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Are retail investors less aggressive on small price stocks?

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ABSTRACT

We investigate whether number processing impacts the limit order aggressiveness of retail investors. When posting non-marketable orders, individual investors are less aggressive on small price stocks than on large price stocks. This difference is not explained by differences in liquidity and other usual drivers of order aggressiveness. No such difference exists for limit orders of high-frequency traders. The small price bias is detrimental to retail investors since it increases the costs borne when trading small price stocks.

1. Introduction

According to conventional finance theory, nominal stock prices are irrelevant for firm valuation, yet a number of papers provide empirical evidence that nominal prices do impact investor behavior. Institutional investors have a preference for large price stocks (Gompers and Metrick, 2001; Fernando et al., 2004; Dyl and Elliott, 2006), while retail investors are attracted by small price stocks as a result of their affordability and gambling-like skewness (Kumar and Lee, 2006; Kumar, 2009). Firms also acknowledge the importance of price magnitude by managing their nominal share price accordingly (Baker and Gallagher, 1980). To attract additional investors, firms proceed to stock splits (Copeland, 1979; Schultz, 2000). Similarly, the IPO price is a strong determinant of the investor composition (Fernando et al., 2004). A remarkable feature of nominal stock prices is their stability over time. The average magnitude of U.S. share prices has remained roughly constant since the Great Depression despite the strong growth of market capitalization. Weld et al. (2009) suggest that firms comply with a market norm, splitting their stock to stay in an appropriate price range. Baker et al. (2009) argue that firms choose to split their stocks and decrease the nominal price when investors are ready to pay a premium for low-priced stocks.² Birru and Wang (2016) indicate that investors overestimate the skewness of returns on low-priced stocks. Finally, Roger et al. (2018) show that analysts issue more optimistic price forecasts on small price stocks than on large price stocks.

In this paper, we argue that investors are influenced by nominal price magnitude as a result of a different perception of small and large numbers. Research in neuroscience indicates that individuals map symbolic numbers onto a mental line. While children initially represent numbers on a logarithmic scale (Nieder, 2005), the acquisition of formal mathematical education leads to a linear processing of numbers (Siegler and Opfer, 2003; Laski and Siegler, 2007). This shift from a logarithmic to a linear representation of numbers is however imperfect and both representations have been found to coexist in adults. More specifically, smaller numbers are

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² Their findings are however rebutted by a later paper (Perez and Shkilko, 2017).

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processed with a linear scale while a logarithmic scale remains for larger numbers (Dehaene et al., 2008; Viarouge et al., 2010). As a result, relative distances between small numbers are perceived differently than the same relative distances between larger numbers.

The perception of numbers has been shown to influence the behavior of economic agents. Peters et al. (2008) and Schley and Peters (2014) show that the way the brain maps symbolic numbers onto mental magnitudes has implications for conceptualizations of value, risk aversion, intertemporal choice, and dual-process theories of decision making. Millroth and Juslin (2015) provide evidence that probability weighting in decision making is influenced by numeracy (and thus number perception). Similarly, Mueller et al. (2018) show that approximate number processing skills lead to better decision making under objective risk. Park and Cho (2018) show that the precision of the mental number representation has an impact on the rationality of individuals' financial decisions.

To investigate the influence of price magnitude on investor behavior, we use a unique database that consists of all the orders and transactions of securities traded on Euronext Paris from March to December 2017. We focus on limit orders placed by individual investors since these orders are more likely to reflect behavioral biases and less likely to come from automated trading compared to orders placed by institutional investors. We focus on the aggressiveness of limit orders. Order aggressiveness is defined as the distance between the order price and the best opposite limit of the order book (Bessembinder et al., 2009). We discriminate between marketable limit orders, which are limit orders placed beyond the best opposite limit and as such are immediately executable under normal conditions, and non-marketable limit orders, which are limit orders placed within the best opposite limit and thus not executed immediately.

We conjecture that distances between numbers are processed linearly on small price stocks (i.e., in absolute values), while these distances are processed logarithmically on large price stocks (i.e., in percentages). As a consequence, a given distance (in percentages) between the order price and the best limit is perceived as being smaller on small price stocks than on large price stocks. Thus, we expect retail investors to issue less (more) aggressive non-marketable (marketable) limit orders on small price stocks than on large price stocks.

To test this hypothesis, we use a sample of more than 3 million limit orders by retail investors on 334 stocks of the CAC All-Tradable index (Euronext Paris) from March to December 2017. We find that order aggressiveness magnitude is positively linked with nominal stock prices. Specifically, we group stocks according to six price categories: 0 to 10 euros, 10 to 20 euros, 20 to 30 euros, 30 to 40 euros, 40 to 50 euros, and above 50 euros. For marketable orders, the order aggressiveness ranges from 0.10% to 0.04% and is monotonically decreasing in the price categories. While statistically significant, the differences in order aggressiveness do not appear to be economically relevant and are more likely explained by other drivers of aggressiveness that correlate with stock prices. For non-marketable limit orders, the order aggressiveness is equal to -3.52% for stocks that are priced below 10 euros. It decreases monotonically in the price categories to reach -1.57% for stocks priced above 50 euros. For non-marketable orders, these differences are both statistically and economically relevant.

Other factors that influence order aggressiveness may correlate with stock price levels. For instance, liquidity is likely to differ across price categories. To confirm that the link between order aggressiveness and stock price magnitude is indeed driven by number perception, we control for a number of other factors. The first liquidity issue that comes to mind is the relative tick size (Angel, 1997). While relative tick size may have an impact on order aggressiveness, the rules in place (MIFID 1) for stocks traded on Euronext Paris over our sample period imply very small relative tick sizes. The tick size is 0.001 euros for stock prices between 0 and 9.999 euros, 0.005 euros between 10.000 and 49.995 euros, 0.01 euros in the 50.00–99.99 range, and 0.05 euros above 100 euros. Excluding stocks priced below 1 euro, the maximum relative tick size is 0.1%.

Beyond the relative tick size, other factors may influence order aggressiveness. Previous studies show that the state of the order book, the trading conditions, the characteristics of orders, as well as firm-specific factors are likely to influence both the type of order investors select (limit orders/market orders) and its price (for limit orders). Griffiths et al. (2000) find that traders submit aggressively priced orders when the bid–ask spread is narrow, same-side order depth is high, and other-side depth is low, consistent with the crowding out hypothesis of Parlour (1998). Rinaldo (2004) and Bessembinder et al. (2009) report that slow order arrival and high trading activity are associated with more aggressive orders, consistent with the theoretical prediction of Foucault et al. (2005). Griffiths et al. (2000) find that the likelihood of an aggressive order decreases with firm size. Finally, Rinaldo (2004), Bessembinder et al. (2009), and Lo and Sapp (2010) observe that in turbulent market conditions characterized by high volatility, orders are less aggressive, consistent with the theoretical prediction of Foucault (1999).

In our main analysis, we regress the aggressiveness of non-marketable orders on price category dummies while controlling for factors known to influence order aggressiveness. We include in the controls the following variables: the relative spread, the same-side and opposite-side depth at the best prices, the order book imbalance, the number of transactions, and the volatility. Our results indicate that the relation between order aggressiveness and stock price holds when the usual drivers of aggressiveness are controlled for. We find statistically significant evidence of a monotonic link between order aggressiveness and price categories even when the different controls are introduced.

To test for the possibility that our results are driven by differences in market dynamics between small price stocks and large price stocks, we analyze limit orders issued by high-frequency traders (HFTs). Since orders submitted by such market players often result from an automated process, they are not influenced by behavioral biases. It follows that we should not observe any difference in order aggressiveness between small price stocks and large price stocks when controlling for liquidity differences. The empirical analysis of HFT orders confirms our conjecture. We do not find a link between price level and order aggressiveness for such market players.

We also examine the consequences of this small price bias on the costs faced by retail investors. The less aggressive an order, the lower its execution cost (if executed), but the lower its execution probability. We find that the non-marketable limit orders submitted by retail investors have positive implementation costs, since their favorable price impacts are fully offset by their opportunity

costs of non-execution. The imbalance between the favorable price impacts and the opportunity costs of non-execution is more pronounced for small price stocks. Since opportunity costs greatly outweigh price improvements, small price stocks exhibit higher implementation costs compared to large price stocks.

Our paper contributes to several strands of literature. First, we add to the microstructure literature and, more specifically, to the literature on order aggressiveness. Most researchers analyze order aggressiveness through the lens of market liquidity. Order aggressiveness has been shown to be driven by the state of the order book (Parlour, 1998; Griffiths et al., 2000) and by market dynamics (Foucault, 1999; Rinaldo, 2004; Bessembinder et al., 2009; Lo and Sapp, 2010). Others look at order characteristics (Lo and Sapp, 2010) and firm characteristics (Griffiths et al., 2000) to explain the aggressiveness of market and limit orders. Finally, Bian et al. (2017) provide evidence that the disposition effect and the house money effect influence the aggressiveness of orders submitted by retail investors. Our paper offers new insights by showing that nominal price level matters for individual investors' limit orders.

Second, our paper contributes to the literature on nominal stock prices. Previous papers show that individual investors have a preference for low-priced stocks (Copeland, 1979; Schultz, 2000; Kumar and Lee, 2006; Kumar, 2009). Birru and Wang (2016) explain this preference by nominal price illusion, that is, investors overestimating the room to grow for low-priced stocks. Our results are at odds with this explanation since we find that individual investors issue less aggressive non-marketable limit orders for small price stocks than for large price stocks. Our empirical results provide support, however, to a behavioral bias caused by a differential processing of small prices and large prices.

Our paper contributes to a better understanding of retail investors' behavior and has potential implications for policy making. In this regard, we contribute to the growing literature on financial literacy. As defined by Lusardi and Mitchell (2014), financial literacy refers to the ability of individuals to process economic information and make informed decisions. Numeracy and, more generally, number perception precede the acquisition of financial literacy.³ Identifying the biases in number perception and addressing them is thus crucial. As highlighted by Campbell (2006) in his AFA presidential address, "If household finance can achieve a good understanding of the sources of investment mistakes, it may be possible for the field to contribute ideas to limit the costs of these mistakes.". Our paper contributes to a better knowledge of the behavior of individual investors by identifying a systematic bias in number perception, which impacts order submission and hurts retail investment performance. Since this bias in number perception is deeply rooted in the human brain, it is likely that all investors exhibit such a bias, regardless of their financial literacy.

2. Data and measures

2.1. Data

Our data come from the European High Frequency Database BEDOFIH.⁴ This database provides order and trade records on all financial instruments admitted to trading on Euronext Paris for which the Autorité des Marchés Financiers (AMF), the French financial market regulator, is the competent supervisory authority.⁵ The data contain detailed information on every order and trade including, among other things, the price, the size, the initiating side of the order (buyer- or seller-initiated), the date and time of submission, the date and time of the transaction(s) related to the order (if any), and the date and time of revision, cancellation, or expiration (if any). Finally, one of the fields associated with each order, the Account Code, specifies whether the order originates from a retail investor and is executed by a Retail Member Organization (RMO). When an order is flagged with the dedicated RMO flag, it receives preferential routing through Euronext's Best of Book service where dedicated liquidity providers (Retail Liquidity Providers, RLPs) offer price improvement.⁶ The Best of Book service provides an additional layer of liquidity for retail flow within Euronext's Central Order Book. A group of RLPs compete to offer quotes that are placed at or better than the European Best Bid and Offer (EBBO). In addition to price improvement, the Best of Book service also offers lower execution costs to retail investors since no charge applies to executed orders. At the end of 2017, Euronext reports that all Euronext's retail brokers use the Best of Book service.⁷ For the empirical analysis, Euronext Paris order book and Retail Liquidity Provider (RLP) quotes are rebuilt at every point in time. Another key feature of the data set is that for each order the type of the member who submits it is known. The type refers to the classification of Euronext Paris's members defined by the AMF based on the lifetime of canceled orders (pure-HFTs, investment banks with HFT activity (IB-HFTs), and non-HFTs).⁸

³ In fact, the standard set of questions commonly used to evaluate financial literacy (Lusardi and Mitchell, 2008) starts with a question designed to estimate numeracy.

⁴ <https://www.eurofidai.org/en/high-frequency-data-bedofih>.

⁵ The AMF is the competent supervisory authority for instruments whose market of reference is Euronext Paris.

⁶ The Best Execution service for retail orders has been offered by Euronext since 2013. At launch, the service, called Retail Matching Facility (RMF), was only available for the component securities of the major national indices (for Euronext Paris, the components of the CAC 40). In June 2016, building on the existing RMF service, Euronext launched the Extended RLP Programme, which covers a much larger set of instruments (for Euronext Paris, the components of the CAC 40, CAC Next 20, CAC Mid 60, and some other midcaps). Euronext changed the name of its Best Execution service to Best of Book in November 2016.

⁷ <https://bit.ly/3723dqk>.

⁸ The AMF classifies Euronext Paris members according to the lifetime of their canceled orders (Autorité des Marchés Financiers, 2017). A participant is considered as a pure-HFT if it meets one of the following conditions: (1) the average lifetime of its canceled orders is less than the average lifetime of all orders in the book and it has canceled at least 100,000 orders during the year; (2) the participant must have canceled at least 500,000 orders with a lifetime of less than 0.1 s and the top percentile of the lifetime of its canceled orders must be less than 500 microseconds. If an investment bank meets one of these conditions, it is described as a mixed HFT or as an investment bank with HFT activity (IB-HFT). A participant is considered as non-HFT if it meets none of the above criteria. The classification is revised once a year but changes are rare. According to the AMF, there are 10 to 20 pure-HFTs, 10 to 20 IB-HFTs, and 100 to 150 non-HFTs operating on Euronext Paris.

Table 1
Sample selection and descriptive statistics.

Panel A: Stock selection	
Instruments	46,669
Equities	971
Traded continuously	596
Traded on regulated market	455
Stocks in the CAC All-Tradable index	345
Foreign equities trading groups	(3)
Compulsory buy-out offer trading group	(2)
Stocks with missing data	(6)
Stocks included in the final sample	334
Stocks with a Retail Liquidity Provider	286
Panel B: Order statistics and selection	
All trading phases	
New order submissions	1,663,187,707
Account	
by Retail Member Organizations (RMOs)	5,355,313
by Retail Liquidity Providers	153,911,361
by Liquidity Providers	1,088,772,083
by other accounts	415,148,950
Member type	
by pure high frequency traders (HFTs)	977,192,232
by Investment Banks HFT	664,406,730
by non-HFTs	21,588,745
Continuous trading phase	
Number of traded shares	22,478,028,702
by Retail Member Organizations	2,866,860,517
Trading volume in euro	609,444,157,786
by Retail Member Organizations	17,171,132,733
New order submissions by RMOs	3,680,154
Market orders	421,773
Limit orders	3,239,818
Marketable limit orders	974,447
Non-marketable limit orders	2,265,371
Panel C: Descriptive statistics	
Average daily market capitalization (millions of euros)	6125
Average daily relative spread (basis points)	65.80

Panel A details how the 334 sample stocks are chosen among the instruments available in the BEDOFIH AMF Euronext Paris database from March 2017 to December 2017. The database includes equities, exchange-traded funds, bonds, and structured products traded either continuously or through auctions, on Euronext Paris regulated market or on multilateral trading facilities operated by Euronext Paris. Panel B describes the nature of the market participants. The account indicates whether the order is submitted by a Retail Member Organization (RMO), a Retail Liquidity Provider, or a Liquidity Provider. The type refers to the classification of members defined by the Autorité des Marchés Financiers based on the lifetime of canceled orders (pure-HFT, investment bank with HFT activity and non-HFT). Panel B also show the number of shares traded and the trading volume in euro by all market participants and by RMO as well as the nature of the orders submitted by RMOs during the continuous trading phase. Panel C reports the average daily market capitalization and relative spread of the sample stocks.

2.2. Sample selection and statistics

We examine the relation between retail investors' order aggressiveness and nominal prices for a broad cross-section of firms listed on Euronext Paris. Panel A of [Table 1](#) provides details on our stock selection process. Our initial sample consists of all instruments available in the BEDOFIH AMF Euronext Paris database between March 1, 2017 and December 29, 2017. We first restrict the sample to equity-type instruments ($N = 971$) and eliminate stocks only traded through auctions or not listed on Euronext Paris regulated market.⁹ We then focus on stocks that are part of the CAC All-Tradable index in 2017. The CAC All-Tradable contains all the stocks traded on Euronext Paris that have an annual free float velocity of at least 20%.¹⁰ We also exclude stocks that belong to foreign equities, compulsory buy-out offer trading groups, and stocks with missing data. These filters reduce the sample size to 334 stocks. For 286 of them, there is at least one RLP.

⁹ Other instrument types include exchange-traded funds, bonds, and structured products. Euronext Paris also operates multilateral trading facilities: the Free Market (Euronext Access) and Alternext (Euronext Growth).

¹⁰ The free float velocity is defined as the ratio of the regulated trading volume to the free float adjusted number of shares issued by the company.

Table 2
Order aggressiveness and nominal stock prices.

	Average aggressiveness	Average aggressiveness of non-marketable orders	Average aggressiveness of marketable orders
All stocks	-0.0191	-0.0277	0.0008
<10 €	-0.0262	-0.0352	0.0010
[10,20[-0.0165	-0.0242	0.0008
[20,30[-0.0153	-0.0223	0.0009
[30,40[-0.0136	-0.0206	0.0007
[40,50[-0.0110	-0.0175	0.0006
≥50 €	-0.0090	-0.0157	0.0004
Difference	-0.0173***	-0.0195***	0.0006***
Welch <i>t</i> -statistics	-244.55	-190.20	81.80

The table reports the average aggressiveness for all limit orders, for non-marketable limit orders, and for marketable limit orders submitted by retail investors via Retail Member Organizations. Order aggressiveness is defined as the distance between the limit order price and the best opposite limit of the order book divided by the midpoint at the time of order submission. The first row displays average values across all stocks. The remaining rows show the average order aggressiveness in the different price ranges where orders are assigned to price ranges according to the stock opening price. Difference is the aggressiveness differential between stocks priced below 10 euros and stocks priced above 50 euros. *** denotes statistical significance of the difference according to the Welch test at the 1% level.

Table 3
Order aggressiveness — Double sort on market capitalization (liquidity) and nominal stock prices.

Panel A: Market capitalization				
	Small	Medium	Large	
<10 €	-0.0434	-0.0257	-0.0233	
[10,20[-0.0246	-0.0262	-0.0207	
[20,30[-0.0267	-0.0232	-0.0185	
[30,40[-0.0229	-0.0207	-0.0187	
[40,50[-0.0257	-0.0202	-0.0145	
≥50 €	-0.0233	-0.0182	-0.0141	
Difference	-0.0200***	-0.0074***	-0.0093***	
Welch <i>t</i> -statistics	-33.76	-46.99	-23.64	
Panel B: Liquidity (relative spread, in %)				
	Low	Medium	High	
<10 €	-0.0450	-0.0293	-0.0202	
[10,20[-0.0278	-0.0246	-0.0215	
[20,30[-0.0261	-0.0230	-0.0194	
[30,40[-0.0235	-0.0207	-0.0190	
[40,50[-0.0254	-0.0199	-0.0149	
≥50 €	-0.0242	-0.0173	-0.0143	
Difference	-0.0208***	-0.0121***	-0.0060***	
Welch <i>t</i> -statistics	-65.43	-66.50	-37.48	

Panel A reports the average order aggressiveness of non-marketable limit orders submitted by retail investors for stocks that are sorted on nominal stock price and, respectively, on firm size (Panel A) and liquidity (Panel B). In Panel A, the three size categories are defined with the following market capitalization breakpoints: 30% (small), 40% (medium) and 30% (large). In Panel B, the three liquidity categories are defined with the following relative spread (measured as the difference between the best ask and the best bid divided by the midpoint at the time of order submission, in percent) breakpoints: 30% (low), 40% (medium) and 30% (high). Difference is the aggressiveness differential between stocks priced below 10 euros and stocks priced above 50 euros. *** denotes statistical significance of the difference according to the Welch test at the 1% level.

In Panel B of [Table 1](#), we describe the order selection process. During the sample period, market participants submit more than 1.6 billion orders for our sample stocks. More than 1.2 billion orders are posted by (retail) liquidity providers and 5.4 million orders are submitted by retail investors via Retail Member Organizations (RMOs). An overwhelming proportion of the order messages come from fast traders (Pure-HFTs and IB-HFTs). We focus on RMO orders posted during the continuous trading session (between CET 9:00 am and 5:30 pm); orders submitted during the opening auction, closing auction, and trading-at-last phase are excluded. There are 421,773 market orders and 3,239,818 limit orders submitted by RMOs during the continuous trading phase. Seventy percent of limit orders are not immediately executable (non-marketable), which indicates that retail investors use limit orders mostly to post passive orders (buy orders below the best ask or sell orders above the best bid).

Finally, Panel C of [Table 1](#) reports descriptive statistics for the selected sample. The average daily market capitalization of the stocks is 6.13 billion euros and the average daily spread is 65.8 bps.¹¹

¹¹ Daily market capitalizations come from the EUROFIDAI daily stock database.

2.3. Order aggressiveness measure

We follow Bessembinder et al. (2009) and define the aggressiveness of an order as the distance of the limit order price from the opposite best price divided by the midpoint price. The price aggressiveness of a limit order i submitted at time t is defined as:

$$\begin{aligned} \text{Aggressiveness}_{i,t} &= \frac{P_{i,t} - \text{Ask}_t}{\text{Midpoint}_t} && \text{for a buy order} \\ &= \frac{\text{Bid}_t - P_{i,t}}{\text{Midpoint}_t} && \text{for a sell order.} \end{aligned} \quad (1)$$

where $P_{i,t}$ is the price at which a retail investor submits the order, Bid_t and Ask_t are the best bid and offer at time t , and $\text{Midpoint}_t = \frac{(\text{Bid}_t + \text{Ask}_t)}{2}$ is the midpoint price at time t . Since retail orders submitted via RMOs can be executed against RLP quotes or against the order book, the opposite best price is defined as the best of the two (the highest bid for a sell order and the lowest ask for a buy order). The measure is suitably signed such that a higher value indicates a more aggressively priced order and a positive (negative) measure indicates a (non-)marketable limit order.

3. Empirical analysis

3.1. Univariate analysis

Table 2 shows the relation between nominal stock prices and order aggressiveness. Limit orders are assigned to six price ranges based on the opening price (0–10, 10–20, 20–30, 30–40, 40–50, and above 50 euros). Overall, the average aggressiveness is negative, which is consistent with the fact that there is a greater proportion of non-marketable limit orders than immediately executable ones. We observe a monotonic relation between the stock price and the aggressiveness. This dependence between aggressiveness and prices seems to be predominant for non-marketable limit orders. The relation is much weaker for marketable orders. It is unlikely, however, that marketable orders would exhibit any aggressiveness pattern. Indeed, for a typical retail investor who wishes to have its order executed immediately, it is usually sufficient to post an order at the opposite best limit or slightly above (below for a sell order). Since trades from individuals tend to be small, there is virtually no difference between posting a slightly aggressive order and a very aggressive one. Both order types will end up being executed under the same conditions. On the contrary, the aggressiveness of non-marketable limit orders has a direct link to stock valuation and the profit of the investment strategy. Hence, the choice of the order price has more economic meaning. As a result, non-marketable limit orders are more likely to exhibit aggressiveness patterns. We thus focus on this type of order in the remainder of the paper. In Table 2, the patterns we find for non-marketable limit orders are consistent with the use of different scales for small numbers and large numbers. The aggressiveness for non-marketable limit orders placed on stocks whose price is below 10 euros is equal to -3.52% , while it is -1.57% for stocks whose price is above 50 euros. This difference is statistically significant.

Obviously, these differences in aggressiveness between small price stocks and large price stocks may also be caused by differences in firm characteristics and especially by differences in liquidity. To disentangle the price effect with alternative effects, such as a size effect or a liquidity effect, we first use double sorts based on the price categories previously defined, and then use categories based on market capitalization (respectively, relative spread). Panel A of Table 3 provides the average order aggressiveness of non-marketable orders in the different price categories for each size category. Overall, the relation between stock price and order aggressiveness is not impacted when we discriminate with respect to size or liquidity. In Panel A, we find that order aggressiveness increases with stock price. The difference in order aggressiveness between stocks priced below 10 euros and stocks priced above 50 euros, while being slightly smaller for larger market capitalization, is negative and statistically significant for the three size categories. We obtain similar results in Panel B when we assess the relation between order aggressiveness and stock price while filtering for liquidity. Again, we find that order aggressiveness is higher when stock price is larger. The differences in order aggressiveness are statistically significant for all three liquidity categories even though the magnitude of the effect is smaller for more liquid stocks. These different results confirm the idea that part of the effect we find in Table 2 is caused by small and large price stocks having different characteristics. However, these results also confirm that a price effect remains after discriminating by size and liquidity.

3.2. Multivariate analysis

3.2.1. Model

We use pooled ordinary least squares (OLS) regressions to analyze the relation between nominal stock price and order aggressiveness, controlling for a number of variables that have been shown in previous studies to explain order aggressiveness. We estimate the following regression:

$$\text{AGGRESSIVENESS}_{i,j,t} = \alpha + \sum_{k=1}^5 \beta_k \text{PRICE CATEGORY}_{i,j,t}^k + \gamma \text{CONTROLS}_{i,j,t} + \epsilon_{i,j,t}, \quad (2)$$

where $\text{AGGRESSIVENESS}_{i,j,t}$ is the aggressiveness of an order i posted at time t to buy or sell stock j . The five price-based dummy variables $\text{PRICE CATEGORY}_{i,j,t}^k$ identify the first five price categories (0–10, 10–20, 20–30, 30–40, and 40–50 euros). Specifically, $\text{PRICE CATEGORY}_{i,j,t}^k$ is equal to 1 if the opening price of stock j is in price category k ($k = 1, \dots, 5$) on day t and is 0 otherwise. Finally, $\text{CONTROLS}_{i,j,t}$ is a set of control variables discussed in Section 3.2.2. The statistical significance reported in the regressions is based on robust standard errors clustered by firm and day.

Table 4
Results of regressions of order aggressiveness on price categories.

	Model 1	Model 2
Intercept	-1.5699*** (0.0785)	-1.3204*** (0.0667)
<10 dummy	-1.9498*** (0.3171)	-0.9120*** (0.1263)
[10,20[dummy	-0.8530*** (0.1575)	-0.5495*** (0.1459)
[20,30[dummy	-0.6587*** (0.1168)	-0.4371*** (0.0969)
[30,40[dummy	-0.4915 (0.0965)	-0.2973*** (0.0907)
[40,50[dummy	-0.1775 (0.1371)	-0.1422* (0.0833)
Relative spread		-1.2205*** (0.0498)
Same side depth		-0.0000 (0.0002)
Opposite side depth		-0.0003* (0.0001)
Order book imbalance		0.5846*** (0.0887)
Number of transactions		0.0359 (0.0454)
Volatility		-0.1823*** (0.0368)
Market capitalization		-0.0005 (0.0017)
Number of observations	2,265,371	2,265,371
Adjusted R-squared	1.44%	7.97%

The table reports parameter estimates and standard errors of pooled OLS regressions of retail order aggressiveness on price categories. Order aggressiveness is defined as the distance between the limit order price and the best opposite limit of the order book divided by the midpoint at the time of order submission (in percent). The five price-based dummy variables identify the first five price categories (0–10, 10–20, 20–30, 30–40, and 40–50 euros). Each dummy equals one if the stock opening price is in its price category and 0 otherwise. Model 2 includes control variables: the ratio of the quoted spread to the midpoint, in percent (relative spread); the displayed depth on the same side as the order, in thousands of shares (same side depth); the displayed depth on the opposite side, in thousands of shares (opposite side depth); the ratio of the difference between the displayed depth on the same and opposite sides in the 10 best limits to the total displayed depth in the 10 best limits, suitably signed (order book imbalance); the number of transactions in the last 30 min, in thousands of shares (number of transactions); the 1-minute realized volatility of midpoint returns over the last 30 min, in percent (volatility); the daily market capitalization, in billion euros (market capitalization). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on robust standard errors (in parentheses) clustered by firm and day.

3.2.2. Control variables

Previous studies show that the state of the order book, the trading conditions, order characteristics, as well as some firm-specific factors are likely to influence order aggressiveness (Griffiths et al., 2000; Rinaldo, 2004; Bessembinder et al., 2009; Lo and Sapp, 2010). We include the following variables to control for these alternative explanations.

Relative spread is the difference between the best ask and the best bid divided by the midpoint at the time of submission, in percent. Griffiths et al. (2000) point out that a wide bid–ask spread allows traders to submit passive orders that gain priority over the limit orders standing in the order book. Moreover, Handa et al. (2003) show that the bid–ask spread is a function of both adverse selection and differences in valuation. As a result, when the bid–ask spread is wide, limit order traders ask for a larger compensation to supply liquidity and limit orders are less aggressively priced. We, therefore, expect a negative relation between the relative spread and order aggressiveness.

Same-side and opposite-side depth at the best prices are the displayed depth on the same side as the order (for a sell order, the depth at the best bid and for a buy order at the best ask) and on the opposite side, in thousands of shares. Parlour (1998) shows that traders take into account the state of the order book at the time of submission, as well as the expected order flow to determine the execution probability of their order and that both sides of the market affect traders' decisions. On one hand, due to price-time priority rules, the greater the depth at the best quote on the order side, the lower the execution probability of an order submitted at the best quote or below. To increase the likelihood of execution, traders need to submit more aggressive orders. On the other hand, the higher the depth at the best quote on the opposite side, the more aggressive the future orders are expected to be on the other side, and therefore the higher the execution probability of a limit order. We expect to see a positive (negative) relation between same-side (opposite-side) depth and order aggressiveness.

Order book imbalance is the ratio of the difference between the displayed depth on the same and opposite sides in the 10 best limits to the total displayed depth in the 10 best limits, suitably signed (the order book imbalance is positive if same-side depth

Table 5
Results of regressions of high frequency traders' order aggressiveness on price categories.

	Model 1	Model 2
Intercept	−0.0607*** (0.0039)	0.0063 (0.0133)
<10 dummy	−0.1352** (0.0572)	0.0143 (0.0387)
[10,20[dummy	−0.0402*** (0.0091)	0.1026 (0.0918)
[20,30[dummy	−0.0228** (0.0114)	0.0431 (0.0396)
[30,40[dummy	−0.0271* (0.0163)	0.0154 (0.0101)
[40,50[dummy	0.0101 (0.0085)	0.0043 (0.0040)
Relative spread		−1.6282*** (0.1721)
Same side depth		−0.0151 (0.0133)
Opposite side depth		−0.0162 (0.0145)
Order book imbalance		0.0152*** (0.0041)
Number of transactions		0.0045 (0.0065)
Volatility		−0.0132 (0.0228)
Market capitalization		0.0002 (0.0002)
Number of observations	9,401,319	9,401,319
Adjusted R-squared	0.49%	6.42%

The table reports parameter estimates and standard errors of pooled OLS regressions of pure-HFT order aggressiveness on price categories. The Autorité des Marchés Financiers identifies HFTs on Euronext Paris according to the lifetime of their canceled orders. For each firm, each day we randomly pick one percent of pure-HFT orders. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on robust standard errors (in parentheses) clustered by firm and day.

exceeds opposite-side depth). Following [Parlour \(1998\)](#), we expect a positive relation between order book imbalance and order aggressiveness.

Number of transactions is the number of transactions in the last 30 min, in thousands of shares. [Bessembinder et al. \(2009\)](#) suggest that traders post more aggressive orders when recent trading activity is important. We expect a positive relation between the number of transactions and the order aggressiveness.

Volatility is the 1-minute realized volatility of the midpoint returns over the last 30 min, in percent. [Foucault \(1999\)](#) finds that the volatility of the asset is a main determinant of the market/limit order tradeoff. In his model, traders cannot revise or cancel the limit orders they post. An increase in volatility raises the risk of being picked off. As a result, limit order traders ask for a larger compensation, trading using market orders or marketable limit orders becomes more costly, and more traders switch from market to limit orders. We expect a negative relation between volatility and order aggressiveness.

Firm size is the daily market capitalization in billion euros. Small firms tend to have lower analyst coverage ([Bhushan, 1989](#)) and therefore more information asymmetry than large firms. To profit from this advantage, informed traders are expected to place more aggressive orders ([Griffiths et al., 2000](#)) whereas liquidity traders are expected to place less aggressive limit orders. We expect a positive relation between firm size and non-marketable order aggressiveness.

3.2.3. Results

[Table 4](#) reports the multivariate regression results. The first column shows the coefficients and standard errors of the baseline model (Model 1), in which no control variables are included. The coefficients of the price category dummies are negative and highly significant (except for the [40,50[dummy). More importantly, the magnitude of the coefficient decreases monotonically in the price level. These results are similar to the analysis for [Table 2](#). In Model 2, we add control variables to take into account potential differences in liquidity, trading conditions, and risk, between small price stocks and large price stocks. The coefficient for the lowest price category dummy variable (< 10 euros) is equal to −0.9029 and is significant at the 1% level. Similarly, the coefficients of the other price category dummy variables are negative and increase monotonically with the price level. The inclusion of controls does not alter the link between order aggressiveness and price level. The signs of the control variables are as expected.

Table 6
Results of regressions of order aggressiveness on price categories by order size magnitude.

	Small orders		Large orders	
	Model 1	Model 2	Model 3	Model 4
Intercept	-1.6897*** (0.0977)	-1.2026*** (0.0939)	-1.4910*** (0.0929)	-1.3962*** (0.0749)
<10 dummy	-2.0567*** (0.3072)	-1.0655*** (0.1270)	-1.7397*** (0.3415)	-0.7756*** (0.1562)
[10,20[dummy	-0.7803*** (0.2392)	-0.5648** (0.2516)	-0.8763*** (0.2152)	-0.5878*** (0.1372)
[20,30[dummy	-0.6010*** (0.1096)	-0.5006*** (0.1016)	-0.6792*** (0.1830)	-0.4100*** (0.1498)
[30,40[dummy	-0.3447*** (0.0978)	-0.3322*** (0.0938)	-0.5990*** (0.1503)	-0.2963** (0.1440)
[40,50[dummy	-0.3364*** (0.1249)	-0.1913 (0.1230)	-0.0480 (0.1679)	-0.1108 (0.0920)
Relative spread		-1.1634*** (0.0517)		-1.3519*** (0.0670)
Same side depth		0.0000 (0.0002)		-0.0003* (0.0002)
Opposite side depth		-0.0004** (0.0002)		-0.0001*** (0.0000)
Order book imbalance		0.5537*** (0.1026)		0.6296*** (0.0895)
Number of transactions		-0.0731 (0.0698)		0.1133*** (0.0339)
Volatility		-0.2042*** (0.0429)		-0.1310*** (0.0365)
Market capitalization		-0.0067* (0.0036)		0.0022 (0.0014)
Number of observations	1,176,234	1,176,234	1,089,137	1,089,137
Adjusted R-squared	1.57%	9.75%	1.19%	5.94%

The table reports parameter estimates and standard errors of pooled OLS regressions of retail order aggressiveness on price categories. Models 1 and 2 (3 and 4) correspond to the subsample of small orders (large orders). An order is considered small (large) if it is smaller (larger) than the median order (about 1960 euros for our sample). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on robust standard errors (in parentheses) clustered by firm and day.

3.3. Small price bias and HFT investors

While the previous results are consistent with the co-existence of two different processing scales for small price stocks and large price stocks, we cannot dismiss the possibility that the differences in order aggressiveness between small price stocks and large price stocks are driven by differences in economic factors and market dynamics. To tackle this issue, we consider an additional analysis involving a different type of market player, pure-HFTs. Since limit orders from HFT players are most often automated and/or follow pre-determined strategies, they should not exhibit a behavioral bias. Thus, if the difference in order aggressiveness we find among individual investors relates to a behavioral bias, it should not be observed when studying HFT limit orders. On the contrary, if the difference in order aggressiveness is caused by market dynamics, we will also find a difference in order aggressiveness between small price stocks and large price stocks. For each firm in our sample, each day we randomly pick one percent of pure-HFT orders. [Table 5](#) provides the results of the regression of order aggressiveness on the different price dummies. As in [Table 4](#), we first present results without controls (Model 1) and we then add controls (Model 2). In Model 1, the coefficients of the price dummies are mainly increasing in the price level and are significant. However, the inclusion of controls in Model 2 sharply changes the magnitude and significance of the price dummies. We no longer find a relation between price level and order aggressiveness. This negative result for HFTs provides support for our previous findings on individual investors and indicate the existence of a behavioral bias.

3.4. Differences in information versus small price bias

An alternative explanation for our results could be the possibility that investors who trade on small price stocks and large price stocks differ in terms of available information.¹² Indeed, as shown by [Griffiths et al. \(2000\)](#), informed traders are likely to use aggressive orders to ensure execution. The general view is that retail investors are noise traders. However, recent studies ([Kelley and Tetlock, 2013, 2017](#)) show that retail investors' orders are predictive of future returns. Hence, a difference in order aggressiveness between small price stocks and large price stocks could be found if more informed retail investors trade large price stocks. This subsection is dedicated to discarding this alternative explanation.

¹² We thank the reviewer for pointing out this alternative explanation.

Table 7
Proportion of market orders and marketable limit orders by price, firm size and liquidity categories.

	Market orders			Marketable limit orders		
	Small firms			Small firms		
	Illiquid	Medium	Liquid	Illiquid	Medium	Liquid
<10 €	7.02	7.84	12.47	20.32	31.08	45.65
[10, 20[6.72	6.47	8.33	16.71	23.92	49.16
[20, 30[9.02	8.40	11.18	22.64	31.22	44.53
[30, 40[9.79	12.13	11.15	24.32	33.29	48.22
[40, 50[10.34	13.35	15.95	27.41	32.38	47.99
≥50 €	6.02	11.18	13.15	21.85	39.11	53.00
	Medium-sized firms			Medium-sized firms		
	Illiquid	Medium	Liquid	Illiquid	Medium	Liquid
	Illiquid	Medium	Liquid	Illiquid	Medium	Liquid
<10 €	6.59	8.00	11.52	19.33	26.10	23.42
[10, 20[7.75	8.57	12.56	20.22	25.44	36.47
[20, 30[8.60	9.57	12.22	20.84	26.23	40.80
[30, 40[9.58	10.24	12.96	21.44	26.89	39.95
[40, 50[9.04	10.46	13.12	22.29	25.73	39.99
≥50 €	7.83	10.34	12.74	20.03	29.08	41.95
	Large firms			Large firms		
	Illiquid	Medium	Liquid	Illiquid	Medium	Liquid
	Illiquid	Medium	Liquid	Illiquid	Medium	Liquid
<10 €	11.47	13.00	14.06	19.42	33.22	45.51
[10, 20[60.00	14.86	16.58	50.00	25.33	43.98
[20, 30[33.33	15.64	17.14	16.67	42.44	37.78
[30, 40[21.43	14.12	19.40	36.36	49.90	48.97
[40, 50[30.00	15.92	17.90	28.57	40.20	42.20
≥50 €	17.73	16.42	21.63	17.24	40.68	47.00

The table reports the proportion of market orders (Columns 2 to 4) and marketable limit orders (Columns 5 to 7) submitted by retail investors for stocks that are sorted on nominal stock price, firm size and liquidity. The three size categories are defined with the following market capitalization breakpoints: 30% (small), 40% (medium), and 30% (large). The three liquidity categories are defined with the following relative spread (measured as the difference between the best ask and the best bid divided by the midpoint at the time of order submission) breakpoints: 30% (low), 40% (medium), and 30% (high). The proportion of market orders is defined as the ratio of market orders submitted to the total number of orders (limit orders and market orders), in percent. The proportion of marketable limit orders is defined as the ratio of marketable limit orders submitted to the total number of limit orders (marketable and non-marketable limit orders), in percent.

In a first approach, we consider that more wealthy retail investors are more likely to issue orders driven by information. Since our data do not allow us to identify traders, we use order size as a proxy for investor wealth. We split our sample into two subsamples: one containing small orders (below the median order size of 1960 euros) and one containing large orders (above the median order size). If the differences in aggressiveness between small price stocks and large price stocks are driven solely by differences in information, these differences should disappear when considering only small orders, which are less likely to be information-driven. [Table 6](#) provides the regression results for the two subsamples split by order size. Models 1 and 2 (3 and 4) correspond to the subsample of small orders (large orders). Overall, there are no major differences in aggressiveness between small orders and large orders. In both cases, we find that order aggressiveness is monotonically increasing in the price categories.

Another approach to test the information-driven explanation for the differences in order aggressiveness consists in looking at the proportion of market orders (respectively, marketable limit orders) compared to limit orders (non-marketable limit orders). If the observed differences in aggressiveness are driven by differences in information, we should also find that the proportion of market orders (respectively, marketable limit orders) issued by retail investors varies with price categories. Otherwise, we should not find any relation between the type of orders used and stock prices. Since the choice of order type by retail investors is also influenced by firm characteristics, such as size and liquidity, we triple sort stocks on price categories, size categories, and liquidity categories. [Table 7](#) provides the proportion of market orders and marketable limit orders for each sort. Overall, no clear patterns emerge, indicating that the choice between market orders and limit orders (respectively, marketable limit orders and non-marketable limit orders) is not influenced by the underlying price level.

Finally, since buy orders are more likely to be motivated by information ([Griffiths et al., 2000](#)), we investigate whether differences in aggressiveness across price categories can also be observed on sell orders, and not only on buy orders. [Table 8](#) presents the results of regressions of order aggressiveness on the different price dummies for the subsamples of buy orders and sell orders. The results are unchanged when looking at buy orders and sell orders separately: the coefficients associated to the price category dummies are negative and increase monotonically in the price level.

Overall, the results indicate that the differences in order aggressiveness between small price stocks and large price stocks are not caused by differences in information and suggest that a behavioral bias is indeed at play here.

Table 8
Results of regressions of order aggressiveness on price categories by order type (buy and sell).

	Buy orders		Sell orders	
	Model 1	Model 2	Model 3	Model 4
Intercept	-1.3975*** (0.0613)	-1.0715*** (0.0534)	-1.7770*** (0.1240)	-1.6705*** (0.1112)
<10 dummy	-1.2238*** (0.2582)	-0.3495*** (0.0823)	-2.8070*** (0.3890)	-1.5406*** (0.2024)
[10,20[dummy	-0.3857*** (0.1180)	-0.1306 (0.1018)	-1.3490*** (0.2590)	-0.9547*** (0.2464)
[20,30[dummy	-0.2244*** (0.0826)	-0.0585 (0.0546)	-1.1630*** (0.2240)	-0.8550*** (0.2029)
[30,40[dummy	-0.2175*** (0.0773)	-0.0942 (0.0658)	-0.8000*** (0.1820)	-0.5096*** (0.1673)
[40,50[dummy	-0.0414 (0.1280)	0.0249 (0.0816)	-0.3450** (0.1610)	-0.3410*** (0.1254)
Relative spread		-1.0863*** (0.0397)		-1.3565*** (0.0746)
Same side depth		0.0001 (0.0001)		-0.0003 (0.0002)
Opposite side depth		-0.0005*** (0.0001)		-0.0001 (0.0001)
Order book imbalance		0.2963*** (0.0418)		0.8862*** (0.1234)
Number of transactions		-0.0255 (0.0400)		0.0986* (0.0573)
Volatility		-0.1958*** (0.0393)		-0.1487*** (0.0432)
Market capitalization		-0.0015 (0.0014)		0.0017 (0.0024)
Number of observations	1,220,646	1,220,646	1,044,725	1,044,725
Adjusted R-squared	1.48%	13.20%	1.72%	6.76%

The table reports parameter estimates and standard errors of pooled OLS regressions of retail order aggressiveness on price categories. Models 1 and 2 (3 and 4) correspond to buy orders (sell orders). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on robust standard errors (in parentheses) clustered by firm and day.

Table 9
Implementation shortfall of non-marketable limit orders.

	All stocks	<10 €	[10,20[[20,30[[30,40[[40,50[≥50 €	Difference
Fill rate	47.01	43.90	45.86	51.09	50.79	53.95	53.25	-9.35***
Time to full execution	45	48	41	43	48	41	43	5***
PI of executed orders	-0.4837	-0.6727	-0.4216	-0.3669	-0.2790	-0.2635	-0.2071	-0.4656***
OPC for unfilled orders	0.5930	0.8698	0.5102	0.4688	0.3544	0.3821	0.3189	0.5509***
Change in midpoint	0.4233	0.5082	0.3854	0.4276	0.2947	0.2651	0.2010	0.3072***
PI of a market order	0.1697	0.3616	0.1180	0.1170	0.1248	0.0597	0.0413	0.3203***
Implementation shortfall	0.0861	0.1911	0.0817	0.0403	0.0317	0.0336	0.0387	0.1524***

The table reports the implementation shortfall of non-marketable limit orders submitted by retail investors. The fill rate (FR) is the ratio of shares traded to the order size in shares, in percent. Time to full execution is the time the order stays in the order book before full execution (conditional on FR = 1), in minutes. The price impact (PI) of an executed sell order is computed as the logarithm of the ratio of the midpoint prevailing at order arrival time $t = 0$ divided by the volume-weighted fill price of the order, in percent. The opportunity cost (OPC) of an unfilled sell order is defined as the change in midpoint from the order arrival time $t = 0$ until the time the order expires, is canceled, or modified $t = T$ plus the average execution cost of a market order for the appropriate price category, in percent. These two cost measures are analogously defined for buy orders. The implementation shortfall of an order is the sum of the product of the fill rate and the price impact and the product of one minus the fill rate and the opportunity cost, in percent. Difference in means between small and large price stocks are shown in the last column. *** denotes statistical significance of the difference according to the Welch test at the 1% level.

3.5. Order submission costs and small price bias

We next examine the consequences of the small price bias on the costs faced by retail investors. The less aggressive an order, the lower its execution cost (if executed), but the lower its execution probability. The potential favorable price impact must therefore be weighed against the opportunity cost of non-execution.

To measure the net cost for retail investors, we use the implementation shortfall (Perold, 1988). The implementation shortfall $ISF_{i,j}$ of order i on stock j is the sum of an effective execution cost (or price impact) $PI_{i,j}$ and an opportunity cost $OPC_{i,j}$:

$$ISF_{i,j} = FR_{i,j} \times PI_{i,j} + (1 - FR_{i,j}) \times OPC_{i,j}, \quad (3)$$

where $FR_{i,j}$ is the order i fill rate (i.e., the ratio of shares traded to the order size in shares).

Following Griffiths et al. (2000), the effective execution cost of an executed sell order is computed as the logarithm of the ratio of the midpoint prevailing at order arrival time $t = 0$ divided by the volume-weighted fill price of the order, and analogously for a

Table 10
Results of regressions of fill rate and order submission costs on price categories.

	Fill rate (%)	Price impact of executed non-marketable limit orders (%)	Opportunity cost for unfilled orders (%)	Implementation shortfall (%)
Intercept	52.2046*** (1.1447)	-0.1064*** (0.0083)	0.2729*** (0.0165)	0.0491*** (0.0081)
<10 dummy	-6.7712*** (1.4611)	-0.1355*** (0.0207)	0.3431*** (0.0262)	0.1386*** (0.0103)
[10,20[dummy	-6.6925*** (2.1447)	-0.0587*** (0.0136)	0.0652 (0.0399)	0.0329** (0.0136)
[20,30[dummy	-1.5597 (1.3596)	-0.0372*** (0.0110)	0.0335 (0.0276)	-0.0087 (0.0113)
[30,40[dummy	-1.0270 (1.4060)	0.0011 (0.0118)	-0.0305* (0.0173)	-0.0169** (0.0072)
[40,50[dummy	-0.1146 (1.3855)	-0.0236 (0.0186)	0.0408* (0.0218)	-0.0001 (0.0137)
Relative spread	-3.8617*** (0.9016)	-0.3445*** (0.0225)	-0.0028 (0.0103)	-0.0336*** (0.0114)
Same side depth	-0.0010 (0.0032)	-0.0001 (0.0001)	0.0003** (0.0002)	0.0004** (0.0002)
Opposite side depth	0.0027 (0.0020)	-0.0002*** (0.0001)	-0.0002 (0.0001)	-0.0003 (0.0002)
Order book imbalance	4.9647*** (0.7089)	0.1020*** (0.0112)	0.1565*** (0.0296)	0.0831*** (0.0250)
Number of transactions	1.8009*** (0.4612)	-0.0061 (0.0063)	0.0120 (0.0152)	-0.0180*** (0.0047)
Volatility	0.5136*** (0.1789)	-0.1591*** (0.0087)	0.1958*** (0.0181)	0.0231*** (0.0075)
Market capitalization	-0.0026 (0.0189)	0.0004** (0.0002)	-0.0017** (0.0007)	-0.0000 (0.0002)
Number of observations	1,838,413	1,838,413	986,946	1,838,413
Adjusted R-squared	1.49%	2.18%	4.36%	0.56%

The table reports parameter estimates and standard errors of pooled OLS regressions of fill rate and order submission costs on price categories and control variables. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, based on robust standard errors (in parentheses) clustered by firm and day.

buy order:

$$\begin{aligned}
 PI_{i,j,sell} &= \log\left(\frac{\text{Midpoint}_{j,0}}{\text{Fill price}_i}\right) \\
 PI_{i,j,buy} &= \log\left(\frac{\text{Fill price}_i}{\text{Midpoint}_{j,0}}\right).
 \end{aligned} \tag{4}$$

A negative price impact reflects the price improvement relative to the midpoint prevailing at the time of order submission.

The opportunity cost of an unfilled sell order is defined as the change in midpoint from the order arrival time ($t = 0$) until the order expires, is canceled, or modified ($t = T$), plus the execution cost of a market order, and analogously for a buy order:

$$\begin{aligned}
 OPC_{i,j,sell} &= \log\left(\frac{\text{Midpoint}_{j,0}}{\text{Midpoint}_{j,T}}\right) + PI_{\text{Market Order}} \\
 OPC_{i,j,buy} &= \log\left(\frac{\text{Midpoint}_{j,T}}{\text{Midpoint}_{j,0}}\right) + PI_{\text{Market Order}}.
 \end{aligned} \tag{5}$$

Opportunity costs are related to adverse selection. If some informed traders possess positive (negative) private information, they will buy (sell) prior to a market increase (decrease). As a consequence, buy (sell) limit orders will not be executed and have a positive opportunity cost. Implicitly, we assume that a canceled or expired order is immediately resubmitted as a market order (Harris and Hasbrouck, 1996).

Table 9 presents the fill rate, the time to full execution, and the implementation shortfall of non-marketable limit orders for the different price categories. We focus on orders that are executed, modified, or canceled within the day they were submitted. These orders represent 81.15% of the non-marketable limit orders submitted by the retail investors in our sample. The average fill rate across all stocks is 47.01% and the average time to full execution is 45 min. Non-marketable limit orders on small price stocks have lower fill rates (43.90% for stocks whose price is below 10 euros) compared to large price stocks (53.25% for stocks whose price is above 50 euros) but do not take longer to execute.

The price impacts of non-marketable limit orders (conditional on partial execution $FR > 0$) show that orders on small price stocks have lower effective costs than orders on large price stocks. It is not surprising though because these orders are less aggressive and thus end up being more profitable if successfully executed. On the other hand, the opportunity costs (conditional on non-full

execution $FR < 1$) decrease in price categories. The higher opportunity costs for small price stocks are caused both by more adverse price movements after order submission and larger execution costs of market orders. For all price categories, the favorable price impacts are offset by the opportunity costs of non-execution. Hence, non-marketable limit orders of retail investors have positive implementation costs. For small price stocks, opportunity costs greatly outweigh price improvements, thus resulting in higher implementation costs compared to large price stocks.

To account for potential differences in liquidity, market conditions, and risk between small price stocks and large price stocks, we next regress the fill rate, price impact, opportunity cost, and implementation shortfall on price dummies and control variables. Table 10 shows results consistent with the findings in Table 9. The coefficients of the price dummies are mainly increasing in the price level for the fill rate and the price impact whereas they are mainly decreasing in the price level for the opportunity cost and the implementation shortfall. Overall, the small price bias is detrimental to retail investors since it increases the costs they support when trading small price stocks.

4. Conclusion

We provide additional evidence that market participants, and more generally individuals, process small prices and large prices differently. We use a unique database that allows us to study limit orders submitted by both retail investors and HFTs on Euronext Paris. In line with the existence of a behavioral bias that impacts small price stocks, we find that retail investors submit orders that are further away from the best limit (i.e., less aggressive) on small price stocks than on large price stocks. This difference in order aggressiveness is not explained by differences in liquidity and market dynamics. We do not find differences in order aggressiveness when studying limit orders submitted by HFTs. This result is consistent with the idea that HFTs do not suffer from behavioral biases. Our paper adds to previous papers that look at the influence of stock price level (Birru and Wang, 2016; Roger et al., 2018). Our evidence does not support the idea that retail investors think of small stock prices as having more “room to grow” (Birru and Wang, 2016) but rather is consistent with a differential processing of large and small numbers (Roger et al., 2018, 2021). Finally, our paper relates, albeit more loosely, to the studies on the differential processing of prices and returns (Glaser et al., 2019; Shue and Townsend, 2021).

References

- Angel, J.J., 1997. Tick size, share prices, and stock splits. *J. Finance* 52 (2), 655–681.
- Autorité des Marchés Financiers, 2017. Study of the behaviour of high-frequency traders on Euronext Paris. Tech. rep., Autorité des Marchés Financiers.
- Baker, H.K., Gallagher, P.L., 1980. Management's view of stock splits. *Finan. Manage.* 32 (3), 73–77.
- Baker, M., Greenwood, R., Wurgler, J., 2009. Catering through nominal share prices. *J. Finance* 64 (6), 2559–2590.
- Bessembinder, H., Panayides, M., Venkataraman, K., 2009. Hidden liquidity: An analysis of order exposure strategies in electronic stock markets. *J. Financ. Econ.* 94 (3), 361–383.
- Bhushan, R., 1989. Firm characteristics and analyst following. *J. Account. Econ.* 11 (2), 255–274.
- Bian, J., Chan, K., Shi, D., Zhou, H., 2017. Do behavioral biases affect order aggressiveness? *Rev. Finance* 22 (3), 1121–1151.
- Birru, J., Wang, B., 2016. Nominal price illusion. *J. Financ. Econ.* 119 (3), 578–598.
- Campbell, J.Y., 2006. Household finance. *J. Finance* 61 (4), 1553–1604.
- Copeland, T.E., 1979. Liquidity changes following stock splits. *J. Finance* 34 (1), 115–141.
- Dehaene, S., Izard, V., Spelke, E., Pica, P., 2008. Log or linear? Distinct intuitions of the number scale in Western and Amazonian indigene cultures. *Science* 320, 1217–1220.
- Dyl, E.A., Elliott, W.B., 2006. The share price puzzle. *J. Bus.* 79 (4), 2045–2066.
- Fernando, C.S., Krishnamurthy, S., Spindt, P.A., 2004. Are share price levels informative? Evidence from the ownership, pricing, turnover and performance of IPO firms. *J. Financial Mark.* 7 (4), 377–403.
- Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order market. *J. Financial Mark.* 2 (2), 99–134.
- Foucault, T., Kadan, O., Kandel, E., 2005. Limit order book as a market for liquidity. *Rev. Financ. Stud.* 18 (4), 1171–1217.
- Glaser, M., Iliewa, Z., Weber, M., 2019. Thinking about prices versus thinking about returns in financial markets. *J. Finance* 74 (6), 2997–3039.
- Gompers, P., Metrick, A., 2001. Institutional investors and equity prices. *Q. J. Econ.* 116 (1), 229–259.
- Griffiths, M.D., Smith, B.F., Turnbull, D.S., White, R.W., 2000. The costs and determinants of order aggressiveness. *J. Financ. Econ.* 56 (1), 65–88.
- Handa, P., Schwartz, R., Tiwari, A., 2003. Quote setting and price formation in an order driven market. *J. Financial Mark.* 6 (4), 461–489.
- Harris, L., Hasbrouck, J., 1996. Market vs. Limit orders: The superdot evidence on order submission strategy. *J. Financ. Quant. Anal.* 31 (2), 213–231.
- Kelley, E.K., Tetlock, P.C., 2013. How wise are crowds? Insights from retail orders and stock returns. *J. Finance* 68 (3), 1229–1265.
- Kelley, E.K., Tetlock, P.C., 2017. Retail short selling and stock prices. *Rev. Financ. Stud.* 30 (3), 801–834.
- Kumar, A., 2009. Who gambles in the stock market? *J. Finance* 64 (4), 1889–1933.
- Kumar, A., Lee, C.M.C., 2006. Retail investor sentiment and return comovements. *J. Finance* 61 (5), 2451–2486.
- Laski, E.V., Siegler, R.S., 2007. Is 27 a big number? Correlational and causal connections among numerical categorization, number line estimation, and numerical magnitude comparison. *Child Develop.* 78 (6), 1723–1743.
- Lo, I., Sapp, S.G., 2010. Order aggressiveness and quantity: How are they determined in a limit order market? *J. Int. Financial Mark. Inst. Money* 20 (3), 213–237.
- Lusardi, A., Mitchell, O.S., 2008. Planning and financial literacy: How do women fare? *Amer. Econ. Rev.* 98 (2), 413–417.
- Lusardi, A., Mitchell, O.S., 2014. The economic importance of financial literacy: Theory and evidence. *J. Econ. Lit.* 52 (1), 5–44.
- Millroth, P., Juslin, P., 2015. Prospect evaluation as a function of numeracy and probability denominator. *Cognition* 138, 1–9.
- Mueller, S.M., Schiebener, J., Delazer, M., Brand, M., 2018. Risk approximation in decision making: approximative numeric abilities predict advantageous decisions under objective risk. *Cogn. Process.* 19 (3), 297–315.
- Nieder, A., 2005. Counting on neurons: The neurobiology of numerical competence. *Nat. Rev.* 6, 177–190.
- Park, I., Cho, S., 2018. The influence of number line estimation precision and numeracy on risky financial decision making. *Int. J. Psychol.* 54, 530–538.
- Parlour, C.A., 1998. Price dynamics in limit order markets. *Rev. Financ. Stud.* 11 (4), 789–816.
- Perez, M.F., Shkilkov, A., 2017. Catering through nominal share prices revisited. *Crit. Finance Rev.* 6 (1), 43–75.
- Perold, A.F., 1988. The implementation shortfall. *J. Portf. Manag.* 14 (3), 4–9.

- Peters, E., Slovic, P., Västfjäll, D., Mertz, C.K., 2008. Intuitive numbers guide decisions. *Judgment Decis. Making* 3 (8), 619–635.
- Ranaldo, A., 2004. Order aggressiveness in limit order book markets. *J. Financial Mark.* 7 (1), 53–74.
- Roger, T., Bousselmi, W., Roger, P., Willinger, M., 2021. Number processing and price dynamics: A market experiment. Working paper.
- Roger, T., Roger, P., Schatt, A., 2018. Behavioral bias in number processing: Evidence from analysts' expectations. *J. Econ. Behav. Organ.* 149, 315–331.
- Schley, D.R., Peters, E., 2014. Assessing economic value: Symbolic-number mappings predict risky and riskless valuations. *Psychol. Sci.* 25 (3), 753–761.
- Schultz, P., 2000. Stock splits, tick size, and sponsorship. *J. Finance* 55 (1), 429–450.
- Shue, K., Townsend, R.R., 2021. Can the market multiply and divide? Non-proportional thinking in financial markets. *J. Finance* 76 (5), 2307–2357.
- Siegler, R.S., Opfer, J.E., 2003. The development of numerical estimation: Evidence for multiple representations of numerical quantity. *Psychol. Sci.* 14 (3), 237–243.
- Viarouge, A., Hubbard, E., Dehaene, S., Sackur, J., 2010. Number line compression and the illusory perception of random numbers. *Exp. Psychol.* 57 (6), 446–454.
- Weld, W.C., Michaely, R., Thaler, R., Benartzi, S., 2009. The nominal share price puzzle. *J. Econ. Perspect.* 23 (2), 121–142.