Milestone ages, social pressure, and risk-taking in stock markets*

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Abstract

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Keywords: Social pressure; milestone age; risk-taking; culture influence; financial well-being

JEL: A13, A14, D14, G11, G41, G51

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Abstract

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"*At thirty, I stood firm; at forty, I had no doubts; and at fifty, I knew the decrees of Heaven*."
-Confucius

1. Introduction

Milestone ages, such as 30, 40, and 50, are significant markers for reflection on personal achievements and future planning in ancient, modern, eastern, and western societies. These milestones prompt introspection that can amplify feelings of social pressure, particularly when individuals perceive a gap between their accomplishments and societal expectations. A compelling example appears in the popular U.S. TV show "Friends," in the episode "The One Where They All Turn Thirty," where characters confront anxiety over unmet goals at age 30. Similarly, a 2022 UK nationwide poll revealed that respondents reported feeling pressure to reach life milestones.[1] Such a phenomenon is also prevalent in Confucian-influenced societies in East Asia. These anecdotal pieces of evidence suggest that the pressure accompanying milestone ages is universal, transcending cultural boundaries.

In this paper, we examine whether and how social pressure, triggered by proximity to milestone ages, alters individuals' risk preferences, thereby affecting their investment behavior in stock markets. We are interested in the milestone age effect on the risk preference as it is central to individuals' economic decision-making in various domains, including labor market participation, saving, consumption, innovation, and investment.

[1] https://www.relate.org.uk/get-help/milestone-anxiety-rise-among-millennials-and-gen-z

While conventional economic models assume that an individual's risk preference is relatively stable over time (Stigler and Becker, 1977), recent studies argue that the extent to which and when it varies is an empirical question (e.g., Schildberg-Hörisch, 2018). Several factors have been shown to affect individuals' risk preferences, including life cycles, economic conditions (Shiller 1981; Campbell and Shiller 1989; Cochrane 2011), trauma from conflict or violence (e.g., Callen et al., 2014), natural disasters (e.g., Chuang and Schechter, 2015; Cameron and Shah, 2015; Hanaoka et al., 2018), and culture (e.g., Rieger et al., 2015).

Moreover, the existing psychological literature provides mixed evidence regarding the relation between social pressure and risk-taking behaviors (e.g., Maner et al., 2007; Hardin et al., 2009; Kashdan et al., 2009; Lorian and Grisham, 2010). In particular, earlier studies argue that social pressure characterizes the prototypical person as a risk-averse one. However, such a stereotype is challenged by recent studies (e.g., Kashdan and McKnight, 2010). Kashdan et al. (2009) document that individuals with higher levels of social anxiety are more likely to exhibit risk-taking behaviors, such as heavy drinking and illicit drug use. Reynolds et al. (2013) use a quasi-experimental design and show that when exposed to the high-stress condition, the high-social-pressure group shows greater risk-taking behaviors than the low-social-pressure group. Pailing and Reniers (2018) also show that social pressure revealed through surveys is linked with poor psychological maturity, which contributes to a greater risk-taking tendency observed in experiments.

Given the mixed findings in the literature, we argue that exploring the influence of social pressure on individuals' risk preferences in high-stakes decisions, i.e., trading stocks, is not only intriguing but also relevant. However, there are two major empirical challenges to establishing causal relationships between social pressure and stock trading. First, operationalizing and quantifying investors' social pressure can be quite difficult. Second, the data availability of detailed risk-taking behaviors in the financial markets that are directly related to social pressure can be rather limited.

We deal with the first challenge by assessing the shock of social pressure conditional on an individual's proximity to milestone ages, as both anecdotal evidence and psychological studies suggest that milestone ages could trigger social pressure. Milestone ages occur exogenously and periodically in life, yet they represent occasions for existential stock-taking that may magnify the feeling of failure and emptiness in life. Alter and Hershfield (2014) find that people undertake a search for existential meaning when they approach a new decade in chronological age. Miron-Shatz et al. (2015) show that the temporal landmarks of milestone birthdays punctuate people's mental maps of their life cycle: milestone agers (relative to non-milestone agers) place less weight on positive emotions in overall life satisfaction judgments, whereas negative emotions remain influential. Matsubayashi et al. (2019) document that suicides occur more frequently on milestone birthdays. Motivated by these studies, we argue that approaching milestone ages induces a shock to an individual's social pressure level, thereby enabling us to provide causal inferences between social pressure and risk-taking in the stock markets.

We deal with the second challenge by utilizing account-level trading data with demographic information from a large representative brokerage house in China from July 2016 to March 2023. If milestone-age-triggered social pressure does affect individuals' risk preferences in stock markets, we expect these individuals to trade more aggressively when approaching milestone birthdays. The account-level trading records, together with demographic data, enable us to investigate the trading behaviors of milestone agers as approaching birthdays and to compare them with non-milestone agers.

To formalize our research idea, we propose three hypotheses. The first hypothesis, ***H1***, is that *individuals temporarily exhibit heightened risk-taking tendency as they approach milestone-age birthdays, compared to the periods immediately before or after these birthdays.* We also expect this effect to be more pronounced among individuals (i) with less financial wealth, as they are more likely to perceive themselves as underachieving and (2) less sophisticated, e.g., those with limited investment experience who are thus more easily influenced by non-fundamental factors when making investment decisions. Accordingly, our second hypothesis, ***H2***, is that *individuals with less financial wealth and less investment experience are more likely to temporarily display increased risk-taking tendency as they approach milestone birthdays, compared to their counterparts.*

Moreover, risk preferences and the associated trading behavior driven by social pressure are more likely to be transient and associated with poor psychological maturity (Pailing and Reniers, 2018). Thus, our third hypothesis, ***H3***, is that *trades conducted as*

individuals approach milestone birthdays result in worse financial performance than trades executed in periods immediately before or after.

We begin our analyses by examining shifts in individuals' self-reported pressure levels and risk preferences as approaching milestone ages. Drawing on the 2021 wave of the China General Social Survey (CGSS 2021), we find that individuals exhibit a heightened tendency to search for information related to pressure and anxiety preceding their milestone ages. Furthermore, our analysis of the 2013–2019 waves of the China Household Finance Survey (CHFS) reveals a marked surge in risk preferences as individuals approach milestone ages, with the effect concentrated among those who perceive themselves as underachievers.

Next, we leverage brokerage account-level data to examine the trading behavior of individuals as they approach milestone ages. We include only those with accounts that have been active from the beginning of the sample period, and exclude accounts subject to stringent regulations, such as those of investors aged over 70 and algorithmic trading accounts. The average age of our sample investors is 41, with a median age of 39.

For each investor, we record the years when they reach milestone ages (i.e., 30, 40, and 50). The birthdays corresponding to each of these milestone ages are termed milestone birthdays. We exclude the milestone age of 20 because these individuals are in the early stages of adulthood and are less likely to actively participate in stock markets. Considering the legal retirement age in China is 55 for females and 60 for males, we also exclude

milestone ages beyond 50, as individuals approaching retirement are not the primary participants in the stock markets and are less susceptible to social pressure in terms of wealth. After these filters, we randomly select 500,000 individuals to be included in our final sample.

We define a 90-day period leading up to an investor's birthday as the birthday window, and compare trades executed during this window and the two 90-day windows immediately before and after (the pre-window and post-window). The indicator variable $BirthQ_{i,j}$ equals one for observations within the birthday window, and zero otherwise. We follow the literature to characterize retail investors' risk-taking tendency using their trading intensities (e.g., Coval and Shumway, 2005; Dorn and Huberman, 2005; Liu et al, 2010; Ben-David, Birru, and Prokopenya, 2018). For individuals reaching milestone ages, we observe a surge in the trading intensity during the birthday window, compared to the adjacent pre- and post-windows, in contrast to non-milestone agers. The results hold after including individual-, age-, rolling 90-day- and window-fixed effects throughout the tests. The first two fixed effects account for influences specific to individuals and related to age, such as IQ or life cycle considerations. The third captures influence associated with time-varying factors present within each of the three 90-day windows (birthday-, pre-, and post-windows). This setup helps pin down the positive impact of approaching milestone birthdays on trading intensities, which is consistent with ***H1***.

We also examine risk-taking through an alternative perspective: the propensity to trade risky stocks (e.g., those with high idiosyncratic volatility or lottery-like features).

We find that individuals reaching milestone birthdays exhibit a significantly higher propensity to trade risky stocks. This finding aligns with our results using trading intensity, providing further support for our hypothesis.

We then identify a subgroup comprising those with both financial wealth and investment experience below the sample median. This subgroup, representing 30.57% of the full sample, primarily drives our results, supporting ***H2***. In subsequent analyses, we focus on this subgroup of investors, as their heightened susceptibility to social pressure and limited investment experience make them especially relevant for our investigation.

To verify that the intensified trading is attributed to approaching milestone birthdays, we analyze individuals' trading during their birthday windows in non-milestone years, specifically those occurring five years before and four years after their milestone ages. Throughout these nine years, when individuals do not reach milestone ages, they do not exhibit increased trading tendencies in the birthday windows. This finding confirms that the intensified trading is not linked to mood changes associated with birthdays in general but is specifically tied to milestone birthdays.

Next, we perform three sets of heterogeneity tests to provide deeper insight. While individuals generally experience social pressure upon reaching milestone ages, we expect the effect to be stronger among males, individuals from regions more influenced by the Confucian clan culture, and migrants from low- to high-tier cities. In most East Asian societies under the influence of Confucian values, the norms impose greater pressure on

men to achieve financial success and stability. Individuals from regions heavily influenced by the Confucian clan culture are naturally more likely to internalize expectations of attaining specific life goals and fulfilling familial and societal obligations. Migrants from low- to high-tier cities typically relocate for better opportunities and higher incomes, often carrying heightened family expectations and responsibilities. These groups thus face intensified social pressure during introspection as they approach milestone ages, increasing their propensity to take risks in trading. We find supportive evidence for all these heterogeneity tests.

To draw a welfare implication, we assess individuals' post-trading performance to examine the real effect of milestone-age-induced social pressure on investor financial welfare. Trades conducted during the milestone birthday window are accompanied by worse performance compared to those made in the pre- and post-90-day windows. The results support ***H3*** that the trades made due to impulsive decision-making driven by milestone-related social pressure tend to underperform.

We conduct one additional analysis to provide corroborative evidence for our main hypothesis. We scrutinize individuals' trading over shorter intervals of 30-day windows within the birthday window and the pre- and post-windows. Specifically, we examine individuals' trading in the six and three 30-day windows before and after the milestone birthdays. If the heightened trading activity, indicative of increased risk preferences, is driven by social pressure related to reaching milestone ages, we expect a hump-shaped pattern to emerge. That is, we should observe a peak in trading in the 30-day window

immediately preceding the milestone birthday, followed by a decline in 30-day windows further from the date. We do document such a hump-shaped pattern.

Finally, we perform a series of robustness tests. Our findings are robust to alternative measures of individuals' trading intensity. They are also robust to sample selection. In constructing the initial sample, we require individuals to have executed at least 10 buy and 10 sell trades during the sample period to be classified as active traders and included in our analysis. Our findings remain similar when this restriction is either loosened (requiring five buy and five sell trades) or tightened (requiring 20 buy and 20 sell trades or 50 buy and 50 sell trades). We also conduct placebo tests by assigning pseudo-ages to sample individuals. Tests with pseudo milestone ages reveal no effect, suggesting that the observed milestone age effect is not a statistical artifact.

Our study contributes to the literature in several ways. First, we add to the literature on determinants of investors' risk preferences in financial markets. Our study is deeply rooted in the studies of psychology and social finance that emotional states influence risk-taking behavior, and social pressure is one such emotional experience (e.g., Reynolds et al., 2013; Hirshleifer, 2020). Our contribution is to establish the first causal link between social pressure and investors' risk preferences in trading. Because we utilize the temporal surge in individuals' social pressure when they are approaching milestone ages, our paper is related to but differs from the prior studies based on the Keeping up with the Joneses preference (e.g., Hong, Jiang, Wang, and Zhao, 2014; Agarwal, Mikhed, and Scholnick, 2019). Specifically, the milestone age effect on trading is time-varying within each

investor, which kicks in only when underachievement in life becomes more salient before the milestone birthdays. Such an effect does not necessarily hinge on cross-sectional comparison with peers.

Second, we join the debate regarding the direction of the influence of social pressure on individuals' risk-taking tendencies by providing evidence from stock investment decisions. The existing studies mainly rely on surveys or experiments to investigate the influences of social pressure on individuals' risk-taking in settings, such as conditions involving health/safety issues (whether to wear a seat belt when sitting in the front seat), social interaction, betting on a sporting event, drinking, drug-taking, etc. However, the current evidence is inconclusive about the effect of social pressure on risk-taking intention (e.g., Maner et al., 2007; Hardin et al., 2009; Kashdan et al., 2009; Lorian and Grisham, 2010; Kashdan and McKnight; Reynolds et al., 2013; Pailing and Reniers, 2018). We argue that financial markets provide an ideal setting for shedding new insight into the debate, where risk-taking behavior could be more clearly defined and measured. Moreover, the tests could be performed using a larger and more representative sample than prior studies.

Finally, we expand the studies on the impact of temporal landmarks on individuals' behavior. Current studies have shown that although a milestone age occurs exogenously and periodically in life, it still stimulates individuals to assess their status quo. As a result, approaching milestone age may highlight failures and underachievement for some individuals. The effect of such a temporal landmark could be devastating (e.g., Miron-

Shatz et al., 2015; Matsubayashi, 2019). In the same vein, Dai et al. (2014) examine the landmark effect using the setting of New Year's resolutions and conjecture that people are more likely to tackle their goals immediately following salient temporal landmarks, which often limit their goal attainment. By assessing investors' risk-taking around their milestone ages and subsequent performance, we provide a new angle from the financial markets regarding how temporal landmarks could drive some individuals to trade more aggressively as a potential solution for the underachievement in life, leading to a suboptimal deviation from rational investment behavior.

2. Data and measures

2.1 Survey Data

We use data from two representative nationwide surveys to present evidence on the changes in individuals' self-reported pressure levels and risk preferences as approaching milestone ages. The first is the 2021 wave of the China General Social Survey (CGSS 2021), which is run by a Chinese academic institution (Renmin University of China).[2] It incorporates the East Asia Social Survey module, which asked respondents how frequently they had searched for information related to pressure or anxiety during the past 12 months. We convert the responses into an ordinal variable $Pressure_i$, ranging from 1 ("never") to 5 ("very frequently"), to serve as an indicator of perceived pressure. The survey also provides participants' self-assessed social status, from 1 (lowest) to 10

[2] For detailed information about CGSS 2021, see "http://cgss.ruc.edu.cn/sjycg/cbyfb.htm."

(highest). In subsample analysis, we identify participants with this score at or below 5 as those perceiving underachievement in life. Our CGSS 2021 sample contains 1,889 individual observations.

The second survey is the China Household Finance Survey (CHFS), which has been widely used in prior research (e.g., Liu et al., 2020; Li et al., 2021; Fisman et al., 2023).[3] Following Fisman et al. (2023), we define $Take\text{Risk}_{i,t}$ as a dummy variable equal to one if the respondent did not choose the option "5. Unwilling to take any risk" in response to the question "What is your choice among combinations of risk and return?." Our final CHFS sample comprises 94,478 observations from 65,437 households.

2.2. Retail investor data and variables

2.2.1 Data and sample selection

We obtain account-level data from a large brokerage firm in China, which includes information on investors' daily transactions, asset holdings, and demographic information over the period from July 2016 to March 2023. Variable definition is detailed in Table A1 in the Appendix. Table A2 shows that the demographic characteristics of investors from this brokerage are comparable with those reported in other studies utilizing Chinese account-level data (e.g., Liao et al., 2022; Liu et al., 2022). We also present the distribution of investors' birth months in Figure A2, which is consistent with findings from the prior research (Zhang et al., 2023).

[3] https://chfs.swufe.edu.cn/.

We apply several filters to obtain our final sample. First, to be included in our sample, we require sample investors to have conducted at least 10 buy trades and 10 sell trades during the sample period, following Liao et al. (2022). This criterion effectively excludes inactive investors from our analysis. In robustness checks, we repeat our tests by adjusting the trade number requirement (for both buy and sell) to be 5, 20, and 50, and the results remain similar.

Second, we only retain accounts opened before July 2016 and remain active throughout the sample period. This filter ensures a sufficient number of birthdays for conducting within-individual analysis, i.e., six birthdays for each sample investor. Third, we exclude accounts that are subject to stringent regulations, such as accounts opened by investors over the age of 70 and algorithmic trading accounts. These accounts represent less than 1% of the initial sample. After applying these filters, we randomly select 500,000 unique individual investors to be included in our final sample.[4] We also obtain market and stock-level information from the China Stock Market & Accounting Research Database (CSMAR).

2.2.2 Variables and summary statistics

For each sample individual, we set three 90-day windows surrounding each of his birthdays within the sample period. A 90-day period leading up to the birthday of an individual, including the birthday itself, is referred to as his birthday window. A 90-day

[4] The results are robust and similar in economic magnitude if we use the filtered full sample.

period immediately before and after the birthday window is defined as the pre- and post-window, respectively. A dummy $BirthQ_{i,j}$ is set to one if the observation falls within the birthday window of individual *i* in year *t*, and zero otherwise. Figure A1 in the appendix illustrates the definition.

For milestone ages, we focus on ages 30, 40, and 50, and set a dummy variable $MilestoneAge_{i,t}$ that equals one for individuals turning into these ages in year *t*. We exclude the milestone age of 20 because individuals at this stage are typically in the early phases of their adult lives and careers, making them less prone to social pressure related to financial achievements that can be solved by aggressive stock trading. Furthermore, given that the legal retirement age in China is 55 for females and 60 for males, we exclude milestone ages of and beyond 50, as individuals nearing retirement are not active participants in the stock markets and are subject to less social pressure in wealth.

We employ two sets of measures to capture individual risk-taking in stock markets: trading intensity and the propensity to trade risky stocks. In the literature, trading intensity, such as trading value and the number of trades, is frequently used to capture retail investor risk-taking (e.g., Coval and Shumway, 2005; Liu et al, 2010; Ben-David, Birru, and Prokopenya, 2018). Accordingly, we use the value of executed buy ($BuyValue_{i,j,t}$) and sell ($SellValue_{i,j,t}$) orders separately, and the sum of the two ($TotalValue_{i,j,t}$) to quantify individuals' risk-taking. We construct these measures for each individual *i* in year *t* during his 90-day birthday window, $BirthQ_{i,j}$, and compare them with those constructed during the two adjacent 90-day windows (the pre- and post-windows). While we rely on the value

of trades for our baseline tests, we also report results, in the Appendix, using alternative trading intensity measures, including the number of trades executed, the number of shares traded, and turnover.

To capture an individual's propensity to trade risky stocks, we investigate whether the investor tilts his trading activity toward stocks characterized by high idiosyncratic volatility or lottery-like features. First, we estimate each stock's idiosyncratic risk using daily returns over the six months preceding the pre-window, based on the Fama–French three-factor model. Stocks in the top quintile (20%) are classified as high-risk stocks. We then construct $Ivol_Total_{i,j,t}$ as the difference between the investor's total trading value in high-risk stocks and that in all other stocks, scaled by the investor's total trading value in the same window and multiplied by 100. We compute $Ivol_Buy_{i,j,t}$ and $Ivol_Sell_{i,j,t}$ analogously using value of buy and sell trades, respectively.

Next, following Liu et al. (2022), we identify lottery-type stocks using the frequency of up-limit events.[5] We count the number of up-limit-hit days for each stock over the six months preceding the pre-window. Stocks whose up-limit hit counts fall in the top quintile are classified as lottery stocks. For investor *i* in window *j* of year *t*, we define $Up_Total_{i,j,t}$ analogously as the difference between total trading value in lottery stocks and in all other

[5] China imposes a daily price fluctuation limit on A-share stocks. While this limit was historically capped at 10% across all boards, it was relaxed to 20% for the STAR Market upon its launch in July 2019, and subsequently for the ChiNext board effective in August, 2020. Leveraging this institutional feature, Liu et al. (2022) use the frequency of "limit-up" hits (i.e., the number of days a stock hits its daily price ceiling) to proxy for positive return skewness and identify lottery-type stocks.

stocks, scaled by the investor's total trading value in that window. We compute $Ivol_Buy_{i,j,t}$ and $Ivol_Sell_{i,j,t}$ analogously using value of buy and sell trades, respectively.[6]

During the investigation, we control variables that might affect an individual's trading, including the total value of his stock holdings at the end of the pre-window ($StkHolding_{i,j-1,t}$), the number of trades executed ($\#\ of\ Trades_{i,j-1,t}$), and the number of stocks traded ($\#\ of\ Stocks_{i,j-1,t}$). All continuous variables are winsorized at the 1% level.

Table 1 presents summary statistics of the main variables The average age of sample individuals is 41.46, with a median of 39. The average value of buy orders executed over a 90-day window is approximately CNY 281,359, while sell orders average around CNY 278,829. In contrast, the median values are CNY 2,915 for buy orders and CNY 3,010 for sell orders. The large discrepancy in mean and median values indicates a strong skewness in the trading value. On average, sample individuals maintain stock holdings valued at approximately CNY 97,746, with a median value of CNY 16,839.

[Insert Table 1 about here]

3. Milestone ages, pressure, and risk preference – Evidence from surveys

3.1 Milestone ages and pressure

We begin by examining the relationship between milestone ages and individuals' perceived pressure levels using data from CGSS 2021. This survey provides both respondents' birth dates and interview dates, allowing us to calculate their exact ages at

[6] Stocks with fewer than 60 daily return observations are excluded.

the time of the interview. We construct an indicator variable, $MilestoneAge_{-1,i}$, which equals one if a respondent was surveyed at age 30, 40, or 50 — corresponding to behaviors at ages 29, 39, and 49, when individuals were approaching a milestone birthday. We estimate the following regression model:

$$Pressure_i = \alpha + \beta_0 MilestoneAge_{-1,i} + f(Age_i) + \beta_c Controls_i + \varepsilon_{i,t}, \quad (1)$$

where $Pressure_i$ represents i's self-reported pressure level, as detailed in Section 2.1, and $f(Age_i)$ controls for age using both age and age squared. The control variables include a set of demographic characteristics such as gender, employment status, education level, marital status, political affiliation, and urban residency. We further include the resident province fixed effects. In addition, we stratify the sample by self-reported social status and re-estimate the model separately for each subgroup. If individuals indeed experience greater pressure as approaching milestone ages, we expect β_0 to be significantly positive.

The results reported in Table 2 are consistent with our predictions. In Column (1), the estimate of β_0 is positive and statistically significant, indicating that individuals search more frequently for information related to pressure or anxiety as they approach milestone ages. We further conduct subsample analysis conditional on the respondents' self-assessed social status score. Columns (2) and (3) show that the effect concentrates among individuals with a lower self-assessed social status score, which is consistent with our expectation that those perceiving underachievement in life are more susceptible to heightened pressure during introspection as approaching milestone ages.

[Insert Table 2 about here]

3.2 Milestone ages and risk preference

We further examine whether individuals' risk preferences shift as they approach milestone ages using data from the China Household Finance Survey (CHFS). Following Fisman et al. (2023), we set a dummy variable, $TakeRisk_{i,t}$, to indicate the individual's willingness to take risk in making investment decisions in year t.[7] We then re-estimate Eq. (1) but replace the dependent variable with $TakeRisk_{i,t}$, with the control of year fixed effects to account for time-specific influence.

As CHFS does not contain self-reported measures of social status, we stratify individuals based on the median value of household assets. Again, we expect β_0 to be significantly positive, particularly among those with household assets below the median, who are more likely to perceive themselves as relatively less successful in life. The results, reported in Table 3, are consistent with our expectation. Moreover, the signs of the other variables align with the findings of Fisman et al. (2023).

[Insert Table 3 about here]

[7] Following Fisman et al. (2023), we set $TakeRisk_{i,t}$ to one if the participant did not select option 5 ("Unwilling to take any risk") in response to the question "What is your choice among combinations of risk and return?," and zero otherwise.

4. Milestone ages and risk-taking in stock markets

4.1 Baseline tests

Section 3 conducts the investigation using individuals' self-reported pressure levels and risk preferences from large-scale surveys. In this section, we extend the analysis by employing high-frequency, account-level trading data from a major Chinese brokerage firm. This dataset allows us to observe actual risk-taking behavior at a daily frequency and contains exact birth dates, enabling us to precisely pinpoint individuals' milestone birthdays and examine their trading behavior surrounding the dates.

4.1.1 Full sample tests

Our ***H1*** predicts that individuals' risk-taking tendencies increase when approaching their milestone birthdays. We use the following regression to test this hypothesis:

$$Trade_{i,j,t}=\alpha+\beta_0 BirthQ_{i,j}\times MilestoneAge_{i,t}+\beta_c Controls_{i,j,t}+\varepsilon_{i,j,t}, \quad (2)$$

where $Trade_{i,j,t}$ represents investor i's trading intensity within a 90-day window j in year t, measured by either $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, or $SellValue_{i,j,t}$. Window j could correspond to the 90-day birthday, the pre-90-day, or post-90-day window. $BirthQ_{i,j}$ equals one when window j is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if the investor reaches 30, 40, or 50 in year t. Control variables include $StkHolding_{i,j-1,t}$, $\#\ of\ Trades_{i,j-1,t}$, and $\#\ of\ Stocks_{i,j-1,t}$. The construction of these variables is described in Section 2.2.2. Three fixed effects are included: individual, age, and

individual×age×90-day window fixed effect.[8] Standard errors are double-clustered by individual and age. We expect the coefficient on $BirthQ_{i,j} \times MilestoneAge_{i,t}$ to be significantly positive.

Table 4 presents results for the full sample. The coefficient on $BirthQ_{i,j} \times MilestoneAge_{i,t}$ is significantly positive at the 5% level across all three columns, indicating that investors trade more aggressively when they approach their milestone birthdays. For example, column (1) shows that an investor increases stock trading by more than CNY 4,500 during the 90-day birthday window compared to his trading in the adjacent pre- and post-90-day windows. The increase is about 4.6% of the average value of sample investors' stock holdings as reported in Table 1.

[Insert Table 4 about here]

4.1.2 The effect of financial wealth and investment experience

The ***H2*** predicts that the milestone age effect is particularly strong among investors with lower financial wealth and less investment experience. To test this hypothesis, we construct subsamples at the beginning of the sample period. Individuals whose average total financial wealth during the year preceding the sample period is below the sample median are classified into the low financial wealth group. Individuals with investment

[8] This fixed effect does not introduce collinearity with $BirthQ_{i,j} \times MilestoneAge_{i,t}$ because, within the same 90-day period, some investors reach the birth-day window of a milestone birthday, while others reach the birth-day window of a non-milestone birthday.

experience, measured by the number of years since their first trade in stock markets, below the sample median are categorized into the low investment experience group.

We begin the subsample tests with a single sort: financial wealth or investment experience. As expected, results in Table A3 indicate that the milestone age effect is more pronounced among individuals with lower financial wealth or less investment experience compared to their counterparts. We then proceed to construct four subsamples using double sorts. The "Low & Low" ("High & High") group consists of individuals whose financial wealth and investment experience are both below (above) the sample median. The "Low & High" ("High & Low") group consists of individuals whose financial wealth is below (above) the sample median, but investment experience is above (below) the median. We expect our findings to be particularly strong in the "Low & Low" group.

Table A4 presents summary statistics for the "Low & Low" group. This group represents approximately 30% of the total investors in our full sample. Individuals in this group tend to be younger, with an average age of about 35, compared to an average age of 41 in the full sample, as reported in Table 1. Their average stock holdings value and trading volume over a 90-day window, around CNY 32,000 and CNY 280,000, are much lower than the CNY 98,000 and CNY 560,000 averages in the full sample.

More importantly, Table 5 shows that the effect of the milestone age effect is much stronger in the "Low & Low" group than in the other three groups combined, i.e., the "Others" group. The coefficient on $BirthQ_{i,j} \times MilestoneAge_{i,t}$ is positive and highly

significant for the "Low & Low" group, with a magnitude nearly twice as large as that observed in the full sample. This is noteworthy given that, on average, these investors have lower trading volumes and stock holdings than those in the full sample.

[Insert Table 5 about here]

For the sake of brevity, we do not report the regression results separately for the "Low & High," "High & Low," and "High & High" groups. Instead, Figure 1 illustrates the coefficient on the variable of interest, $BirthQ_{i,j} \times MilestoneAge_{i,t}$, when the baseline tests are conducted within each of these groups. As expected, the coefficient is the highest for the "Low & Low" group. The results collectively support ***H2***. As individuals in the "Low & Low" group are particularly relevant for our analyses, we focus on individuals in this group for the test of our empirical tests.

[Insert Figure 1 about here]

4.1.3 Analysis of age-specific milestone effects

In this subsection, we examine individuals' trading aggressiveness when they approach a specific milestone birthday, at the age of 30, 40, or 50. We introduce dummies $Age30_{i,t}$, $Age40_{i,t}$, and $Age50_{i,t}$, which equal one if individual *i* reaches the age of 30, 40, or 50 in year *t*, respectively, and zero otherwise. We replace $BirthQ_{i,j} \times MilestoneAge_{i,t}$, in Eq. (1) with interactions between $BirthQ_{i,j}$ and each of these three dummies. This modification enables us to examine the effect associated with each specific milestone age separately. Results in Table A5 indicate that the effect is present for all three milestone ages.

4.2 Milestone vs. non-milestone birthdays

To ensure that individuals' intensified trading activities are driven by the milestone age effect rather than mood fluctuations associated with all birthdays, we compare their trading activities when they approach milestone birthdays versus non-milestone birthdays.

We define a set of dummy variables, $MilestoneAge_{n,i,t}$, which indicate the n^{th} age relative to the milestone age. Using these dummies, we compare trading activities in the 90-day window leading up to milestone birthdays with those in the 90-day window preceding non-milestone birthdays at ages −5, −4, …, −1, +1, …, +4 relative to the milestone age. The comparison is carried out using the following equation:

$$Trade_{i,j,t}=\alpha+\sum_{n=-5}^{+4}\beta_n BirthQ_{i,j}\times MilestoneAge_{n,i,t}+\beta_c Controls_{i,j,t}+\varepsilon_{i,j,t}. \quad (3)$$

Figure 2 plots the coefficients on the variables of interest, i.e., the interactions between the indicator for the 90-day window preceding the date of birth and the dummy variables for both milestone and non-milestone ages for a visual comparison. The results show that intensified trading activities are observed only when individuals are approaching their milestone birthdays, not when they are approaching non-milestone birthdays. The magnitude of the coefficient on the interaction terms is also the greatest for the year of milestone age. The complete results are presented in Table 6.

[Insert Table 6 about here]

[Insert Figure 2 about here]

4.3 Risk-taking characterized by the propensity to trade risky stocks

In previous tests, we measure individuals' risk-taking using their trading intensity following the literature (Coval and Shumway, 2005; Liu et al, 2010; Ben-David, Birru, and Prokopenya, 2018). In this section, we provide additional evidence by examining individuals' propensity to trade risky stocks, characterized by high idiosyncratic volatility or lottery-like features. Intuitively, individuals with stronger risk preferences should allocate a larger share of their trading to stocks with high idiosyncratic volatility or lottery-like features, the latter of which not only have volatile returns but also offer the potential for outsized gains. We use $Ivol_Total_{i,j,t}$, $Ivol_Buy_{i,j,t}$, and $Ivol_Sell_{i,j,t}$ to capture individuals' tendency to trade stocks with high idiosyncratic volatility, and $Up_Total_{i,j,t}$, $Up_Buy_{i,j,t}$, and $Up_Sell_{i,j,t}$ to quantify their tendency to trade lottery-type stocks. The construction of these variables is discussed in detail in Section 2.2.2.

Table 7 shows that individuals approaching milestone birthdays increase their trading of both high-risk stocks and lottery-type stocks. We further verify robustness by constructing alternative idiosyncratic volatility measures based on the Fama–French five-factor model (Fama and French, 2015) and the Chinese four-factor model (Liu et al., 2019) and report the results in Table A6. The results remain qualitatively unchanged.

[Insert Table 7 about here]

In sum, the results of tests in this subsection, where individuals' risk-taking tendency is captured by their propensity to trade risky stocks, yield the same conclusion as those when trading intensity is used to measure risk-taking, and further support our hypothesis.

4.4 Heterogeneity tests

In this section, we perform heterogeneity tests. We expect our results to be stronger for males, individuals from regions heavily influenced by Confucian clan culture, and migrants from low- to high-tier cities.

4.4.1 Gender

To examine the milestone age effect conditional on gender, we run the following regression, with $Male_i$ serving as an indicator for male investors:

$$Trade_{i,j,t}=\alpha+\beta_0 BirthQ_{i,j}\times MilestoneAge_{i,t}\times Male_i + \beta_1 BirthQ_{i,j}\times MilestoneAge_{i,t}$$

$$+\beta_2 BirthQ_{i,j}\times Male_i + \beta_3 MilestoneAge_{i,t}\times Male_i + \beta_c Controls_{i,j,t}+\varepsilon_{i,j,t}. \quad (4)$$

Table 8 shows that the coefficient on $BirthQ_{i,j}\times MilestoneAge_{i,t}\times Male_i$ is positive and significant at the 10% and 5% level in columns (1) and (2), respectively, and marginally significant in column (3). When $TotalValue_{i,j,t}$ is examined in column (1), the coefficient on $BirthQ_{i,j}\times MilestoneAge_{i,t}\times Male_i$ is about 70% of that on $BirthQ_{i,j}\times MilestoneAge_{i,t}$, indicating that the effect is substantially stronger among males.

[Insert Table 8 about here]

4.4.2 Confucian clan culture influence

Following Chen et al. (2022), we measure the strength of Confucian clan culture influence at the city-level using the number of genealogies scaled by local population. We set an indicator, $ClanRank_i$, categorized into quintiles to represent the scaled number of

genealogies of the city from which investor *i* originates. We then replace $Male_i$ in Eq. (4) with $ClanRank_i$ and report the results in Table 9.

[Insert Table 9 about here]

The coefficient on $BirthQ_{i,j} \times MilestoneAge_{i,t} \times ClanRank_i$ is significantly positive at the 1% level across all three columns, confirming that the Confucian clan culture amplifies the milestone age effect. The coefficient on $BirthQ_{i,j} \times MilestoneAge_{i,t}$ turns nonsignificant, suggesting that investors from cities with the least influence of the Confucian clan culture are not materially affected by the milestone age effect.

4.4.3 Migration conditions

We classify Chinese cities into low- and high-tier cities based on the "2022 City Commercial Attractiveness Ranking."[9] The variable $Move_i$ equals one for investors who are migrants from a low-tier city to a high-tier city, and zero otherwise. We replace $Male_i$ in Eq. (4) with $Move_i$ and report the results in Table 10.

[Insert Table 10 about here]

The coefficients of $BirthQ_{i,j} \times MilestoneAge_{i,t} \times Move_i$ and $BirthQ_{i,j} \times MilestoneAge_{i,t}$ are both significantly positive at the 1% level across columns, as expected. To further control

[9] Cities ranked as Tier One and New Tier One in the 2022 City Commercial Attractiveness Ranking are classified as high-tier cities (including Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Chongqing, Hangzhou, Xi'an, Wuhan, Suzhou, Zhengzhou, Nanjing, Tianjin, Changsha, Dongguan, Ningbo, Foshan, Hefei, and Qingdao), while all other cities are classified as low-tier cities.

for potential income differences between city tiers, we rerun the regressions using only investors currently living in first-tier cities in unreported tests. The results remain robust.

5. Assessment of post-trading performance

Our ***H3*** predicts that trades executed by individuals approaching milestone birthdays are likely to have a negative impact on their financial performance, as these trades tend to be induced by social pressure rather than rational or informed decisions.

We assess the performance of trades executed within the 90-day birthday window and compare it with the performance of trades executed in the adjacent pre- and post-90-day windows. We calculate profits generated from buy and sell orders, separately, within each 90-day window using Eqs. (5) and (7). The net profit is the sum of the two.

$$BuyProfit_{i,j,t,k}=\sum_{n=1}^{N}(Shares_{i,j,t,n}\times Prc_{i,j,t,n,k}-Value_{i,j,t,n}), \quad (5)$$

$$SellProfit_{i,j,t,k}=\sum_{n=1}^{N}(-Shares_{i,j,t,n}\times Prc_{i,j,t,n,k}+Value_{i,j,t,n}), \quad (6)$$

$$NetProfit_{i,j,t,k}=BuyProfit_{i,j,t,k}+SellProfit_{i,j,t,k}. \quad (7)$$

The variable $BuyProfit_{i,j,t,k}$ ($SellProfit_{i,j,t,k}$) represents the profit from buy (sell) orders within window *j*, up to the k^{th} trading day after the window's conclusion. These are calculated by summing the profits from all buy (sell) orders within the window. The variable *n* denotes the n^{th} buy or sell trade that took place during the 90-day window, with $Shares_{i,j,t,n}$ and $Value_{i,j,t,n}$ representing the number of shares involved in the trade and the

value of the trade. $Prc_{i,j,t,n,k}$ is the closing price of the stock involved in the n^{th} trade in the window on the k^{th} trading day after the window ends. $NetProfit_{i,j,t,k}$ is the sum of buy and sell profit. We measure post-trading performance over varying windows with k equal to 30, 60, 90, and 120. The post-trading performance is assessed using Eq. (8):

$$Profit_{i,j,t,k}=\alpha+\beta_0 BirthQ_{i,j}\times MilestoneAge_{i,t}+\beta_c Controls_{i,j,t}+\varepsilon_{i,j,t}. \quad (8)$$

Results in Table 11 confirm that trades executed by individuals approaching their milestone birthdays often yield lower profits compared to those made outside this period. This finding aligns with our conjecture that investment decisions driven by social pressure, rather than sound investment strategies, tend to underperform and adversely impact individuals' financial well-being.

[Insert Table 11 about here]

6. Additional analysis and robustness checks

6.1 Additional analysis: Scrutinize trading activities over shorter intervals

In this subsection, we analyze individuals' trading behavior over shorter intervals: in 30-day windows within each of the three 90-day windows surrounding milestone birthdays. This more refined test includes six 30-day windows before the milestone birthdays and three afterwards. We expect a hump-shaped pattern to emerge: a peak in trading during the 30-day window immediately before the milestone birthday, followed by a decline in both the preceding and following intervals.

We set a dummy $BirthM_{0,i,t}$ to be one for the 30-day window ending right on the date of the birthday of investor *i*. The n^{th} 30-day window relative to the birthday window is indicated by a dummy variable $BirthM_{n,i,t}$. We then run the regression in Eq. (9):

$$Trade_{i,j,t} = \sum_{n=-4}^{+3} \beta_n BirthM_{n,i,j} \times MilestoneAge_{i,t} + \beta_c Controls_{i,j,t} + \varepsilon_{i,j,t}. \quad (9)$$

Table 12 shows the regression results, and Figure 3 offers a visual comparison of the coefficients. Overall, the coefficients display a hump-shaped pattern, with the estimation of β_0 being the largest and most significant. The only exception is that the coefficient of $BirthM_{-4,i,j} \times MilestoneAge_{i,t}$ is slightly greater than that of $BirthM_{-3,i,j} \times MilestoneAge_{i,t}$. Other than that, the magnitude and significance of the coefficients increase steadily from the interaction term of $BirthM_{-3,i,j}$ to $BirthM_{0,i,j}$, after which the coefficients decrease rapidly across the three windows following the birthday. These results further substantiate the link between risk-taking behavior and milestone birthdays, illustrating that investors tend to trade more aggressively as they approach these milestone birthdays.

[Insert Table 12 about here]

[Insert Figure 3 about here]

6.2. Robustness checks

6.2.1 Alternative measures

To ensure that our results are not dependent on the specific trading intensity measure used in previous tests, we employ three alternative sets of trading intensity measures. The first

and second sets of measures are the number of trades executed and the number of shares traded. These measures capture aspects of trading intensity that differ from those captured by the value of trades and are less likely to be influenced by the price of the stocks traded. For the third set of trading intensity measures, we use turnover, which is calculated by scaling the value of trades by the value of the investors' stock holdings. Our findings remain robust, as shown in Table A7.

6.2.2 Poisson regression

We follow the recommendation of Cohn, Liu, and Wardlaw (2022) to perform Poisson regressions for count-like dependent variables such as the number of trades or shares traded. The results are reported in Table A8, and our findings remain robust.

6.2.3 Alternative samples

To ensure that our sample consists of active traders, we have applied a sample selection criterion requiring investors to have executed at least 10 buy and 10 sell trades during the sample period. We perform further analyses where this restriction is either loosened (requiring only 5 buy and 5 sell trades) or tightened (requiring either 20 buy and 20 sell trades or 50 buy and 50 sell trades). The results remain robust as reported in Table A9.

6.2.4 Placebo test

Finally, we perform placebo tests by assigning pseudo-ages to each investor. Specifically, we alter the investor's birth year by adding a random non-zero digit ranging from −5 to 5. Using these frictional ages, we recalculate and redefine $MilestoneAge_{i,t}$ accordingly. This process is repeated 100 times, and the distribution and *t*-test results for β_0 in Eq. (2) are

presented in Table A10. The coefficient on the interaction term between pseudo milestone age and birthday window indicator is smaller than that derived using actual age variables in most cases, and the *t*-test indicates that the mean of the placebo coefficients is not significantly different from zero. These findings further support the conclusion that investors' risk-taking tendency is amplified only as they approach milestone ages.

7. Conclusion

We examine the impact of social pressure, triggered by approaching individuals' milestone ages, on their risk-taking behavior in financial markets. Utilizing detailed account-level trading data from a large brokerage, we examine investors' stock trading behavior surrounding a birthday. We find investors tend to increase trading intensity and tilt their trading toward risky stocks in the 90-day window leading up to their milestone-age birthday, compared with the window preceding or following it. This means a temporary surge in risk-taking tendency when investors are approaching their milestone-age birthdays.

Our analysis also reveals that the milestone-age effect is particularly pronounced among investors with lower financial wealth and lower investment experience. These individuals are more susceptible to social pressure and are more likely to be influenced by non-fundamental factors when making investment decisions. Additionally, our results indicate that the effect is stronger for males and individuals born in regions with a stronger influence of Confucian clan culture. Social expectations and cultural norms may amplify the pressure associated with milestone ages for these people.

Furthermore, we assess the financial consequences of this temporary increase in risk-taking and find that trades executed during the window leading up to milestone-age birthdays tend to underperform. This suggests that pressure-driven trading decisions can have detrimental effects on individuals' financial well-being, underscoring the significant role of emotional states in shaping economic behavior. By integrating insights from psychology, behavioral finance, and cultural studies, our research contributes to a deeper understanding of how social pressure causally influences financial decision-making. Our findings challenge the traditional assumption of stable risk preferences and highlight the importance of incorporating psychological and social factors into financial models.

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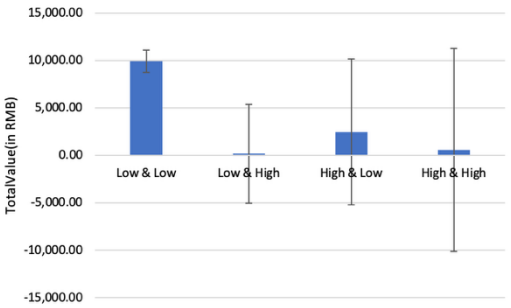
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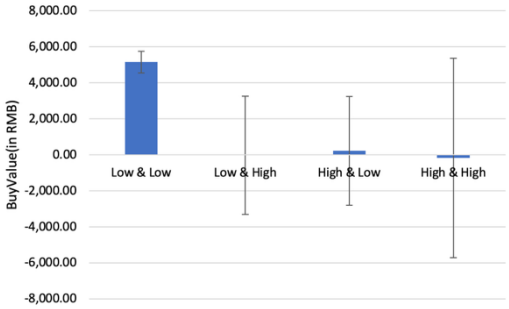
Figure 1. Milestone birthdays and trading intensities: subsample tests

This figure illustrates the regression coefficients of β_0 from Eq. (1) with its 90% confidence interval, estimated for subsamples constructed conditional on individuals' financial wealth and investment experience. Panels (A) to (C) plot the coefficients when the dependent variable in Eq. (1), the trading intensity, is captured by the value of all trades, buy trades, and sell trades, respectively. The subsample "Low & Low" ("High & High") consists of individuals whose financial wealth and investment experience are both below (above) the sample median. The subsample "Low & High" ("High & Low") consists of individuals whose financial wealth is below (above) the sample median, but investment experience above (below) the median.

(A) Total value



(B) Buy value



(C) Sell Value

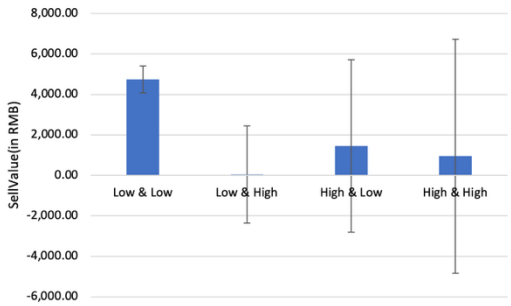
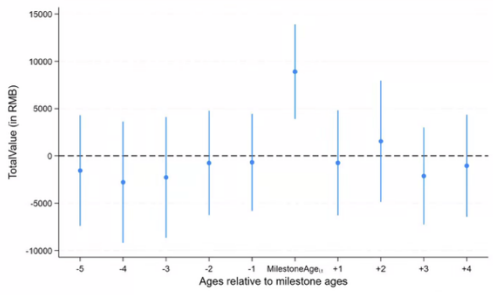


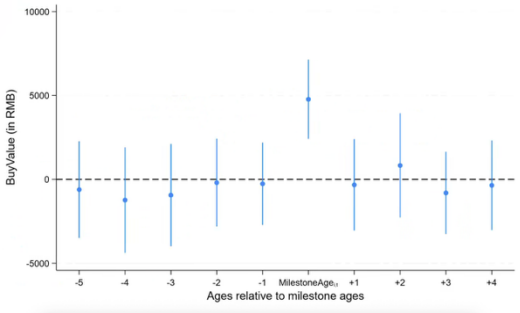
Figure 2. Trading intensities around milestone vs. non-milestone birthdays.

This figure illustrates the regression coefficients from Eq. (2) with the 90% confidence interval, depicting individuals' trading intensities during a 90-day period leading up to their birthdays, for both milestone and non-milestone ages. Panels (A) to (C) plot the coefficients when the dependent variable in Eq. (2), the trading intensity, is captured by the value of all trades, buy trades, and sell trades, respectively.

(A) Total value



(B) Buy value



(C) Sell Value

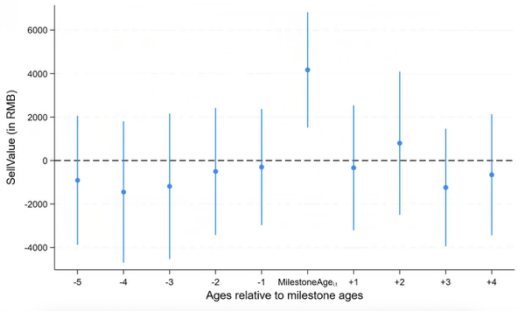
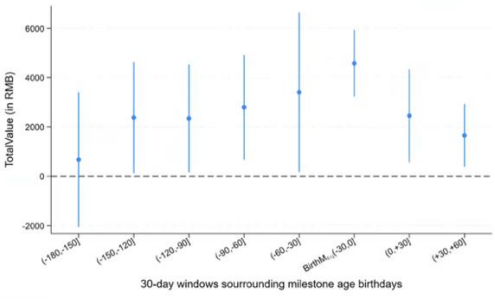


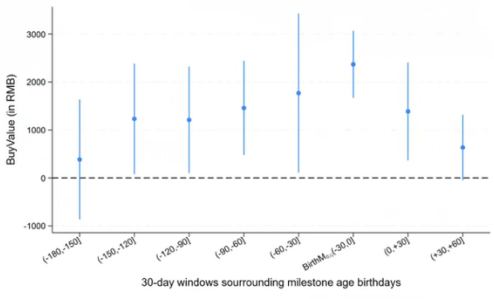
Figure 3. Trading over shorter intervals surrounding milestone birthdays

This figure illustrates the regression coefficients and the associated 90% confidence intervals from Eq. (9), over 30-day windows within the birth- and post-window of one birthday. Panels (A) to (C) display the estimated coefficients when the dependent variable in Eq. (9) is measured by the value of all trades, buy trades, and sell trades, respectively.

(A) Total value



(B) Buy value



(C) Sell Value

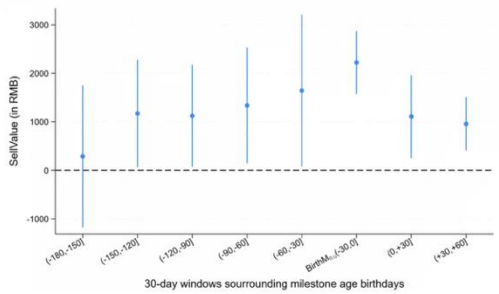


Table 1: Summary statistics

This table reports summary statistics of the main variables. $Age_{i,t}$ is the age of individual i in year t. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ is the value of all trades, buy trades, and sell trades, respectively, executed by individual i during a 90-day window in year t, which could correspond to his birthday window or the 90-day window immediately before or after. $Ivol_Total_{i,j,t}$ is the difference in total trading value between high-ivol stocks and all other stocks, scaled by the investor's total trading value. $Ivol_Buy_{i,j,t}$ ($Ivol_Sell_{i,j,t}$) is defined by analogy but using only value of buy (sell) trades. $Up_Total_{i,j,t}$ is the difference in total trading value between lottery stocks and all other stocks, scaled by the investor's total trading value. $Up_Buy_{i,j,t}$ ($Up_Sell_{i,j,t}$) is defined by analogy but using only value of buy (sell) trades. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual i at the end of the 90-day window preceding window j, or window $j-1$. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual i during window $j-1$. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1.

	# of obs	Mean	STD	P25	Median	P75
$Age_{i,t}$	9,000,000	41.46	11.02	33	39	48
$TotalValue_{i,j,t}$	9,000,000	560,453.66	1,702,966.00	0	11,664.00	240,565.17
$BuyValue_{i,j,t}$	9,000,000	281,358.70	855,875.57	0	2,915.00	120,246.00
$SellValue_{i,j,t}$	9,000,000	278,828.89	850,330.19	0	3,010.00	118,320.50
$Ivol_Total_{i,j,t}$ (%)	9,000,000	−32.00	51.17	−99.08	0	0
$Ivol_Buy_{i,j,t}$ (%)	9,000,000	−28.94	50.71	−90.16	0	0
$Ivol_Sell_{i,j,t}$ (%)	9,000,000	−28.62	50.44	−88.81	0	0
$Up_Total_{i,j,t}$ (%)	9,000,000	−28.04	51.62	−85.79	0	0
$Up_Buy_{i,j,t}$ (%)	9,000,000	−25.48	51.04	−78.60	0	0
$Up_Sell_{i,j,t}$ (%)	9,000,000	−24.98	50.82	−76.79	0	0
$StkHolding_{i,j-1,t}$	9,000,000	97,746.49	220,788.94	0	16,839.00	84,853.00
$\#\ of\ Trades_{i,j-1,t}$	9,000,000	21.64	51.13	0	2	17
$\#\ of\ Stocks_{i,j-1,t}$	9,000,000	4.63	8.71	0	1	5

Table 2: Milestone ages and pressure: Tests using CGSS 2021 survey data

This table utilizes data from the 2021 wave of Chinese General Social Survey (CGSS) to examine individuals' pressure levels when approaching their milestone ages. $Pressure_i$ ranges from 1 ("Never") to 5 ("Very frequent"), measuring how frequently respondents searched for information related to pressure or anxiety during the 12 months prior to the survey. $MilestoneAge_{-1,i}$ equals one if a respondent was surveyed at age 30, 40, or 50, corresponding to behaviors at ages 29, 39, and 49. Control variables are self-explanatory. Participants are classified into two groups based on their self-assessed social-status rank: below (ranks 1–5) and above (ranks 6–10). All continuous variables are winsorized at the top and bottom 1% levels. Fixed effect for the living province is controlled. Robust standard errors are clustered at age level, with t-statistics in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

	$Pressure_i$		
	(1) All Sample	(2) Below	(3) Above
$MilestoneAge_{-1,i}$	0.189**	0.246**	−0.127
	(2.22)	(2.22)	(−1.06)
Age_i	−0.027***	−0.032***	−0.002
	(−3.85)	(−3.57)	(−0.11)
Age_i^2	0.000	0.000	-0.000
	(1.27)	(1.57)	(−0.79)
$Male_i$	−0.082**	−0.090**	−0.026
	(−2.41)	(−2.12)	(−0.32)
$Employed_i$	0.032	0.051	−0.085
	(0.77)	(1.12)	(−0.89)
$Education_i$	0.097***	0.102***	0.094*
	(4.02)	(3.67)	(1.71)
$Single_i$	−0.071	−0.124	0.079
	(−0.96)	(−1.34)	(0.39)
$Political_i$	0.034	0.078	−0.067
	(0.55)	(1.14)	(−0.57)
$Rural_i$	−0.149***	−0.101*	−0.310***
	(−3.12)	(−1.78)	(−3.46)
Constant	2.706***	2.778***	2.284***
	(13.83)	(10.94)	(3.86)
Prov FE	Yes	Yes	Yes
Number of Obs.	1,889	1,494	395
Adj. R^2	0.21	0.21	0.20

Table 3: Milestone ages and risk preference: Tests using CHFS survey data

This table utilizes data from the 2013, 2015, 2017, and 2019 China Household Finance Survey (CHFS) to examine individuals' risk preferences when approaching their milestone ages. $TakeRisk_{i,t}$ is a dummy variable that equals one for individual *i* who has expressed willingness to take risks in making investment decisions in year *t*, and zero otherwise. $MilestoneAge_{-1,i,t}$ equals one for individuals who are 29, 39, or 49, and zero otherwise. Control variables are self-explanatory. Individuals are split into two groups based on the median of household assets. All continuous variables are winsorized at the top and bottom 1% levels. Fixed effects for survey waves and living provinces are all controlled. Standard errors are clustered at the individual and age levels, with t-statistics in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

	$TakeRisk_{i,t}$		
	(1) All Sample	(2) Below	(3) Above
$MilestoneAge_{-1,i,t}$	0.019*	0.025***	0.015
	(1.69)	(3.86)	(0.88)
$Age_{i,t}$	−0.017***	−0.022***	−0.014***
	(−17.06)	(−18.36)	(−11.26)
$Age_{i,t}^2$	0.000***	0.000***	0.000***
	(6.86)	(10.43)	(2.99)
$Male_i$	0.069***	0.074***	0.064***
	(14.82)	(11.46)	(12.07)
$Employed_i$	0.019***	0.015***	0.026***
	(4.19)	(2.65)	(3.70)
$Education_i$	0.077***	0.058***	0.075***
	(27.05)	(15.40)	(21.15)
$Single_i$	−0.043***	0.004	−0.051***
	(−4.64)	(0.33)	(−4.56)
$Political_i$	0.021***	0.025***	0.013**
	(4.71)	(3.61)	(2.20)
$Rural_i$	−0.057***	−0.029***	−0.047***
	(−13.19)	(−5.28)	(−6.57)
Constant	1.019***	1.084***	0.975***
	(38.40)	(32.38)	(32.06)
Survey Wave FE	Yes	Yes	Yes
Prov FE	Yes	Yes	Yes
Number of Obs.	94,470	44,616	49,854
Adj. R^2	0.17	0.13	0.18

Table 4: Baseline regression - Full sample

This table examines individuals' trading intensities when approaching milestone birthdays. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represents the value of all trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $BirthQ_{i,j}$ is a dummy variable that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual *i* at the end of the 90-day window preceding window *j*, or window *j−1*. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual *i* during window *j−1*. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, and individual×age×90-day window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
$BirthQ_{i,j}\times MilestoneAge_{i,t}$	4,567.59**	1,991.07**	2,420.28**
	(2.21)	(2.09)	(2.20)
$StkHolding_{i,j-1,t}$	2.41***	1.09***	1.32***
	(53.12)	(45.84)	(60.70)
$\#\ of\ Trades_{i,j-1,t}$	12,632.29***	6,368.17***	6,268.87***
	(95.82)	(98.48)	(92.54)
$\#\ of\ Stocks_{i,j-1,t}$	3,324.67***	1,711.06***	1,628.53***
	(7.59)	(7.73)	(7.45)
Constant	35,825.22***	29,187.66***	6,635.73**
	(6.70)	(10.63)	(2.55)
Individual FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Rolling 90-day FE	Yes	Yes	Yes
Window FE	Yes	Yes	Yes
Number of Obs.	9,000,000	9,000,000	9,000,000
Adj. R^2	0.60	0.60	0.61

Table 5: Subsamples formed based on double sorts: financial wealth and investment experience

This table examines individuals' trading intensities when approaching milestone birthdays in subsamples. The group "Low and Low" consists of individuals whose financial wealth and investment experience are both below the sample median. The "Others" group comprises all remaining individuals. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*, respectively. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $BirthQ_{i,j}$ is a dummy variable that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual *i* at the end of window *j−1*. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual *i* during window *j−1*. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	Low & Low Group			Others		
	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$	(4) $TotalValue_{i,j,t}$	(5) $BuyValue_{i,j,t}$	(6) $SellValue_{i,j,t}$
$BirthQ_{i,j}\times MilestoneAge_{i,t}$	9,928.36***	5,157.42***	4,740.59***	1,179.41	42.53	916.09
	(13.86)	(14.18)	(11.87)	(0.40)	(0.03)	(0.54)
$StkHolding_{i,j-1,t}$	3.34***	1.57***	1.77***	2.30***	1.03***	1.26***
	(48.66)	(44.85)	(52.05)	(69.08)	(58.87)	(79.83)
$\#\ of\ Trades_{i,j-1,t}$	11,269.17***	5,657.33***	5,618.18***	12,835.14***	6,475.31***	6,364.04***
	(55.76)	(55.62)	(55.87)	(77.81)	(79.35)	(75.76)
$\#\ of\ Stocks_{i,j-1,t}$	−3,677.28***	−1,789.74***	−1,892.35***	6,549.45***	3,333.81***	3,236.99***
	(−5.98)	(−5.80)	(−6.17)	(16.81)	(16.91)	(16.70)
Constant	17,008.69***	12,289.23***	4,739.94**	43,623.60***	36,406.91***	7,205.51**
	(4.49)	(6.46)	(2.50)	(6.07)	(9.88)	(2.06)
Various FE as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662	6,250,338	6,250,338	6,250,338
Adj. R^2	0.54	0.53	0.55	0.61	0.60	0.61

Table 6: Milestone vs. non-milestone birthdays

This table compares individuals' trading intensities when approaching milestone-age birthdays with those when approaching non-milestone birthdays. We focus on the "Low and Low" group, which consists of individuals with both financial wealth and investment experience below sample median. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual i executes over a 90-day window j in year t. Window j could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $BirthQ_{i,j}$ is a dummy that equals one when window j is the birthday window, and zero otherwise. $MilestoneAge_{n,i,t}$ indicates the n^{th} age relative to milestone ages. Control variables are the same as in Table 4. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
$BirthQ_{i,j}\times MilestoneAge_{-5,i,t}$	−1,547.57	−613.89	−909.56
	(−0.44)	(−0.36)	(−0.51)
$BirthQ_{i,j}\times MilestoneAge_{-4,i,t}$	−2,773.86	−1,236.23	−1,448.52
	(−0.72)	(−0.66)	(−0.74)
$BirthQ_{i,j}\times MilestoneAge_{-3,i,t}$	−2,268.58	−941.09	−1,185.17
	(−0.59)	(−0.51)	(−0.59)
$BirthQ_{i,j}\times MilestoneAge_{-2,i,t}$	−750.84	−199.07	−501.55
	(−0.23)	(−0.13)	(−0.29)
$BirthQ_{i,j}\times MilestoneAge_{-1,i,t}$	−674.88	−264.16	−299.24
	(−0.22)	(−0.18)	(−0.19)
$BirthQ_{i,j}\times MilestoneAge_{i,t}$	8,904.02***	4,773.13***	4,170.31**
	(2.97)	(3.37)	(2.62)
$BirthQ_{i,j}\times MilestoneAge_{+1,i,t}$	−734.52	−327.48	−334.38
	(−0.22)	(−0.20)	(−0.19)
$BirthQ_{i,j}\times MilestoneAge_{+2,i,t}$	1,550.30	828.06	797.23
	(0.40)	(0.44)	(0.40)
$BirthQ_{i,t}\times MilestoneAge_{+3,i,t}$	−2,123.15	−810.56	−1,240.11
	(−0.69)	(−0.55)	(−0.76)
$BirthQ_{i,t}\times MilestoneAge_{+4,i,t}$	-1,037.91	−357.83	−654.07
	(−0.32)	(−0.22)	(−0.39)
Constant	17,350.04***	12,417.28***	4,929.98**
	(4.33)	(6.18)	(2.45)
Controls as in Table 4	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Adj. R^2	0.54	0.53	0.55

Table 7: Risk-taking characterized by the propensity to trade risky stocks.

This table examines individuals' propensity to trade risky stocks as they approach milestone birthdays. We focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. In Panel A, we estimate each stock's idiosyncratic volatility using the Fama-French three-factor model over the six months preceding the pre-window. A stock is classified as high idiosyncratic risk if its idiosyncratic volatility is in the top quintile of all stocks. For investor *i* in window *j* of year *t*, $Ivol_Total_{i,j,t}$ measures the difference in total trading value between high-ivol stocks and all other stocks, scaled by the investor's total trading value in that window. We compute $Ivol_Buy_{i,j,t}$ and $Ivol_Sell_{i,j,t}$ by analogy but using only value of buy and sell trades, respectively. In Panel B, we count, for each stock, the number of days it hits the upper limit during the six months preceding the pre-window. A stock is classified as a lottery stock if its up-limit hit count ranks in the top quintile. For investor *i* in window *j* of year *t*, $Up_Total_{i,j,t}$ is the difference in total trading value between lottery stocks and all other stocks, scaled by the investor's total trading value in that window. We compute $Up_Buy_{i,j,t}$ and $Up_Sell_{i,j,t}$ by analogy but using only value of buy and sell trades, respectively. $BirthQ_{i,j}$ is a dummy variable that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual *i* at the end of the 90-day window preceding window *j*, or window *j*−*1*. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual *i* during window *j*−*1*. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Propensity to trade stocks with high idiosyncratic risk

	(1) $Ivol_Total_{i,j,t}$	(2) $Ivol_Buy_{i,j,t}$	(3) $Ivol_Sell_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	0.324*	0.290***	0.346**
	(1.99)	(3.09)	(2.23)
$StkHolding_{i,j-1,t}$	−0.000***	−0.000***	−0.000***
	(−42.09)	(−38.62)	(−46.23)
$\#\ of\ Trades_{i,j-1,t}$	0.086***	0.069***	0.084***
	(35.19)	(31.07)	(34.99)
$\#\ of\ Stocks_{i,j-1,t}$	−1.045***	−1.014***	−1.093***
	(−69.27)	(−67.68)	(−79.64)
Constant	−23.238***	−20.430***	−19.690***
	(−570.53)	(−520.25)	(−505.50)
Individual FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Rolling 90-day FE	Yes	Yes	Yes
Window FE	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Adj. R^2	0.17	0.16	0.14

Panel B: Propensity to trade lottery-type stocks

	(1) $Up_Total_{i,j,t}$	(2) $Up_Buy_{i,j,t}$	(3) $Up_Sell_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	0.283**	0.211***	0.284*
	(2.10)	(2.69)	(1.79)
$StkHolding_{i,j-1,t}$	−0.000***	−0.000***	−0.000***
	(−40.09)	(−38.69)	(−43.17)
$\#\ of\ Trades_{i,j-1,t}$	0.065***	0.050***	0.062***
	(29.85)	(25.08)	(28.18)
$\#\ of\ Stocks_{i,j-1,t}$	−0.793***	−0.768***	−0.831***
	(−50.71)	(−53.99)	(−54.06)
Constant	−19.671***	−17.382***	−16.562***
	(−389.94)	(−384.93)	(−340.36)
Individual FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Rolling 90-day FE	Yes	Yes	Yes
Window FE	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Adj. R^2	0.15	0.14	0.13

Table 8: Heterogeneity tests - Gender

This table examines individuals' trading intensities when approaching their milestone birthdays conditional on gender. We focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $BirthQ_{i,j}$ is a dummy variable that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual *i* at the end of the 90-day window preceding window *j*, or window $j-1$. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual *i* during window $j-1$. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
$BirthQ_{i,j}\times MilestoneAge_{i,t}\times Male_i$	5,014.51**	2,689.64**	2,499.93**
	(2.12)	(2.40)	(2.08)
$BirthQ_{i,j}\times MilestoneAge_{i,t}$	6,642.32***	3,396.26***	3,101.10***
	(4.34)	(4.49)	(4.32)
$BirthQ_{i,j}\times Male_i$	−764.73	−541.62	−259.64
	(−0.53)	(−0.73)	(−0.37)
$MilestoneAge_{i,t}\times Male_i$	−7,707.86	−4,031.63	−3,732.03
	(−0.77)	(−0.81)	(−0.75)
$StkHolding_{i,j-1,t}$	3.34***	1.57***	1.77***
	(48.67)	(44.85)	(52.05)
$\#\ of\ Trades_{i,j-1,t}$	11,269.16***	5,657.32***	5,618.17***
	(55.76)	(55.62)	(55.87)
$\#\ of\ Stocks_{i,j-1,t}$	−3,677.38***	−1,789.79***	−1,892.40***
	(−5.98)	(−5.80)	(−6.18)
Constant	17,705.26***	12,684.07***	5,053.37***
	(4.67)	(6.63)	(2.67)
Individual FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Rolling 90-day FE	Yes	Yes	Yes
Window FE	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Adj. R^2	0.54	0.53	0.55

Table 9: Heterogeneity tests - Confucian clan culture influence

This table examines individuals' trading intensities when approaching their milestone birthdays, conditional on the influence of Confucian clan culture. We focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $BirthQ_{i,j}$ is a dummy variable that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. $ClanRank_i$ is a quintile indicator representing the extent of clan influence, measured by the number of genealogies scaled by city population, in the city from which investor *i* originates. A higher $ClanRank_i$ indicates stronger Confucian clan culture. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual *i* at the end of the 90-day window preceding window *j*, or window *j*−*1*. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual *i* during window *j*−*1*. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
$BirthQ_{i,j}\times MilestoneAge_{i,t}\times ClanRank_i$	4,591.56***	2,105.01***	2,466.47***
	(4.33)	(3.39)	(5.66)
$BirthQ_{i,j}\times MilestoneAge_{i,t}$	−72.58	611.67	−627.93
	(−0.04)	(0.52)	(−0.75)
$BirthQ_{i,j}\times ClanRank_i$	−392.26	−166.24	−225.41
	(−0.75)	(−0.63)	(−0.86)
$MilestoneAge_{i,t}\times ClanRank_i$	1,023.36	564.22	469.20
	(0.87)	(0.93)	(0.81)
$StkHolding_{i,j-1,t}$	3.26***	1.53***	1.73***
	(45.09)	(41.92)	(47.92)
$\#\ of\ Trades_{i,j-1,t}$	11,331.59***	5,690.08***	5,648.50***
	(54.31)	(54.08)	(54.58)
$\#\ of\ Stocks_{i,j-1,t}$	−3,523.04***	−1,716.46***	−1,815.85***
	(−5.53)	(−5.35)	(−5.74)
Constant	16,466.69***	12,032.91***	4,436.93**
	(4.21)	(6.11)	(2.27)
Individual FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Rolling 90-day FE	Yes	Yes	Yes
Window FE	Yes	Yes	Yes
Number of Obs.	2,361,582	2,361,582	2,361,582
Adj. R^2	0.54	0.53	0.54

Table 10: Heterogeneity tests – Migration condition

This table examines individuals' trading intensities when approaching their milestone birthdays, conditional on whether they are migrants from low- to high-tier cities. We focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $BirthQ_{i,j}$ is a dummy variable that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. $Move_i$ takes one for investors who are migrants from low- to high-tier cities, and zero otherwise. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual *i* at the end of the 90-day window preceding window *j*, or window $j-1$. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual *i* during window $j-1$. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
$BirthQ_{i,j}\times MilestoneAge_{i,t}\times Move_i$	15,335.73***	7,307.88***	7,275.66***
	(3.86)	(3.64)	(2.84)
$BirthQ_{i,j}\times MilestoneAge_{i,t}$	9,019.94***	4,724.99***	4,309.42***
	(12.21)	(12.34)	(11.60)
$BirthQ_{i,j}\times Move_i$	−4,252.36	−2,211.53	−1,941.99
	(−1.24)	(−1.28)	(−1.15)
$MilestoneAge_{i,t}\times Move_i$	−14,732.86**	−7,174.19*	−7,542.32**
	(−2.11)	(−1.97)	(−2.22)
$StkHolding_{i,j-1,t}$	3.34***	1.57***	1.77***
	(48.66)	(44.85)	(52.05)
$\#\ of\ Trades_{i,j-1,t}$	11,269.15***	5,657.31***	5,618.17***
	(55.76)	(55.62)	(55.87)
$\#\ of\ Stocks_{i,j-1,t}$	−3,677.07***	−1,789.63***	−1,892.25***
	(−5.98)	(−5.80)	(−6.17)
Constant	17,182.32***	12,376.47***	4,824.34**
	(4.55)	(6.52)	(2.55)
Individual FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Rolling 90-day FE	Yes	Yes	Yes
Window FE	Yes	Yes	Yes
Number of Obs.	2,361,582	2,361,582	2,361,582
Adj. R^2	0.54	0.53	0.55

Table 11: Assessment of post-trading performance

This table assesses the post-trading performance of trades executed during the 90-day window leading up to milestone birthdays, with a focus on the "Low & Low" group—individuals whose financial wealth and investment experience are both below the sample median. $BuyProfit_{i,j,t,k}$, $SellProfit_{i,j,t,k}$, and $NetProfit_{i,j,t,k}$ represent the cumulative profits from buy, sell, and all trades, respectively, up to the k^{th} trading day after the 90-day window. The table displays the estimates of β_0 in Eq. (7) at different k. $StkHolding_{i,j-1,t}$, $\#\ of\ Trades_{i,j-1,t}$, and $\#\ of\ Stocks_{i,j-1,t}$ are included as control variables. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	$NetProfit_{i,j,t,k}$				
	$k = 0$	$k = 30$	$k = 60$	$k = 90$	$k = 120$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	−77.85***	−115.60***	−160.54***	−149.07***	−173.15***
	(−7.81)	(−4.10)	(−5.46)	(−4.03)	(−4.47)
$StkHolding_{i,j-1,t}$	−0.00***	−0.00***	−0.00	0.00	0.00
	(−4.90)	(−2.71)	(−1.23)	(0.48)	(1.06)
$\#\ of\ Trades_{i,j-1,t}$	−15.17***	−16.28***	−16.91***	−15.87***	−15.36***
	(−16.43)	(−12.44)	(−11.94)	(−9.81)	(−9.61)
$\#\ of\ Stocks_{i,j-1,t}$	−58.64***	−69.45***	−69.26***	−76.78***	−81.57***
	(−13.91)	(−13.54)	(−12.88)	(−13.54)	(−14.48)
Constant	−46.12**	−78.13***	−108.22***	−156.10***	−216.56***
	(−2.60)	(−3.56)	(−4.60)	(−6.14)	(−8.13)
Individual FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Rolling 90-day FE	Yes	Yes	Yes	Yes	Yes
Window FE	Yes	Yes	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662	2,749,662	2,749,662
Adj. R^2	0.04	0.03	0.02	0.01	0.01

Table 12: Trading activities over shorter intervals

This table examines individuals' trading intensities when approaching their milestone birthdays over shorter windows. Each 90-day window surrounding individual *i*'s birthday in year *t* is divided into three 30-day windows, with $BirthM_{0,i,j}$ taking the value of one for the 30-day window ending on the date of the birthday. The n^{th} 30-day window relative to the birthday window is indicated by a dummy variable $BirthM_{n,i,j}$. The 30-day windows within the pre-window period are used as the benchmark. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the total value of all trades, buy trades, and sell trades executed by individual *i* over the 30-day window right before his birthday in year *t*. $MilestoneAge_{i,t}$ equals one is individual *i* turns into a milestone age in year *t*, and zero otherwise. Control variables are the same as in Table 4. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
$BirthM_{-5,i,j} \times MilestoneAge_{i,t}$	678.00	384.85	287.99
	(0.41)	(0.51)	(0.33)
$BirthM_{-4,i,j} \times MilestoneAge_{i,t}$	2,385.30*	1,231.21*	1,171.14*
	(1.77)	(1.78)	(1.76)
$BirthM_{-3,i,j} \times MilestoneAge_{i,t}$	2,350.46*	1,210.04*	1,123.03*
	(1.79)	(1.81)	(1.79)
$BirthM_{-2,i,j} \times MilestoneAge_{i,t}$	2,797.72**	1,459.09**	1,337.86*
	(2.20)	(2.48)	(1.87)
$BirthM_{-1,i,j} \times MilestoneAge_{i,t}$	3,406.66*	1,770.50*	1,643.26*
	(1.76)	(1.78)	(1.75)
$BirthM_{0,i,j} \times MilestoneAge_{i,t}$	4,585.47***	2,367.58***	2,223.32***
	(5.65)	(5.65)	(5.71)
$BirthM_{+1,i,j} \times MilestoneAge_{i,t}$	2,455.00**	1,387.06**	1,109.31**
	(2.17)	(2.27)	(2.16)
$BirthM_{+2,i,j} \times MilestoneAge_{i,t}$	1,657.72**	635.32	956.29***
	(2.17)	(1.56)	(2.90)
Controls as in Table 4	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes
Number of Obs.	8,248,986	8,248,986	8,248,986
Adj. R^2	0.55	0.54	0.55

Appendix

Figure A1: Window definition

This figure illustrates the days covered by each of the three 90-day windows surrounding a birthday.

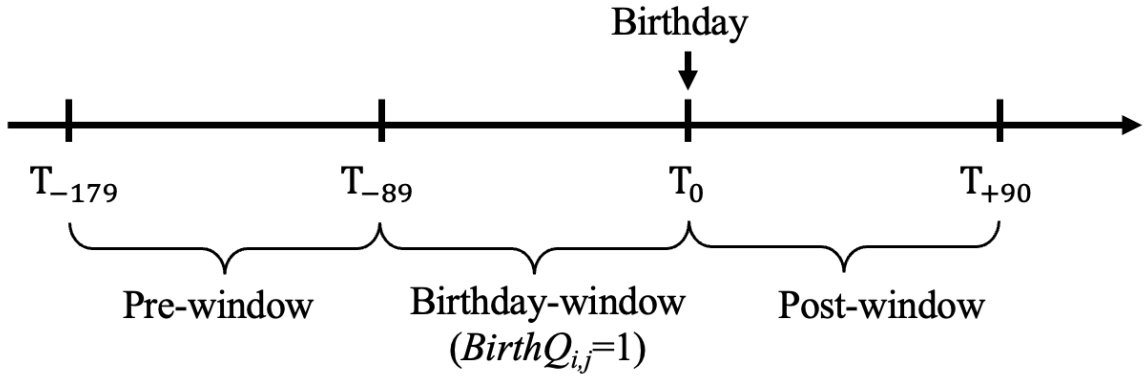


Figure A2: Birth month distribution

This figure shows the distribution of birth months for individuals in our full sample.

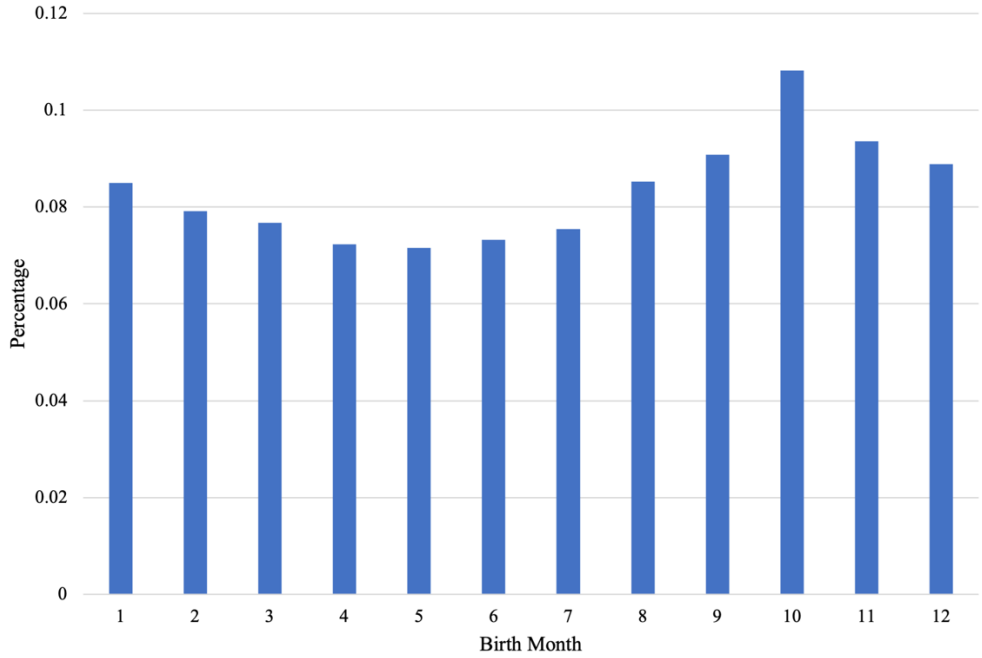


Table A1: Variable definition

Variable		Definition
$Age_{i,t}$		The difference between year *t* and the birth year of investor *i*.
$MilestoneAge_{i,t}$		An indicator that takes the value of 1 if investor *i* is aged 30, 40, or 50 in year *t*; otherwise, 0.
$AgeK_{i,t}$	Age and birthday-related variables	*K* = 30, 40, or 50. An indicator representing a specific milestone age.
$MilestoneAge_{n,i,t}$		*n* = −5 to +4. An indicator representing the n^{th} age relative to the milestone age.
$BirthQ_{i,j}$		An indicator that takes the value of 1 if window *j* covers the 90-day period before the birthday of investor *i*, otherwise, 0.
$BirthM_{n,i,j}$		*n* = −5 to +3. An indicator for the n^{th} 30-day window around the birthday.
$BuyValue_{i,j,t}$		The total value (in CNY) of buy transactions executed in window *j* of year *t*.
$SellValue_{i,j,t}$		The total value (in CNY) of sell transactions executed in the window.
$TotalValue_{i,j,t}$		The sum of $BuyValue_{i,j,t}$ and $SellValue_{i,j,t}$.
$BuyTrades_{i,j,t}$		The total number of buy transactions executed in the window.
$SellTrades_{i,j,t}$	Trading intensity	The total number of sell transactions executed in the window.
$TotalTrades_{i,j,t}$		The sum of $BuyTrades_{i,j,t}$ and $SellTrades_{i,j,t}$.
$BuyShares_{i,j,t}$		The total number of shares purchased in the window.
$SellShares_{i,j,t}$		The total number of shares sold in the window.
$TotalShares_{i,j,t}$		The sum of $BuyShares_{i,j,t}$ and $SellShares_{i,j,t}$.
$Turnover_{i,j,t}$		$TotalValue_{i,j,t}$ scaled by the value of investor *i*'s stock holdings at the beginning of the window *j* in year *t*.
$Ivol_Total_{i,j,t}$		The difference in total trading value between high-ivol stocks and all other stocks, scaled by the investor's total trading value. High-ivol stocks are those with idiosyncratic volatility in the top quintile.
$Ivol_Buy_{i,j,t}$		Similar to $Ivol_Total_{i,j,t}$ but using buy-side trading values only.
$Ivol_Sell_{i,j,t}$	Trading of risky stocks	Similar to $Ivol_Total_{i,j,t}$ but using sell-side trading values only.
$Up_Total_{i,j,t}$		The difference in total trading value between lottery-type stocks and all other stocks, scaled by the investor's total trading value. Lottery-type stocks are those with up-limit hit counts in the top quintile.
$Up_Buy_{i,j,t}$		Similar to $Up_Total_{i,j,t}$ but using buy-side trading values only.
$Up_Sell_{i,j,t}$		Similar to $Up_Total_{i,j,t}$ but using sell-side trading values only.
$BuyProfit_{i,j,t,k}$		The cumulative profit from buy transactions up to the *k*th trading day within a window.
$SellProfit_{i,j,t,k}$	Trading profit	The cumulative profit from sell transactions up to the *k*th trading day within a window.
$NetProfit_{i,j,t,k}$		The sum of $BuyProfit_{i,j,t,}$ and $SellProfit_{i,j,t,k}$.
$StkHolding_{i,j-1,t}$		The total stock holding value of an account on the last trading day in the window before window *j*.
$\#\ of\ Stocks_{i,j-1,t}$	Control variables	The number of unique stocks traded in the window before window *j*.
$\#\ of\ Trades_{i,j-1,t}$		The total number of trades executed in the window before window *j*.
$Male_i$		A binary indicator that takes the value of 1 for male investors.
$ClanRank_i$	Variables used in heterogeneity tests	A quintile indicator representing the extent of clan influence, measured by the number of genealogies scaled by city population, in the city from which investor *i* originates.
Move		A binary indicator that takes the value of one for investors who are migrants from low- to high-tier cities.

Table A2: Demographic distribution of individuals in the initial sample

This table presents the demographic distribution of individuals in our initial sample, which includes all investors with at least one stock transaction between July 2016 and March 2023. The distribution of demographic characteristics is compared with those reported in Liu et al. (2022) and Liao et al. (2022).

Demographic character	(1) Our ample	(2) Liu et al. (2022)	(3) Liao et al. (2022)
Gender			
Female	36.95%	28.30%	48.00%
Male	63.05%	71.70%	51.00%
Education			
Middle School or Below	3.42%	7.30%	8.70%
High School	13.99%	24.70%	23.90%
Professional School	27.83%	26.00%	30.70%
College	38.11%	23.60%	32.20%
Graduate School and Above	9.68%	3.40%	4.50%
Others or Missing	6.98%	14.80%	/
Age2017			
<30	19.75%	21.30%	14.70%
30 to 40	39.95%	27.40%	30.40%
40 to 50	23.85%	24.50%	29.30%
50 to 60	10.45%	15.10%	16.60%
>=60	6.00%	11.70%	9.10%
Self Report Income (CNY)			
<100K	16.49%	21.00%	/
100K to 500K	56.21%	59.00%	/
500K to 1M	18.95%	12.60%	/
>=1M	8.18%	7.50%	/
Missing	0.17%	/	/

Table A3: Subsamples formed based on single sort: financial wealth or investment experience

This table examines individuals' trading intensities when approaching milestone birthdays, segmented by subsamples formed based on the single sort. Investors are classified in Low financial wealth *FinWealth* (investment experience *InvestExp*) or High *FinWealth* (*InvestExp*) group by the median of $FinWealth_i$ ($InvestExp_i$). $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $BirthQ_{i,j}$ is a dummy variable that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. Control variables are the same as in Table 4. All continuous variables are winsorized at the top and bottom 1% levels. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Subsamples constructed based on financial wealth *FinWealth*

	Low *FinWealth*			High *FinWealth*		
	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$	(4) $TotalValue_{i,j,t}$	(5) $BuyValue_{i,j,t}$	(6) $SellValue_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	6,601.94***	3,388.91***	3,132.87***	1,519.76	49.94	1,230.01
	(5.24)	(4.92)	(5.01)	(0.29)	(0.02)	(0.44)
Controls as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	4,500,000	4,500,000	4,500,000	4,500,000	4,500,000	4,500,000
Adj. R^2	0.54	0.53	0.55	0.62	0.61	0.62

Panel B: Subsamples constructed based on investment experience *InvestExp*

	Low *InvestExp*			High *InvestExp*		
	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$	(5) $TotalValue_{i,j,t}$	(6) $BuyValue_{i,j,t}$	(7) $SellValue_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	7,760.05***	3,623.68***	3,817.94***	439.12	−111.65	596.53
	(3.73)	(3.85)	(3.34)	(0.14)	(−0.08)	(0.34)
Controls as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	4,501,350	4,501,350	4,501,350	4,498,650	4,498,650	4,498,650
Adj. R^2	0.59	0.58	0.59	0.61	0.60	0.62

Table A4: Summary statistics: individuals in the "Low & Low" group

This table reports summary statistics of the main variables for individuals in the "Low and Low" group. This group consists of individuals whose financial wealth and investment experience are both below the sample median. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual i executes over a 90-day window j in year t. Window j could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $Ivol_Total_{i,j,t}$ is the difference in total trading value between high-ivol stocks and all other stocks, scaled by the investor's total trading value. $Ivol_Buy_{i,j,t}$ ($Ivol_Sell_{i,j,t}$) is defined by analogy but using only value of buy (sell) trades. $Up_Total_{i,j,t}$ is the difference in total trading value between lottery stocks and all other stocks, scaled by the investor's total trading value. $Up_Buy_{i,j,t}$ ($Up_Sell_{i,j,t}$) is defined by analogy but using only value of buy (sell) trades. $StkHolding_{i,j-1,t}$ indicates the value of stock holdings for individual i at the end of the 90-day window preceding window j, or window $j-1$. $\#\ of\ Trades_{i,j-1,t}$ and $\#\ of\ Stocks_{i,j-1,t}$ are the number of trades executed and the number of stocks traded by individual i during window $j-1$. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1.

	# of obs	Mean	STD	P25	Median	P75
$Age_{i,t}$	2,749,662	35.42	8.08	30	33	39
$TotalValue_{i,j,t}$	2,749,662	277699.82	1099170.00	0	0	72,948.00
$BuyValue_{i,j,t}$	2,749,662	139955.21	552548.15	0	0	37,137.00
$SellValue_{i,j,t}$	2,749,662	137740.95	548207.80	0	0	35,242.00
$Ivol_Total_{i,j,t}$	2,749,662	−27.02	49.41	−82.53	0	0
$Ivol_Buy_{i,j,t}$	2,749,662	−24.13	48.36	−70.26	0	0
$Ivol_Sell_{i,j,t}$	2,749,662	−23.80	48.16	−68.61	0	0
$Up_Total_{i,j,t}$	2,749,662	−22.94	49.67	−68.24	0	0
$Up_Buy_{i,j,t}$	2,749,662	−20.58	48.50	−56.35	0	0
$Up_Sell_{i,j,t}$	2,749,662	−20.09	48.36	−54.01	0	0
$StkHolding_{i,j-1,t}$	2,749,662	32,034.73	96,297.17	0	4,081.00	24,247.00
$\#\ of\ Trades_{i,j-1,t}$	2,749,662	14.77	39.81	0	0	10
$\#\ of\ Stocks_{i,j-1,t}$	2,749,662	3.54	7.55	0	0	4

Table A5: Analysis of specific milestone ages

This table examines individuals' trading intensities as they approach their milestone birthdays at ages 30, 40, and 50, separately. We focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. $Age30_{i,t}$, $Age40_{i,t}$, and $Age50_{i,t}$ equals one if individual *i* turns into the age of 30, 40, or 50 in year *t*, respectively, and zero otherwise. Control variables are the same as in Table 4. All continuous variables are winsorized at the top and bottom 1% levels. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
$BirthQ_{i,j} \times Age30_{i,t}$	10,099.04***	5,191.19***	4,964.94***
	(15.67)	(15.90)	(15.44)
$BirthQ_{i,j} \times Age40_{i,t}$	8,999.99***	4,684.34***	4,084.25***
	(12.10)	(12.61)	(10.91)
$BirthQ_{i,j} \times Age50_{i,t}$	11,112.71***	6,184.04***	4,753.31***
	(16.57)	(18.11)	(14.37)
Controls as in Table 4	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Adj. R^2	0.54	0.53	0.55

Table A6: Trading of risky stocks – alternative definition of stocks with high idiosyncratic volatility

This table replicates the tests in Panel A of Table 7 but defines high-risk stocks using alternative volatility measures. In Panel A, idiosyncratic risk is computed from the Fama–French five-factor model, and in Panel B, it is computed from the Chinese four-factor model of Liu et al. (2019). The definitions of $IVol_Total_{i,j,t}$, $Ivol_Buy_{i,j,t}$ and $Ivol_Sell_{i,j,t}$ are the same as Table 7. $BirthQ_{i,j}$ is a dummy variable that equals one when window j is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual i turns into a milestone age in year t, and zero otherwise. Control variables are the same as in Table 4. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Idiosyncratic volatility measured by the Fama-French 5-factor model			
	(1) $IVol_Total_{i,j,t}$	(2) $Ivol_Buy_{i,j,t}$	(3) $Ivol_Sell_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	0.316*	0.257***	0.370***
	(1.88)	(2.65)	(2.75)
Controls as in Table 4	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Adj. R^2	0.17	0.16	0.15
Panel B: Idiosyncratic volatility measured by the Chinese 4-factor model of Liu et al. (2019)			
	(1) $IVol_Total_{i,j,t}$	(2) $Ivol_Buy_{i,j,t}$	(3) $Ivol_Sell_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	0.204**	0.236***	0.128*
	(2.08)	(2.91)	(1.81)
Controls as in Table 4	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Adj. R^2	0.12	0.11	0.10

Table A7: Alternative measures of trading intensity

This table examines individuals' trading intensities when approaching their milestone birthdays, using alternative trading intensity measures. We focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. In Panel A, trading intensity is measured by the number of trades executed. $TotalTrades_{i,j,t}$, $BuyTrades_{i,j,t}$, and $SellTrades_{i,j,t}$ represent the number of total trades, buy trades, and sell trades that individual *i* executes over a 90-day window *j* in year *t*. Window *j* could correspond to the 90-day birthday window ending right before the individual's date of birth, or the 90-day window immediately before or after. In Panel B, trading intensity is measured by the number of shares traded. $BuyShares_{i,j,t}$, and $SellShares_{i,j,t}$ represent the number of shares bought and sold, respectively, and $TotalShares_{i,j,t}$ is the sum of the two. In Panel C, trading intensity is measured by turnover $Turnover_{i,j,t}$, which is the value of all trades executed over the 90-day birthday window scaled by the value of total stock holdings at the beginning of the pre-window. $BirthQ_{i,j}$ is a dummy that equals one when window *j* is the birthday window, and zero otherwise. $MilestoneAge_{i,t}$ equals one if individual *i* turns into a milestone age in year *t*, and zero otherwise. Control variables are the same as in Table 4. All continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Trading intensity measured by the number of trades executed

	$TotalTrades_{i,j,t}$		$BuyTrades_{i,j,t}$		$SellTrades_{I,j,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	0.25***		0.15***		0.10***	
	(4.08)		(4.20)		(3.64)	
$BirthQ_{i,j} \times Age30_{i,t}$		0.19***		0.11***		0.07***
		(6.01)		(6.22)		(5.44)
$BirthQ_{i,j} \times Age40_{i,t}$		0.32***		0.16***		0.15***
		(10.12)		(9.12)		(11.11)
$BirthQ_{i,j} \times Age50_{i,t}$		0.55***		0.36***		0.20***
		(21.46)		(22.59)		(19.45)
Controls as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662	2,749,662	2,749,662	2,749,662
Adj. R^2	0.64	0.64	0.63	0.63	0.65	0.65

Panel B: Trading intensity measured by the number of shares traded						
	TotalShares$_{i,j,t}$		*BuyShares*$_{i,j,t}$		*SellShares*$_{I,j,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BirthQ$_{i,j}$×*MilestoneAge*$_{i,t}$	713.43***		369.34***		341.33***	
	(5.59)		(5.39)		(5.23)	
BirthQ$_{i,j}$×*Age30*$_{i,t}$		838.75***		434.38***		407.57***
		(14.73)		(14.34)		(14.77)
BirthQ$_{i,j}$×*Age40*$_{i,t}$		401.33***		191.36***		187.05***
		(6.40)		(5.74)		(6.22)
BirthQ$_{i,j}$×*Age50*$_{i,t}$		571.21***		339.37***		236.86***
		(8.96)		(10.08)		(7.67)
Controls as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662	2,749,662	2,749,662	2,749,662
Adj. R^2	0.50	0.50	0.49	0.49	0.51	0.51

Panel C: Trading intensity measured by turnover		
	(1) *Turnover*$_{i,j,t}$	(2) *Turnover*$_{i,j,t}$
BirthQ$_{i,j}$×*MilestoneAge*$_{i,t}$	0.10**	
	(2.02)	
BirthQ$_{i,j}$×*Age30*$_{i,t}$		0.04***
		(2.85)
BirthQ$_{i,j}$×*Age40*$_{i,t}$		0.19***
		(12.58)
BirthQ$_{i,j}$×*Age50*$_{i,t}$		0.25***
		(16.58)
Controls as in Table 4	Yes	Yes
Various FE as in Table 4	Yes	Yes
Number of Obs.	2,500,805	2,500,805
Adj. R^2	0.36	0.36

Table A8: Poisson regression

This table reports the results of Poisson regressions using transaction- and share-related dependent variables. We focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. All variable definitions are consistent with those in Table A7, and continuous variables are winsorized at the top and bottom 1% levels. All variables are defined in Table A1. Individual-, age-, rolling 90-day- and window-fixed effects are all controlled. Standard errors are clustered at the individual and age levels. The pseudo R^2 of Poisson regressions is reported. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Trading intensity measured by the number of trades executed			
	(1) $TotalTrades_{i,j,t}$	(2) $BuyTrades_{i,j,t}$	(3) $SellTrades_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	0.02***	0.02***	0.02***
	(3.18)	(3.29)	(2.89)
Controls as in Table 4	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Pseudo R^2	0.64	0.62	0.62
Panel B: Trading intensity measured by the number of shares traded			
	(1) $TotalShares_{i,j,t}$	(2) $BuyShares_{i,j,t}$	(3) $SellShares_{i,j,t}$
$BirthQ_{i,j} \times MilestoneAge_{i,t}$	0.03***	0.03***	0.03***
	(4.41)	(4.36)	(4.16)
Controls as in Table 4	Yes	Yes	Yes
Various FE as in Table 4	Yes	Yes	Yes
Number of Obs.	2,749,662	2,749,662	2,749,662
Pseudo R^2	0.72	0.71	0.72

Table A9: Alternative samples

In all the previous tests, we require investors to have executed at least 10 buy trades and 10 sell trades during the sample period to be included in our sample, ensuring that they are active traders. In this table, we employ alternative criteria for identifying active investors by changing the "10 buy + 10 sell" requirement to be "20 buy + 20 sell", "50 buy + 50 sell", or "100 buy + 100 sell". We then repeat the tests in Table 3 with these alternative samples. Again, for each alternative sample, we focus on the "Low and Low" group, which consists of individuals whose financial wealth and investment experience are both below the sample median. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of total trades, buy trades, and sell trades that individual *i* executed over a 90-day window *j* surrounding his date of birth in year *t*. For brevity, we only report the coefficient on the variable of interest, or $BirthQ_{i,j} \times MilestoneAge_{i,t}$, in the table. Model specifications are identical to those in Table 3. All continuous variables are winsorized at the top and bottom 1% levels. The *t*-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Threshold	(1) $TotalValue_{i,j,t}$	(2) $BuyValue_{i,j,t}$	(3) $SellValue_{i,j,t}$
20 buy & 20 sell	8,438.65***	4,484.93***	3,966.12***
	(7.70)	(7.97)	(6.96)
50 buy & 50 sell	12,442.66***	6,596.20***	5,867.48***
	(6.47)	(6.48)	(6.15)
100 buy & 100 sell	16,309.90***	8,740.64***	7,615.88***
	(7.43)	(7.47)	(6.86)

Table A10: Placebo test

This table presents the results of placebo tests in which we assign fictitious ages to each investor by adding a random non-zero digit, ranging from −5 to 5, to their birth year. With these adjusted ages, we recalculate and redefine $MilestoneAge_{i,t}$, which is reset to one if individual i reaches the fictional milestone age in year t, and zero otherwise. We then repeat the estimation of Eq. (1) 100 times. $TotalValue_{i,j,t}$, $BuyValue_{i,j,t}$, and $SellValue_{i,j,t}$ represent the value of all trades, buy trades, and sell trades that individual i executes over a 90-day window j, which could correspond to his birthday window or the 90-day window immediately before or after. Model specifications are identical to those in Table 3. All continuous variables are winsorized at the top and bottom 1% levels. We report the distribution and the associated t-test for the coefficient on the variable of interest, or $BirthQ_{i,j} \times MilestoneAge_{i,t}$, in the table. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Dep. Var.	Real coefficient	Distribution of placebo coefficient						
		N	Mean	Std	P10	Median	P90	t-value
$TotalValue_{i,j,t}$	9,928.36***	100	−728.25	2,736.55	−4,432.96	−892.57	2,910.04	−0.27
$BuyValue_{i,j,t}$	5,157.42***	100	−367.66	1,387.60	−2,238.82	−518.25	1,534.01	−0.26
$SellValue_{i,j,t}$	4,740.59***	100	−356.81	1,358.52	−2,146.59	−401.71	1,426.74	−0.26