Lin (2021) for instance.

experience—particularly the cumulative number of trading days—and profitability, with this adverse effect being more pronounced among male traders than female traders. Two competing hypotheses exist regarding the impact of trading experience on profitability. The first is the "learning-by-doing" hypothesis, which posits that experience leads to accumulating trading skills and thus improved profitability. The second is the overconfidence bias hypothesis, which suggests that increased experience may exacerbate overconfidence, ultimately impairing trading performance. When evaluating the relationship between trading days and profitability, the observed effect is the net outcome of these conflicting influences, and the dominant effect determines the direction of the empirical result. In the present study, the overall findings indicate that cumulative trading days negatively affect profitability, implying that the detrimental influence of overconfidence bias outweighs the potential benefits of learning-by-doing. Moreover, this negative impact is stronger among male traders than female traders, at least within the sample's observed range of cumulative trading experience. Thus, the second explanation for why female traders outperform their male counterparts is that male traders exhibit a higher degree of overconfidence bias.

The third factor pertains to behavioral differences between male and female traders following successful trades, i.e., after generating positive returns. Specifically, women are more likely than men to continue trading after experiencing a profitable trade. More precisely, while the likelihood (hazard rate) of exiting the market declines for all traders after achieving a positive return, the magnitude of this decline is greater for female traders than for their male counterparts. This finding suggests that self-selection mechanisms in the retail FX market operate more effectively among women. Consequently, female traders exhibit higher overall returns when examining aggregate profitability in the market than male traders. This constitutes the third explanatory factor behind the observed outperformance of female traders identified in this study.

Thaler (2021) highlight that men are more prone to motivated reasoning, which can impair decision quality. He demonstrated this through an online experiment involving approximately 1,000 participants, comparing behavioral patterns between men and women. Numerous prior studies using individual investor stock trading data have suggested that men, due to a stronger overconfidence bias than women, tend to trade more frequently, potentially eroding their profitability through the accumulation of transaction costs. Furthermore, statistically significant gender differences have been observed in trading behavior following realized gains or losses, with women often exhibiting more disciplined decision-making than men. These empirical patterns may reflect underlying behavioral biases between genders, as Thaler (2021) discussed. The findings of this study corroborate the existence of such gender-based behavioral differences in profitability within the retail foreign exchange (FX) market as well.

The rest of the paper is organized as follows. Section 2 reviews the related literature.

It first surveys studies on stock markets that utilize individual investor trading data, followed by a discussion of the relatively limited body of research on the FX market. Section 3 provides an overview of the dataset employed in this study. Section 4 presents the empirical finding that women exhibit higher profitability than men in FX trading. Sections 5 and 6 explore the underlying reasons for this gender-based profitability difference. Section 5 focuses on differences in trading strategies, while Section 6 investigates differences in behavioral biases, analyzing how gender-specific experience effects and success experiences influence market entry and exit, as well as subsequent trading behavior.

2. Literature Review

Analyses using individual investor trading data have been extensively conducted for stock markets. The landmark study by Barber and Odean (2000) found that individual investors trade excessively, significantly undermining their portfolio performance. This theme of detrimental overtrading is also discussed in Odean (1999), which attributes poor performance to overconfidence—a behavioral bias that leads investors to trade more than is optimal. Barber, Odean, and Zhu (2009a) and Kaniel, Saar, and Titman (2008) explored how retail trades influence stock prices by extending the analysis to market impact. The former demonstrates that individual trades, while small in scale, cumulatively affect market dynamics, particularly in less liquid stocks. The latter identifies a short-term return continuation following intense individual investor buying, implying some predictive power in retail flows. In terms of financial losses, Barber et al. (2009b) quantify how much individual investors lose by trading using comprehensive Taiwanese data. The study shows that retail investors incur significant losses due to poor timing and adverse selection, often subsidizing institutional profits.

A growing body of research explores gender differences in investment profitability using individual trading data. The seminal work by Barber and Odean (2001) revealed that men trade more frequently than women due to overconfidence, leading to significantly lower net returns. Subsequent studies confirmed that this behavioral trait persists across various contexts, with women generally achieving higher risk-adjusted returns. Research by Hibbert et al. (2018) found that, after incurring losses, many men keep investing in stocks, whereas most women withdraw. Despite prior outcomes, women are more inclined than men to anticipate unfavorable market conditions, indicating greater pessimism or risk aversion. Studies also show that gender differences in information access, financial literacy, and cultural biases further contribute to performance gaps. For instance, financial literacy mitigates male overconfidence, narrowing the gender gap (Hsu and Lin, 2021). Overall, women tend to be more disciplined and less speculative, resulting in comparatively superior investment outcomes.

In contrast to the extensive body of literature on stock markets, research investigating the determinants of profitability in retail FX markets remains relatively limited. Abbey and Doukas (2015) examine the profitability of individual currency traders and show that, on average, these traders lose money due to high transaction costs and poor timing, highlighting the challenges retail investors face in FX markets. They use account-level data for individual retail spot currency traders obtained from Collective2 (www.collective2.com). Ben-David et al. (2018) used transaction data provided by a large international broker based in Poland. The dataset includes around 3,000 FX accounts. They find no persistent relationship between past and future profitability—investors who have been profitable in the past do not necessarily continue to be so, and vice versa. Their analysis further reveals that trading volume and frequency increase following profitable trades and decrease after losses. Heimer and Imas (2022) explore how financial constraints influence investor behavior and performance using a dataset compiled by a social networking platform that contains information on individual retail forex transactions. They find that constrained investors, despite their limited resources, are less prone to excessive trading and thus avoid common behavioral biases, ultimately achieving better investment outcomes. Collectively, these studies emphasize the role of market structure, information asymmetries, and behavioral factors in shaping individual trading performance.

Hayley and Marsh (2016) is the most closely related work to this research. They utilize data from approximately 85,000 FX trading accounts to demonstrate that retail investors with shorter or younger investment experiences are more likely to reduce future trading activity after incurring losses. Hayley and Marsh (2016) define a "career success rate" as the proportion of trading days yielding positive returns relative to total trading days. They interpret a high career success rate as indicative of strong investment aptitude. Importantly, their findings suggest that while there is no clear evidence of a learning-by-doing effect—whereby experience alone leads to improved aptitude—investors may develop self-awareness of their investment ability over time, a process they term "learning the ability." This self-assessment enables those with higher innate aptitude to persist in the market and continue achieving superior cumulative returns, as reflected by a high career success rate.

Inspired by the analytical framework of Hayley and Marsh (2016), this study hypothesizes that gender-based differences in trading profitability can be explained by two interrelated factors: gender differences in how trading experience affects profitability over time and gender differences in the propensity to remain in or exit the FX market based on accumulated trading experience. Moreover, this study extends the existing literature by exploring gender differences in trading strategies—an area not addressed by Hayley and Marsh (2016).

An illustrative example utilizing data from Japanese FX traders is presented in a series of studies by Kentaro Iwatsubo. Notably, Hayo and Iwatsubo (2022) analyzed the determinants of trading performance based on survey data conducted between February 23 and March 1, 2018, on behalf of the Financial Futures Association of Japan. This survey targeted 1,000 traders representing the broader Japanese trader population. The authors examined three categories of potential determinants: (1) socio-demographic and economic conditions, (2) investment strategies and trading behavior, and (3) financial literacy. Their findings indicate that variables in these three domains significantly influence trading performance.[2] This study shares a commonality with the aforementioned series of studies by Kentaro Iwatsubo in that it also utilizes transaction data from Japanese FX traders. For example, Hayo and Iwatsubo (2022) report that older traders tend to exhibit lower profitability—a finding that aligns with the results of this study. Moreover, while Iwatsubo and Rieger (2024) highlight the detrimental effect of behavioral biases on profitability, this study similarly suggests, focusing on trading experience, that behavioral biases may negatively impact trading performance. Both Hayo and Iwatsubo (2022) and Iwatsubo and Rieger (2024) also explore gender differences in trading outcomes, with the latter finding that female traders tend to outperform their male counterparts. The most notable distinction of this study from those prior works lies in its in-depth investigation into the reasons behind women's superior trading performance.

Like Iwatsubo and Rieger (2024), this research was conducted in collaboration with SBI FXT. However, it differs significantly in scope, as it covers all accounts in the dataset, yielding a sample of over 120,000 traders. This large sample size enables a more granular analysis, particularly in gender-specific subsample examinations. On the other hand, this study relies solely on transaction data. Thus, it cannot incorporate individual-level attributes related to behavioral biases extracted via survey methods conducted by Iwatsubo and Rieger (2024). Therefore, this study and Iwatsubo and Rieger (2024) are best viewed as mutually complementary.

3. Data and Descriptive Statistics

Table 1 presents descriptive statistics for two profitability measures (success dummy and return rate) and three measures of trading method (market order share, limit order share and stop order share).[3] The success dummy is a binary variable that takes the value

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[2] Also, Iwatsubo (2024) analyzed the trading behavior of FX investors in the immediate aftermath of the COVID-19 outbreak (March 2020) by utilizing large-scale customer transaction data provided by an FX broker. In addition, Iwatsubo and Rieger (2024), based on a survey conducted in collaboration with SBI FXT involving over 1,300 traders, combined the survey results with trading records to demonstrate that behavioral biases substantially influence trader performance.

[3] Table A1 in the Appendix provides descriptive statistics for the IFD (if done) order share, OCO (one cancels the other) order share, and IFO (IFD and OCO) order share. These order types represent

of 1 if a positive profit is reported on the observation day and zero otherwise. The return rate is calculated by dividing the total profit on the observation day by the total order amount on the same day. Regarding the return rate, statistics are reported for the full sample and for a subsample excluding the top and bottom three percentiles to mitigate the influence of outliers. Furthermore, for confidentiality reasons, the minimum and maximum values of the return rate are represented by the average values of the bottom and top 1 percentiles, respectively. Panel A reports statistics for the full sample, Panel B is limited to male traders, and Panel C covers female traders. Since some traders did not disclose their gender, the sample size in Panel A exceeds the sum of those in Panel B and C.

=== Table 1 ===

Panel A presents the results for the full sample. Success dummy exhibits mean value exceeding 0.5, indicating that, on average, traders in the sample achieved positive returns on more than half of their trading days. The average return rate for the full sample is −0.1%; however, after excluding outliers, the mean return becomes 0.04%. This observation suggests that while the overall sample displays a negative return relative to the transaction amount, a positive average return is observed when extreme values are removed. Regarding trading methods, market orders account for the largest share at 70.3%. The shares of limit orders and stop orders are 13.4% and 2.9%, respectively. These figures imply that most traders do not engage in scheduled transactions through limit or stop orders, but instead predominantly execute trades at prevailing market prices via market orders.

Panels B and C report descriptive statistics for male and female traders. A key observation is that female traders outperform their male counterparts across success dummy and return rate without outliers. For example, the average success rate is 53.9% for men, compared to 58.5% for women. The standard deviation is also slightly smaller for women, indicating less variability. This observation indicates that, in terms of trading success rates, female traders not only outperform males on average but also exhibit lower dispersion. About the return rate excluding outliers, the mean return is higher for women, although the standard deviation is also greater, implying higher average returns but with higher variability.

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combinations of limit and stop orders; however, our dataset does not provide detailed information on how individual limit or stop orders are specified within these composite orders. Therefore, the primary analysis in this paper focuses specifically on limit and stop orders. Table A2 reports the extended regression results based on the specification in Table 2, additionally controlling for the shares of IFD, OCO, and IFO orders. Consistent with the main findings, a significant gender gap in profitability measures remains observable.

A second notable finding concerns differences in trading methods between genders. Male traders exhibit a market order share that is 1.2 percentage points higher than that of female traders. The gap in limit order share is more pronounced, with women using limit orders 4.9 percentage points more than men. Conversely, men use stop orders 1.5 percentage points more than women. These results indicate that women are more inclined to employ limit orders and less likely to use stop orders than men. Although not reported in the main text, similar patterns hold when trading behavior is measured by the number of transactions rather than by transaction volume.

4. Gender Differences in Profitability Measures

The observations in Table 1 indicate that female traders outperform male investors. In the following sections, we assess the robustness of this observation and explore the underlying factors driving this phenomenon. We estimate the following equation to examine the robustness of the descriptive observation that female traders outperform their male counterparts in profitability using the ordinary least squares (OLS) method.

$$Profitability_{i,t} = \alpha + \beta Female_i + \gamma Controls_i + \delta Controls_{i,t} + f_t + \varepsilon_{i,t} \tag{1}$$

$Profitability_{i,t}$ is the trader i's profitability measure (success dummy or return rate without outliers) reported in the trading day t. $Female_i$ is a dummy variable that takes a value of one for female traders, and zero otherwise. As noted earlier, a subset of traders did not disclose their gender. Given that the objective of this section is to examine whether profitability differs by gender, accounts with undisclosed gender are excluded from the analysis. Also, we restrict the sample to observed days with nonzero profits. $Controls_i$ is the vector of other trader's characteristics including the age in the beginning of the sample period (*Age*), and indicators of income and personal assets that the trader declared when he/she made the account. $Controls_{i,t}$ is the vector of explanatory variables, which vary across traders and sample days. This vector includes limit order share (*Limit*), stop order share (*Stop*), and cumulative number of trading days (*Days*). The cumulative number of trading days captures the trader's experience in the FX market. We also employ a cumulative number of transactions (*Counts*) instead of a cumulative number of trading days. We also employ the square terms of those experience variables. f_t is the sample-day fixed effect (FE), which may control for macroeconomic variables such as exchange rates, stock prices and production. $\varepsilon_{i,t}$ is the error term. We use robust standard errors clustered at the account (trader) level.

Table 2 presents the estimation results of Equation (1). Column (I) reports the results where the dependent variable is success dummy. The coefficient on the female dummy is positive and statistically significant, indicating that female traders have a daily trading success rate of 5 per cent points higher than male traders. This result is broadly consistent in magnitude with the descriptive observation reported in Table 1. No statistically significant gender differences are observed in profitability measures within the highest income bracket. In other words, male traders in the highest income group achieve a comparable level of profitability to female traders. As I show in the next section, this finding may be partly attributable to differences in trading strategies.

Initial age at the beginning of the sample period has a negative and significant effect on the success dummy, implying that older traders tend to have lower success rates in trading. This finding may suggest the presence of overconfidence bias associated with experience based on increasing age.

=== Table 2 ===

Limit order share is positively associated with the success dummy. This result suggests that traders often generated profits within the range-bound fluctuations of exchange rates by placing limit orders to buy at lower prices or selling existing positions at higher prices relative to the current market rate. In contrast, stop order share exhibits a negative effect. This result may indicate that trades relying on exchange rate trends—such as buying during upward movements or selling during downward trends—were less successful in contributing to success.

Cumulative trading days positively affect profitability, and the coefficient for the squared term of cumulative trading days is estimated to be negative. At first glance, this result suggests a positive experience effect, whereby trading success rates improve with accumulated trading experience, albeit at a diminishing rate. However, as Hayley and Marsh (2017) demonstrated, various trader-specific characteristics influence profitability, and the experience effect may be incorrectly estimated without properly controlling for these trader-specific attributes. In light of this, Table 3 presents results incorporating trader FE instead of the female dummy and other trader characteristics. The table presents separate estimation results for male and female traders to examine gender differences in experience effects. For both genders, the cumulative number of trading days has a negative effect on both success dummy and return rate, while the squared term of this variable exerts a positive effect. This result implies that once the trader FE is controlled for, success rate tends to decline with additional trading days, but the magnitude of this negative effect diminishes over time. These findings are consistent with the results reported by Hayley and Marsh (2017), which state that overconfidence bias becomes more significant for more experienced traders. In other words, within the sample used in this study, the negative impact of experience—arising from overconfidence bias that leads to a decline in profitability with prolonged trading—outweighs the positive impact of experience gained through learning by doing, which would otherwise enhance profitability over time. Moreover, the negative effect of the cumulative number of trading days on both the success dummy and the return rate is more pronounced for male traders than for female traders. Figure 1, based on the estimation results from Table 3, compares the relationship between trading days and the impact of trading days on profitability measures—Panel A for the success dummy and Panel B for the return rate—by gender.[4] The figure shows that, regardless of the number of trading days, the negative impact of trading days on profitability is more substantial for men than for women within the range of trading days in the sample. Barber and Odean (2001) demonstrate that in the stock market, men tend to be more overconfident and engage in more frequent trading, which ultimately deteriorates their investment performance. Our finding—that cumulative trading days negatively impact profitability and that this impact is more pronounced for men than women—is consistent with Barber and Odean (2001). This indicates that men are more susceptible to overconfidence bias, resulting in a more significant decline in profitability through experience.

=== Figure 1 and Table 3 ===

Columns (III) and (IV) of Table 2 present the estimation results in which the cumulative number of trades is used as a proxy for trading experience instead of cumulative trading days. The estimated effects of the female dummy, age, limit order share, and stop order share remain consistent with previous specifications. Specifically, female traders exhibit higher success and return rates, while older traders perform worse regarding both profitability measures. The limit order share is positively associated with trading performance, whereas the stop order share is negatively correlated. Column (III) indicates that neither the level nor the quadratic term of cumulative trade count has a statistically significant effect on the success rate. In contrast, Column (IV) shows that while the level of cumulative trade count has a negative effect on the return rate, its square term exerts a positive effect, suggesting a non-linear relationship. Nonetheless, similar to the results using cumulative trading days (Columns I and II), these specifications (Columns III and IV) may not fully control for the trader-specific unobserved heterogeneity that influences trading performance. According to Column (III) of Table 3, in which we controlled for the trader FE, the cumulative number of transactions has no statistically significant effect on the success dummy for either gender; its squared term shows a negative and significant impact. Therefore, the effect of cumulative trade count on the success dummy provides weaker support for the overconfidence bias hypothesis than the effect of cumulative trading days. Column (IV) of Table 3 shows the signs of the

[4] For example, the effect of trading days on the success dummy for male traders (Figure 1, Panel A, "Male") is calculated as $-1.02E^{-04} + 7.87E^{-08} \times Trading\ days$. In the figure, the maximum value on the horizontal axis is set to 781, corresponding to the maximum number of trading days in the sample.

coefficients on cumulative trade count, and its square terms are negative and positive, respectively. This pattern is consistent with the overconfidence bias hypothesis.

As discussed thus far, the empirical results confirm the finding observed in Table 1 that female traders outperform their male counterparts in terms of success and return rates. In addition, the analysis reveals that both profitability measures are negatively associated with age and stop order share, while they are positively associated with limit order share. Although some variation arises depending on whether cumulative trading days or a cumulative number of trades is used as a proxy for experience, the estimates incorporating trader FEs (Table 3) suggest that profitability declines with increased trading experience, with a larger decline for men.

We conduct additional robustness checks regarding the evidence that female traders outperform male traders in the Appendix. For instance, Table A2 extends the baseline model by including IFD, OCO, and IFO order shares as explanatory variables, in addition to limit and stop order shares. Table A3 re-estimates the main specifications using monthly-aggregated data to capture a longer-term perspective. Considering that women outperform men in terms of the daily return rate, it may be interpreted that male traders manage to adjust their performance over a month, thereby achieving a comparable monthly return rate to that of female traders.[5] In the following section, we further investigate potential explanations for why female traders outperform their male counterparts, focusing on differences in trading strategies and learning the ability between genders.

5. How Are Male and Female Traders *Differently* Trading?

[5] Table A4 examines how the effects of trading experience manifest over a longer time horizon compared to daily-level analyses. Specifically, using monthly-aggregated data and controlling for trader FEs, we estimate the impact of cumulative trading days and cumulative number of trades on both the success dummy and return rate separately for male and female traders. The results show that, for both genders, cumulative trading days and its squared term have a negative and positive effect, respectively, on the success dummy. When return rate is used as the dependent variable, the coefficient on cumulative trading days is negative but statistically insignificant, whereas the squared term is positively and significantly associated with return rate. As for the cumulative number of trades, the level term significantly negatively affects the success dummy for both men and women. While the squared term is positive for both groups, it is statistically significant only for female traders. Regarding return rate, the cumulative number of trades exhibits a significant positive effect only for women, and the squared term is insignificant for both genders. These findings suggest that, similar to the daily-level results, the relationship between a cumulative number of trades and profitability indicators remains relatively weak at the monthly frequency. However, the effect of cumulative trading days coincides with the overconfidence bias hypothesis, especially for the success dummy, even when analyzed over a longer time horizon.

Building on the evidence presented in the previous section that female traders outperform male traders in terms of both success rate and return rate, this section examines whether trading strategies differ between men and women. Specifically, we estimate the following equation using the OLS method.

$$TradingMethod_{i,t} = \eta + \theta Female_i + \kappa Controls_i + \lambda Controls_{i,t} + f_t + \epsilon_{i,t} \qquad (2)$$

$TradingMethod_{i,t}$ is the trader i's a measure of trading method reported in the trading day t. We employ four measures of trading method: market order share, limit order share, stop order share, and the number of days from the previous trading day (*Intensity*).[6] Most control variables are the same as in the previous section. $Female_i$ is a dummy variable that takes a value of one for female traders, and zero otherwise. As in the estimation of equation (1), we exclude accounts with undisclosed gender. $Controls_i$ and $Controls_{i,t}$ are the vector of trader's characteristics and the vector of explanatory variables, which vary across traders and sample days. Specifically, we use traders' age at the beginning of the sample period and income and asset brackets as trader characteristics. As with the estimation of Equation (1), income and assets are not precisely measured; therefore, we do not report the estimation results for these variables. Moreover, trading methods may also vary depending on trading experience. Accordingly, we use cumulative trading days and cumulative trades as experience variables. f_t is the sample-day FE, and $\epsilon_{i,t}$ is the error term. We use robust standard errors clustered at the account level.

Table 4 presents the estimation results. Columns (I)–(IV) use cumulative trading days as the experience variable, whereas columns (V)–(VIII) employ a cumulative number of trades. Column (I) shows that female traders have a market order share one percentage point lower than male traders. Conversely, as indicated in column (II), female traders exhibit a limit order share of six percentage points higher. According to column (III), the stop order share is two percentage points lower for female traders compared to male traders. These results, including the magnitude of the effects, are broadly consistent across columns (V)–(VII), which use a cumulative number of trades as the measure of experience. As shown in column (IV), the number of days between trades is 88% higher for female traders than for male traders, indicating that women trade less frequently than men in terms of trading days. When cumulative number of trades is used instead as the experience variable (column VIII), the magnitude of this effect decreases to 34%; nevertheless, the finding that women leave longer intervals between trades remains robust. The analysis results concerning the shares of limit orders, stop orders, and trading intensity remain broadly robust across estimations stratified by income and asset brackets.

[6] Table A5 in the Appendix presents estimation results in which the shares of trading methods other than market, limit, and stop orders are used as dependent variables. The table shows that female traders tend to have a higher share of IFD orders, while their shares of OCO and IFO orders are lower.

However, the effect of the female dummy on the shares of limit and stop orders becomes statistically insignificant in the highest income and asset brackets. This observation may partially account for the insignificant effect of the female dummy on daily profitability measures within the highest income group that I observed in Section 4.

=== Table 4 ===

The other explanatory variables also exhibit statistically significant effects across nearly all trading method outcomes. For instance, age positively affects both market order share and limit order share, while it negatively affects stop order share. Additionally, age is negatively associated with trading intensity. These results suggest that older traders rely more on the market, limit orders, and engage more frequently than younger traders. In contrast, younger traders are more likely to utilize stop orders compared to their older traders.

Cumulative trading days have a negative effect on the market order share, while the squared term is positively associated with it. A similar pattern is observed for the limit order share. These results suggest that as traders accumulate more trading days, their use of market and limit orders increases, but the marginal effect of experience diminishes over time. Although the coefficient on cumulative trading days is positive for the stop order share, it is statistically insignificant, whereas the squared term shows a significant negative effect. Regarding trading intensity, cumulative trading days are negatively associated with the number of days between trades, while the squared term has a positive effect. This result indicates that as traders gain more experience, the interval between trades tends to shorten, although this effect diminishes with further experience.

As in the profitability analysis, unobserved trader-specific characteristics not fully captured by the current specification may also influence trading methods. To address this concern, in Table 5, we replace the female dummy, age, income bracket, and asset bracket with trader FEs and examine the impact of trading experience on trading behavior separately by gender. Columns (I)–(IV) of Table 5 focus on the impact of cumulative trading days. The signs of the coefficients on the level and squared terms of cumulative trading days are broadly consistent with those reported in Table 4 for both genders. Notably, the coefficient for cumulative trading days becomes significant with stop order share as the dependent variable, as shown in Column (III) of both panels. These results confirm that, even after controlling for trader FEs, there is a consistent tendency among both men and women to decrease the share of limit orders—which positively affects profitability with experience—and to increase the share of stop orders—which negatively affects profitability with experience. Limit orders are often used to generate profits from intra-range fluctuations in exchange rates by buying low and selling high. In contrast, stop orders are typically employed to gain from large exchange rate trends by buying in upward movements and selling in downward ones. The observed tendency to shift from limit to stop orders with increased experience may reflect a behavioral bias toward seeking profits from major trends. This finding sheds light on a specific mechanism underlying the decline in profitability with experience, potentially driven by overconfidence bias. Our ability to analyze these behavioral shifts in detail, in relation to changes in profitability, is a key advantage of our empirical approach, which incorporates detailed information on trading methods.

The impact of a cumulative number of trades on trading methods appears to be highly sensitive to gender and the inclusion of trader-FEs and does not yield consistently robust results. For instance, in columns (V)–(VII) of Table 4, both the level and squared terms of cumulative trade count are statistically significant across all specifications. However, when trader FEs are included, as shown in columns (V)–(VII) of Table 5, statistical significance disappears in many cases, regardless of gender. These findings suggest that, at least within the context of this sample, cumulative trading days serve as a more reliable proxy for capturing experience effects on trading behavior and profitability than cumulative number of trades.

=== Table 5 ===

6. How Do Male and Female Traders Learn Their Innate Ability?

In this section, we investigate the impact of prior trading success on subsequent trader behavior. Specifically, our analysis proceeds in two parts. First, we examine whether experiencing a successful trade reduces the likelihood that a trader exits the market. To this end, we employ the Andersen–Gill (AG) model, which allows for repeated events, to assess changes in trading continuity. Second, we analyze how successful trading experiences influence the trader's behavior in terms of order size, number of trades, and trading frequency. In both parts of the analysis, particular attention is paid to gender differences, enabling us to explore potential heterogeneity in behavioral responses between male and female traders.

6.1. Decision to Quit

We hypothesize that success in current trading activities influences future trading behavior. For instance, Hayley and Marsh (2017) demonstrate, using a Cox proportional hazards model, that successful trading reduces the likelihood of a trader exiting the market. Their study also reveals that following a successful trade, traders tend to increase their transaction amounts and counts, and shorten the interval days between trades. To examine whether similar behavioral patterns can be observed in our sample, we employ the AG model, an extension of the Cox model that accommodates multiple event occurrences per subject and time-varying covariates. This modeling approach is particularly suitable for our context, as traders often suspend trading temporarily and subsequently resume it, potentially multiple times. Following Hayley and Marsh (2017), we assume that a trader has exited from the market if there is a gap of 30 days or more between two trading dates. Our analysis focuses on whether the impact of trading success on the hazard of market exit varies by gender. The hazard function of the AG model is given by

$$h_{i,l}\left(t \middle| \boldsymbol{Z}_{i,l}(t)\right) = h_0(t)\, exp\left(\boldsymbol{b}\boldsymbol{Z}_{i,l}(t)\right) \tag{3}$$

$h_{i,l}\left(t \middle| \boldsymbol{Z}_{i,l}(t)\right)$ denotes the hazard function at time t for trader t's l-th exit event. $h_0(t)$ represents the baseline hazard function. $\boldsymbol{Z}_{i,l}(t)$ denotes the vector of covariates at time t corresponding to trader i's l-th event. $\boldsymbol{b}$ is the regression coefficients associated with the covariates. $\boldsymbol{Z}_{i,l}(t)$ includes prior trading success, operationalized through two measures: a success dummy (*Success*) and a career success rate (*Career*) on the last trading day. The success dummy has been used in preceding analyses. The career success rate is defined as the proportion of days with positive profits relative to the cumulative number of trading days up to the observation date. To assess gender differences in the impact of trading success on the hazard rate, we include interaction terms between the success variables and a female dummy variable. We also control for the female dummy to account for potential gender differences in hazard rates. Although the estimation results are not reported in the paper, we include the cumulative trading amount and a cumulative number of trades as covariates, following the approach of Hayley and Marsh (2017). To adjust for differences in the baseline hazard across trader characteristics and observation dates, all estimations include income and asset brackets and the observation date as strata variables. We use robust standard errors clustered at the account level. The analysis is restricted to traders who opened their accounts during the sample period when we use the success rate as the explanatory variable so that we calculate their true success rate.

Table 6 presents the estimation results of the AG model. The table represents hazard ratios; a value below 1 indicates that an increase in the explanatory variable is associated with a decrease in the probability of a trader exiting the market, whereas a value above 1 implies an increase in exit probability. Column (I) reports the result using only the success dummy as the explanatory variable. The hazard ratio for the success dummy is estimated at 0.97 and is statistically significant. This result suggests that traders who recently recorded a positive profit experience a 3% lower probability of exiting the market thereafter. Column (II) shows the result using only the career success rate as the explanatory variable. Similarly, it suggests that a 10-percentage-point increase in the cumulative success rate reduces the probability of market exit by 4.7%. Column (III) presents the results when the success dummy and the career success rate are included simultaneously. Even in this case, consistent with Columns (I) and (II), successful experience is associated with a reduced probability of market exit. However, the hazard ratios for both explanatory variables are significantly higher than when each variable is used individually, implying a certain degree of correlation between the two variables. This correlation is likely to be more pronounced among traders with less investment experience, such as traders who started trading within our sample period. Therefore, these two explanatory variables are used separately for the analysis in the subsequent estimations.[7]

=== Table 6 ===

Column (IV) presents the results of adding a female dummy variable alongside the success dummy to examine gender differences in hazard rates. The effect of the success dummy remains consistent with earlier analyses. The hazard ratio for the female dummy is below 1, indicating that women have an 11% lower probability of exiting the market than men. In Column (V), an interaction term between the success dummy and the female dummy is included to investigate whether the effect of success on hazard rates differs by gender. The hazard ratio for the interaction term is not statistically significant, suggesting that there is no gender difference in how recent success affects the likelihood of market exit.

Columns (VI) and (VII) present the results of an analysis similar to that in Columns (IV) and (V), but using the career success rate instead of the success dummy. Column (VI) shows that even when using the career success rate, women have a lower probability of exiting the market than men. The magnitude of this effect is broadly consistent with the result in Column (II). The analysis including the interaction term between the career success rate and the female dummy shown in Column (VII) reveals that the hazard ratio for the interaction term is significantly below 1. This result indicates that while cumulative success reduces the exit probability for both genders, the reduction is greater for women. Specifically, a 10% increase in the cumulative success rate lowers the exit probability by 4.4% for male traders and 6.2% for female traders. These findings explain why, at the aggregate level, female traders may outperform their male counterparts in profitability. Female traders who accumulate success over time exhibit a higher probability of remaining in the market than male traders with similar levels of cumulative success. In other words, self-selection functions more effectively for female traders than male traders, resulting in a market composition in which female traders with higher innate ability are

[7] Hayley and Marsh (2017) conducted their analysis using the success dummy and the career success rate simultaneously. In their baseline analysis, the estimated hazard ratios were 0.842 for the success dummy and 0.848 for the career success rate. Accordingly, our estimation results presented in Table 6, Column (III), which also incorporate both the success dummy and the career success rate, are broadly consistent with their findings in quantitative terms.

more likely to persist.

Although not presented in the main text, we discuss the findings from stratified analyses based on income and personal asset levels. The results remain robust across all brackets: recent success (*Success*) and an increase in cumulative success probability (*Career*) are consistently associated with a lower likelihood of market exit. Similarly, the finding shown in Column (V)—that the interaction term between *Success* and the female dummy is statistically insignificant—holds across all income and asset brackets.

However, heterogeneity is observed regarding the interaction between *Career* and the female dummy (cf. Column VII). Specifically, this interaction term is statistically significant only within the lowest income bracket but insignificant in relatively higher income groups. This result suggests that the tendency for women to remain in the market with increasing cumulative success is observed only among low-income traders.

Put differently, among high-income male traders, the self-selection mechanism through "learning the ability" operates to a similar extent as it does for high-income female traders. In contrast, low-income male traders exhibit a relatively stronger tendency to remain in the market despite failure, implying that self-selection is less effective in this group.

In the analysis by personal asset bracket, the interaction between *Career* and the female dummy is statistically significant only among traders in the second-lowest asset bracket. The absence of a significant effect in the lowest asset group prevents us from concluding as clearly as those based on income bracket. Nevertheless, for traders in the higher asset brackets (i.e., the top two brackets), the lack of gender-based differences aligns with the findings from the income-based analysis, suggesting a potentially similar interpretation.

6.2. Experience Impacts on Trades

In the preceding subsection, we examined how prior success experiences influence the hazard of market exit. This subsection focuses on how those successful experiences affect subsequent trading behavior. Specifically, we estimate the following equation to examine the impact of success experience on trading behavior:

$$Trade_{i,t} = \mu + \nu z_{i,t} + \xi\left(z_{i,t} \times Female_i\right) + oTrade_{i,t-1} + f_i + f_t + u_{i,t} \qquad (4)$$

$Trade_{i,t}$ is the trader i's a measure of trading behavior reported in the trading day t. We employ three measures of trading method: transaction volume, number of transactions, and the number of days elapsed since the last trading day. We take the natural logarithm for all three variables. $z_{i,t}$ captures prior trading success, operationalized through two measures: a success dummy and a career success rate on the last trading day; both have been used in preceding analyses. $Female_i$ is a dummy variable that takes a value of one for female traders, and zero otherwise. We also employ the lagged dependent variable ($Trade_{i,t-1}$) to control for the inertia of trading behavior. f_i and f_t are the trader and sample-day FEs, respectively. In some cases, we use FEs for income and asset brackets instead of the trader FE. $u_{i,t}$ is the error term. We use robust standard errors clustered at the account level.

=== Table 7 ===

Impacts on the Trading Value

Table 7 presents the results of our empirical analysis. As the FEs employed vary across columns, we explicitly indicate the types of FEs used at the bottom of each column. "T" denotes trader FEs, "D" indicates date FEs, "S" refers to FEs for income brackets, and "A" represents FEs for asset brackets. Because trader-FEs provide a more granular control than the income and asset bracket FEs, we exclude the latter two when trader-FEs are included. Although the lagged dependent variable is included in all specifications, its estimation results are omitted from the table due to space constraints.

In Panel A, we use the trading value as a dependent variable. Column (I) reports the result using the success dummy. In this specification, the coefficient on the success dummy is not statistically significant, suggesting that, on average, a recent success does not necessarily affect the current transaction volume. Column (II) presents results using the career success rate as the explanatory variable. In contrast to the success dummy, the career success rate significantly positively affects transaction volume. This result implies that traders who accumulate success over time tend to increase their trading volume.

Column (III) simultaneously includes the success dummy and the career success rate. The coefficient on the career success rate remains positive and significant, whereas the coefficient on the success dummy now becomes positive and statistically significant. This result suggests a potential multicollinearity issue arising from the correlation between the two success measures. Consequently, we include the success dummy and the career success rate separately in the subsequent columns.

In Column (IV), we estimate the effects of the success dummy and a female dummy variable. Since the female dummy captures a trader-specific characteristic, it cannot be used with the trader-FEs. Thus, we substitute trader FEs with income and asset bracket FEs. The success dummy exhibits a significantly negative impact. However, as Column (I) indicates, the effect becomes insignificant once trader-FEs are controlled. This result suggests that the estimated effect of the success dummy may be biased if trader heterogeneity is not adequately accounted for. Therefore, as in Column (I), it is reasonable to conclude that the success dummy has no significant effect at the aggregate level. The coefficient on the female dummy is significantly negative, indicating that female traders, on average, have lower daily transaction volumes than their male counterparts.

Column (V) extends the analysis by including an interaction term between the success dummy and the female dummy, along with the success dummy itself. Trader FEs are included to control for trader characteristics rigorously. The success dummy has a significantly positive coefficient, while the interaction term is significantly negative. The sum of the coefficients on the success dummy and the interaction term is approximately -0.04, suggesting that recent success increases transaction volume for male traders but decreases it for female traders. This offsetting effect may explain why the success dummy appears insignificant in Column (I).

Column (VI) reports the results using the career success rate and the female dummy as explanatory variables. As in Column (IV), FEs for income and asset brackets are included instead of trader FEs. The coefficient on the career success rate is positive and statistically significant. However, its magnitude is smaller than those reported in Columns (II) and (III), where trader-FEs are employed. This discrepancy suggests that rigorously controlling for trader characteristics is essential when assessing the impact of the career success rate.

Column (VII) presents the results based on the career success rate and its interaction with the female dummy. We employ trader FEs in this specification. The coefficient on the career success rate is positive and significant, while the interaction term does not have a significant effect. These results indicate that traders with higher cumulative success tend to increase their trading volume regardless of gender.

Impacts on the Number of Trade

Panel B presents the results in which the dependent variable is the number of orders. Column (I) shows that the success dummy has a significantly positive effect on the number of orders, indicating that traders tend to increase their daily order counts following a recent success. Column (II) uses the career success rate as the explanatory variable and finds a similarly positive and statistically significant effect. These findings suggest that a higher cumulative success rate, like a recent success, is associated with an increase in the number of orders.

Column (III) includes both the success dummy and the career success rate. Although the changes in coefficients from Columns (I) and (II) are relatively minor compared to Panel A, both *Success* and *Career* will be included separately in the subsequent analyses to account for potential correlation between these two explanatory variables. Column (IV) incorporates the success dummy and the female dummy. The success dummy remains significantly positive, while the coefficient on the female dummy is significantly negative, indicating that female traders place fewer daily orders than their male counterparts. The finding in the table that women engage in fewer trades is consistent with Barber and

Odean's (2001) finding for the stock market. In Column (V), we extend the model by including the interaction term between the success dummy and the female dummy. The success dummy is positively and significantly associated with the number of orders, while the interaction term is significantly negative. The sum of these coefficients is approximately zero, suggesting that male traders increase their order counts in response to recent success, whereas female traders do not change daily order counts.

Column (VI) reports the results using the career success rate and the female dummy. The career success rate has a significantly positive effect, while the female dummy remains significantly negative, consistent with the findings in Column (IV) using the success dummy. Finally, Column (VII) includes the career success rate and its interaction with the female dummy. The career success rate is positively associated with daily order counts, and the interaction term is negative and insignificant.

Impacts on the Trade Intensity

Panel C presents the estimation results, where the dependent variable is defined as the number of days since the last trading day. Column (I) reports the result using the success dummy as the explanatory variable, indicating that a 3 per cent reduction follows a successful trade in the number of days between transactions. Column (II) employs the career success rate as the explanatory variable. It shows that a 10 per cent point increase in cumulative success rate is associated with a 1.9 per cent decrease in the inter-trade interval. Column (III) includes both explanatory variables simultaneously, and both *Success* and *Career* are found to exert statistically significant negative effects. As in Panels A and B, to account for the potential correlation between *Success* and *Career*, subsequent columns employ these two explanatory variables separately.

Column (IV) presents the estimation results incorporating both the success dummy and a female dummy variable. The coefficient on the success dummy remains negative and statistically significant, while the coefficient on the female dummy is statistically insignificant. This finding suggests no significant gender difference in the number of days between trades.

Column (V) introduces an interaction term between *Success* and the female dummy. The coefficient on *Success* continues to be negative and statistically significant, and the interaction term is also estimated to be significantly negative. These results imply that male and female traders reduce the interval between trades following a successful transaction (i.e., increase their trading frequency). Still, the degree of this reduction is greater for female traders.

Column (V) findings suggest that female traders may be more responsive than male traders in increasing their trading activity after recognizing their innate ability. However, similar analyses using the career success rate yield less consistent evidence. Column (VI) includes the career success rate and the female dummy. As in Column (II), an increase in the cumulative success rate is associated with a shorter interval between trades, indicating more frequent trading. Nevertheless, Column (VII) introduces the interaction between career success rate and the female dummy, and the positive coefficient on the interaction term suggests that the degree of interval reduction is smaller for women. This finding is not entirely consistent with the results based on the success dummy, indicating the need for further investigation.

7. Conclusion

This study investigates gender differences in trading performance among retail foreign exchange (FX) investors using detailed account-level data from SBI FXTRADE Co., Ltd., covering 2021–2023. The empirical evidence consistently indicates that female traders outperform their male counterparts across two profitability measures: the probability of generating positive returns and the profit-to-order ratio. These findings are robust across most income and personal asset brackets, except for the highest income group, where gender-based differences become statistically insignificant.

Three mechanisms help explain this observed gender gap in profitability. First, women are more likely to use limit orders and less likely to use stop orders—trading strategies that are positively and negatively associated with profitability, respectively. Second, the negative impact of trading experience on profitability—interpreted as a manifestation of overconfidence bias—is more pronounced among male traders. Third, successful trading experience is more strongly associated with continued market participation among women, suggesting a more effective self-selection mechanism whereby higher-ability female traders are more likely to persist in the market.

Although the profitability advantage for women diminishes in higher income and asset brackets, the aggregate findings suggest that female traders display more disciplined trading behaviors, lower susceptibility to behavioral biases such as overconfidence, and more effective learning and self-selection processes. These insights contribute to the growing literature on gender and financial decision-making and offer practical implications for investor education and platform design in the retail FX market.

Overall, the study underscores the importance of behavioral factors in shaping trading outcomes and highlights the role of gender as a salient determinant of performance. Future research may extend this framework to other asset classes or explore the dynamic interaction between gender, experience, and risk preferences in retail investment contexts. Also, it is difficult to rule out the possibility that unobservable factors such as educational background may influence the current results. Therefore, the factors contributing to gender differences require further in-depth investigation.

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Table 1. Descriptive statistics of profit measures and trading methods

Panel A: Full sample					
	Obs.	Mean	S.D.	Minimum	Maximum
Success dummy	8,935,666	0.548	0.498	0	1
Return rate	6,935,727	-0.001	1.047	-0.2078	0.0702
Return rate (without outliers)	6,519,585	0.0004	0.0016	-0.0057	0.0069
Market order share	8,601,548	0.703	0.366	0	1
Limit order share	8,601,548	0.134	0.276	0	1
Stop order share	8,601,548	0.029	0.118	0	1
Panel B: Male					
	Obs.	Mean	S.D.	Minimum	Maximum
Success dummy	7,101,407	0.539	0.498	0	1
Return rate	5,518,070	-0.001	1.152	-0.2075	0.0646
Return rate (without outliers)	5,194,193	0.0004	0.0015	-0.0057	0.0069
Market order share	6,847,044	0.705	0.362	0	1
Limit order share	6,847,044	0.124	0.267	0	1
Stop order share	6,847,044	0.032	0.124	0	1
Panel C: Female					
	Obs.	Mean	S.D.	Minimum	Maximum
Success dummy	1,783,690	0.585	0.493	0	1
Return rate	1,375,917	-0.001	0.456	-0.2115	0.0929
Return rate (without outliers)	1,285,819	0.0006	0.0016	-0.0055	0.0070
Market order share	1,704,940	0.693	0.381	0	1
Limit order share	1,704,940	0.173	0.308	0	1
Stop order share	1,704,940	0.017	0.089	0	1

Notes: This table presents the descriptive statistics for three profitability measures (success dummy and return rate) and trading methods (shares of market orders, limit orders, and stop orders) separately for the full sample, male traders, and female traders. For the return rate, the table shows statistics of the rate, including and excluding outliers (the top and bottom three percentiles). Furthermore, for confidentiality reasons, the maximum and minimum values of the return rate are reported as the averages of the top and bottom one percentile, respectively.

Table 2. Gender differences in the profitability measures

	(I)	(II)	(III)	(IV)
Dependent variable:	Success dummy	Return rate	Success dummy	Return rate
Female	0.05 ***	1.14E-04 ***	0.05 ***	1.11E-04 ***
	0.00	*1.01E-05*	*0.00*	*9.87E-06*
Age	-8.52E-04 ***	-5.33E-06 ***	-4.69E-04 ***	-4.20E-06 ***
	9.94E-05	*3.58E-07*	*9.85E-05*	*3.37E-07*
Limit	0.26 ***	6.31E-04 ***	0.27 ***	6.32E-04 ***
	0.00	*1.59E-05*	*0.00*	*1.55E-05*
Stop	-0.31 ***	-4.76E-04 ***	-0.31 ***	-4.95E-04 ***
	0.01	*2.51E-05*	*0.01*	*2.54E-05*
Days	3.00E-04 ***	2.51E-07 ***		
	1.24E-05	*4.39E-08*		
*Days*Days*	-2.25E-07 ***	-2.82E-10 ***		
	2.15E-08	*6.77E-11*		
Count			1.14E-07	-5.92E-09 ***
			1.10E-07	*4.10E-10*
*Count*Count*			1.40E-13	1.06E-14 ***
			2.79E-13	*1.76E-15*
Obs.	6,707,319	6,333,966	6,707,319	6,333,966
Adj. R2	0.048	0.032	0.045	0.034

Notes: The dependent variable is shown in each column. In columns (II) and (IV), the return rate excluding outliers is used as the dependent variable. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for income brackets, personal asset brackets, and dates. Moreover, in all columns, observation days with zero profit and traders whose gender was not reported are excluded from the analysis sample.

Table 3. Experience variables and profitability measures

Panel A: Male	(I)	(II)	(III)	(IV)
Dependent variable:	Success dummy	Return rate	Success dummy	Return rate
Days	-1.02E-04 ***	-6.70E-07 ***		
	1.30E-05	*4.56E-08*		
*Days*Days*	7.87E-08 ***	5.89E-10 ***		
	1.58E-08	*5.67E-11*		
Counts			8.43E-08	-9.31E-10 ***
			6.58E-08	*1.85E-10*
*Counts*Counts*			-2.17E-13 *	1.65E-15 ***
			1.20E-13	*4.25E-16*
Obs.	5,366,803	5,075,004	5,366,803	5,075,004
Adj. R2	0.168	0.202	0.168	0.202
Panel B: Female	(I)	(II)	(III)	(IV)
Dependent variable:	Success dummy	Return rate	Success dummy	Return rate
Days	-6.61E-05 **	-5.09E-07 ***		
	2.59E-05	*1.05E-07*		
*Days*Days*	6.64E-08 **	4.41E-10 ***		
	3.13E-08	*1.18E-10*		
Counts			1.35E-07	-1.73E-09 ***
			1.38E-07	*4.64E-10*
*Counts*Counts*			-4.36E-13 ***	1.45E-15 **
			1.53E-13	*6.32E-16*
Obs.	1,326,695	1,245,862	1,326,695	1,245,862
Adj. R2	0.193	0.260	0.193	0.260

Notes: The dependent variable is shown in each column. In columns (II) and (IV), the return rate excluding outliers is used as the dependent variable. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for traders and dates. Panels A and B present the analysis results for male and female traders, respectively. In all specifications, observation days with zero profit and traders whose gender was not reported are excluded from the analysis sample.

Table 4. Gender differences in trading methods

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variable:	Market order share	Limit order share	Stop order share	Intensity	Market order share	Limit order share	Stop order share	Intensity
Female	-0.01 **	0.06 ***	-0.02 ***	0.88 ***	-0.01 **	0.06 ***	-0.02 ***	0.34 ***
	0.01	*0.00*	*0.00*	*0.07*	*0.01*	*0.00*	*0.00*	*0.08*
Age	1.16E-03 ***	1.27E-03 ***	-3.76E-04 ***	-0.03 ***	8.12E-04 ***	1.35E-03 ***	-3.65E-04 ***	-0.11 ***
	1.74E-04	*1.12E-04*	*3.90E-05*	*0.00*	*1.70E-04*	*1.12E-04*	*3.80E-05*	*0.00*
Days	-2.10E-04 ***	-6.17E-05 ***	7.63E-06	-0.14 ***				
	2.08E-05	*1.39E-05*	*5.91E-06*	*0.00*				
*Days*Days*	2.10E-07 ***	8.78E-08 ***	-2.89E-08 ***	1.85E-04 ***				
	3.53E-08	*2.45E-08*	*1.01E-08*	*1.40E-06*				
Counts					1.04E-06 ***	-8.87E-07 ***	-1.90E-07 ***	-1.56E-04 ***
					1.73E-07	*1.24E-07*	*4.79E-08*	*1.05E-05*
*Counts*Counts*					-1.88E-12 ***	1.61E-12 ***	3.51E-13 ***	2.92E-10 ***
					4.53E-13	*3.68E-13*	*1.15E-13*	*4.80E-11*
Obs.	8,551,984	8,551,984	8,551,984	8,885,093	8,551,984	8,551,984	8,551,984	8,885,093
Adj. R2	0.010	0.025	0.007	0.099	0.010	0.026	0.007	0.065

Notes: The dependent variable is shown in each column. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for income brackets, personal asset brackets, and dates. Moreover, in all columns, traders whose gender was not reported are excluded from the analysis sample.

Table 5. Experience variables and trading methods

Panel A: Male	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variable:	Market order share	Limit order share	Stop order share	Intensity	Market order share	Limit order share	Stop order share	Intensity
Days	-7.82E-05 ***	-3.91E-05 ***	3.76E-05 ***	-0.08 ***				
	1.53E-05	*1.16E-05*	*6.31E-06*	*0.00*				
*Days*Days*	1.09E-07 ***	5.29E-08 ***	-4.80E-08 ***	8.54E-05 ***				
	2.04E-08	*1.57E-08*	*9.07E-09*	*8.67E-07*				
Counts					-2.68E-07 ***	2.07E-07 ***	-6.25E-08 *	-3.44E-05 ***
					8.24E-08	*5.92E-08*	*3.73E-08*	*3.50E-06*
*Counts*Counts*					3.75E-13 *	-1.99E-13 *	1.52E-13	6.47E-11 ***
					1.91E-13	*1.16E-13*	*1.30E-13*	*1.38E-11*
Obs.	6,838,686	6,838,686	6,838,686	7,083,375	6,838,686	6,838,686	6,838,686	7,083,375
Adj. R2	0.633	0.536	0.422	0.193	0.633	0.536	0.422	0.190
Panel B: Female	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variable:	Market order share	Limit order share	Stop order share	Intensity	Market order share	Limit order share	Stop order share	Intensity
Days	-6.64E-05 **	-6.25E-05 **	4.09E-05 ***	-0.08 ***				
	2.95E-05	*2.79E-05*	*8.47E-06*	*0.00*				
*Days*Days*	6.51E-08 *	5.18E-08	-4.47E-08 ***	8.34E-05 ***				
	3.74E-08	*3.59E-08*	*1.06E-08*	*1.61E-06*				
Counts					3.72E-08	-1.24E-07	4.20E-08	-5.16E-05 ***
					1.49E-07	*1.40E-07*	*4.12E-08*	*6.26E-06*
*Counts*Counts*					-4.35E-14	1.91E-13	-6.84E-14	6.41E-11 ***
					1.61E-13	*1.55E-13*	*5.09E-14*	*1.40E-11*
Obs.	1,701,449	1,701,449	1,701,449	1,775,583	1,701,449	1,701,449	1,701,449	1,775,583
Adj. R2	0.712	0.605	0.434	0.202	0.712	0.605	0.434	0.199

Notes: The dependent variable is shown in each column. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for traders and dates. Moreover, in all columns, traders whose gender was not reported are excluded from the analysis sample.

Table 6. Decision to quit: Andersen-Gill analysis

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Success	0.97 ***		0.73 ***	0.97 ***	0.98 *		
	0.01		*0.02*	*0.01*	*0.01*		
*Success*Female*					0.97		
					0.02		
Career		0.53 ***	0.71 ***			0.53 ***	0.56 ***
		0.02	*0.03*			*0.02*	*0.03*
*Career*Female*							0.82 **
							0.08
Female				0.89 ***	0.90 ***	0.84 ***	0.92
				0.01	*0.02*	*0.02*	*0.05*
Obs.	5,814,321	1,538,052	1,538,052	5,779,193	5,779,193	1,526,346	1,526,346

Notes: The table reports hazard ratios for ceasing trade estimated based on the Andersen-Gill model. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. In all estimations, income brackets, personal asset brackets, and date are used as strata variables. The analysis is restricted to traders who opened their accounts during the sample period in columns (II), (III), (VI), and (VII). Additionally, traders whose gender was not reported are excluded from the analysis sample in columns (IV)-(VII).

Table 7. Impact of success on trade activity

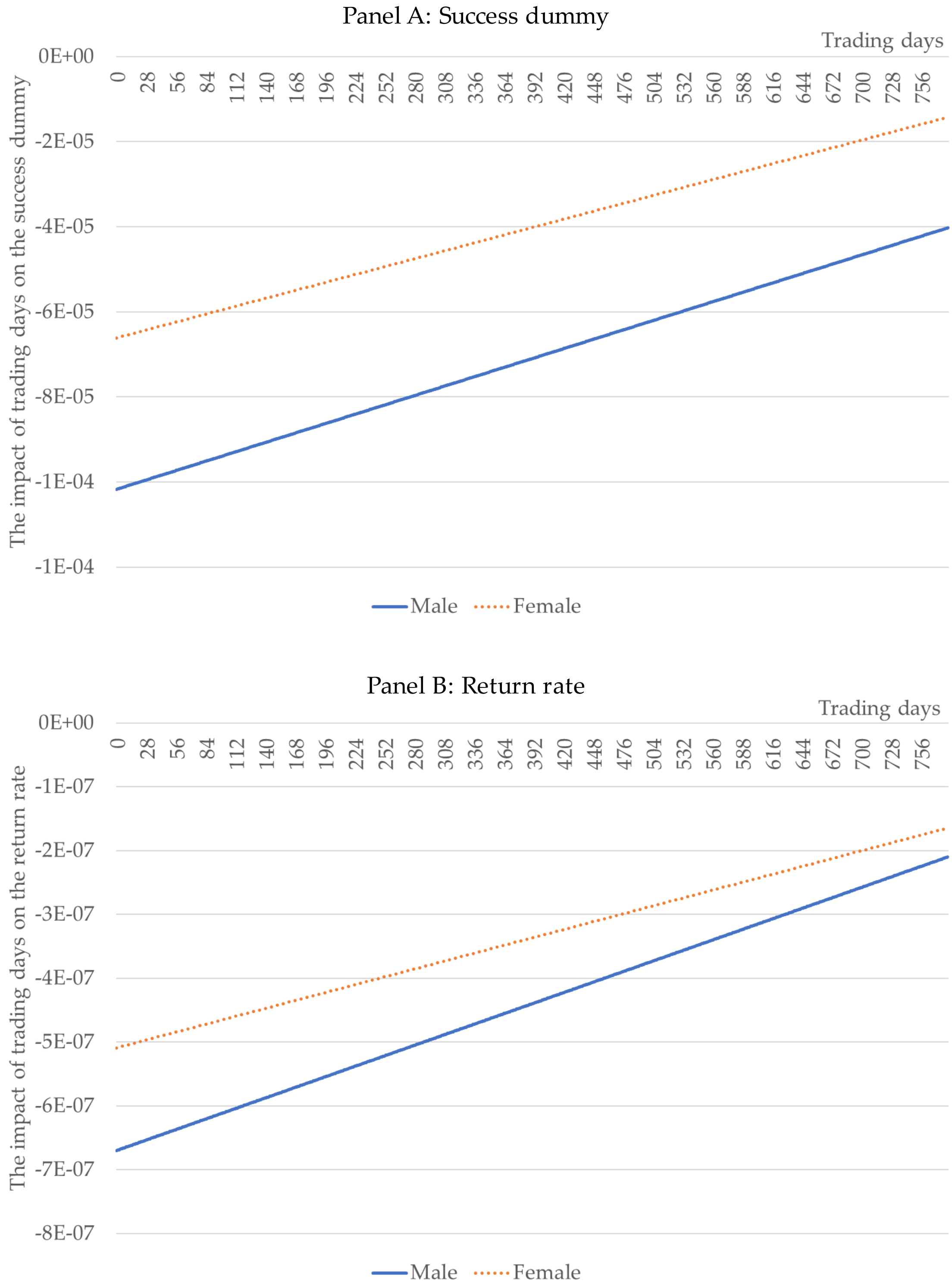
Panel A: Order value	**(I)**		**(II)**		**(III)**		**(IV)**		**(V)**		**(VI)**		**(VII)**	
Success	0.00				0.01	*	-0.06	***	0.01	***				
	0.00				*0.00*		*0.00*		*0.00*					
*Success*Female*									-0.05	***				
									0.00					
Career			0.53	***	0.52	***					0.08	***	0.55	***
			0.02		*0.02*						*0.01*		*0.03*	
*Career*Female*													-0.09	
													0.05	
Female							-0.02	***			-0.04	***		
							0.00				*0.01*			
FE	T, D		T, D		T, D		S, A, D		T, D		S, A, D		T, D	
Obs.	8,160,692		1,876,540		1,876,540		8,118,316		8,112,631		1,863,340		1,860,946	
Adj. R2	0.844		0.852		0.852		0.820		0.843		0.828		0.851	
Panel B: Number of orders	**(I)**		**(II)**		**(III)**		**(IV)**		**(V)**		**(VI)**		**(VII)**	
Success	0.04	***			0.03	***	0.03	***	0.04	***				
	0.00				*0.00*		*0.00*		*0.00*					
*Success*Female*									-0.04	***				
									0.00					
Career			0.23	***	0.20	***					0.22	***	0.24	***
			0.02		*0.02*						*0.01*		*0.02*	
*Career*Female*													-0.06	
													0.04	
Female							-0.03	***			-0.02	**		
							0.00				*0.01*			
FE	T, D		T, D		T, D		S, A, D		T, D		S, A, D		T, D	
Obs.	8,160,696		1,876,542		1,876,542		8,118,320		8,112,635		1,863,342		1,860,948	
Adj. R2	0.624		0.605		0.605		0.552		0.624		0.536		0.604	

Table 7. Impact of success on trade activity (continued)

Panel C: Intensity	(I)		(II)		(III)		(IV)		(V)		(VI)		(VII)	
Success	-0.03	***			-0.02	***	-0.07	***	-0.03	***				
	0.00				*0.00*		*0.00*		*0.00*					
*Success*Female*									-0.01	***				
									0.00					
Career			-0.19	***	-0.16	***					-0.28	***	-0.20	***
			0.01		*0.01*						*0.01*		*0.01*	
*Career*Female*													0.03	*
													0.02	
Female							0.00				0.00			
							0.00				*0.00*			
FE	T, D		T, D		T, D		S, A, D		T, D		S, A, D		T, D	
Obs.	8,690,994		1,984,973		1,984,973		8,648,653		8,641,240		1,971,281		1,968,942	
Adj. R2	0.223		0.199		0.199		0.111		0.223		0.087		0.198	

Notes: In Panels A, B, and C, we use the order value, the number of orders, and the number of days between trading days (*Intensity*) as dependent variables. These variables are defined in natural logarithms. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. Although the results are not reported, all estimations include the lagged dependent variable as an explanatory variable. Columns (IV) and (VI) incorporate FEs for income brackets, personal asset brackets, and dates, while the other columns incorporate FEs for traders and dates. The analysis is restricted to traders who opened their accounts during the sample period in columns (II), (III), (VI), and (VII). Moreover, in columns (IV) and (VI), traders whose gender was not reported are excluded from the analysis sample.

Figure 1. Impact of trading days on profit measures



Notes: The figure compares the impact of trading days on profitability measures between men and women based on the estimation results from Equation (1). Panel A depicts the effect on the success dummy, while Panel B illustrates the impact on the return rate. The horizontal axis represents the number of trading days, with its maximum value set to 781, corresponding to the highest number of trading days observed in the sample.

Appendix

Table A1. Descriptive statistics of other variables

	Obs.	Mean	S.D.	Minimum	Maximum
Panel A: Full sample					
IFD order share	8,601,548	0.054	0.216	0	1
OCO order share	8,601,548	0.062	0.176	0	1
IFO order share	8,601,548	0.019	0.124	0	1
Panel B: Male					
IFD order share	6,847,044	0.050	0.207	0	1
OCO order share	6,847,044	0.068	0.184	0	1
IFO order share	6,847,044	0.021	0.129	0	1
Panel C: Female					
IFD order share	1,704,940	0.071	0.247	0	1
OCO order share	1,704,940	0.034	0.135	0	1
IFO order share	1,704,940	0.011	0.097	0	1

Notes: This table presents the descriptive statistics for shares of IFD orders, OCO orders, and IFO orders) separately for the full sample, male traders, and female traders.

Table A2. Other trading methods

	(I)	(II)	(III)	(IV)
Dependent variable:	Success dummy	Return rate	Success dummy	Return rate
Female	0.03 ***	7.42E-05 ***	0.03 ***	6.92E-05 ***
	0.00	*8.80E-06*	*0.00*	*8.61E-06*
Age	-4.03E-04 ***	-2.53E-06 ***	-8.55E-05	-1.90E-06 ***
	8.96E-05	*2.73E-07*	*8.83E-05*	*2.64E-07*
Days	2.67E-04 ***	-3.70E-08		
	1.15E-05	*3.72E-08*		
*Days*Days*	-2.29E-07 ***	-1.40E-10 **		
	2.02E-08	*6.31E-11*		
Counts			1.57E-07	-5.77E-09 ***
			1.02E-07	*3.88E-10*
*Counts*Counts*			-1.23E-14	1.00E-14 ***
			2.55E-13	*1.69E-15*
Limit	0.25 ***	6.90E-04 ***	0.25 ***	6.85E-04 ***
	0.00	*1.56E-05*	*0.00*	*1.53E-05*
Stop	-0.33 ***	-3.83E-04 ***	-0.33 ***	-4.00E-04 ***
	0.01	*2.44E-05*	*0.01*	*2.45E-05*
IFD	0.25 ***	1.54E-03 ***	0.26 ***	1.53E-03 ***
	0.00	*3.06E-05*	*0.00*	*3.01E-05*
OCO	-0.28 ***	-4.72E-04 ***	-0.28 ***	-4.69E-04 ***
	0.00	*8.59E-06*	*0.00*	*8.72E-06*
IFO	-0.14 ***	-9.26E-05 ***	-0.14 ***	-1.02E-04 ***
	0.01	*2.66E-05*	*0.01*	*2.82E-05*
Obs.	6,707,319	6,333,966	6,707,319	6,333,966
Adj. R2	0.073	0.078	0.072	0.081

Notes: The dependent variable is shown in each column. In columns (II) and (IV), the return rate excluding outliers is used as the dependent variable. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for income brackets, personal asset brackets, and dates. Moreover, in all columns, observation days with zero profit and traders whose gender was not reported are excluded from the analysis sample.

Table A3. Gender differences in profitability measures: Monthly analysis

	(I)	(II)	(III)	(IV)
Dependent variable:	Success dummy	Return rate	Success dummy	Return rate
Female	0.06 ***	-1.78E-04	0.06 ***	-1.75E-04
	0.00	*1.25E-04*	*0.00*	*1.23E-04*
Age	-1.49E-03 ***	-2.92E-06	-1.06E-03 ***	-4.75E-06
	1.64E-04	*5.46E-06*	*1.62E-04*	*4.75E-06*
Days	3.51E-04 ***	-8.35E-06 ***		
	3.79E-05	*2.59E-06*		
*Days*Days*	-3.87E-07 ***	2.27E-08 ***		
	9.66E-08	*5.97E-09*		
Counts			-4.23E-06 ***	1.52E-08 ***
			4.68E-07	*4.96E-09*
*Counts*Counts*			1.59E-11 ***	-4.85E-14
			2.68E-12	*1.88E-14*
Limit	0.40 ***	1.39E-03 *	0.37 ***	1.47E-03 ***
	0.01	*5.49E-04*	*0.01*	*5.58E-04*
Stop	-0.36 ***	2.04E-04	-0.38 ***	1.85E-04
	0.03	*7.26E-04*	*0.03*	*7.35E-04*
Obs.	202,745	215,074	202,745	215,074
Adj. R2	0.027	0.001	0.027	0.001

Notes: The dependent variable is shown in each column. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for income brackets, personal asset brackets, and year/month. Moreover, in all columns, traders whose gender was not reported are excluded from the analysis sample.

Table A4. Experience variables and profitability measures: Monthly analysis

Panel A: Male	(I)	(II)	(III)	(IV)
Dependent variable:	Success dummy	Return rate	Success dummy	Return rate
Days	-7.22E-04 ***	-4.43E-07		
	6.07E-05	*6.18E-06*		
*Days*Days*	7.88E-07 ***	1.68E-08 ***		
	1.07E-07	*5.27E-09*		
Counts			-1.31E-06 ***	4.68E-08
			4.68E-07	*3.17E-08*
*Counts*Counts*			2.56E-12	-1.22E-13
			1.69E-12	*8.97E-14*
Obs.	150,258	159,907	150,258	159,907
Adj. R2	0.145	-0.075	0.144	-0.075
Panel B: Female	(I)	(II)	(III)	(IV)
Dependent variable:	Success dummy	Return rate	Success dummy	Return rate
Days	-8.23E-04 ***	-5.87E-06		
	1.10E-04	*5.12E-06*		
*Days*Days*	8.36E-07 ***	2.19E-08 ***		
	1.81E-07	*6.43E-09*		
Counts			-4.47E-06 ***	6.31E-08 **
			1.62E-06	*3.14E-08*
*Counts*Counts*			4.31E-11 ***	-2.79E-13
			1.62E-11	*2.20E-13*
Obs.	40,978	43,769	40,978	43,769
Adj. R2	0.188	0.046	0.187	0.045

Notes: The dependent variable is shown in each column. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for traders and year/month. Panels A and B present the analysis results for male and female traders, respectively. In all specifications, traders whose gender was not reported are excluded from the analysis sample.

Table A5. Gender differences in other trading methods

	(I)	(II)	(III)	(IV)	(V)	(VI)
Dependent variable:	IFD order share	OCO order share	IFO order share	IFD order share	OCO order share	IFO order share
Female	0.02 ***	-0.04 ***	-0.01 ***	0.02 ***	-0.04 ***	-0.01 ***
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Age	-2.19E-03 ***	-2.35E-05	1.56E-04 ***	-1.89E-03 ***	-5.12E-05	1.49E-04 ***
	1.36E-04	*6.96E-05*	*5.13E-05*	*1.29E-04*	*6.89E-05*	*5.20E-05*
Days	2.19E-04 ***	6.20E-05 ***	-1.65E-05 **			
	1.43E-05	*9.86E-06*	*6.54E-06*			
*Days*Days*	-1.54E-07 ***	-1.21E-07 ***	6.79E-09			
	2.38E-08	*1.59E-08*	*1.16E-08*			
Counts				-9.47E-08	2.80E-07 ***	-1.49E-07 ***
				8.55E-08	*8.23E-08*	*5.41E-08*
*Counts*Counts*				3.17E-13	-6.47E-13 ***	2.49E-13 ***
				2.08E-13	*1.68E-13*	*8.60E-14*
Obs.	8,551,984	8,551,984	8,551,984	8,551,984	8,551,984	8,551,984
Adj. R2	0.023	0.010	0.002	0.015	0.010	0.002

Notes: The dependent variable is shown in each column. ***, **, and * represent significance at the 1%, 5%, and 10% statistical levels, respectively. Parentheses contain the heteroscedasticity-consistent standard error. Standard errors are clustered at the trader level and reported in italic. We employ the OLS estimation method in all estimations. All columns incorporate FEs for income brackets, personal asset brackets, and dates. Moreover, in all columns, traders whose gender was not reported are excluded from the analysis sample.

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