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Measuring speculation beyond day trading and bets on lottery-like stocks

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ABSTRACT

We offer a new metric of stock market speculative intensity: the proportion of share purchases that are swiftly reversed, i.e., sold within a *short* time window. An example of this metric is a 14-day trading horizon. We use it to identify retail traders who aim for quick profits. Based on a vast set of trading accounts in Belgium (2003–2012), we observe that the scale of quick round-trip trading is far above what would be seen with a single focus on day trading. Simply put, amateur speculation is not limited to day traders. Measuring speculative trading through quick round-trip transactions delivers a variety of insights. Amateur speculators are more likely to be male, younger, with lower sophistication and lower levels of wealth. They hold concentrated portfolios and focus their efforts on only a few stocks at a time. They earn low returns, and they are prone to the disposition effect. They are liable to bet on lottery-like stocks, and their passion for trading is persistent.

1. Introduction

What is the true difference between "investing" and "speculation"? Investments always have a speculative element since all people desire the value of their assets to rise rapidly over time. It is often said, however, that "true investors" collect dividends and wait patiently for long-term capital appreciation. In their literature review of the relationship between gambling, investing, and speculation, Arthur et al. (2016) argue that investment is distinct from gambling, but speculation and gambling have conceptual overlap. According to these authors, there is widespread consensus on defining investing as "purchasing or allocating money into an asset with the expectation of long-term capital appreciation or profits deriving from that asset." Regarding speculation, there is less agreement in the literature. Compared to investing, speculation ordinarily refers to "financial market activities that tend to be shorter term, higher risk, with higher and lower gains and losses, and with a primary focus on making a monetary profit from price movement without regard for the fundamental value of the asset."

Building on the above definitions, one of the most relevant distinctions between investment and speculation is the duration of the holding period, also labeled the trading horizon. This paper adds to the literature by defining a new metric of speculative intensity based on *quick round-trip trades* and we use it with a twofold purpose. First, we provide innovative empirical evidence about the large magnitude of short-term speculative trading among retail investors. Next, we offer a portrait of the individual amateur stock speculator, i.e., the "little guy."[1] Specifically, we define the purchase and sale of a given stock by one-and-the-same retail trader within a short time window as "a quick round-trip trade." The main windows that we consider are 24 h, 3, 7 and 14 calendar days. Note that these window lengths are chosen as representative examples. Nothing prevents one from studying longer time frames since our methods are fully flexible and can be adapted to any time horizon of interest.

Measuring speculative trading through quick round-trip trades has advantages. The approach is less limiting than a focus on day trading –a rather extreme version of short-term trading. There is no doubt that day traders are speculators (Barber et al., 2014). However, the purchase and sale of the same stock by the same person over a few calendar days is also likely to be prompted by speculative motives. Hence, considering short-term windows beyond one day allows a more penetrating examination.

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[1] There is a wide assortment of products (workshops, software, manuals) that are marketed as explicit alternatives to the offerings of investment funds, banks, and insurance companies. Their core element is not money management or financial advice but instruction and facilitation. Low-cost easy-access online trading platforms fall within this category. For an historical perspective on the evolution of the self-reliant amateur speculator in stocks, see Wansleben (2013). Wycoff (1910) is a standard reference work. Amateur speculation extends beyond shares to include land, real estate and commodities. Smidt (1965) offers an early study of amateur speculation in commodity futures.

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Day traders are usually regarded as a fringe phenomenon, a "curiosity" that does not define or decisively influence market behavior. However, what we find as the round-trip trading window is gradually stretched out from 1 to 14 days, suggests otherwise. As the trading window is drawn-out, we capture an enormous fraction of all trading executed by retail traders. Note again the inclusiveness of our new measure. It can be easily calibrated to different time lengths. This flexibility has value and prevents an analysis that is too narrow. For example, it is already well-known that retail day traders (e.g., Linnainmaa, 2005) are less active than institutional day traders (e.g., Garvey & Murphy, 2005).[2]

Prior literature relates speculation in the stock market to excessive trading but also to sensation-seeking and gambling (Grinblatt & Keloharju, 2009). This second association highlights that trading has an entertainment aspect (Barber & Odean, 2013). The detection of stocks with lottery-like characteristics is regularly used as a technique to study stock market gambling (e.g., Bali et al., 2011; Frino et al., 2019; Kumar, 2009). Lottery-like stocks are often defined as exhibiting high idiosyncratic volatility, high idiosyncratic skewness, and a low price, all at the same time. Needless to say, the identification of such stocks is problematic since historical price data are called for. By contrast, measuring quick round-trip trades only requires transaction data. Furthermore, quick round-trip trades can detect speculative trading *on any stock* or *asset*, i.e., including those without lottery-like features, and not commonly regarded as speculative assets. Put differently, measuring speculative intensity with quick round-trip trades is easy, regardless of the features of the asset.

Using our new metric to gain insights into the significance of amateur speculators among retail traders, our work follows the spirit of Andrew Lo's (2004) adaptive markets hypothesis which "is based on an evolutionary approach" (p.15) and which invites researchers to study "distinct groups of market participants, each behaving in a common manner" (p. 23). According to this adaptative markets hypothesis, long-run survival "is the only objective that matters" (p. 25). At times, irrational behavior is so pervasive as to overwhelm the forces of rational arbitrage. Still, by and large, there are enough chances for profit in adaptive markets to compensate agents for the costs of information gathering, study and trading, but "investment strategies undergo cycles of profitability" and "unsuccessful [noise] traders are eventually eliminated" (p. 24). In this view, individuals make choices based on past experience and their best guess as to what might be optimal, and they learn by receiving positive or negative reinforcement. By doing so, individuals might develop maladaptive heuristics (Lo, 2004). Our analysis below does not test for either the use or profitability of specific trading heuristics.[3] Yet, consistent with the adaptive markets hypothesis, we accept that Darwinian selection is at work in determining the profiles of effective and ineffective speculators. Although profit opportunities fade as they are being made use of, new profit opportunities are constantly being created as certain investors exit the market, as others start trading, and as economic and market conditions change.

To present our new metric of speculative intensity and sketch the portrait of amateur speculators, we rely on the trading accounts of a large Belgian online brokerage house. The data span the period between January 2003 and March 2012 and include socio-demographic indicators as well as surveys of individual traders. First, we find the extent of short-term stock trading and the overlap with lottery-like stocks. Second, we present a profile of the typical short-term trader. In particular, we examine the behavior of these traders by analyzing their stock holdings, their disposition effect, and their performance. We also investigate whether there is persistence in short-term trading.

Our main results are as follows. Short-term speculative trading is far from an aberration. Whereas 13.5 % of aggregate traded value is reversed within 24 h, this proportion rises to an extraordinary 42.1 % when one considers round-trip trades reversed within 14 calendar days. If we place individuals into deciles by the fraction of short-term trading that is reversed within 14 days, the statistics for the top decile are truly impressive: quick round-trip trades account for 71.4 % (78.2 %) of all their trades (monetary trading volume).

It is of utmost importance to recognize that there is only a limited overlap between the top decile of 14-day round-trip traders and the top decile of day traders. When expanding the window from 1 to 14 days, we additionally cover around 30 % of traders who completed many 14-day round trip trades but cannot be identified as day traders. Hence, focusing only on day trading misses out on much retail speculative trading in stocks. Consonant with a link between speculation and gambling, we find that short-term traders typically show a higher average ratio (both in number of stocks and in market value) of lottery-like stocks in end-of-month portfolios than their counterparts.

The archetypal retail speculator is younger than average, has a lower level of education, and is more likely to be male. These results are in line with past research. Also, this short-term trader declares a slightly higher than average return objective while he/she reports lower financial literacy, financial experience, horizon, income, and invested wealth. Lower sophistication and lower wealth levels again tie in with prior findings. All the evidence points in one direction: retail speculators are described by heavy trading activity, a small concentrated portfolio, and intense trading of a few stocks.

Our findings further reveal unambiguously lower performance for short-term traders. The poor risk-adjusted performance is chiefly explained by a heavy burden of transaction costs. Among all traders, speculators realize the worst risk-adjusted performance. With regard to the inclination to sell past winners early and to delay the realization of paper losses, we find mixed results. Although cross-sectional regression models confirm a positive and significant relationship between that tendency and the proportion of quick round-trip trades, hazard models do not show that short-term traders display a stronger disposition effect than their counterparts. Finally, as we track different cohorts of traders over time, we find steadfastness and persistence, up to two years later, in 14-day round-trip trading.

The remainder of this paper is organized as follows. Section II presents the data and the sample. Section III studies the prevalence of short-term trading. Section IV examines the profile and behavior of the typical amateur speculator. Section V concludes.

2. Data and sample

Our primary data are retail trading accounts from a large Belgian online brokerage house. These data cover 111 months between January 2003 and March 2012. We have detailed information about each trade such as the financial instrument involved, the timestamp, the trade price, the trade direction (buy or sell), the executed quantity, and explicit transaction costs.[4] For the purpose of this study, we concentrate on trades (i.e., executed orders) on common stock investments. Using

[2] Our approach would allow any short-term trading windows shorter than one day to measure speculative intensity among institutional investors at the intraday level.

[3] Unlike Cookson and Niessner (2020), we do not have access to information on the retail investors' investment approaches (e.g., technical, fundamental, momentum, value, growth). Nothing in the data at hand allows us to know whether retail investors use specific trading rules, tools or strategies. We cannot rule out that it might be the case for some of them, but we don't have any evidence.

[4] These costs cover brokerage commissions, market fees (including clearing and settlement costs), and taxes (like the Belgian tax on stock exchange operations for transactions when they are entered into or executed in Belgium). We have the bundled amount paid for each trade, but not the details of each component. These transaction costs are usually flagged as explicit because they are paid by the investor in addition to (in reduction of) the price at which his/her buy (sell) order is executed on the market.

Table 1
How common are quick round-trip trades?

	% of all *trades* reversed within …					% of all *trading value* reversed within …				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	24 h	3 days	7 days	14 days	# trades	24 h	3 days	7 days	14 days	value
Panel A: All subjects										
	7.58	13.38	21.66	30.22	2123	13.50	21.69	32.27	42.06	17,185,160
Panel B: Deciles based on 14-day quick round-trip trades										
Deciles 1–5	0.39	0.98	2.21	4.28	654	0.38	0.91	1.95	3.81	3,374,795
Decile 6	1.84	4.12	8.43	15.02	218	1.56	3.54	7.51	13.47	1,537,681
Decile 7	2.40	5.64	11.81	20.52	227	2.59	5.90	11.82	20.77	1,410,464
Decile 8	4.17	9.49	18.60	30.20	264	4.54	10.03	19.51	31.10	1,755,267
Decile 9	8.20	16.99	30.43	44.90	330	9.08	18.52	32.27	47.10	3,426,972
Decile 10	25.82	40.69	58.42	71.38	429	32.65	48.39	66.01	78.15	5,679,981

This table reports statistics for the full sample and for deciles of traders when they are sorted into ten groups according to the fraction of trading volume (in €) that is reversed within 14 calendar days. This percentage of quick round-trip trades is determined over the full trading history of each individual. The lowest five deciles are combined into a single group (Deciles 1–5). Columns (1) through (4) list the fractions, multiplied by 100, of all aggregate buy and sell transactions that investors in a given decile undo within 24 h, 3, 7 or 14 days. We divide the number of quick round-trip trades by the total number of trades in the decile. Likewise, columns (6) through (9) show the percentage of aggregate trading value that quick round-trip trades represent. Column (5) indicates the total number of trades, in thousands, executed by individuals in a given decile; column (10) shows the total value, in k€, of the matching trading volume.

the stock trading data, we build end-of-month portfolios for each investor. We supplement the trading records with historical price data supplied by Bloomberg and EUROFIDAI[5] to find monthly portfolio market values.

Combining end-of-month portfolio market values with the corresponding aggregate cash-flows, we calculate monthly gross and net returns (i.e., after transaction costs) for each individual portfolio. Specifically, we calculate portfolio returns using an approximation of the so-called Modified Dietz Method which aims to deliver a return close to the money-weighted rate of return (Shestopaloff & Shestopaloff, 2007). It is assumed that all purchases (sales) executed in a given month take place on the first (last) day of the month. Mathematically, $R_t = \frac{EMV_t - EMV_{t-1} - P_t + S_t}{EMV_{t-1} + P_t}$, where R_t represents the stock portfolio gross return for month *t*, EMV_t is the end-of-month portfolio value at month *t*, and P_t and S_t are the aggregate monetary value of all purchases and sales executed during month *t*. To calculate net returns, we subtract from the numerator the total amount paid as transaction costs during month *t*.

In addition to trading data, we have matching socio-demographic indicators and survey-based data. Socio-demographic indicators include age, gender, and the level of education. The survey data are psychological and financial descriptors, collected by the brokerage house within the context of the MiFID regulation that came into effect in European Union member states in late 2007.[6] In a nutshell, MiFID is at the core of the *Know Your Customer* process for investment firms and requires them to gather specific information about their retail clients' needs and preferences. In practice, firms submit questionnaires to their clients (so-called "MiFID tests" or "MiFID questionnaires") in order to assess their level of financial knowledge and experience, investment objectives and financial situation.

Aiming to remove dormant accounts as well as short-lived traders with very few stock transactions, we build a sample based on three filters. First, we include individuals who over the full 2003–2012 period have a trading history of one year or more, either because they hold a stock portfolio for a minimum of 12 months, or because the stretch of time that passes between their first and last trades exceeds 12 months. Second, we select traders who execute at least twenty stock trades. Lastly, we only take persons with a complete set of socio-demographic and survey data. We end up with 14,037 traders.[7]

Our sample is overwhelmingly male (91 %). The average investor is 46.8 years old in 2008. Education is coded at three levels: (i) no school qualification; (ii) secondary/high school qualification; and (iii) university degree or equivalent. Most individuals (74 %) belong in the third category. Regarding the survey data, we specifically focus on answers to questions related to the return that investors hope to earn (target return, ***TARGET***), their risk tolerance (***RISKTOL***), financial literacy (***FINLIT***), financial experience (***FINEXP***), investment horizon (***HORIZON***), household income (***INCOME***), and amount of wealth invested in financial assets (***WEALTH***). All the survey items are subjective and are recorded on the trading platform by investors themselves, without intermediaries.[8] Descriptive statistics are presented later in Section IV.

3. The perplexing level of short-term trading

3.1. Quick round-trip trades

Table 1 (panel A) shows quick round-trip trades as a proportion of all retail trading but varying with the time windows allowed for round-trips. It is abundantly clear that short-term trading is not an

[5] The data was obtained via EUROFIDAI Equipex PLADIFES ANR-21-ESRE-0036.

[6] MiFID stands for the *Markets in Financial Instruments Directive*. MiFID I (2004/39/EC) was the initial version of this directive while a revision, implemented in January 2018, is known as MiFID II (2014/65/UE). See the European Commission website (https://ec.europa.eu/info/law/markets-financial-instruments-mifid-ii-directive-2014-65-eu_en).

[7] How relevant are retail investors who trade on their own behalf to overall trading volume in Belgium? Unfortunately, data limitations do not allow us to say. Unlike market authorities in the U.S. or China, the Financial Markets and Services Authority (FSMA, i.e., the Belgian equivalent of the SEC) does not compute or publish, on a regular basis, aggregate statistics about the magnitude of direct retail trading in Belgium. Building on FSMA material, we know that more than half a million Belgians (out of a population of about 11 million individuals) traded shares over the recent period 2018–2021, and that this was an increase over previous years. But, because of the lack of reporting by foreign brokers, the estimate is low. No estimates of the number of retail traders in Belgium, or their aggregate traded value, are available for the 2003–2012 period considered by our paper.

[8] Alas, the records do not list either the initial survey date or the time of later updates.

Table 2
Overlaps between short-term traders and day traders.

	H1	H3	H7	H14	H30	H90
Panel A: Numbers of traders						
H1	1404					
H3	1175	1404				
H7	1074	1211	1404			
H14	989	1117	1225	1404		
H30	922	1034	1112	1203	1404	
H90	800	886	943	1018	1113	1404
Panel B: Percentages of traders						
H1	100					
H3	84	100				
H7	76	87	100			
H14	70	80	87	100		
H30	66	74	79	86	100	
H90	57	63	67	73	79	100

This table shows how the number of short-term traders varies in a given top decile when considering different time windows to determine quick round trip trades. Six windows of time are defined: one day (H1), three days (H3), seven days (H7), fourteen days (H14), thirty days (H30) and ninety days (H90). Panel A provides results in number of investors while Panel B reports them in percentages. By construction, the number of traders in each top decile (see the diagonal in Panel A) is equal to 1404, that is, 10 % of the sample of 14,037 individuals.

aberration: 13.5 % of aggregate trading value is executed within 24 h.[9] This fraction rises to 42.1 % if we consider trades reversed within 14 days. The cumulative value of 14-day round-trip trades adds up to more than €7.2 billion. The ratios of quick round-trip trades are somewhat less extreme when based on the number of trades rather than trading value. Round-trips within 24 h or 14 days are, respectively, 7.6 % and 30.2 % of the aggregate number of trades.

Due to manifest heterogeneity in trading activity, we classify investors into deciles based on the proportion of short-term trading. Table 1 (panel B) reports the percentages of aggregate 14-day quick round-trip trades for each decile. As said before, a window of 14 days is chosen as a representative example, but our methods may be adapted to any other short time period. Since the lowest five deciles contain investors who complete few quick round-trip trades, we combine them into a single group named 'Deciles 1–5'. The statistics for the top decile of individuals are impressive: their 14-day round-trip trades represent 71.4 % of their total trades and account for 78.2 % of their total trading volume. In monetary value, the top decile 14-day round-trip trades are worth €4.4 billion (i.e., €5.7 billion multiplied by 78 %). This amount includes 1.8 billion of transactions undone within 24 h (i.e., €5.7 billion multiplied by 33 %). From here on out, we refer to short-term traders in the 10th decile as "amateur speculators."

3.2. Short-term trading versus day trading

Why do prior investigations put slight emphasis on the sheer scale of amateur speculation? It may be because past studies typically focus on day trading. Thus, it is interesting to address explicitly what the study of multiple-day round-trips adds to the usual analysis. We already learned that, as the trading window lengthens from 1 to 14 days, the share of quick round-trips taken by top-decile 14-day traders gets multiplied by about 2.75. (The multiplier is 2.4 in terms of traded value.) It is natural to ask how much that top decile coincides with the top decile of 1-day round-trip traders. Put differently, is the top decile of 14-day round-trip traders chiefly composed of day traders?

Table 2 reports on the overlaps between various demarcations of "short-term" traders. Six windows of, respectively, 1, 3, 7, 14, 30 and 90 days are considered. In each instance, traders are sorted into deciles by the fraction of traded value that is reversed within that window of time. Every top-decile window lists 1404 people, i.e., 10 % of all traders in the sample. The table reveals the extent to which the same people show up in various windows. It does so in two ways: panel A offers counts of intersection, and panel B lists matching percentages.

It emerges that, in the top decile of 90-day round-trip traders, 800 out of 1404 individuals (or 57 %) are also day traders. In the top decile of 30-day round-trip traders, 922 out of 1404 (66 %) are day traders. Of 14-day top-decile round-trip traders, 989 (or 70 %) are day traders. The exercise plainly demonstrates that an undivided focus on day trading is overly restrictive and that it limits our understanding of speculative trading among retail investors.

Fig. 1 provides complementary insight into how considering multiple-day round-trips adds to the usual analysis of day trading. In the broad sample, day trading represents 7.58 % in number of transactions (13.49 % in monetary value) while 14-day short-term trading reaches approximately 30 % in number of transactions (42 % in monetary value). Based on the aggregate trading activity in the sample, this means that the share of quick round-trips in number of transactions (in monetary value) triples (doubles) as the trading window lengthens from 1 to 14 days. The corresponding increases remain impressive when focusing exclusively on the 14-day top-decile round-trip traders. The share of their quick round-trips in the aggregate trading activity increases by about 176 % in number of transactions (139 % in terms of traded value) as the trading window lengthens from 1 to 14 days. In the broad sample, day trading of the top decile traders represents 5.22 % in number of transactions (10.79 % in monetary value) while their 14-day quick round-trip trades represent up to about 14 % of all the transactions executed or 26 % of the aggregate monetary value.

3.3. Short-term trading and lottery-like stocks

As stated earlier, speculative trading is often related to gambling and sensation-seeking. The seminal work of Kumar (2009) shows that lottery-like stocks –typified by low price, high idiosyncratic volatility and high idiosyncratic skewness– attract the same socio-economic clienteles as lotteries do. Since amateur speculators are gamblers, we assess their propensity to hold lottery-like stocks.

Our methods build on Kumar (2009).[10] Hence, shares that belong to the lowest 50th stock price percentile, the highest 50th volatility percentile, and the highest 50th skewness percentile are labeled lottery-like. The percentiles are defined across all stocks traded in the sample. To judge the propensity to hold lottery-like stocks, we compute two ratios. The first ratio (***LLS1***) is defined as the number of lottery-like stocks held in the end-of-month portfolio divided by the total number of stocks held in that portfolio at the end of the month. In the same way, the second one (***LLS2***) equals the market value (in €) of lottery-like stocks held in the end-of-month portfolio divided by the total market value of the portfolio.

Table 3 reports, across trader deciles, cross-sectional means and medians for the two ratios. In all cases, the ratios for the 10th-decile rank at (or near to) the top. So, amateur speculators are disposed to hold more lottery-like stocks than other individuals and this tendency rises with the inclination to engage in quick round-trip trading. The disparity between

[9] The broker that provided us with the data allows its clients who have cash in their trading account to trade several times the same stock (and/or different securities) without waiting for the first trade to be settled. On its website, the broker only mentions in the section on trading rules that "If you wish to use the revenue of a sell, you must take into account the value date of the generated cash".

[10] Since a given stock may be lottery-like during one month but not the next, we update the categorization of stocks each month. Volatility and skewness are appraised with daily returns over the past six months. We work with total volatility and total skewness given that Kumar finds that idiosyncratic and total measures yield similar results.

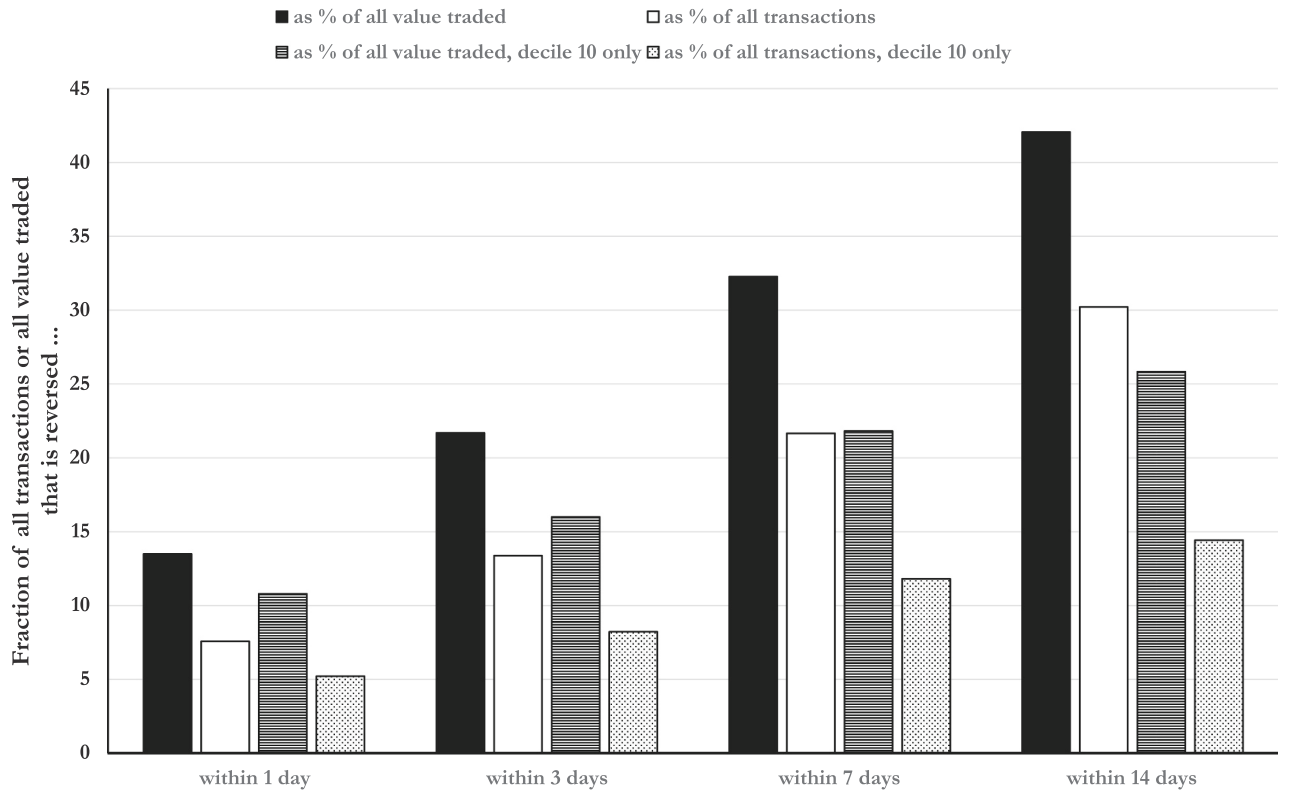

Fig. 1. How relevant is short-term trading?

the average ratios for the 10th decile and the ones for the bottom group reaches 2 % (in number of stocks) or 2.40 % (in monetary value). It is statistically significant at the 1 % level. The cross-sectional medians exhibit an analogous pattern. Thus, the propensity to hold lottery-like stocks is greater among short-term traders. These findings bolster the judgment that many are gamblers.

4. Amateur speculators

4.1. Who are they?

Table 4 sketches a brief portrait of short-term traders and compares them to other retail investors. As before, people are sorted into deciles based on the fraction of their stock purchases that are undone within 14 days.

Panel A contrasts selected socio-demographic indicators. The typical short-term trader is younger than the average individual in the bottom five deciles (43.0 vs. 48.4 years old). Consistent with Kumar (2009) and others, the top decile also reveals a somewhat higher proportion of men (93 % vs. 90 %) and a lower proportion of university-educated persons (67 % vs. 77 %). Each difference is statistically significant.

Panel B summarizes survey responses. The average trader in the sample declares a return objective of "5% to 7% above inflation"; considers himself/herself as risk tolerant; reports "above-average" financial knowledge; has an investment horizon longer than 5 years; earns an annual net income in the range of €20,000 to €75,000; invests between €20,000 and €250,000 in financial instruments; and reports "average" levels of experience with risks inherent to financial instruments.

Interestingly, compared to the bottom five deciles, 10th-decile traders declare (on average) significantly higher return targets but risk tolerance that is similar. They also report significantly lower financial literacy, experience, horizon, income, and investments. Lesser sophistication and wealth both agree with Kumar (2009) and fit the profile of gamblers.

Table 3
Short-term trading and lottery-like stocks.

Deciles	Cross-sectional means		Cross-sectional medians	
	LLS1	LLS2	LLS1	LLS2
1–5	4.69 %	4.17 %	4.01 %	3.28 %
6	5.36 %	4.97 %	4.50 %	3.84 %
7	5.77 %	5.45 %	4.92 %	4.44 %
8	6.10 %	5.82 %	5.11 %	4.55 %
9	6.42 %	6.20 %	5.47 %	4.87 %
10	6.69 %	6.57 %	5.45 %	5.10 %
D10 minus (D1-D5)	2.00 %***	2.40 %***	1.44 %	1.82 %

This table reports cross-sectional means and medians for ratios of lottery-like stocks. We follow the methods of Kumar (2009) to flag lottery-like stocks. These shares belong to the lowest 50th stock price percentile, the highest 50th volatility percentile, and the highest 50th skewness percentile. The first ratio of lottery-like stocks (***LLS1***) equals {the number of lottery-like stocks held in portfolio} divided by {the total number of stocks held in portfolio}. Similarly, the second ratio (***LLS2***) is {the market value of lottery-like stocks held in portfolio} divided by {the total market value of the portfolio}. The ratio calculations are repeated at the end of each month. Next, for each trader, the monthly ratios are averaged over time. Lastly, traders are sorted into deciles according to the fraction of trading volume that is reversed within 14 calendar days. This fraction is determined over the full trading history of each individual. The lowest five deciles are combined into a single group (1–5). The bottom row in the table shows the difference between the estimates for decile #10 and (D1-D5). ***, **, and * indicate significance at 1 %, 5 % and 10 %, respectively.

Survey responses may, or may not, match actual conduct. Table 5 lists a set of variables chosen to describe trading behavior. The relevant data are first gathered for every person and summed or averaged over their separate "activity intervals," possibly as long as the entire sample period of 111 months. Later, traders are sorted into groups. Table 5 states group means and medians.

Table 4
Trader characteristics.

	All	D1-D5	D6	D7	D8	D9	D10	Difference
N	14,037	7019	1403	1403	1404	1404	1404	
Panel A: Socio-demographic indicators								
AGE	46.8	48.4	47.1	46.1	45.0	44.4	43.0	−5.4***
MALE	91.1	90.2	91.4	91.9	90.9	92.5	93.3	3.1***
HighEDUC	74.1	77.2	74.0	74.1	69.4	70.8	67.0	−10.2***
Panel B: Subjective individual characteristics								
TARGET	3.36	3.23	3.37	3.42	3.44	3.50	3.67	0.44***
RISKTOL	3.98	4.01	3.98	3.94	3.97	3.90	3.96	−0.05
FINLIT	3.52	3.55	3.52	3.53	3.48	3.49	3.49	−0.06**
HORIZON	3.62	3.78	3.66	3.63	3.44	3.37	3.19	−0.59***
INCOME	1.59	1.68	1.59	1.55	1.46	1.50	1.45	−0.23***
WEALTH	1.62	1.79	1.58	1.54	1.41	1.40	1.28	−0.51***
FINEXP	1.22	1.23	1.22	1.23	1.19	1.21	1.19	−0.05**

This table reports cross-sectional means for trader deciles as well as the full sample. Traders are sorted according to the fraction of trading volume (in €) that is reversed within 14 calendar days. It is determined over the full trading history of each individual. The lowest five deciles are combined into a single group (D1-D5). The column furthest to the right shows the difference between the averages for decile #10 and for the bottom group (D1-D5). We test whether these differences differ from zero. ***, **, * indicate statistical significance at the 1 %, 5%, and 10 %, respectively. ***N*** denotes the number of traders in each group. The sociodemographics in panel A include ***AGE*** (investor age in 2008, in years), ***MALE*** (proportion of men, in percent), and ***HighEDUC*** (the fraction of investors with a university education). Panel B summarizes survey responses. ***TARGET*** refers to the return objective that subjects seek to earn (5-level scale — 1: "a positive yield without any risk of capital loss"; 5: "more than 12 % per year over-and-above the annual inflation rate"). ***RISKTOL*** indicates risk tolerance (5-level scale — 1: low risk tolerance; 5: high risk tolerance). ***FINLIT*** refers to financial literacy and understanding of financial markets (5-level scale —1: basic knowledge; 5: very high knowledge). ***HORIZON*** shows the investment horizon (5-level scale — 1: less than 2 years; 5: more than 7 years). ***INCOME*** refers to annual household net income after taxes on a 5-level scale that ranges between 0 (less than €20,000) and 4 (more than €150,000). ***WEALTH*** signifies the sum of wealth invested in various financial instruments (5-level scale — 0: less than 20,000 Euro; 4: more than one million Euro). Lastly, ***FINEXP*** refers to trader knowledge of the risks inherent in financial products (3-level scale — 0: no knowledge; 2: good knowledge).

Table 5
Trader behavior.

	All	D1-D5	D6	D7	D8	D9	D10	Difference
N	14,037	7019	1403	1403	1404	1404	1404	
Panel A: Cross-sectional means								
NTR	151	93	156	162	188	235	306	213***
TRVAL (k€)	1224	481	1096	1005	1250	2441	4046	3565***
NST	8.1	10.4	8.3	6.9	5.6	4.5	3.1	−7.4***
PVAL (k€)	66.7	78.4	97.4	53.4	46.1	48.8	29.6	−48.8***
UST	35.8	33.5	38.6	39.4	37.2	37.9	36.9	3.4***
ND	40	18	36	49	60	70	97	80**
TOP5 (#trades)	45.53	40.42	43.69	46.21	50.68	53.75	58.80	18.38***
TOP5 (€)	53.36	47.91	51.14	54.24	59.06	62.31	67.34	19.43***
Panel B: Cross-sectional medians								
NTR	72	56	81	81	91	108	137	
TRVAL (k€)	253	170	271	276	354	540	941	
NST	5.8	8.3	5.9	4.7	3.9	3.1	1.9	
PVAL (k€)	19.3	25.4	19.8	15.9	14.7	12.9	8.7	
UST	24	24	26	25	23	23.5	22	
ND	0	0	0	0	0	0	0	
TOP5 (#trades)	42.22	37.63	40.98	43.06	47.97	52.09	58.32	
TOP5 (€)	51.25	45.92	48.88	53.21	58.26	62.95	69.51	

This table reports cross-sectional means (in Panel A) and medians (in Panel B). Traders are sorted into deciles according to the fraction of trading volume (in €) that is reversed within 14 calendar days. This percentage of quick round-trip trade is determined over the full trading history of each individual. The lowest five deciles are combined into a single bottom group (D1-D5). The column furthest to the right indicates the difference between the average estimates for decile #10 and the bottom group (D1-D5). ***, **, * indicate statistical significance at the 1 %, 5%, and 10 %, respectively. ***N*** stands for the number of investors; ***NTR***, the number of buy and sell transactions over the sample period; ***TRVAL***, the total monetary value (in k€) of all transactions that ***NTR*** summarizes; ***NST***, the average number of stocks held in portfolio at the end of each month; ***PVAL*** is the average end-of-month value of the portfolio (in k€); ***UST*** is the universe of different stocks traded, in number of stocks; ***ND***, the number of option and warrant transactions; ***TOP5*** shows the fraction of investor trading executed through his/her top 5 stocks, in both number of trades and in monetary value (in €).

Table 6
Portfolio performance and realized vs. unrealized (paper) gains and losses.

	All	D1-D5	D6	D7	D8	D9	D10	Difference
N	14,037	7019	1403	1403	1404	1404	1404	
Panel A: Cross-sectional means								
R	−3.68	−1.92	−3.25	−4.19	−5.86	−5.64	−8.25	−6.33***
Rnet	−6.10	−3.66	−5.55	−6.92	−8.80	−8.89	−12.56	−8.90***
TC	5.0	2.6	4.4	4.7	5.6	8.9	13.4	10.8***
DE	2.4	0.5	1.2	1.6	2.8	4.6	10.7	10.1***
%STpg	37.0	39.4	36.4	35.6	33.9	34.2	33.3	−6.1***
Panel B: Cross-sectional medians								
R	−3.06	−1.87	−2.72	−3.36	−4.80	−5.08	−7.03	
Rnet	−5.02	−3.28	−4.89	−5.71	−7.64	−8.27	−11.26	
TC	1.8	1.3	1.9	2.0	2.3	3.2	4.6	
DE	0.6	0.3	0.7	1.0	1.6	2.3	5.8	
%STpg	36.1	38.5	34.7	34.3	32.1	32.6	30.9	

This table reports cross-sectional means (in Panel A) and medians (in Panel B) for trader deciles and the full sample. Subjects are sorted according to the fraction of trading volume (in €) that is reversed within 14 calendar days. This proportion of quick round-trip trades is determined over the full trading history of each individual. The lowest five deciles are combined into a single group (D1-D5). The column furthest to the right indicates the difference between the average estimates for decile #10 and the bottom group (D1-D5). ***, **, * indicate statistical significance at the 1 %, 5%, and 10 %, respectively. ***N*** denotes the number of investors. ***R*** symbolizes the annualized gross stock portfolio return. ***Rnet*** is ***R*** corrected for transaction costs. ***TC*** represents trading costs paid on all stock trades over the sample period (in k€). ***DE***, Barber et al. (2007)'s measure of the disposition effect, is estimated by the average gap (%) between the fraction of gains and the fraction of losses that are realized at the end of each day during the sample period. ***%STpg*** is the average proportion of stocks in portfolios with (unrealized) paper gains at the end of each month. We check whether the current end-of-month market price of each stock in an individual's portfolio exceeds what he or she originally paid for it.

We calculate the total number of stock transactions (***NTR***) and their corresponding value (***TRVAL***). We use the monthly average number of stocks held in portfolio (***NST***) and the universe of different stocks traded (***UST***) as two simple measures of diversification. We further compute the average end-of-month portfolio market value (***PVAL***). In addition, we determine the total number of trades executed on options and warrants (***ND***). This variable is a proxy for financial "learnedness" since derivatives trading carries high entry barriers that block people who are not money-wise (see, e.g., Goetzmann & Kumar, 2008, or Hsiao & Tsai, 2018). Lastly, we compute for each person the fraction of trading accomplished with the top five stocks (***TOP5***), both in number of transactions and in value.[11]

The average trader executes 151 stock transactions with a combined value of €1,224,000. He or she holds an eight-stock portfolio with an average end-of-month value of circa €66,700. He/she trades a set of almost 36 stocks and also completes about 40 trades on options and warrants. Although the average trader works with quite a large universe of stocks, around half of the trading activity concerns the top five: ***TOP5*** equals 45.5 % in number of trades or 53.4 % in monetary value.

When we study the same statistics for the top decile, striking differences appear. First, the average amateur speculator trades much more, both in stocks (306 trades with an aggregate value of €4,046,000) and in derivatives (97 trades). Second, he or she holds a smaller portfolio of three stocks with an end-of-month value of €29,600. Third, the speculator carries out a larger share of his/her activity on the top five stocks (58.8 % in trades or 67.3 % in monetary value) while the universe of stocks remains close to the full sample average (36.9 vs. 35.8). Each difference between the 10th decile and the bottom group (D1-D5) is statistically significant. From a comparison of panels A and B, we learn that the medians are frequently below the corresponding means. This indicates positive skewness. Yet, the overall pattern in results remains the same.

4.2. Gross and net returns, and behavior towards gains and losses

How lucrative are speculators' trading strategies? To address this issue, we first assess performance with gross and net returns defined, respectively, as the annualized stock portfolio returns before (***R***) and after transaction costs (***Rnet***).[12] We also aggregate the total transaction costs paid on stock trades over the whole sample period (***TC***) – an indicator of special interest with respect to individuals who behave like gamblers.

In addition, we consider traders' reluctance to realize losses, i.e., the so-called disposition effect (***DE***). A key distinction is between gains or losses that exist "on paper" and gains and losses that are actually realized. We follow the methods of Barber et al. (2007) to calculate the difference between the proportion of stock gains (PGR) and the proportion of stock losses that are realized (PLR).[13] We further determine the average proportion of winning stocks held in end-of-month portfolios (***%STpg***), a statistic that is negatively related to the disposition effect.[14] Table 6 reports cross-sectional means and medians for the above-listed variables.

In the broad sample, the average investor earns a negative return, i.e., −3.68 % before and − 6.10 % after transaction costs. It is noteworthy that the corresponding median returns are higher but still negative, i.e., −3.06 % and − 5.02 %, respectively. Such poor realized returns are not a surprise since our sample period includes the 2008 financial crisis. Average total transaction costs amount to about €5000 (with a median of €1800). This represents 0.41 % of the average total traded value. However, if we look into the equivalent median values, the percentage

[11] We identify for each trader the five stocks that he or she trades the most. Thus, the top five differ between individuals.

[12] Given the high volatility of monthly returns over the sample period, we use the geometric average of monthly returns. The geometric average is a better representation of realized performance.

[13] Following Barber et al. (2007), we compute the number of paper gains and losses with data collected for every single day, rather than only on those days that a sale took place.

[14] This variable is the average proportion of stocks in portfolios with (unrealized) paper gains at the end of each month. It is found by checking whether the current end-of-month market price of each stock in a given trader's portfolio exceeds what he or she originally paid for it.

Table 7
The disposition effect and the ratio of quick round-trip trades.

	Panel A: Results from estimating cross-sectional linear regressions			
Dependent variable	Intercept	Ratio_EUR_14	NTR	R^2
PGR-PLR	−0.265***	0.130***		0.157
PGR-PLR	−0.152*	0.134***	−0.001***	0.160
PGR/PLR	8.775***	0.075***		0.003
PGR/PLR	9.312***	0.092***	−0.006***	0.007

	Panel B: Results from estimating hazard models				
Dependent variable	TGI	Ratio_EUR_14	TGI * Ratio_EUR_14	NTR	LR
h(t,TGI(t))	1.4094***	0.0272***	0.0008		361,027.22***
h(t,TGI(t))	1.4093***	0.0272***	0.0007	0.0000	361,081.05***

	Panel C: Results from estimating hazard models (with control for the crisis period)				
Dependent variable	TGI	Crisis	TGI * Crisis	NTR	LR
h(t,TGI(t)) – entire sample	1.3254***	−0.0779***	0.2397***		186,810.40***
h(t,TGI(t)) – entire sample	1.3252***	−0.0769***	0.2397***	0.0001	191,036.18***
h(t,TGI(t)) – top decile only	1.1524***	0.1173***	0.0713		33,513.71***

In Panel A, this table reports on cross-sectional linear regressions in which the dependent variable is a measure of the disposition effect for trader *i* (DE) and the explanatory variables are the ratio of quick round-trip trades of trader *i* and the total number of trades executed by trader *i* over the sample period. DE is either the difference between the proportions of realized gains and realized losses (***PGR-PLR***) or the ratio between these same proportions (***PGR/PLR***). In Panels B and C, this table reports on Cox proportional hazard models that explicitly model the time to an event (here the sale of a portfolio position) to estimate the DE. The baseline hazard function, $\mathbf{h_0(t)}$, is unknown and **TGI** represents the trading gain indicator. In Panel B, the set of explanatory variables includes the ratio of quick round-trip trades of trader *i* and the total number of trades executed by trader *i* over the sample period. In Panel C, explanatory variables include a binary variable intended to control for the 2008 financial crisis period and the total number of trades executed by trader *i* over the sample period. ***Ratio_EUR_14*** is the fraction of trading volume (in €) that is reversed within 14 calendar days. It is computed over the full sample period. ***NTR*** is the total number of buy and sell transactions over the sample period. ***Crisis*** is a dummy set to one for the period December 2007–June 2009. ***, **, and * indicate significance at 1 %, 5 % and 10 %, respectively.

goes up to 0.71 % (€1800/€253,000). Also as anticipated, the average person in our full sample is prone to the disposition effect: DE equals 2.4 %. Fittingly, the average proportion of winning stocks in end-of-month portfolios is 37 %. People are more likely to hang on to losing than to winning stocks. This inclination is similarly evident in the matching medians.

In contrast, the typical 10th-decile trader earns much lower returns: −8.25 % before and − 12.56 % after transaction costs. The differences with the portfolio returns achieved by those who place in the bottom group (−6.33 % and − 8.90 %) are economically substantial and highly significant. On average, short-term traders also incur higher transaction costs than (D1-D5) traders: €13,400 vs. €2600. However, transaction costs represent 0.33 % of the average total traded value in the top decile while they account for 0.54 % of the average traded value in (D1-D5). Once more, if we compare the means to the medians, we notice heterogeneity. This is consistent with Barber and Odean (2013) who also find that aggregate performance masks tremendous variation in behaviors and outcomes across individuals. The typical amateur speculator is also statistically more prone to the disposition effect. DE equals 10.7 % for the 10th decile and 0.5 % for (D1-D5). Likewise, the proportion of winning stocks in his or her portfolio is smaller too (33.3 % vs 39.4 %).

Ideally, measures of the disposition effect count paper gains and losses on the exact days when retail traders actively decide, regardless of whether they choose to sell or to hold a given stock position (De Winne, 2021). This information is missing, however. As a result, it is not easy to compare DE measures across traders who monitor their portfolios and transact at different frequencies. Past literature proposes several approaches to tackle this difficulty. The use of complex hazard models is one option. A simple alternative, suggested by Dhar and Zhu (2006), is to work with a ratio (PGR/PLR) instead of the difference (PGR-PLR) that was initially proposed by Odean (1998). Here we apply both approaches to compare short-term traders with individuals who trade much less frequently. On the one hand, we estimate cross-sectional OLS regression models of the relationship between a person's DE and his or her proportion of quickly reversed trades –while controlling for trading activity. On the other hand, we run Cox proportional hazard models[15] that explicitly model the time to an event, that is, the sale of a portfolio position in our case. Such models represent an attractive and very suitable approach to estimate the DE using control variables (e.g., Feng & Seasholes, 2005, and De Winne, 2021).

Table 7 reports the results. In Panel A, the dependent variable in the OLS regression models is either the difference between the proportion of gains and the proportion of losses that are realized or the ratio of these proportions. Whatever the model, its coefficient estimate is positive and highly significant. This outcome strengthens the earlier finding that the DE tends to be higher for short-term traders.

Results from estimating hazard models are provided in Panels B and

[15] Among the hazard models, a Cox proportional hazard model has the following form:

$$h(t,x(t)) = h_0(t).exp\left(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \gamma_1 z_{1,t} + \gamma_2 z_{2,t} + \ldots + \gamma_q z_{q,t}\right)$$

where the explanatory variables can be time-varying ($z_{i,t}$) or not (x_i).A Cox proportional hazards model is semi-parametric since the baseline hazard function, $h_0(t)$, is unknown. From the parameter estimates, it is possible to compute a hazard ratio which provides information about the change in the hazard rate following the increase of the independent variable by one unit. The hazard ratio associated with a given variable is constant over time and is computed as the exponential of the parameter estimate.

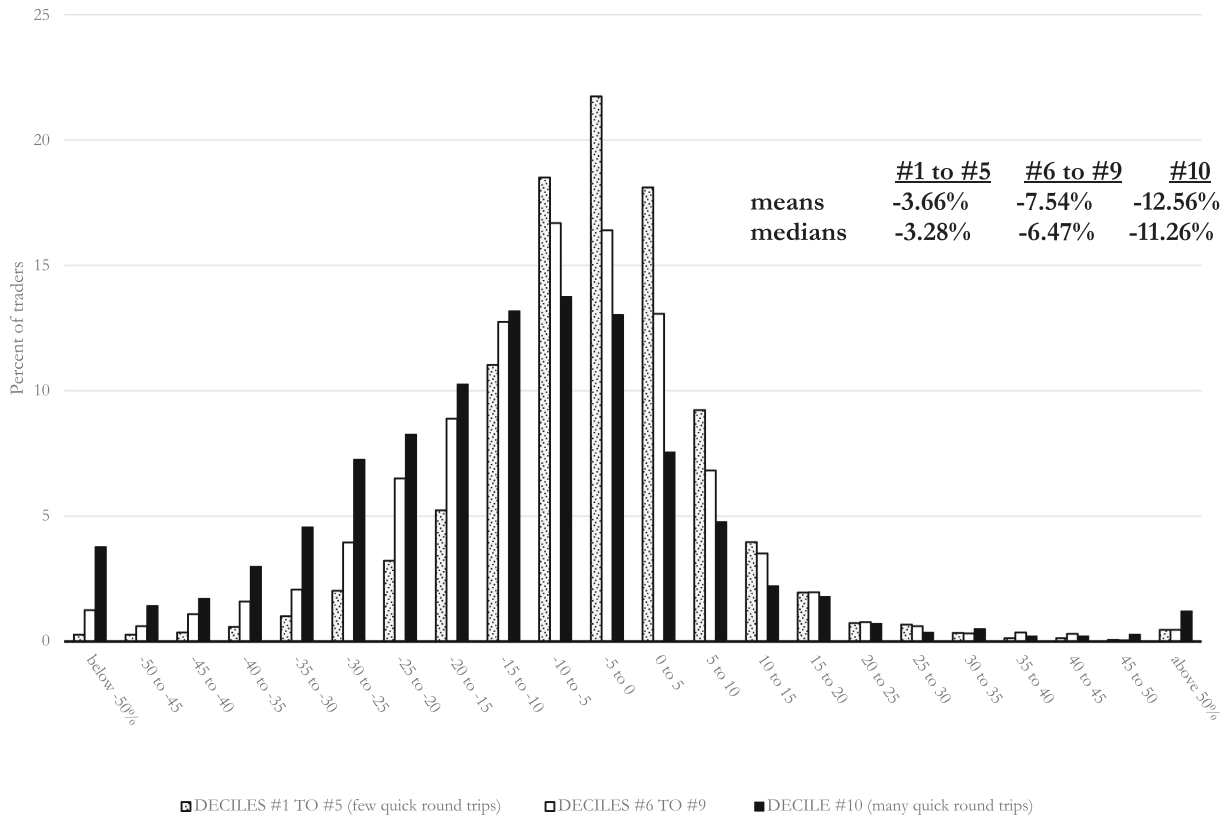

Fig. 2. : The cross-section of net annualized returns earned by traders.

C. In Panel B, the coefficient estimate of the trading gain indicator (TGI) is equal to 1.4094, which means that the hazard rate of selling a position at gain is about 4 times [exp(1.4094) = 4.09] the hazard rate of selling a position at loss (all other things being equal). This finding confirms that the retail investors in our sample are prone to the DE. However, when we consider the interaction between the trading gain indicator and the proportion of quickly reversed trades, the coefficient estimate is not significant (at any conventional levels), indicating that the DE is not significantly stronger for short-term traders.[16] Hence, these results based on hazard models slightly contrast with those reported above.

In Panel C, we use hazard models to check whether retail investors were more reluctant to realize their losses during the 2008 financial crisis, which might potentially exacerbate the DE. When running the hazard models using the entire sample of investors, we find that the DE is indeed higher during the crisis (i.e., the coefficient estimate of the interaction between the trading gain indicator and the crisis dummy is positive and significant). However, when estimating the hazard model using only the subset of top decile investors, the outcome is no longer the same. This suggests that short-term traders' DE did not markedly change during this high-volatility period. This finding is consistent with amateur speculators enjoying volatility, regardless of the general market circumstances.

The devastating impact of short-term trading on actual returns is highlighted by Fig. 2 which depicts cross-sectional net annualized returns. The distribution of the top decile investors is especially skewed to the left.[17] When we look at the cross-section of gross annualized returns in Fig. 3, the disparities are much less striking.[18] Fig. 4 further illustrates the extent to which transaction costs are a financial burden for quick round-trip traders. Remarkably, nearly 40 % of traders incur costs that account for more than 5 % of traded values. With such heavy penalties, it is sensible to wonder whether short-term traders are addicted to stock trading.

In Table 11 (available in appendix), a comparison between short-term traders and traders with large portfolios confirms that heavy quick-round trip trading is detrimental to portfolio returns. Individuals who run large portfolios (in the top decile based on end-of-month portfolio monetary values, see panel A), and who therefore can be expected to trade a great deal, achieve on average *positive* gross and net returns. These traders display an average portfolio turnover of about 12 %. By contrast, short-term traders (in the top decile based on the fraction of quick-round trip trades reversed within 14 calendar days, see panel B) exhibit on average a turnover that reaches 635 %! This striking difference in turnover clearly highlights the need to distinguish between large portfolio traders and short-term traders.[19] Only the latter are true amateur speculators who earn, on average, very poor returns on their stock portfolios.

4.3. How profitable are quick round-trip trades?

The results so far point to lower returns, higher transaction costs, and a higher disposition effect for short-term traders when we consider each

[16] If we replace the proportion of quickly reversed trades by a dummy variable intended to flag top decile investors, the results are similar.

[17] The differences in means across trader groups are statistically significant at the 1 % level.

[18] While the differences in means across trader groups are lower for gross than for net returns, they remain nonetheless statistically significant at the 1 % level.

[19] Yet, as a comparison of the top rows in panels A and B of Table 11 shows, the average annualized values of total trading (TVALy) are rather similar across deciles of both sets of traders. Interestingly, the same is true for TVAL14y (the average values of total trading that are reversed within 14 days) and even more so for NTRy (the average annual number of transactions).

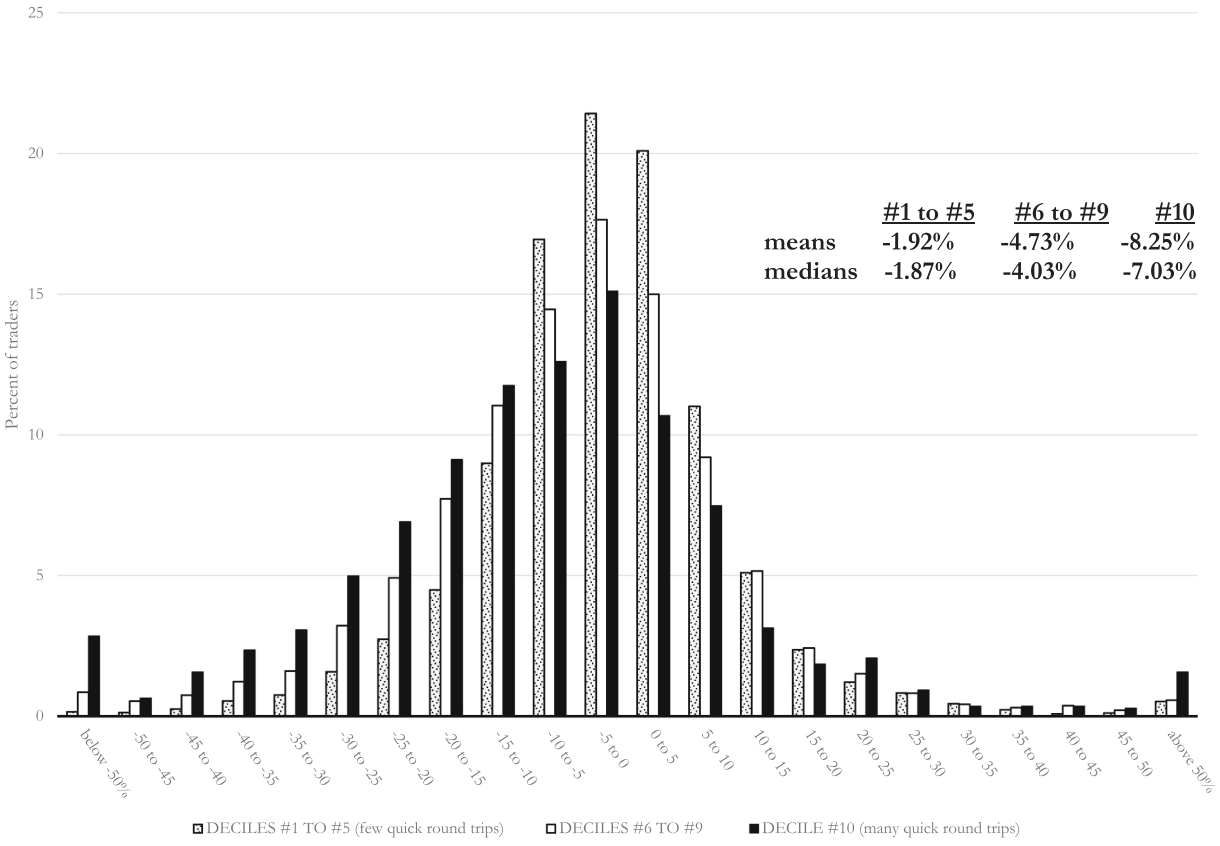

Fig. 3. : The cross-section of gross annualized returns earned by traders.

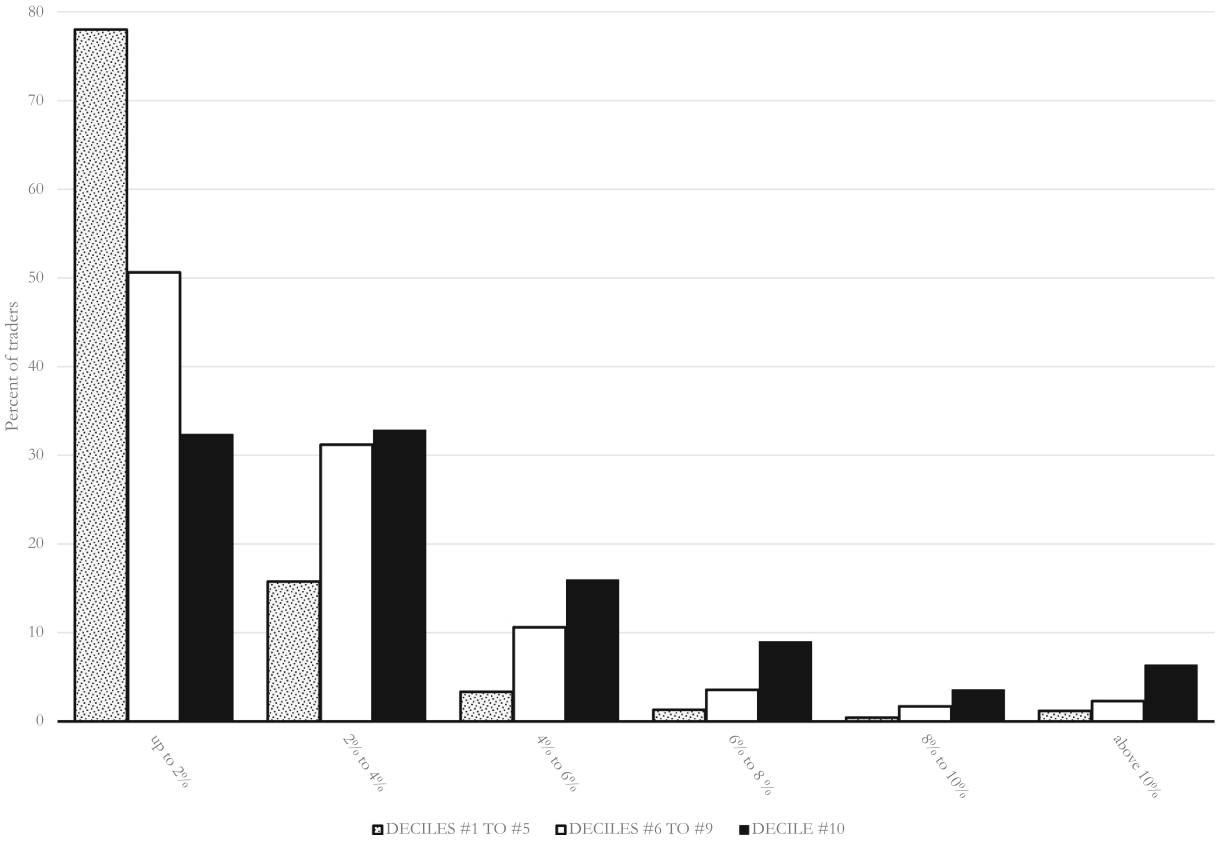

Fig. 4. : Annualized trading costs.

Table 8
How profitable are quick round-trip trades?

	All	D1-D5	D6	D7	D8	D9	D10	Difference
N	14,037	7019	1403	1403	1404	1404	1404	
				Panel A: Cross-sectional means				
R14	2.41	0.32	1.39	1.82	3.79	7.71	7.76	7.45***
R14net	0.64	0.22	0.79	0.89	2.13	3.68	−2.16	−2.38**
TC14	1.8	0.1	0.6	0.9	1.7	4.0	9.9	9.8***
%R14 > 0	50.1	34.6	66.2	67.3	67.1	66.2	61.1	26.5***
%R1 > 0	25.7	6.9	26.6	36.1	45.5	55.5	59.3	52.4***
				Panel B: Cross-sectional medians				
R14	0.08	0.00	0.44	0.67	1.07	1.45	1.63	
R14net	0.00	0.00	0.25	0.37	0.53	0.52	−0.37	
TC14	0.2	0.0	0.2	0.4	0.7	1.3	3.1	
%R14 > 0	54.0	0.0	71.4	71.4	70.6	68.6	59.7	
%R1 > 0	0.0	0.0	0.0	0.0	48.1	60.0	61.1	

This table reports cross-sectional means (in Panel A) and medians (in Panel B) for trader deciles as well as the full sample. Subjects are sorted according to the fraction of trading volume (in €) that is reversed within 14 calendar days. This percentage of quick round-trip trades is determined over the full trading history of each individual. The lowest five deciles are combined into a single group (D1-D5). The column furthest to the right indicates the difference between the average estimates for decile #10 and the bottom group (D1-D5). ***R14*** is the annualized gross return produced by short-term trades reversed with 14 calendar days; ***R14net*** is the annualized return, net of transaction costs. ***TC14*** denotes the related trading costs paid by investors (in k€). ***%R14 > 0*** represents the proportion (%) of 14-day round-trip trades, averaged across transactions and investors, that yield positive gross returns. ***%R1 > 0*** is computed similarly but only for transactions that are reversed within 24 h.

Table 9
Risk-adjusted performance across trader deciles.

Deciles	Alpha	MRP	SMB	HML	MOM	R^2
1–5	−0.0054***	0.8917***	0.1991***	0.1391	−0.1226***	0.371
6	−0.0059***	0.8850***	0.2041***	0.2084**	−0.1610***	0.318
7	−0.0066***	0.8358***	0.1902**	0.2300**	−0.1816***	0.267
8	−0.0076***	0.8259***	0.1973**	0.2734***	−0.2018***	0.252
9	−0.0085***	0.7543***	0.1483*	0.2819***	−0.1811***	0.206
10	−0.0116***	0.6351***	0.1167	0.3333***	−0.1703**	0.154

This table reports the estimated coefficients for a panel data regression model. The dependent variable is the risk premium of the portfolio net return of investor *i* in month *t*. The risk-free rate is the 10-year Belgian Treasury Bond rate in month *t*. The explanatory variables are Fama–French–Carhart factors in month *t* applicable to the European market. They are the market risk premium (***MRP***), size (***SMB***), book-to-market (***HML***), and momentum (***MOM***) factors. The model is estimated for each investor decile. Traders are sorted into groups according to the fraction of trading volume that is reversed within 14 calendar days. The proportion of quick round-trip trades is determined over the full trading history of each individual. The lowest five deciles are combined into a single group (1–5). ***, **, and * indicate significance at 1 %, 5 % and 10 %, respectively. Standard errors are clustered by month.

person's total trading activity in stocks. But do we observe the same patterns for quick round-trip trades only? To address that question, we compute several performance proxies that assess the profitability of round-trip trades within 14 calendar days. For both the full sample and deciles, Table 8 provides cross-sectional means and medians. Focusing exclusively on the 14-day round-trip trades, we first find annualized realized gross and net returns (***R14*** and ***R14net***, respectively) as well as the total transaction costs (***TC14***). Next, we consider the fraction of 14-day round-trip trades yielding positive gross returns (***%R14 > 0***) and the same statistic for transactions reversed within 24 h (***%R1 > 0***).

The evidence is clear-cut. Compared to the bottom group (D1-D5), short-term trades in the top decile are associated with much higher gross returns. The difference is 7.45 % and it is statistically significant at the 1 % level. In contrast, a comparison of net returns tells a different story: the gap is now negative (−2.38 %) and significant at the 5 % level. The much higher transaction costs incurred, on average, by retail speculators, €9900 vs. €100, explain this loss of profitability. Even if the proportion of quick round-trip trades with positive gross returns is obviously higher in the top decile than in (D1-D5), speculators pay such large sums in trading fees that they end up with losses. The medians reported in panel B lead to the same conclusion.

4.4. Risk-adjusted performance

Our prior results signal poor performance for typical short-term traders. Still, actual net and gross returns do not control for variation in investment risk. That is why we estimate risk-adjusted performance using the Fama–French–Carhart four-factor model (see, e.g., Hoffmann & Shefrin, 2014, and D'Hondt et al., 2021). In order to compare performance across investor deciles, we estimate a panel data model that controls for exposure to market, size, book-to-market, and momentum factors:

$$r_{i,t} - Rf_t = \alpha + \beta_1.MRP_t + \beta_2.SMB_t + \beta_3.HML_t + \beta_4.MOM_t + \varepsilon_{i,t}$$

In this four-factor model, the dependent variable is the risk premium of the portfolio net return of investor *i* in month *t* ($r_{i,t}$). The risk-free rate is the 10-year Belgian Treasury bond rate in month t (Rf_t). The set of explanatory variables includes the Fama–French–Carhart factors in month *t* for the European market, namely, market risk premium (MRP_t), size (SMB_t), book-to-market (HML_t), and momentum (MOM_t).[20] When estimating this panel data regression model across investors in each decile, we cluster standard errors by month.[21]

[20] Market factors for the European market are provided by EUROFIDAI (http://www.eurofidai.org).

[21] The purpose is to address issues related to cross-sectional correlation (Seasholes & Zhu, 2010).

Table 10
Once a gambler, always a gambler?

year t	year t + 1			year t + 2		
Panel A	investor	speculator	exit	investor	speculator	exit
successful speculator	54.85	44.05	1.10	61.45	33.02	5.53
failing speculator	51.69	46.87	1.44	57.91	37.44	4.65
successful investor	94.87	4.76	0.37	93.26	5.28	1.46
failing investor	92.04	7.48	0.48	90.01	8.64	1.35
Panel B	successful	failing	exit	successful	failing	exit
successful speculator	41.78	57.12	1.10	43.57	50.91	5.53
failing speculator	40.08	58.48	1.44	39.62	55.74	4.65
successful investor	51.54	48.09	0.37	51.80	46.74	1.46
failing investor	49.84	49.68	0.48	48.33	50.33	1.35

With regard to each cohort of traders who start their activities during year *t-1* (say, 2003), we sort every individual into one of four groups based on their intensity of 14-day round-trip trading as well as their performance during their first full year of trading (2004). Individuals are either "***investors***" or "***speculators***." The fraction of stock transactions that "speculators" reverse within 14 days puts them in the top 10 % of all traders for the year under scrutiny. "***Successful***" traders earn an annual return above the cross-sectional median during the first full year of trading; "***failing***" traders, a return below the median. For each group, we find for the next two years (2005 and 2006) their new designations as investors or speculators (Panel A), and as successful or failing (Panel B). Traders who discontinue trading in years $t + 1$ or $t + 2$ are put in an "exit" category. We report average frequencies across all cohorts (2003, 2004, 2005, 2006, 2007, and 2008).

Table 9 shows that, over the entire sample period and regardless of the decile, traders never outperform. In each decile, we obtain a negative and statistically significant alpha coefficient at the 1 % level. It is noteworthy, however, that the lowest alpha coefficient is observed for the top decile. Thus, short-term traders achieve the worst risk-adjusted performance in the sample. In addition, the top decile also exhibits the lowest coefficient estimate for the market risk premium as well as the lowest R^2.

We also estimate the above panel data model by investor to obtain individual alphas. These unreported results (available upon request) are consistent with Table 9 and confirm that the average alpha in the top decile is statistically lower, at the 1 % level, than the average alpha in any of the other deciles. All things considered, we conclude that amateur speculators achieve the most negative risk-adjusted performance over the period under scrutiny.[22]

4.5. Once a gambler, always a gambler?

A remarkable aspect of gambling, e.g., lotteries, or betting on horse races, or trading stocks is that so many people keep it up despite almost continual failure. Speculation and gambling do offer sizzling excitement, of course. One may also whimsically believe that success is just around the corner (Weinstein & Klein, 1996). Besides false optimism, still another cause may be that speculators evaluate past outcomes in a biased manner. Gilovich (1983) reasons that gambling wins are readily accepted as reflections of "skill or the soundness of one's system" while losses "are explained away and discounted" (1983, p. 1111). Subjects isolate fluke events that contribute to failure but take no notice of lucky breaks that enable success. Also, in this way, ostensible near misses animate ongoing play.[23] These are some of the reasons why we study persistence in individual trading behavior.

We split our sample into six cohorts depending on the year in which people began trading (*t-1*). We track individuals for the ensuing three years (t, $t + 1$ and $t + 2$). For instance, the first cohort available to us refers to persons who started trading during 2003 (*t-1*). Based on the intensity of their trading activity and their return performance during 2004 (t), i.e., their first complete year of trading, each person is placed into one of four groups: "successful investors," "successful speculators," "failing investors," and "failing speculators." The 2004 sort between "speculators" and "investors" hinges on the fraction of trades in 2004 that are reversed within 14 days. All traders who form the top decile are considered "speculators." Our methods are the same for later cohorts so that year t runs from 2004 to 2009. Also, whether a given person is labeled successful or failing in t depends on whether his/her portfolio return tops (trails) the cross-sectional median return earned by all traders during year t.

Next, we check what happens during years $t + 1$ and $t + 2$. (That is, 2005 and 2006 for the first, and 2010 and 2011 for the last cohort.) For each group defined in year t, we find the percentage of individuals who are categorized as investors or speculators in $t + 1$ and $t + 2$. Likewise, for each group, we find the fraction who are successful or failing traders in later years. We repeat these separate calculations for each cohort, i.e., for each set of new traders who came into the data set in 2003, 2004, …, up to 2008.[24]

Table 10 lists equally weighted averages across six cohorts. Two main results emerge. First, Panel A shows steadfastness in high 14-day round-trip trading up to year $t + 2$. Individuals who are flagged as "speculators" in year t are far more likely than 10 % to remain in that category. With respect to speculators who performed poorly during t, the probabilities are about 47 % in $t + 1$ and 37 % in $t + 2$. The corresponding probabilities are slightly lower for speculators who did well, i.e., 44 % in $t + 1$ and 33 % in $t + 2$. In contrast, close to 90 % of investors in t remain in that category in later years, no matter their performance during year t.

Panel B reveals a second finding of some interest. Compared to weak-performance investors, feebly managing speculators in year t are more likely to produce below-median returns afterward, 58.5 % vs. 49.7 % in year $t + 1$ and 55.7 % vs. 50.3 % in $t + 2$. This is also true when we look at strong year t performers and compare the portfolio results of speculators and investors in later years.

Finally, Table 10 also indicates the small fractions of retail investors who stop trading stocks after a period of "poor" (i.e., below-median) performance.[25] Speculators are on average more likely than investors

[22] When we assess the four-factor model using gross returns, we find, once again, a statistically significant negative alpha for each decile –with the worst risk-adjusted performance in the top decile. (These results are available upon request.)

[23] Note that biased evaluation of outcomes may explain why gamblers persevere, not why they begin in the first place.

[24] When people discontinue trading, they are put in a category named "exit." The fractions do not add up to 100 % since some people stop trading. Also, since the data set ends in March 2012, our last cohort is made up of people who began trading in 2008 (year *t-1*). Therefore, the analysis does not consider any individual who started trading after 2008. There are 5815 such persons in the sample.

[25] Since we only focus on common stock investments, we do not investigate whether retail investors trade other securities and/or whether they switched from stocks to other securities after bad performance.

to stop trading. Nevertheless, Table 10 shows that there are not many of them. Specifically, after one year of trading, 1.10 % of successful speculators stop trading shares, compared to 0.37 % of successful investors. Similarly, 1.44 % of failing speculators stop trading shares in year $t + 1$ while only 0.48 % of failing investors do so. Regardless of their performance in year t, speculators are indeed more likely to exit the stock market than investors in year $t + 1$, but only few of them behave this way. Also, within each category (speculators or investors), those who achieved a return below the median over the past year are more likely to stop trading shares in year $t + 1$ than those who earned an above-median return. The divergent behavior of speculators and investors is unmistakable after two years of trading. By that time, amateur speculators are more than three times as likely as investors to stop trading shares altogether. That being said, it is less than 5 % of failing speculators who stop trading shares.

5. Conclusion

Speculation operates over a much shorter time frame than investment. Speculators purchase shares in the hope that their prices will climb without delay.

This paper proposes a new metric of speculative intensity. Using a 14-day horizon as an illustrative example, we find that the aggregate value of quick round-trip stock trades was truly colossal in Belgium (2003–2012); that amateur speculation, properly understood, is not a fringe phenomenon but controls much retail trading; and that the responsibility lies with a minority of traders. Amateur speculators, however, are not merely day traders. Still, their profile indicates that, overwhelmingly, they are men with below-average education and wealth. Their intense trading pursuits converge on a few stocks at a time. In most instances, the objective of "aiming for quick profits" is not reached. High transaction costs are a principal reason.

While day trading epitomizes the pinnacle of gambling among retail investors, our new measure presents a more comprehensive point of view. It leads to new insights, and the metric itself may be employed as an easy-to-use tool to locate speculative assets.

One weakness of our study is that it covers the 2008 global financial crisis. This era was especially detrimental to retail trader performance. Some individuals in our sample were hit very hard and this may have distorted their activities. Plausibly, speculative trading was exacerbated during this turbulent period. Further study of whether speculative trading depends on market conditions and/or volatility regimes would be of great interest. Future research could also analyze quick round-trip trades on assets other than stocks. Our paper paves the way for such empirical investigations.

Declaration of competing interest

None.

Data availability

No

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Appendix A. Appendix

Table 11
Short-term traders versus traders with large portfolios.

Panel A: PVAL DECILES						
	D1-D5	D6	D7	D8	D9	D10
TVALy	62	113	150	248	299	860
Ratio_EUR_14y	24.07	17.05	15.64	15.63	13.98	15.24
R	**−6.28**	**−3.05**	**−2.11**	**−2.05**	**−0.23**	**2.04**
Rnet	**−9.67**	**−4.98**	**−3.69**	**−3.53**	**−1.47**	**0.98**
NTRy	17	24	25	32	37	57
TVAL14y	34	52	71	127	125	309
PVAL	8	23	33	50	85	435
TURN	138	20	19	21	15	12
Panel B: Ratio_EUR_14 DECILES						
	D1-D5	D6	D7	D8	D9	D10
TVALy	78	170	154	193	383	694
Ratio_EUR_14y	2.64	13.41	20.78	31.11	46.55	72.85
R	**−1.92**	**−3.25**	**−4.19**	**−5.86**	**−5.64**	**−8.25**
Rnet	**−3.66**	**−5.55**	**−6.92**	**−8.80**	**−8.89**	**−12.56**
NTRy	16	25	26	32	40	57
TVAL14y	3	23	32	60	181	546
PVAL	78	97	53	46	49	30
TURN	7	14	18	28	47	635

This table reports cross-sectional means for trader deciles based on the average of value of end-of-month portfolio in k€ (***PVAL***) in Panel A as well as for trader deciles based on the fraction of trading volume (in €) that is reversed within 14 calendar days (***Ratio_EUR_14***) in Panel B. All these cross-sectional statistics are computed over the 111-month sample period. In both panels, the lowest five deciles are combined into a single group (D1-D5). ***TVALy*** is the traded value per year in k€. ***R*** refers to the gross monthly portfolio return and ***Rnet*** to the net monthly portfolio return, both in %. ***NTRy*** is the number of share transactions per year. ***TVAL14y*** is the traded value reversed within 14 days, per year, in k€. ***Ratio_EUR_14y*** is the ratio of

TVAL14y to TVALy. ***PVAL*** is the average portfolio value, end-of-month, in k€. ***TURN*** is turnover (in %) defined as average monthly ***TVAL*** divided by ***PVAL***.

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