DOI: 10.1111/eufm.12472

ORIGINAL ARTICLE

EUROPEAN FINANCIAL MANAGEMENT WILEY

I will trade, just not today: Individual investor trading activity around birthdays

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Abstract

In this paper we provide new evidence of investor inattention by showing that personal occurrences such as birthdays are able to drive attention away from the stock market. We document that individual investors significantly reduce their trading activity in the 3 days around their birthday. The reduction in the propensity to trade is larger for more active traders, in the event of a decade birthday and when this celebrative event falls on a Friday. Results are robust to analyses focusing only on days when investor attention should be at its peak, as expressed by excess news coverage and trading volumes.

KEYWORDS
investor attention, personal occurrences, trading activity

JEL CLASSIFICATION
G30, G32

We thank the editor and an anonymous referee for their valuable feedback and guidance. We thank Paul Guest, Tobin Hanspal, Nicoletta Marinelli, Bill Skimmyhorn, and participants at the FMA Europe Conference, Southwestern Finance Association, Data Science in Finance with R, Fundação Getulio Vargas, King's College London, University of Queensland for helpful comments.

1 | INTRODUCTION

We study how personal events related to the date of birth affect retail investors' trading activity. Over the last few decades, the literature has provided compelling evidence that actual investor behaviour diverges from the predictions of classical rational financial models. Important biases have been described, including investor overconfidence, familiarity and home biases, the disposition effect, and limited attention, among others. Overconfidence leads to increased and overaggressive trading, harming returns (Barber & Odean, 2001). The tendencies of familiarity and home biases lead investors to overweight familiar, well-known assets, which results in under-diversification (Huberman, 2001). The disposition effect reveals an aversion to selling underperforming assets, causing investors to sell well-performing assets too early and hold onto losing assets for too long (Shefrin & Statman, 1985). Central to this study is the financial literature which reveals that cognitive bias can cause limited attention in investors (Barber & Odean, 2008; Peng, 2005), negatively impacting portfolios by diminishing returns and heightening risks. When abundant news is available, due to cognitive limitations, investors cannot process a large amount of information. As a result, they only analyze a small subset of it, which is generally selected by the media that in turn enhance and channel investor attention toward covered companies (Peng & Xiong, 2006). The vast amount of information load faced by individuals can also lead to investor distraction. Hirshleifer et al. (2009) document that, when a greater number of public announcements are made by other firms competing for investor attention, price and volume reactions tend to be weaker. In a similar vein, Peress and Schmidt (2020) show that investors are distracted by sensational news exogenous to the stock market. During such events investors do not simply scale down but stop their trading activity. The distraction effect is not limited to retail investors. More recently, Schmidt (2019) documents that professional asset managers with a large portion of stocks that have an earnings announcement are significantly less likely to trade in other stocks, suggesting that news disclosure diverts attention from trading decisions for other stocks. Investor distraction has also been shown to be associated with the calendar. DellaVigna and Pollet (2009) report a weaker response to earnings announcements on Fridays, when investor attention is low relative to other weekdays.

Investor distraction may also be triggered by personal drivers. Lu et al. (2016) investigate the performance of hedge fund managers around the time of marriages and divorces. Consistent with the investor distraction hypothesis, they find that these marital transitions negatively affect the fund alpha. These effects are even more pronounced for managers responsible for multiple funds or those who are not part of a team. Marital events do not only distract professional investors. Grant et al. (2022) analyze the trading performance of divorced partners and show that, while they underperform during the litigation period, the situation is reversed once a settlement is reached. This evidence confirms that the stress induced by the divorce has a material impact on investor attention.

While marriages and divorces represent extraordinary personal occurrences, in this paper we show that recurring important events are likewise able to impact trading behaviour. Using a data set of approximately 9000 stock investors and over 1.2 million common stock trades from a large online broker, we document that birthdays are distraction events able to significantly reduce investors' trading activity. A legitimate question is why birthdays should be investor attention-diverting events. Unlike other personal attention-grabbing happenings, such as discontinuities of personal lives (love relationships or mourning) or professional lives (job hiring or firing), birthdays are routine and completely anticipated events. Nevertheless, as Achenbaum and Chudacoff (1990) discuss, although the anniversary of one's birth in the Western culture was rarely formally recognized until the early 1900s, it is nowadays not only a widely celebrated, but also a highly commercialized event providing a distinct life-course milestone. The recent pandemic has offered a confirmation of the social relevance of birthdays. Whaley et al. (2021) document that households with birthdays show a 31% increase in COVID-19 diagnoses compared with households without birthdays, as an effect of the social gatherings that usually take place in these events.

We argue that birthdays and resulting celebrations may drain investor attention and decrease the propensity of investors to trade on market- or firm-specific information. While any birthday is generally associated with social happenings and leisure activities, and likely cause investor inattention, some anniversaries are more celebrated than others. In particular, milestone birthdays (e.g., 40, 50 and 60), that represent symbolic ages usually accompanied by special celebrations with family and friends, should be associated with an even larger investor inattention.

In this paper we present strong evidence that retail investors trade significantly less in a 3-day period around their birthday, with a peak on the day of birth. Importantly, this effect holds controlling for investor, year–month, and day-of-the-week fixed effects. Specifically, results show a 6% (12%) decrease in the number of trades in coincidence with the birthday (in the 3 days around the birthday) with respect to the unconditional mean. The trading reduction is also larger when we look at the Euro value of the transactions that drop over 7.6% in coincidence with the birthday (equivalent to an average of 616 Euro per transaction) and around 19.6% if we consider a 3-day window around it.

While the trading drop is quite similar across sociodemographic characteristics as well as equally observed between purchases and sales, consistent with our expectation decades are instead largely important, triggering a sizeable further reduction in the number of trades. When an investor turns 40, 50 or 60, the trading activity (measured by the number of trades and trading volume) reduces to around double the effect of an ordinary birthday.

To test for the potential drivers for the observed reduction in trading activity, we interact the birthday dummy with Fridays to account for the higher likelihood of celebrations when birthdays are right before the week-end. Consistent with prior findings, trading activity decreases on Fridays but, in accordance with our conjecture, we also document an incremental reduction in trades if the birthday falls on the last day of the week.

The evidence that investors trade less on their birthdays is not per se supportive of the idea that traders are distracted by this personal event. In fact, if the reduction in stock transactions is simply limited to noise trading, investors could still be attentive to news releases regardless of the occurrence of a birthday. To dispel this potential doubt, we operate two empirical strategies. First, for every trading day, we identify the companies the press places in the spotlight through extremely high news coverage. Second, we select the companies experiencing a surge in investor attention by looking at the abnormal trading volumes. In both these approaches, for any trading date we select the companies in the top 1% (of news release or abnormal turnover) and then check whether investors are less likely to trade those highly visible stocks on their birthdays. Regardless of the approach used, we document that the stocks in the spotlight experience a sizeable drop in the frequency and volume of purchases or sales from investors whose birthdays occur on the same day. Therefore, we can rule out that trading reduction is only limited to uninformed trading.

The distraction induced by a birthday might also conceivably affect trading performance. Distracted investors may in fact put less effort into timing their trades or carefully set their limit orders and in turn ending up buying (selling) at higher (lower) prices. As a counter-argument, if the attention-grabbing effect makes the affected investors halting from trading on birthdays, we should observe no effect on those who decide to trade during this special day. We test this hypothesis and find some evidence that investors worsen their trading performance during their birthday selling at lower prices and, even more, buying at higher prices. However, although the drop in trading performance during the birthday is the largest relative to an 11-day window around it, the results are not statistically significant.

We acknowledge that investor inattention during birthdays may not be the only effect influencing trading behaviour. For instance, it is widely documented in the psychology literature that birthdays affect mood, creating a status of euphoria or despair (Matsubayashi & Ueda, 2016) that in turn affect individual behaviour.[1] Prior literature (e.g., Bless et al., 1996; Isen, 2000) has shown that people in good mood make more use of simplifying heuristics to aid decisions and tend to elaborate more on tasks involving neutral or positive (but not negative) stimulus material and in general they make more optimistic decisions. On the opposite, individuals in a bad mood tend to focus on negative material and engage in detailed analytical activity. So, a change in mood driven by the birthday occurrence may likewise affect investor behaviour and her trading activity. While we are not able to fully rule out the effect of mood, we use weather as a well-established proxy for it, leveraging on the documented evidence that weather affects individual trading activity and performance (Bassi et al., 2013; Hirshleifer & Shumway, 2003; Loughran & Schultz, 2004). However, we do not observe any association between decreased trading activity on the date of birth and temperatures or rainfalls.

We also run a battery of robustness tests and our results remain unaltered. First, we implement a logit regression model to analyze the probability of trading around the birthday. Second, we run a placebo test, shifting forward the true investors' birthday by 8 days and find no effect. To alleviate problems of possible outliers, we winsorize the dependent variables at the 1st and 99th percentiles. All these further analyses confirm both qualitatively and quantitatively our main findings.

This paper brings the following main contributions to the literature. First, we provide previously undocumented evidence of investor trading behaviour on the day of birth. While the literature has shown how personal events, such as marriages (Lu et al., 2016), the birth of a child, bereavement (Liu et al., 2023) or career transitions may affect financial decisions, no prior study has documented the effect of a birthday on a trading decision. We believe that this evidence is significant as it shows that not only extraordinary or unanticipated occurrences may affect individual behaviour but also recurring dates, such as the date of birth. Furthermore, this paper contributes to the literature on investor attention. Several papers have shown that overcrowded information disclosure creates investor distraction for investors who become unable to process a large amount of information. In these empirical tests, the distraction is exogenous to the individual and caused by firms or media releasing simultaneous information. Very few studies (Grant et al., 2022; Lu et al., 2016) investigate individual-specific distraction drivers but focus on the (under) performance in a large window period around infrequent and extraordinary personal events. In this paper, leveraging on a proprietary data set from a large online broker over a more than 10-year period we provide strong and robust evidence of a decline in investors' trading activity for an individual-specific recurring event, that is, the birthday. Our findings hold across ages, gender and days where important market- or firm-related news is disclosed. Overall, our findings highlight that personal factors, specifically the

[1]In particular, several studies have documented that birthdays are associated with significantly higher odds of suicide (among others, Stickley et al., 2016), as a result of the stress induced by turning 1 year older. The higher mortality rate around birthdays is not only confined to a deliberate decision to end one's life, as the death excess on the day of birth is also associated with a higher occurrence of accidents (traffic accidents, accidental falls, drowning, and choking), cardiovascular and cerebrovascular diseases and even cancers. Interestingly, a higher incidence of deaths on birthdays is observed regardless of gender, age and marital status (Ajdacic-Gross et al., 2012; Matsubayashi et al., 2019).

sway of birthdays on investment decisions, crucially influence trading patterns. This results in noticeable variations in portfolio strategies and their subsequent performance across investors.

The remainder of the paper is organized as follows: Section 2 describes the proprietary data set and the screening performed to obtain the final sample. Section 3 presents our research design, the empirical results and robustness checks. Finally, Section 4 concludes.

2 | DATA

2.1 | Data collection and filtering

We use a proprietary database from an Austrian online broker over the period June 2001–February 2014. As is common for online brokers, it offers fast and simple access to trading for its clients; the process of placing an order is not impeded by restricted opening hours or a need for personal interaction. Further, as the online broker charges very small trading fees, concerns about high costs are unlikely to negatively affect the propensity to trade. Thus, some of the potential frictions that might impact trading activity are effectively shut off in our data set. We obtain data on all individual equity trades of 19,966 equity investors. For each trade, we get the following information: the trade date, a unique identifier of the traded security (typically the International Securities Identification Number [ISIN]), the quantity traded, the trade price (before transaction costs), a buy–sell indicator, the trade currency, and the relevant exchange rate in case the security has been traded in a currency different from the Euro. While the data are anonymous, we obtain some sociodemographic characteristics of investors, like, gender, nationality and education. Importantly, we obtain the investors' birthdays.

To obtain a data set suitable for analyzing our research question, we apply a comprehensive set of data-cleaning filters: we exclude 165,031 observations where the day of birth is missing, the gender of the investor is not available, or the trade is offset the same day at exactly the same price. We then collapse transactions to avoid multiple counting of orders that have been executed in several parts over the same day. Specifically, we aggregate the trading amount on the investor/security/buy–sell indicator/day level.[2] This leaves us with 1,892,384 trades by 19,801 investors. Second, we restrict the sample to investors who trade actively and have at least one birthday in their active period. We define an investor's active trading period as the time span between her first and her last trade and remove 44,455 trades by 2835 investors who do not have a single birthday in their active trading period.

We further exclude 161,907 trades by 6875 investors with an average trading frequency of less than one trade per month in their active period.[3] Third, to allow a meaningful analysis of attention-grabbing events on a single stock basis, we restrict our sample to the 300 stocks traded most frequently by the investors in our sample.[4] Removing 502,204 trades in less frequently traded stocks reduces the number of investors by 134, leaving us with the final sample of 1,170,182 trades by 8878 investors. Our data set has a comparable number of investors to the data set used by Gargano and

[2]This means that if an investor has bought and sold the same security on a day, this would count as two trades. This reflects the fact that we treat buy and sell transactions, via the buy–sell indicator, separately.

[3]We analyze potential changes in the trading behaviour of investors on their birthdays. To construct a meaningful measure of normal trading activity, we limit our analysis to investors that trade at least once a month on average. Our results are not sensitive to variations in that threshold.

[4]Results are not sensitive to the number of most traded stocks in the data set.

Rossi (2018) with approximately 11,000 accounts, and is comparable in size to the data set consisting of 1.9 million common stock trades executed by 78,000 households which has been used recently by Peress and Schmidt (2020) and originally by Barber and Odean (2000).

We retrieve data on stock prices and volumes from Thomson Reuters Datastream and gather exchange rates from Bloomberg. We obtain information on media coverage of stocks from RavenPack News Analytics. This service is designed to deliver the sentiment analysis most likely to affect financial markets and trading around the world, covering 98% of the investable global market. RavenPack classifies and quantifies relevant news items about firms according to several dimensions, where each score ranges between 0 and 100. Out of the 300 stocks traded most frequently by our investors, RavenPack tracks 275 of them. Of these stocks, we obtain the daily number of news items and we restrict our analysis to those with a relevance score of 100 (meaning the entity was prominent in the news story). To merge news data with the broker data, we use intraday timestamps from RavenPack. In particular, for each day, news data released before 5.30 p.m. (CEST), which corresponds to the closing time of the Vienna Stock Exchange, are assigned to trading data at time t, while news data released after 5.30 p.m. (CEST) are assigned to trading data at time $t+1$.[5]

Finally, we download weather data using the Global Surface Summary of the Day from the US National Centre for Environmental Information. For each day, we obtain the mean temperature and total precipitation amount for the station "Hohe Warte" in Vienna.

We perform our analysis on trading days on the Vienna Stock Exchange. On the basis of the trading day calendar, obtained from Bloomberg, we define Holiday Eve as single trading days between two nontrading days, for example, a bank holiday and the weekend.

2.2 | Descriptive statistics

Table 1 reports descriptive statistics for the investor characteristics. The data set is made up of 8878 retail investors. To compute the time-varying characteristics, we proceed as follows. First, we create a time series for each investor starting from the day of her first trade and ending on the day of her last trade, omitting days when the stock market is closed. This allows us to compute time-series averages for each investor. In the second step, we compute cross-sectional results across investors. These investors show an average (median) age of 42.3 (40.9) years and 72% of the investors are between 30 and 60 years old. Investors older than 60 and 70 years represent 10% and 2% of the data set, respectively. Investors are largely male (88% on average) with a good level of education (approximately 34% of investors have earned a university degree) and the statistics show a 9% share of foreign investors (i.e., investors with a nationality other than Austrian). The breakdown of the investor base with respect to the sociodemographic characteristics shows that investors in our sample are slightly younger and predominantly male if compared with previous studies, but overall not dissimilar. For instance, Barber and Odean (2001) collect a sample with 79% male investors and an average (median) age of 50.9 (48). Gargano and Rossi (2018) have 73% male investors, with a 50.9 (51) average (median) age. While the characteristics of the traders in our data set broadly correspond to those in the above-mentioned studies, there are noticeable differences when comparing the investors in our data set to the general population in Austria: the proportion of males and highly educated persons is much higher (less than 11% of the adult population in Austria held an academic

[5]Unfortunately, we do not observe the time stamp of investors' transactions from the online broker data.

TABLE 1 Descriptive statistics.

This table reports descriptive statistics for the investor characteristics. The statistics are computed first in the time series dimension at the investor level, starting from the day of her first trade and ending on the day of her last trade, omitting days when the stock market is closed. The statistics are then computed cross-sectionally across investors. Age is the age of the investor in years; Age < 30 is a dummy equal to 1 for investors under 30 years of age, zero otherwise; Age 30–39 is a dummy equal to 1 for investors between 30 and 39 years old, zero otherwise; Age 40–49 is a dummy equal to 1 for investors between 40 and 49 years old, zero otherwise; Age 50–59 is a dummy equal to 1 for investors between 50 and 59 years old, zero otherwise; Age 60–69 is a dummy equal to 1 for investors between 60 and 69 years old, zero otherwise; Age > 70 is a dummy equal to 1 for investors above 70 years of age, zero otherwise; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality, zero otherwise; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days window (i.e., a calendar month), ending 10 days before day *t*, to avoid any overlap with the birthdays' dummies used in the regression analyses; No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise.

Statistic	*N*	Mean	SD	Pctl(25)	Median	Pctl(75)
Age	8878	42.32	12.52	32.64	40.94	50.20
Age < 30	8878	0.18	0.36			
Age 30–39	8878	0.30	0.42			
Age 40–49	8878	0.27	0.41			
Age 50–59	8878	0.15	0.33			
Age 60–69	8878	0.08	0.26			
Age > 70	8878	0.02	0.14			
Gender	8878	0.12	0.33			
Degree	8878	0.34	0.47			
Foreign	8878	0.09	0.28			
TradingFreq (21 trading days)	8878	6.56	6.57	2.70	4.34	7.81
No. ISIN	8878	4.43	4.63	1.55	3.01	5.67
Option Trader	8878	0.44	0.50			

degree in 2009). The table likewise reports information on investor trading behaviour: the average trading frequency of these investors (TradingFreq), the number of unique stocks held in the portfolio (No. ISIN) and an indicator variable that detects any investor who has ever traded in options (Option Trader). TradingFreq indicates on day *t* the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day *t*, to avoid any overlap with the birthdays' dummy variables used in our regression analysis.[6] Investors trade on average (median) 6.6% (4.3%) of the days when the stock

[6]For robustness, we also compute the variable averaging the trading frequency over a 2- and 3-month time span and the results are quite similar.

market is open or, in other words, each investor on average buys or sells stocks every 15 days. The interquartile range and the standard deviation suggest that the data set is homogeneous in terms of trading frequency. Investors in the sample hold a fairly undiversified portfolio, as they, on average (median), invest in 4.4 (3.0) unique stocks, but 44% of them have traded at least once in option instruments.[7]

Table 2 shows the descriptive statistics with reference to the trading activity at the investor level. Panel A reports information on the whole data set, while Panels B and C document the same statistics for the subset of male and female investors, respectively. Similarly to Table 1, the statistics are computed from cross-sectional data across investors. Each investor trades on average 0.170 times per day or, equivalently, 3.57 times per month.[8] The data set is rather heterogeneous in terms of trading behaviour, as indicated by the number of trades that predictably denotes a highly skewed distribution.[9] Splitting the trades between buy and sell, we notice a predominance of the former, although the evidence is reverted when we move from the number of trades to Euro value of the transactions. In fact, while the average (median) purchase value is 7.5 (3.3) thousand Euro, investors disinvest 8.5 (4.0) thousand Euro worth in stock when they sell. Lastly, we observe each investor for an average (median) duration of 40.15 (30.87) months, which is the time interval between the first and the last trade. Not surprisingly, we also report that half of the trades concern stocks listed on the Austrian Stock Market (AT). This evidence supports the well-known argument of the home bias, which is the tendency of investors to trade/prefer stocks in the domestic market. The breakdown by gender shows that female investors, who we trace for a shorter time span (34.98 vs. 40.86 months, on average), trade with a similar frequency but with a smaller amount of capital invested. In fact, the average value of the female investors' transactions is less than 80% of the average amount of male investor trade, both for purchases and sales.

Table 3 provides the first evidence of investors' trading behaviour around their birthdays, contrasting trading behaviour on the date of an investor's birth with trading on any other trading day.[10] The table evidences that birthdays are associated with a 12.5% drop in the average number of trades, a reduction that is reflected both in terms of purchases and sales. Interestingly, the decrease in trading activity on birthdays is even more pronounced if the value of the transactions is considered as opposed to the mere number of trades. The average purchase (sale) on the date of the investor's birth is 25.6% (29.0%) lower than on any other day, suggesting that investors not only reduce the frequency of trading on their birthdays but, conditional on trading, they also decrease the average amount of money they invest in or divest from the stock market.

Figure 1 illustrates the frequency of the number of trades among all investors aggregated by the distance from their birthdate. A distance of 0 indicates the day of the investor's birth (circled in red), −1 (+1) stands for the day before (after) the investor's birthday, and so forth. We observe a significant drop in the frequency of the trades when we compare the trading frequency on the birthdate with other days. The drop corresponds approximately to a 12% reduction in the number of transactions, coherently with the figures in Table 3. Overall,

[7]However, while we only look at the stock portfolio, investors may have likewise invested in other assets (e.g., mutual funds).

[8]Note that the statistics on the number of trades take into account multiple trades per day. The previously mentioned TradingFreq variable instead is computed based on the days where the investor traded, that is, without counting how many trades are executed, but simply counting whether at least one trade is reported.

[9]As previously discussed, we filter out traders with less than a trade per month to eliminate the noise from very infrequent traders.

[10]When we look at any other day, in addition to the birthdate, we also exclude the 5 days before and after it.

TABLE 2 Descriptive statistics—Trading behaviour.

This table reports descriptive statistics with reference to the trading activity at the investor level. Panel A reports information on the whole data set, while Panels B and C document information for the subset of male and female investors, respectively. The statistics are computed first in the time series dimension at the investor level, starting from the day of her first trade and ending on the day of her last trade, omitting days when the stock market is closed. The statistics are then computed cross-sectionally across investors.

Statistic	Mean	SD	Pctl(25)	Median	Pctl(75)
Panel A: Investors N = 8878					
Number of days with trading	0.103	0.105	0.043	0.067	0.122
Number of trades	0.170	0.275	0.055	0.091	0.178
Number of buy trades	0.094	0.159	0.032	0.052	0.100
Number of sell trades	0.072	0.123	0.021	0.037	0.076
Euro value of buy trade	7506	75,492	1904	3331	6380
Euro value of sell trade	8503	72,981	2251	4025	7589
Number of active months	40.148	32.055	13.574	30.869	60.713
Number of trades per month	3.550	6.050	1.151	1.890	3.681
Number of AT trades	0.522	0.343	0.212	0.540	0.840
Panel B: Male Investors N = 7800					
Number of days with trading	0.102	0.105	0.042	0.067	0.120
Number of trades	0.169	0.278	0.055	0.091	0.176
Number of buy trades	0.094	0.163	0.032	0.052	0.099
Number of sell trades	0.071	0.124	0.021	0.037	0.075
Euro value of buy trade	7718	80,457	1888	3296	6360
Euro value of sell trade	8717	77,760	2235	4016	7592
Number of active months	40.862	32.368	13.836	31.984	61.869
Number of trades per month	3.543	6.166	1.142	1.878	3.658
Number of AT trades	0.522	0.342	0.214	0.540	0.835
Panel C: Female Investors N = 1078					
Number of days with trading	0.107	0.103	0.045	0.070	0.131
Number of trades	0.175	0.248	0.058	0.095	0.187
Number of buy trades	0.095	0.129	0.032	0.053	0.104
Number of sell trades	0.075	0.117	0.023	0.038	0.080
Euro value of buy trade	5967	9243	1994	3515	6547
Euro value of sell trade	6966	11,379	2405	4107	7563
Number of active months	34.983	29.188	12.238	24.459	51.615
Number of trades per month	3.597	5.128	1.208	1.963	3.896
Number of AT trades	0.526	0.350	0.200	0.538	0.870

TABLE 3 Descriptive statistics—Trading behaviour on birthdays versus other days.

This table reports investors' trading activity, comparing information on the date of investor's birth with information on any other date. The statistical significance of the difference in trading activity (birthdays vs. any other day) is tested using the standard t test and the Wilcoxon signed-ranktest. Under the null hypothesis of the test, the difference equals zero, whereas under the alternative hypothesis the average difference diverges from zero.

	Birthdays					Other days							
Statistic	**Mean**	**SD**	**Pctl (25)**	**Median**	**Pctl (75)**	**Mean**	**SD**	**Pctl (25)**	**Median**	**Pctl (75)**	**Difference in mean**	***t* Test**	**Wilcoxon *p* value**
Number of trades	0.14	0.60	0.00	0.00	0.00	0.16	0.66	0.00	0.00	0.00	−0.02	−4.62	0.00
Number of buy trades	0.08	0.36	0.00	0.00	0.00	0.09	0.41	0.00	0.00	0.00	−0.01	−3.79	0.00
Number of sell trades	0.06	0.35	0.00	0.00	0.00	0.07	0.37	0.00	0.00	0.00	−0.01	−4.03	0.00
Euro value of buy trades	8836	28,439	1987	3475	8160	11,877	269,188	2010	3499	3499	−3040	−3.89	0.06
Euro value of sell trades	10,172	19,876	2271	4551	9531	14,326	347,470	2400	4432	4432	−4154	−5.55	0.93

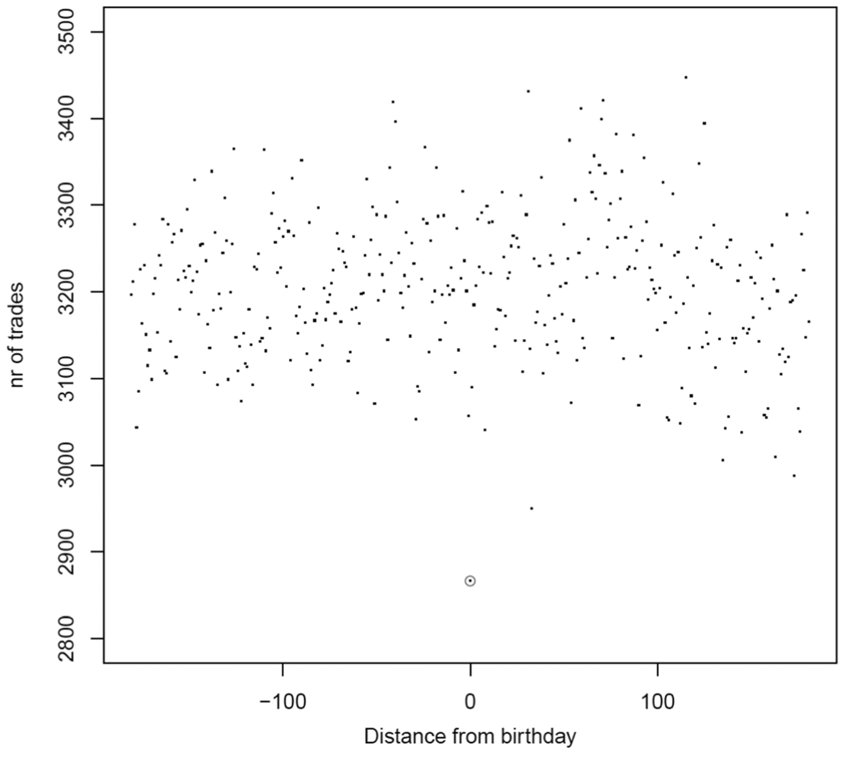

FIGURE 1 Trading frequency around birthday. This figure shows the frequency of the number of trades among all investors aggregated by distance from birthday. In the figure, each point captures the total number of trades executed by all investors whose birthday is on an *x*-day distance. A distance of 0 indicates the day of the investor birth (circled in red), −1 (+1) stands for the day before (after) the investor birthday. Similarly for the other values of distance from birthday.

Figure 1 shows striking evidence that investors trade less on their birthday. In Section 3, we investigate different reasons for this behaviour.

3 | EMPIRICAL ANALYSIS

3.1 | Trading around the birthday

While reduced trading activity on birthdays is evident from the descriptive statistics of our sample, trading is known to be influenced by a number of other factors such as individual investor characteristics and the age or gender of an individual trader, that might interact with the effect of birthdays on trading. To isolate the specific effect of a birthday, we estimate the following multivariate regression:

$$Y_{i,t} = \beta_1 \mathrm{BD}_{i,t} + \beta_2 BD0_{i,t} * \mathrm{InvestorChars}_{i,t} + \beta_3 \mathrm{Controls}_{i,t} + f_t + f_i + \varepsilon_{i,t}. \quad (1)$$

We compute the dependent variable either as log(1 + number of trades) or log(1 + Euro volume of trades), performed by investor i on day t. The log transformation moderates the influence of observations with extremely high trading activity.[11] BD is a set of 11 dummy variables that each take the value 1 on the birthday or on the day with a distance from 5 days before to 5 days after investor *i*'s birthday, respectively, and 0 otherwise. We focus on the time span from 5 days before to 5 days after the birthday to capture any anticipated or postponed effect. The dummy variable related to the birthday itself is denoted by BD0. InvestorChars is a set of investor-specific variables, which includes both sociodemographic and trading characteristics. More specifically, it comprises: age, gender (1 if female, 0 otherwise), degree (1 if the investor has an academic degree, 0 otherwise), nationality (Foreign takes the value 1 if the investor does not have Austrian nationality, zero otherwise), the frequency of trading over the last month (TradingFreq), the portfolio diversification (No. ISIN), as proxied by the number of stock ISINs held by the investor, and the investor sophistication (Option Trader takes the value 1 for investors who traded options at least once, zero otherwise). To capture the potential nonlinear effect of age on trading activity, widely documented in the literature, we further include the age-squared variable. Controls include the time-varying investor-specific characteristics (Age, TradingFreq, No. ISIN). f_i and f_t are investor and time fixed effects. With respect to the latter, we include year–month and day-of-the-week fixed effects to account for common variation across investors in the same year–month, and day of the week. We estimate Equation (1) using standard ordinary least squares (OLS), with standard errors clustered at the account level.

To gauge investors' trading behaviour on and around the birthday only, in some specifications of Equation (1) we exclude investor-specific characteristics and, therefore, the interaction effects. Furthermore, to understand the impact of investors' characteristics alone, in some specifications of Equation (1) we also exclude investor fixed effects. More specifically, Model (1) of Table 4 includes only the birthday dummy variables, controlling for investor and time fixed effects. The results show a clear drop in trading activity in the 5-day window around the birthday, with a peak on the date of birth. This pattern is both evidenced by the coefficients and the statistical significance that monotonically increases from −2 to 0 (birthday) and monotonically decreases afterwards (until +2). Above the strong statistical significance, the coefficients are also economically meaningful: For example, the coefficient of −0.009 on BD0 in Model (1) translates into a 6.2% drop in the number of trades relative to the unconditional mean during birthdays.

Model (2) of Table 4 includes investor attributes and removes investor fixed effects, while Model (3) of Table 4 further includes a potential nonlinear effect of age on trading behaviour. While the effect of gender, nationality and education is not associated with the trading intensity, we do find a positive association between age and the (log of) Euro volume of trades. Unsurprisingly, the past trading frequency is highly correlated with the number of trades and the portfolio diversification proxy (No. ISIN), whereas we document no association between trading frequency and investor sophistication (as proxied by the variable Option Trader). More importantly, once we control for these factors, the reduction in trading activity is unaltered regarding the time window (from −1 to +1) and statistical significance. Specifically, on the date of birth, the results confirm a 6% decrease in trading activity with respect to the unconditional mean and a 12% reduction over the 3 days around it.

Results focusing on the volume of the trades (Models 4–6 of Table 4) are even stronger than the previous models in terms of economic magnitude. The coefficient on day zero suggests that investors trade 7.6% less in Euro values on the day of their birthday and around 19.6% less if we consider the 3-day window around the birthday.

[11]Engelberg and Parsons (2011) use the log of local trading volume as the dependent variable to explain the impact of local media coverage on local trading.

TABLE 4 Trading behaviour around birthday.

This table shows estimates from regressions of investor trading activity on investor attributes and the birthday dummies. Age is the age of the investor in years; Age.sqr is the age-squared; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality, zero otherwise; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days window (i.e., a calendar month), ending 10 days before day t, to avoid any overlap with the birthdays' dummies; No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. BD0, BD(−5), BD(−4), BD(−3),BD(−2), BD(−1), BD(+1), BD(+2), BD(+3),BD(+4), BD(+5) are a set of 11 dummy variables. Each dummy takes the value 1 on the birthday or on the day with a distance from 5 days before to 5 days after investor i's birthday, respectively, and 0 otherwise. Standard errors are clustered at the account level and are reported in parentheses. ***, ** and * denote that estimates are statistically significant at the 1%, 5% and 10% levels, respectively.

	Dependent variable					
	log(1 + number of trades)			**log(1 + Euro volume trades)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Age		−0.00011* (0.00006)	0.00030 (0.00030)		0.00108*** (0.00033)	0.00602*** (0.00162)
Age.sqr			−0.000004 (0.000003)			−0.00005*** (0.00002)
Gender		0.00038 (0.00140)	0.00031 (0.00140)		−0.00635 (0.01005)	−0.00727 (0.01004)
Degree		−0.00272** (0.00107)	−0.00274** (0.00107)		−0.01269* (0.00731)	−0.01291* (0.00731)
Foreign		0.00453 (0.00443)	0.00447 (0.00446)		0.01448 (0.01770)	0.01384 (0.01777)
TradingFreq		0.01173*** (0.00024)	0.01172*** (0.00024)		0.10043*** (0.00107)	0.10040*** (0.00107)
No. ISIN		0.00215*** (0.00022)	0.00216*** (0.00022)		0.01397*** (0.00107)	0.01398*** (0.00106)
Option Trader		0.00046 (0.00100)	0.00050 (0.00100)		−0.00325 (0.00694)	−0.00288 (0.00693)
BD(−5)	−0.00171 (0.00184)	−0.00012 (0.00178)	−0.00012 (0.00178)	−0.01927 (0.01655)	−0.00578 (0.01602)	−0.00574 (0.01603)
BD(−4)	−0.00009 (0.00181)	0.00029 (0.00174)	0.00030 (0.00174)	−0.00082 (0.01651)	0.00237 (0.01597)	0.00244 (0.01597)
BD(−3)	0.00002 (0.00187)	0.00049 (0.00180)	0.00049 (0.00180)	0.00249 (0.01682)	0.00676 (0.01633)	0.00678 (0.01633)
BD(−2)	−0.00341* (0.00185)	−0.00163 (0.00178)	−0.00163 (0.00178)	−0.04014** (0.01639)	−0.02514 (0.01587)	−0.02509 (0.01587)
BD(−1)	−0.00598*** (0.00175)	−0.00444*** (0.00169)	−0.00444*** (0.00169)	−0.06001*** (0.01581)	−0.04680*** (0.01530)	−0.04674*** (0.01530)
BD0	−0.00935*** (0.00172)	−0.00872*** (0.00166)	−0.00872*** (0.00166)	−0.07946*** (0.01575)	−0.07441*** (0.01527)	−0.07434*** (0.01527)

(Continues)

TABLE 4 (Continued)

	Dependent variable					
	log(1 + number of trades)			log(1 + Euro volume trades)		
	(1)	(2)	(3)	(4)	(5)	(6)
BD(+1)	−0.00491*** (0.00179)	−0.00425** (0.00173)	−0.00425** (0.00173)	−0.04602*** (0.01612)	−0.04042*** (0.01561)	−0.04041*** (0.01561)
BD(+2)	−0.00380** (0.00181)	−0.00296* (0.00172)	−0.00296* (0.00172)	−0.04770*** (0.01613)	−0.04063*** (0.01547)	−0.04058*** (0.01547)
BD(+3)	−0.00085 (0.00183)	−0.00045 (0.00173)	−0.00045 (0.00173)	−0.00872 (0.01662)	−0.00540 (0.01583)	−0.00534 (0.01583)
BD(+4)	0.00122 (0.00184)	0.00101 (0.00177)	0.00101 (0.00177)	0.01099 (0.01675)	0.00929 (0.01612)	0.00934 (0.01612)
BD(+5)	−0.00015 (0.00183)	0.00039 (0.00176)	0.00039 (0.00176)	−0.00360 (0.01649)	0.00088 (0.01589)	0.00093 (0.01589)
Year fixed effects (FE)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Month FE	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Day Of the Week FE	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Observations	7,460,139	7,460,139	7,460,139	7,460,139	7,460,139	7,460,139
R^2	0.02423	0.20582	0.20582	0.02157	0.18961	0.18963

As a next step, we add the interaction between each investor's characteristics and the birthday dummy to the baseline regressions,[12] to shed light on the association between investor characteristics and trading behaviour around the birthday. Figure 2 reports the coefficients and the confidence intervals of the interaction variables for the number of trades (Panel A) and the value of the transactions (Panel B). Taken together, the incremental effects over these investor characteristics do not seem to be large, with the only exception of foreign investors whose marginal effect is roughly as large as the trading drop observed during the birthdate, which therefore becomes twice as large as the unconditional average. Although the marginal effect is not extremely sizeable, the trading drop for active traders is more pronounced and it is statistically significant both for trading intensity and value.

The previous results have shown robust evidence for a decrease in trading activity by investors on their birthday and on days immediately around it, and that this effect is more pronounced for active investors with recent frequent trades and foreign investors. However, given the intrinsically noncoincident motivations that drive stock purchases and sales, it is likewise interesting to understand whether the trading drop equally affects the trading direction (Barber & Odean, 2008). Figure 3 reports the results of the baseline regression for the

[12]For the sake of clarity, the Table does not explicitly show the coefficients of the five birthday dummies (from −2 to +2) but the results are unaltered.

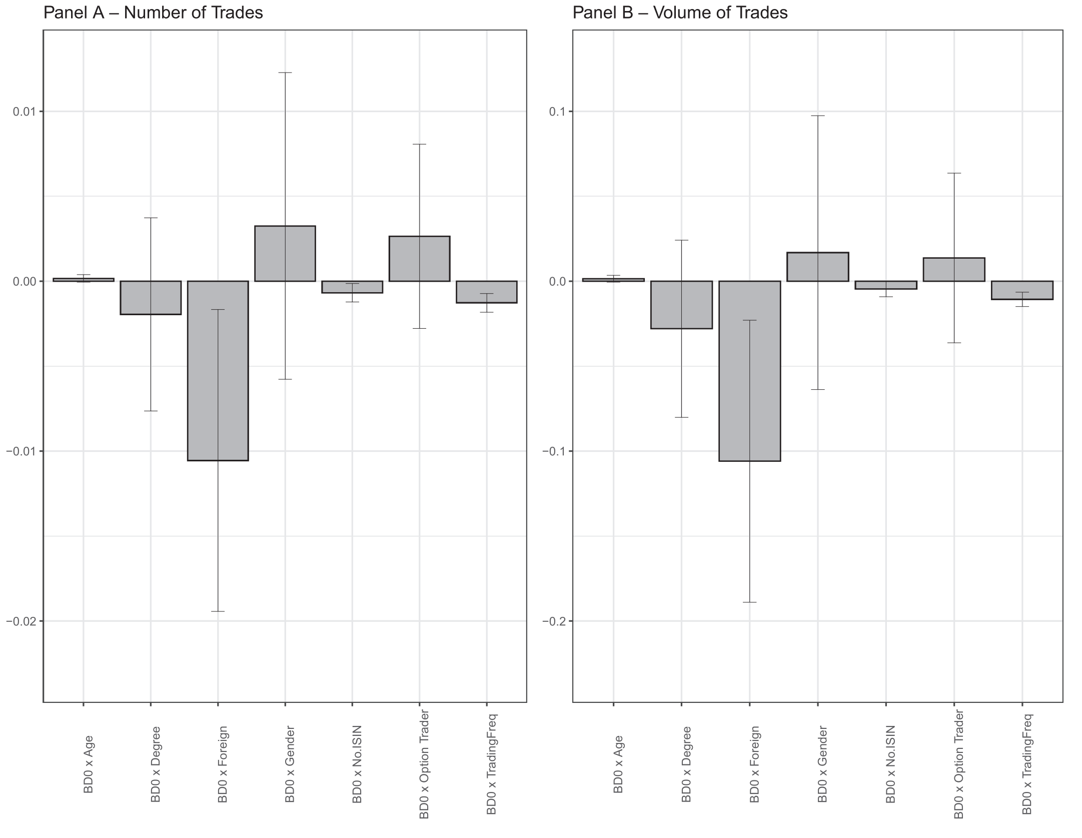

FIGURE 2 Investor characteristics and trading behaviour around the birthday. This figure shows coefficients from the regression of investor trading activity on investor attributes, the birthday dummies and the interaction between each investor's characteristic and the birthday dummy BD0. In Panel A, the dependent variable is log(1 + number of trades); in Panel B, the dependent variable is log(1 + Euro volume of trades). All regressions include Year, Month and Day Of the Week fixed effects. Investors chars include: Age is the age of the investor in years; Age.sqr is the age squared; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality, zero otherwise; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day *t*, to avoid any overlap with the birthdays' dummy variables; No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. The grey bars represent coefficient estimates of the interaction variables and the black lines are the 90% confidence intervals with standard errors clustered at the account level.

number of trades (Panel A) and values of the transactions (Panel B) split between buys and sales. Contrasting the two subsets, we note no substantial differences. The only notable exception is a slight anticipation of the drop for purchases that begin to be statistically significant the day before the birthday (as opposed to the sales where the effect is only marginally significant), both in terms of trading propensity (Panel A) and value of transactions (Panel B). However, on the date of the birthday both subsets show a similar effect, confirming that retail investors decrease their trading activity in the proximity of their birthday, regardless

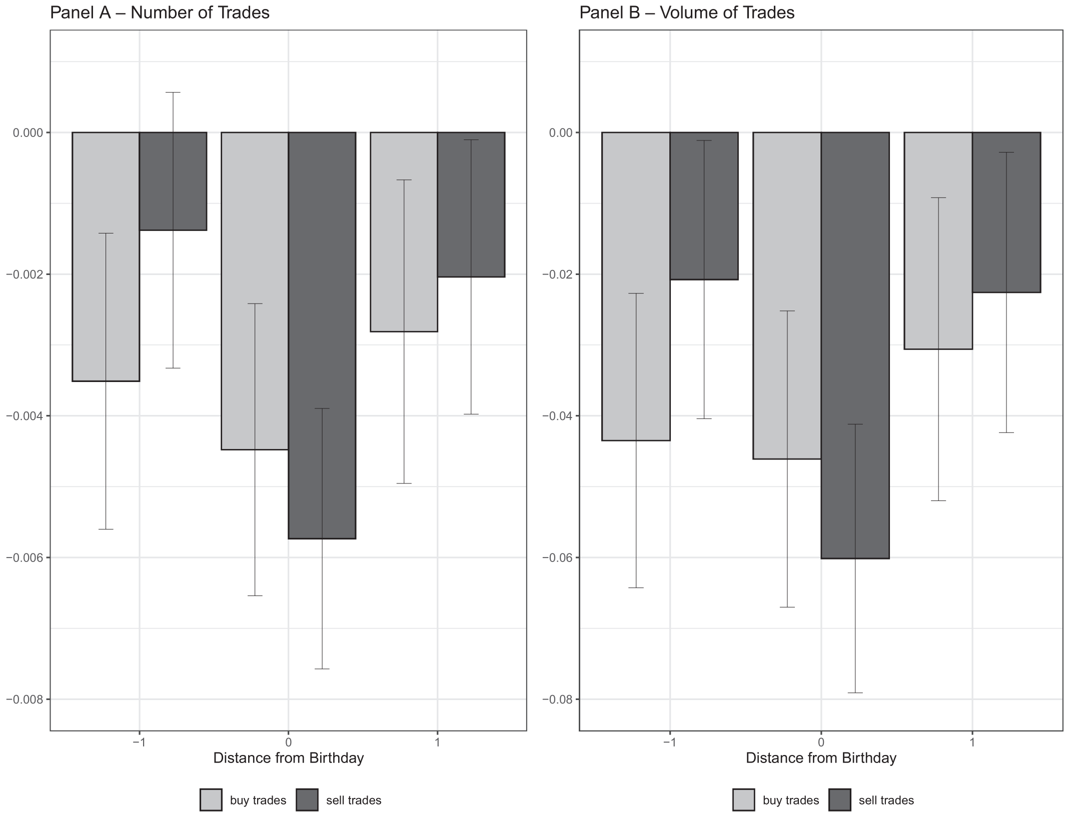

FIGURE 3 Purchases versus sales and trading behaviour around birthday. This figure shows coefficients from regression of investor trading activity on the birthday dummies, investor characteristics, splitting the data set between buy trades (light grey) and sell trades (dark grey). In Panel A the dependent variable is log(1 + number of buy (sell) trades); in Panel B the dependent variable is log(1 + Euro volume of buy (sell) trades). All regressions include Year, Month and Day Of the Week fixed effects. Investors chars include: Age is the age of the investor in years; Age.sqr is the age squared; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality, zero otherwise; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day *t*, to avoid any overlap with the birthdays' dummy variables; No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. The grey bars represent coefficient estimates of the BD(−1), BD0, and BD(+1) birthday dummies and the black lines are the 90% confidence intervals with standard errors clustered at the account level.

of the direction of the trade as we observe that purchases and sales are not statistically different from each other.[13]

Birthdays are undoubtedly relevant events in people's lives. The psychology literature shows that an adult's subjective age can be quite different from their chronological age and

[13]In an unreported analysis we also interact the investor characteristics with the birthday dummy for the two subsamples and, as in Figure 2, we find that the trading drop around the birthday is more pronounced for active traders both for purchases and for sales.

the former is typically a stronger predictor of self-esteem and able to affect the way individuals cognitively organize and process age-related information about themselves (Clements & Montepare, 1996). For instance, higher precautionary saving or safer investment choices that tend to be observed among older individuals, result more from the subjective than the chronological age. Montepare (1996) argues that adults' tendency to hold younger or older age identities reflects a process of anchoring and adjusting one's perceived age in relation to distal and proximal reference points, such as historic (weddings, anniversaries, and reunions), physical (heart attacks, birth of a child or passing of a spouse or parent), or normative (obtaining a driver's license, being married for the first time, and retiring from work). He documents that older men's and women's subjective ages are less youthful the nearer their birthdays. However, not all birthdays are equally important or represent turning points in people's lives.

Figure 4 shows the effect on trading activity in the event of a decade birthday. It is important to note that, since the regression includes the birthday dummies (from −1 to +1), along with the usual control variables and fixed effects, the decade birthday dummies are de facto interaction variables and as such they capture the differential trading activity with respect to any other "ordinary" birthday. The results show that decades are instead largely important, triggering a sizeable further reduction in the number of trades. When an investor turns 40 the drop in trading activity doubles (from 5.2% to 10.6% reduction with respect to the unconditional mean) with respect to a normal birthday; with regard to the 50th and 60th birthdays the drop is even higher.

In light of the previous evidence, a legitimate question arises: Why do birthdays and, in a greater measure, decade birthdays produce such a significant reduction in trading activity? It is generally a consolidated habit to celebrate the date of birth as it represents a distinct life-course milestone. Celebrations, which are usually more festive and lavish for the decade birthdays, drain time, energy and attention from ordinary activities. As a result, they may explain the lowered investor trading intensity. Celebrations with family and friends may also involve taking the day off from work and using the day for extraordinary recreational activities, such as day trips or short vacations that in turn force the investor away from stock markets. Unfortunately, we are unable to control for how each investor has planned her date of birth, to what extent she has been busy with nonroutine activities or the time she has spent at work or in front of the computer.[14] However, if investors are distracted by their birthdays because of being involved in celebrative happenings or leisure, we could expect that the reduction in trading should be stronger or more likely when the birthday falls near a weekend or on the eve of a holiday. It is plausible that a portion of individuals with birthdays occurring early in the week may postpone celebration or related leisure activities to the subsequent weekend, while those with birthdays on a Friday or on a single working day before a holiday are more likely to celebrate on the day and perhaps take a few days off. To test this hypothesis, in Table 5 the investor trading intensity is regressed against the interactions between the birthday and (a) each day of the week and (b) the holiday eve. We find, consistent with DellaVigna and Pollet (2009), that trading activity is lower on Fridays, but, more importantly, we also document a further trading reduction when the birthday occurs on the last of the weekdays. Specifically, when we look at the number of trades, the interaction between Friday and the birthday is significant at the 5%

[14]In our sample from an online broker all the trade orders are submitted via computers.

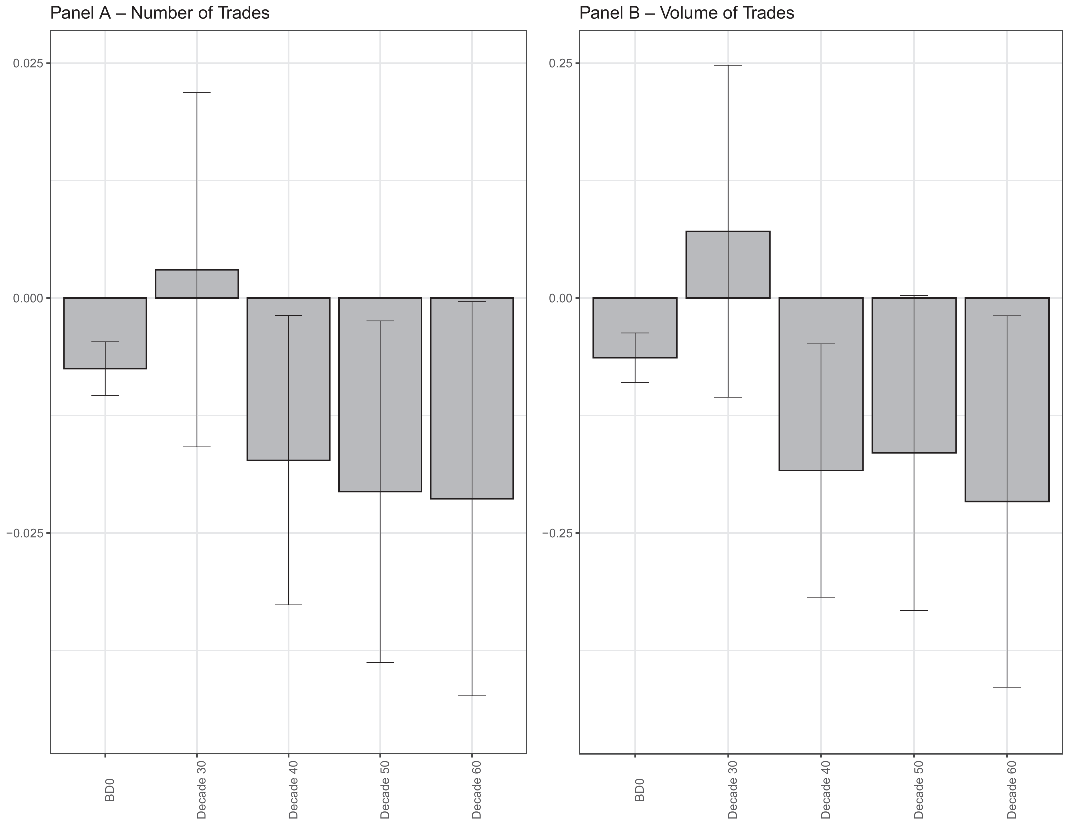

FIGURE 4 Decade effect and trading behaviour around birthday. This figure shows coefficients from regressions of investor trading activity on the birthday dummies, decade dummies and investor characteristics. In Panel A the dependent variable is log(1 + number of trades); in Panel B the dependent variable is log(1 + Euro trade volume). All regressions include Year, Month and Day Of the Week fixed effects. Decade 30 equals to 1 on the day the investor is turning 30 years old, zero otherwise; Decade 40 equals to 1 on the day the investor is turning 40 years old, zero otherwise; Decade 50 equals to 1 on the day the investor is turning 50 years old, zero otherwise; Decade 60 equals to 1 on the day the investor is turning 60 years old, zero otherwise. Investors chars include: Age is the age of the investor in years; Age.sqr is the age squared; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality, zero otherwise; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day *t*, to avoid any overlap with the birthdays' dummy variables; No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. The grey bars represent coefficient estimates of BD0 and the decade variables, and the black lines are the 90% confidence intervals with standard errors clustered at the account level.

threshold and its economic effect is important (7.5% incremental trading reduction). However, this effect weakens if we consider the Euro value of transactions as opposed to the number of trades.

A similar argument is valid for any day before a holiday. Analogously to the Friday-effect, the Table shows that Holiday Eve is strongly and negatively associated with trading activity. However, unlike the Friday, its interaction with the birthday does not turn out to be significant.

TABLE 5 Regression analysis—Birthday and busyness.

This table shows estimates from regressions of investor trading activity on investor attributes, the birthday dummies, the busyness indicators, the interactions between the birthday dummy BD.*t*0 and busyness indicators. As busyness indicators, Models (1) and (3) use the Day-of-the-Week dummies, while Models (2) and (4) use the HolidayEve variable. BD0, B(−1), B(+1) are a set of three dummy variables. Each dummy takes the value 1 on the birthday or on the day before or after investor *i*'s birthday, respectively, and 0 otherwise. Investor chars include: Age is the age of the investor in years; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day *t*, to avoid any overlap with the birthdays' dummy variables, No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. Standard errors are clustered at the account level and are reported in parentheses. ***, ** and * denote that estimates are statistically significant at the 1%, 5% and 10% levels, respectively.

	Dependent variable			
	log(1 + number of trades)		**log(1 + Euro volume trades)**	
	(1)	**(2)**	**(3)**	**(4)**
HolidayEve		−0.00433*** (0.00073)		−0.05203*** (0.00648)
Monday	0.00018 (0.00036)	0.00029 (0.00036)	0.00287 (0.00310)	0.00426 (0.00309)
Tuesday	−0.00075*** (0.00029)	−0.00077*** (0.00029)	−0.00554** (0.00260)	−0.00561** (0.00260)
Thursday	0.00139*** (0.00028)	0.00138*** (0.00028)	0.01454*** (0.00257)	0.01455*** (0.00256)
Friday	−0.00276*** (0.00034)	−0.00254*** (0.00034)	−0.02836*** (0.00309)	−0.02550*** (0.00308)
BD(−1)	−0.00443*** (0.00169)	−0.00443*** (0.00169)	−0.04658*** (0.01529)	−0.04665*** (0.01529)
BD0	−0.00337 (0.00378)	−0.00865*** (0.00168)	−0.04460 (0.03381)	−0.07506*** (0.01539)
BD(+1)	−0.00424** (0.00173)	−0.00424** (0.00173)	−0.04025*** (0.01560)	−0.04027*** (0.01560)
BD0 × Monday	−0.00420 (0.00537)		−0.01735 (0.04903)	
BD0 × Tuesday	−0.00650 (0.00523)		−0.02643 (0.04813)	
BD0 × Thursday	−0.00456 (0.00544)		−0.02257 (0.04906)	
BD0 × Friday	−0.01142** (0.00522)		−0.08100* (0.04803)	
BD0 × HolidayEve		−0.00434 (0.01217)		0.05173 (0.12986)
Investor chars	(Yes)	(Yes)	(Yes)	(Yes)

(Continues)

TABLE 5 (Continued)

	Dependent variable			
	log(1 + number of trades)		log(1 + Euro volume trades)	
	(1)	(2)	(3)	(4)
Year fixed effects (FE)	(Yes)	(Yes)	(Yes)	(Yes)
Month FE	(Yes)	(Yes)	(Yes)	(Yes)
Observations	7,460,139	7,460,139	7,460,139	7,460,139
R^2	0.20582	0.20583	0.18963	0.18963

3.2 | Birthday and attention-grabbing events

If birthdays are associated with a significant reduction in trading activity, it might be argued that this evidence still cannot support the theory that these events make the investor more inattentive than on any other day. The drop in the documented trading activity may indeed be limited to the noise or liquidity trades and investors may yet be equally responsive to information stimuli.

To test if investors behave in the same fashion in the context of high information diffusion, we adopt two empirical strategies to identify the companies for which investor attention should be at its peak. First, for every trading day we identify the companies that the press place in the spotlight through an extremely high news coverage. Second, we select the companies experiencing a surge in investor attention by looking at the abnormal trading volumes. In both these approaches, for any trading date we select the companies in the top 1% (of news release or abnormal turnover) and then check whether investors are less likely to trade those highly visible stocks on their birthdays. We believe these are perfectly complementary approaches. The news-based strategy identifies stocks that are effectively visible for any retail investor regardless of her sophistication or access to privileged information, whereas the abnormal volume approach selects companies for which an unevenly spread information leakage might have occurred. On the other hand, while the former approach tends to overweight large cap companies for which news coverage is higher, the latter strategy allows the consideration of any stock experiencing an unusual surge in trading volume and therefore well represents the small cap stocks in the sample.

As for the former approach, for each date t and stock j, which has relevance score 100 from RavenPack, we sort the stocks with respect to the number of news items released and take the top 1% of its distribution. These stocks are undoubtedly the most visible and those for which presumably investor attention should be at its maximum. After filtering out any stock not included in the top percentile, therefore focusing only on companies experiencing information shocks, we run the following regression:

$$Y_{i,t,j} = \gamma_1 \mathrm{BD}_{i,t} + \gamma_2 \mathrm{Controls}_{i,t} + f_i + \varepsilon_{i,t,j}, \tag{2}$$

where the dependent variable $Y_{i,t,j}$ is the log of (1 + the number of trades) for the investor i on day t and on the stock j, and is regressed against the birthday dummies ($\mathrm{BD}_{i,t}$), along with control variables, including individual time-varying characteristics ($\mathrm{Controls}_{i,t}$) and investor fixed effects (f_i). As for the other analysis, we also run the same models where we use the log(1 + Euro value of transactions) as the dependent variable instead of the log number of trades. The results, reported in Models (1) and (2) of Table 6, show that, while we do not observe a reduced trading activity on the day before and after the birthday, investors diminish the number of trades during their birthdays even for the stocks that

TABLE 6 Attention-grabbing events: News relevance and sentiment.

This table shows estimates from regressions of investor trading activity on investor attributes and the birthday dummies around attention-grabbing events. Models (1) and (2) use data on companies in the top 1% of the cross-sectional distribution of the number of news articles with relevance 100. Models (3) and (4) use data on companies with news relevance 100 and Event Sentiment Score (ESS) equal to 100. Models (5) and (6) use data on companies with relevance 100 and ESS equal to 0. BD0, BD(−1), BD(+1) are a set of three dummy variables. Each dummy takes the value 1 on the birthday or on the day before or after investor *i*'s birthday, respectively, and 0 otherwise. Investor chars include: Age is the age of the investor in years; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day *t*, to avoid any overlap with the birthdays' dummy variables, No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. Standard errors are clustered at the account level and are reported in parentheses. ***, ** and * denote that estimates are statistically significant at the 1%, 5% and 10% levels, respectively.

	Dependent variable					
	log(1 + number of trades)	**log(1 + Euro volume trades)**	**log(1 + number of trades)**	**log(1 + Euro volume trades)**	**log(1 + number of trades)**	**log(1 + Euro volume trades)**
	News	**News**	**Positive Sentiment**	**Positive Sentiment**	**Negative Sentiment**	**Negative Sentiment**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
BD(−1)	−0.000021	−0.000417	−0.00028***	−0.00323***	−0.00031**	−0.00333**
	(0.000134)	(0.001523)	(0.00005)	(0.00059)	(0.00014)	(0.00146)
BD0	−0.000338***	−0.004000***	−0.00029***	−0.00334***	−0.00045**	−0.00426***
	(0.000085)	(0.000982)	(0.00005)	(0.00061)	(0.00018)	(0.00158)
BD(+1)	−0.000007	−0.000251	−0.00029***	−0.00332***	−0.00041***	−0.00393***
	(0.000132)	(0.001518)	(0.00005)	(0.00059)	(0.00015)	(0.00144)
Constant	−0.000128	−0.002226	−0.00085**	−0.00925**	−0.00189**	−0.01543*
	(0.000175)	(0.002085)	(0.00040)	(0.00454)	(0.00096)	(0.00861)
Investor chars	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Observations	8,680,651	8,680,651	95,863	95,863	19,880	19,880
R^2	0.000219	0.000222	0.00033	0.00036	0.00071	0.00054

are in the press spotlight. This result corroborates the hypothesis that birthdays are distractive events able to drive investor attention away from the stock market even when stocks are exceedingly covered.

While the release of a piece of news is likely to attract investor attention, as documented in the financial literature (Peng & Xiong, 2006), the tone or the sentiment of the article is likewise extremely important and able to exert a price effect on the stock (Tetlock, 2007). To check if the birthday effect is still persistent on days when stocks are not only highly covered by the media but also when there is polarized news (i.e., with extremely positive or negative tones), we further break down the data set used in Models (1) and (2) of Table 6 and filter for news with Event Sentiment Score (ESS)[15] above 60 and below 30 to capture positive and negative news, respectively. While there is theoretical justification for hypothesizing that a strongly positive or negative piece of news may be more likely to be associated with investor attention and the resulting trading, we do not observe a significant difference between high (positive) or low (negative) sentiment scores and, more importantly, no effect on the documented drop in investor trading activity around their birthdays as shown in Models (3)–(6) of Table 6.[16]

As for the second empirical strategy, we compute abnormal volume, similarly to Barber and Odean (2008), as the ratio between turnover at time t and the average turnover over the previous 255 trading days. Next, as for the previous approach, we sort the stocks by excess turnover, select stocks in the top 1% and run the regressions specified in Equation (2). Models (1) and (2) of Table 7 confirm what was evidenced from the first empirical approach and show that the reduction of trading activity is persistent even in a setting of high information disclosure or investor attention.

3.3 | Trading performance around birthdays

Previous evidence has clearly shown that investors decrease their trading activity during their birthday and, to a lesser degree, in the previous and following day around it. The reduction in terms of number of trades and average value of transactions is mostly caused by investors refraining from accessing the market on this special day rather than reducing trading activity. This evidence is consistent with Peress and Schmidt (2020), who find that retail traders, who are particularly susceptible to behavioural biases, trade less when distracted by news. They also suggest that reduced trading activity might benefit investors who have a tendency to trade excessively. Following this line of thought, it might be plausible that the decline in market attention triggered by a birthday may likely affect the performance of the trades. In other words, conditional on trading, distracted investors may exert less effort into timing the market or attentively setting their limit orders. Consequently, they could transact at higher prices when buying and lower prices when selling compared with other trading days. Testing this hypothesis is challenging; the effect might be subtle since the most distracted investors may abstain from trading entirely on their birthdays. Thus, we can only observe market timing effects for those who are active, suggesting they might be less influenced by the

[15]The ESS is a score computed by RavenPack. It ranges from 0 to 100 and captures the news sentiment for a company. An ESS of 50 indicates neutral sentiment, values above 50 indicate positive sentiment, whereas values below 50 show negative sentiment.

[16]As a further robustness check, we also split the analysis using news sentiment by buy and sell trades. Research shows that investors are indeed more likely to buy than to sell when positive news, which grab their attention, occurs. Results of this additional analysis are available upon request and document both qualitatively and quantitatively similar outcomes, confirming previous evidence.

TABLE 7 Attention-grabbing events: Abnormal volume.

This table shows estimates from regressions of investor trading activity on investor attributes and the birthday dummies around attention-grabbing events. Models (1) and (2) use data on companies in the top 1% of the cross-sectional distribution of abnormal trading volume. BD0, BD(−1), BD(+1) is a set of three dummy variables. Each dummy takes the value 1 on the birthday or on the day before or after investor *i*'s birthday, respectively, and 0 otherwise. Investor chars include: Age is the age of the investor in years; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day *t*, to avoid any overlap with the birthdays' dummy variables, No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. Standard errors are clustered at the account level and are reported in parentheses. ***, ** and * denote that estimates are statistically significant at the 1%, 5% and 10% levels, respectively.

	Dependent variable	
	log(1 + number of trades) **Abnormal volume** **(1)**	**log(1 + Euro volume trades)** **Abnormal volume** **(2)**
BD(−1)	0.000007 (0.000013)	0.000067 (0.000142)
BD0	−0.000006*** (0.000001)	−0.000075*** (0.000007)
BD(+1)	−0.000006*** (0.000001)	−0.000075*** (0.000007)
Constant	−0.000008 (0.000006)	−0.000111 (0.000068)
Investor chars	(Yes)	(Yes)
Observations	18,671,598	18,671,598
R^2	0.000011	0.000011

attention-disrupting effect of birthdays. However, aware of this limitation, we attempt to test the effect of birthdays on performance by constructing two variables for purchases and sales, respectively, $BUY.G/L = (VWAP - P)/VWAP * 100$ and $SELL.G/L = (P - VWAP)/VWAP * 100$, where VWAP is the average weighted stock price for stock *j* on day *t* and *P* is the trade price on the same stock *j* and day *t*, for the investor *i*. We compute the average of these variables that capture how well (poor) the investor trades in a given stock relative to the other investors, for every investor *i* and day *t* and regress them on the birthday dummies, for the 11 days around the birthday, the investor characteristics and the fixed effects. Figure 5 shows the results for purchases (Panel A) and sales (Panel B). On birthdays we observe the largest drop in the relative performance over the 11-day time span, regardless of the direction of the trade, although the statistical significance does not pass the standard thresholds. Despite the lack of significance, we believe that a mild effect on performance, in particular for purchases, is probably present.[17]

[17]In an unreported analysis we also carry out a long-term performance analysis, but trades operated during birthdays do not produce returns statistically different from other trading days.

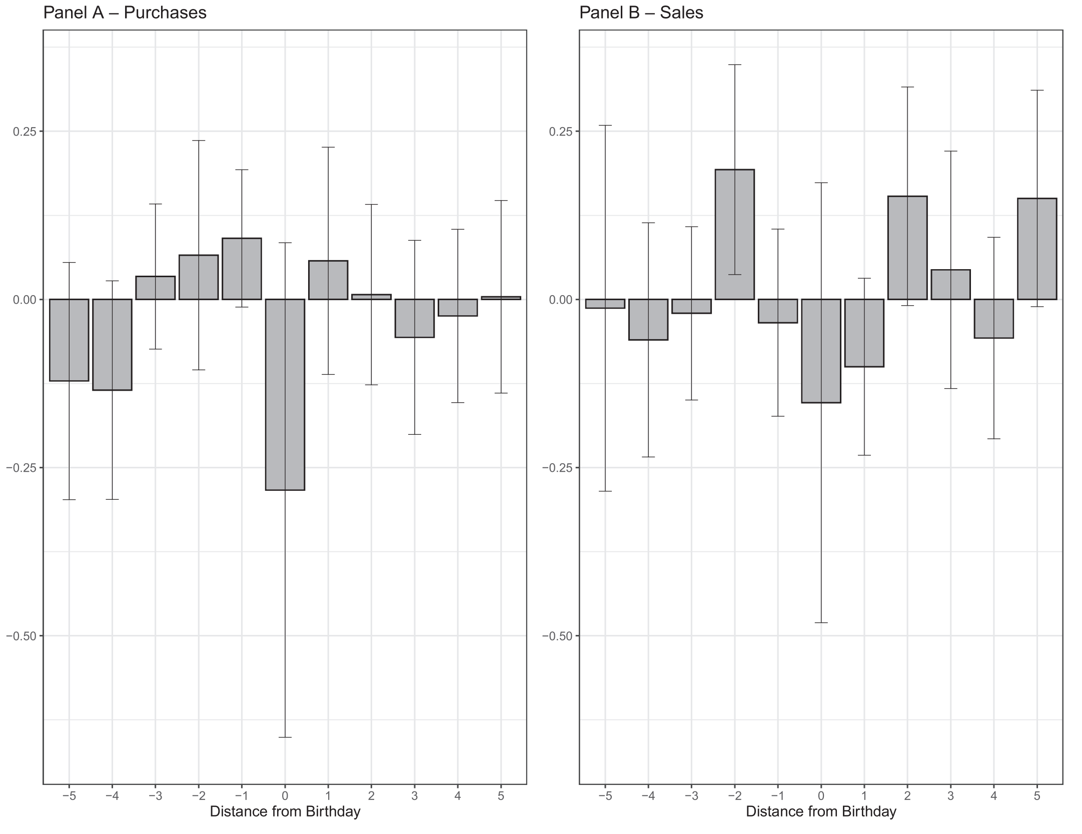

FIGURE 5 Trading performance and investor behaviour around birthday. This figure shows coefficients from regression of investor trading performance on investor attributes and the birthday dummies. The dependent variable in Panel A for buy trades is $BUY.G/L = (VWAP - P)/VWAP * 100$, while the dependent variable in Panel B for sell trades is $SELL.G/L = (P - VWAP)/VWAP * 100$, where P is the transaction price and VWAP is the Volume Weighted Average Price. The grey bars represent coefficient estimates of the BD(−5), BD(−4), BD(−3), BD(−2), BD(−1), BD0, BD(+1), BD(+2), BD(+3), BD(+4), BD (+5) birthday dummies and the black lines are the 90% confidence intervals with standard errors clustered at the account level.

3.4 | Birthdays and investor mood

The stress or the euphoria brought about by the arrival of the birth anniversary may cause an alteration of the investor mood and in turn the propensity to trade stocks. In line with this argument, Fabozzi et al. (1994) find that the trading volume is higher on holidays when the exchange is open. While they put forward several possible motivations (e.g., closing trading positions before the holiday), they also suggest the presence of a generally favourable mood around holidays. The psychology and the financial literature have documented an association between weather and mood, and between mood and investor behaviour, respectively. The former has shown that sunny weather is associated with upbeat mood and the latter have documented that weather can exert an influence on investor behaviour, trading and, in turn, on

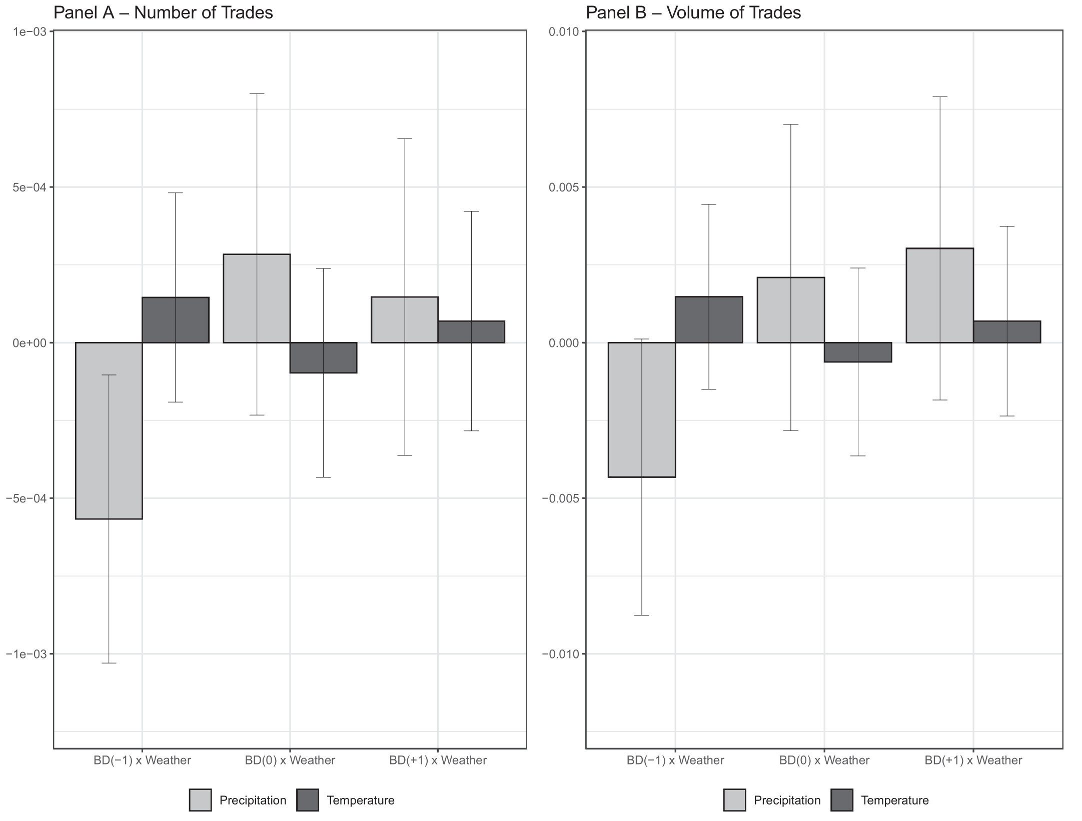

FIGURE 6 Weather conditions and investor behaviour around birthday. This figure shows coefficients from regression of investor trading activity on the birthday dummies, investor characteristics, weather variables, that is, precipitation and temperature, and the interaction between precipitation (light grey) and temperature (dark grey) with the birthday dummies. In Panel A the dependent variable is log(1 + number of trades); in Panel B the dependent variable is log(1 + Euro volume of trades). All regressions include Year, Month and Day Of the Week fixed effects. Investors chars include: Age is the age of the investor in years; Age.sqr is the age squared; Gender is a dummy equal to 1 for female investors, zero otherwise; Degree is a dummy equal to 1 for investors with an academic degree, zero otherwise; Foreign is a dummy equal to 1 for investors that do not have Austrian nationality, zero otherwise; TradingFreq is the percentage of trading days in which the investor has placed at least one order, computed over a 21-trading-days (i.e., a calendar month) window, ending 10 days before day t, to avoid any overlap with the birthdays' dummy variables; No. ISIN is the number of stock ISINs held by the investor; Option Trader is a dummy equal to 1 for investors that traded options at least once, zero otherwise. The grey bars represent coefficient estimates of the BD(−1) × Weather, BD0 × Weather, and BD(+1) × Weather interaction coefficients and the black lines are the 90% confidence intervals with standard errors clustered at the account level.

stock returns.[18] In addition to the psychological effects, the weather is also likely to influence the extent of the birthday celebration. On the one hand, if rainy (sunny) days may induce depression (cheerfulness) and lower (higher) trading activity, on the other hand they also result

[18]Hirshleifer and Shumway (2003) show that sunshine is strongly significantly correlated with stock returns. Bassi et al. (2013) present experimental evidence that good weather promotes risk-taking behaviour and Loughran and Schultz (2004) document that cloudiness and hard rain negatively impact localized trading in the affected areas.

in less (more) pleasing day trips, parties and all sorts of celebrative initiatives that likely drive attention away from stock markets. Although we do not attempt ruling out the effect of mood, nor empirically disentangling it from that caused by investor inattention, to account for the induced-effect of weather, we regress trading activity against two different indicators (temperatures and the amount of precipitations) and their interactions with the birthday dummy. However, Figure 6 shows that the trading reduction during birthdays is not significantly associated with weather conditions.

3.5 | Robustness checks

We perform several additional analyses as robustness checks. First, we investigate if the trading drop is only manifested through a general reduction of volumes (as for the case of the number of trades or the Euro volumes) or instead through a lower propensity to trade. In other words, if our previous analyses show that investors trade less (lower amounts) around their birthday, we aim at investigating if they trade at all during these celebrative events. Table 8 uses as the dependent variable a dummy that takes the value of one if the investor *i* trades on day *t* and zero otherwise and we use a logit as opposed to a pooled OLS approach to account for the dichotomous variable. Results evidence that not only trading volumes drop in the event of birthdays, but also the propensity to trade is drastically reduced as coefficients of birthday dummies remain strongly statistically significant.

TABLE 8 Robustness check—Investor fixed effects and logit regression.

This table shows the estimates of a linear logit model of trading. BD0, BD(−1), BD(+1) are a set of three dummy variables. Each dummy takes the value 1 on the birthday or on the day before or after investor *i*'s birthday, respectively, and 0 otherwise. Control variables include time-varying investor-specific characteristics: Age is the age of the investor in years; No. ISIN is the number of stock ISINs held by the investor. The model controls for investor, year–month and day-of-the-week fixed effects. ***, ** and * denote that estimates are statistically significant at the 1%, 5% and 10% levels, respectively.

	Dependent variable **Probit regression: 1 if trading, others 0** **(1)**
BD(−1)	−0.047045*** (0.013457)
BD0	−0.057606*** (0.013526)
BD(+1)	−0.033997* (0.027100)
Controls	(Yes)
Investor FE	(Yes)
Year–month FE	(Yes)
Day-of-the-week FE	(Yes)
Observations	7,460,310

TABLE 9 Placebo birthdate: News relevance and sentiment.

This table shows estimates from regressions of investor trading activity on placebo birthday dummies around attention-grabbing events and control variables. The placebo birthday is defined by shifting for 8 days the true investor birthday. Models (1) and (2) use data on companies in the top 1% of the cross-sectional distribution of the number of news articles with relevance 100. Models (3)–(6) further break down the data set selecting companies with Event Sentiment Score (ESS) larger than 60, Models (3) and (4), and lower than 40, Models (5) and (6). BD0, BD(−1), BD(+1) are a set of three dummy variables. Each dummy takes the value 1 on the birthday or on the day before or after investor *i*'s birthday, respectively, and 0 otherwise. Control variables include time-varying investor-specific characteristics: Age is the age of the investor in years; No. ISIN is the number of stock ISINs held by the investor. All models control for investor fixed effects. Standard errors are clustered at the account level and are reported in parentheses. ***, ** and * denote that estimates are statistically significant at the 1%, 5% and 10% levels, respectively.

	Dependent variable					
	log(1 + number of trades)	**log(1 + Euro volume trades)**	**log(1 + number of trades)**	**log(1 + Euro volume trades)**	**log(1 + number of trades)**	**log(1 + Euro volume trades)**
	News	**News**	**Positive Sentiment**	**Positive Sentiment**	**Negative Sentiment**	**Negative Sentiment**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
BD(−1)	0.000012	0.000426	0.00010	0.00143	−0.00017	−0.00185
	(0.000138)	(0.001658)	(0.00021)	(0.00252)	(0.00032)	(0.00389)
BD0	0.000101	0.001309	0.00002	0.00065	0.00057	0.00673
	(0.000143)	(0.001693)	(0.00019)	(0.00235)	(0.00049)	(0.00586)
BD(+1)	−0.000001	0.000311	0.00008	0.00121	−0.00013	−0.00150
	(0.000144)	(0.001758)	(0.00024)	(0.00290)	(0.00031)	(0.00371)
Controls	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Investor FE	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Observations	8,680,651	8,680,651	4,185,330	4,185,330	1,167,001	1,167,001
R^2	0.004060	0.004127	0.00406	0.00412	0.00424	0.00439

TABLE 10 Placebo birthdate: Abnormal volume.

This table shows estimates from regressions of investor trading activity on placebo birthday dummies around attention-grabbing events. The placebo birthday is defined by shifting for 8 days the true investor birthday. Models (1) and (2) use data on companies in the top 1% of the cross-sectional distribution of abnormal trading volume. BD0, BD (−1), BD(+1) is a set of three dummy variables. Each dummy takes the value 1 on the birthday or on the day before or after investor *i*'s birthday, respectively, and 0 otherwise. All regressions control for time-varying investor-specific characteristics and include investor fixed effects. Standard errors are clustered at the account level and are reported in parentheses. ***, ** and * denote that estimates are statistically significant at the 1%, 5% and 10% levels, respectively.

	Dependent variable	
	log(1 + number of trades) Abnormal Volume (1)	**log(1 + Euro volume trades) Abnormal Volume (2)**
BD(−1)	0.000021 (0.000019)	0.000253 (0.000229)
BD0	0.000034 (0.000023)	0.000374 (0.000261)
BD(+1)	0.000021 (0.000019)	0.000208 (0.000199)
Controls	(Yes)	(Yes)
Investor FE	(Yes)	(Yes)
Observations	18,671,598	18,671,598
R^2	0.000065	0.000076

Second, to corroborate our finding that investors on their birthday are inattentive to the information released, we run a placebo test by shifting forward the true investor birthdate by 8 days and then rerun regressions specified in Equation (2). Results are reported in Tables 9 and 10 and show no effects. These tests further confirm that the effect is specific to this personal event and does not manifest on a placebo date. Third, we winsorize the dependent variables at the 1st and 99th percentiles and rerun all the main analyses. Results, which are available in the Supporting Information Appendix, remain both qualitatively and quantitatively unchanged, alleviating concerns that our main effect might be due to outliers.

4 | CONCLUSIONS

Leveraging on a large proprietary data set of retail stock investors from an online broker we investigate the trading behaviour around birthdays. These investors significantly reduce the propensity to trade common stocks in the 3 days around the date of birth with the largest effect on the exact date. The trading reduction is not only largely significant but also economically meaningful as we document a 6% (7.6%) decrease in the number of trades (Euro value of transactions). While we do not observe that this reduction is correlated with investor characteristics, such as age, gender or level of education, we do find that this effect is more pronounced for foreign investors and for more active traders. We argue that the lower propensity to trade during birthdays is mainly due to investor inattention to the stock market, likely driven by celebrative initiatives that usually come along with these personal events. We corroborate this assumption with two further pieces of evidence: first, we find that in the event of decade birthdays that represent milestones in people's lives and are generally associated with more extensive celebrations, the trading reduction is larger and progressively higher when investors turn 40, 50 and 60 years old; second, we find that when a birthday falls on a Friday, when there is the highest possibility that people make multi-day plans such as trips out of town, the trading activity further decreases.

In light of the previous results, we argue that birthdays, similarly to nonrecurring personal occurrences such as marriages and divorces (Lu et al., 2016) or overcrowding news releases (Hirshleifer et al., 2009) and sensational news exogenous to the stock market (Peress, 2014), are distractive events able to drive away investor attention from the stock market. To show that the documented reduction in trading around birthdays likewise takes place on days where stocks should be at the highest level of investor attention, we adopt two alternative empirical strategies: first, for every trading day, we identify the companies that the press covers the most; second, we select the companies undergoing a surge in abnormal trading volumes. In both of these approaches, for any trading date, we select the companies in the top 1% and then check whether investors are less likely to trade those highly visible stocks on their birthdays. Regardless of the approach, we still find a highly significant drop in the propensity to trade on the date of birth. We also test if any outcome on trading performance is observable due to the attention-grabbing effect of birthdays, although a test conditional to trading necessarily selects the subsample of investors who chose to trade – as they are presumably less distracted by this personal event – and in turn dilutes the expected magnitude of the effect. We indeed find that investors sell at lower prices and, even more, purchase at higher prices on their birthdays, even though the statistical significance does not pass standard thresholds.

These results contribute to the literature on investor inattention that so far has been mainly focused on events exogenous to the investor, while the few studies that focus on personal occurrences have been only limited to extraordinary and rare events, such as marriages and divorces. In this paper we show that recurring personal events are likewise capable of driving investor attention away from the stock market. Our study shows that personal characteristics, such as the influence of birthdays on decision-making, play an important role in influencing trading behaviour, thereby determining cross-sectional differences in portfolio choices and performance outcomes among investors.

DATA AVAILABILITY STATEMENT

The data set that supports the findings is proprietary.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Bajo, E., Randl, O., & Simion, G. (2023). I will trade, just not today: Individual investor trading activity around birthdays. *European Financial Management*, 1–31. https://doi.org/10.1111/eufm.12472