Are retail investors less aggressive on small price stocks?

Carole Métais[*] Tristan Roger[†]

January 13, 2021

Abstract

In this paper, we investigate whether number processing impacts the limit orders of retail investors. Building on existing literature in neuropsychology that shows that individuals do not process small numbers and large numbers in the same way, we study the influence of nominal stock price level on order aggressiveness. Using a unique database that allows us to identify order and trade records issued by retail investors on Euronext Paris, we show that retail investors, when posting non-marketable orders, are less aggressive on small price stocks than on large price stocks. This difference in order aggressiveness is not explained by differences in liquidity and other usual drivers of order aggressiveness. We provide additional evidence by showing that no such difference exists for limit orders of high frequency traders (HFTs) over the same period and the same sample of stocks. This finding confirms that our results are driven by a behavioral bias and not by differential market dynamics between small price stocks and large price stocks.

[*]LaRGE Research Center, University of Strasbourg – Mailing address: 61 Avenue de la Forêt Noire, 67000 Strasbourg FRANCE – Email: cmetais@unistra.fr. I acknowledge support from the French State through the National Agency for Research under the program Investissements d'Avenir ANR-11-EQPX-006.

[†]DRM Finance, Université Paris-Dauphine, PSL Research University – Mailing address: Place du Maréchal de Lattre de Tassigny, 75775 Paris Cedex 16 FRANCE – Email: tristan.roger@dauphine.fr

1 Introduction

While conventional finance theory posits that nominal stock prices are irrelevant for firm valuation, 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; Dyl and Elliott, 2006; Fernando, Krishnamurthy and Spindt, 2004) 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, Krishnamurthy and Spindt, 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, Michaely, Thaler et al. (2009) suggest that firms comply with a market norm, splitting their stock to stay in an appropriate price range. Baker, Greenwood and Wurgler (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.[1] Birru and Wang (2016) indicate that investors overestimate the skewness of returns on low-priced stocks. Finally, Roger, Roger and Schatt (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 ini-

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

tially 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 processed with a linear scale while a logarithmic scale remains for larger numbers (Dehaene, Izard, Spelke et al., 2008; Viarouge, Hubbard, Dehaene 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, Slovic, Västfjäll 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, Schiebener, Delazer 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 the investor behavior, we use a unique database which consists in all the orders and transactions of the securities traded on Euronext Paris. 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. Our paper focuses 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, Panayides and

Venkataraman, 2009). We discriminate between marketable limit orders - *i.e.*, limit orders that are placed beyond the best opposite limit and as such immediately executable under normal conditions - and non-marketable limit orders -i.e., limit orders that are 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). 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 0.04% to 0.10% 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 stock priced below 10 euros. It decreases monotonically in the price categories to reach -1.57% for stock 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, Smith, Turnbull et al. (2000) find that traders submit aggressively priced orders when 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). Ranaldo (2004) and Bessembinder, Panayides and Venkataraman (2009) report that slow order arrival and high trading activity are associated with more aggressive orders, consistent with the theoretical prediction of Foucault, Kadan and Kandel (2005). Griffiths, Smith, Turnbull et al. (2000) find that the likelihood of an aggressive order decreases with firm size. Finally, Ranaldo (2004), Bessembinder, Panayides and Venkataraman (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 relationship between order aggressiveness and stock price holds when usual drivers of aggressiveness are controlled for. We find statistically significant evidence of a monotonic link between order aggressiveness and price categories even after introducing the different controls. 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 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 differences in liquidity. 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.

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 papers 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, Smith, Turnbull et al., 2000) and by market dynamics (Foucault, 1999; Ranaldo, 2004; Bessembinder, Panayides and Venkataraman, 2009; Lo and Sapp, 2010). Other papers look at order characteristics (Lo and Sapp, 2010) and firm characteristics (Griffiths, Smith, Turnbull et al., 2000) to explain the aggressiveness of market and limit orders. Finally, Bian, Chan, Shi 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 articles 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.

2 Data and measures

2.1 Data

Our data come from the European High Frequency Database BEDOFIH.[2] 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.[3] 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), the date and time of revision, cancellation or expiration (if any). Finally, one of the field 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

[2] `www.eurofidai.org/en/high-frequency-data-bedofih`

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

improvement.[4] 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 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.[5] For the empirical analysis, Euronext Paris order book and 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.[6]

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 the stock selection process. Our initial sample consists of all instruments

[4]The Best Execution service for retail orders is offered by Euronext since 2013. At his 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 launches 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 changes the name of its Best Execution service to *Best of Book* in November 2016.

[5]`https://bit.ly/3723dqK`

[6]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 he 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 second 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 mixed HFT or as an investment bank with HFT activity (IB-HFT). A participant is considered as non-HFT if he 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.

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 regulated market.[7] 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 market that have an annual free float velocity of at least 20%.[8] 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 Retail Liquidity Provider (RLP).

Panel B of Table 1 describes 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 9:00am and 5:30pm); 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. 70% 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

[7]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).

[8]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.

average daily market capitalization of the stocks is 6.13 billion euros and the average daily spread is 65.8 basis points.[9]

2.3 Order aggressiveness measure

We follow Bessembinder, Panayides and Venkataraman (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. The price aggressiveness of a limit order i submitted at time t is defined as:

$$\text{Aggressiveness}_{it} = \frac{P_{it} - \text{Ask}_t}{\frac{(\text{Bid}_t + \text{Ask}_t)}{2}} \qquad \text{for a buy order} \tag{1}$$

$$= \frac{\text{Bid}_t - P_{it}}{\frac{(\text{Bid}_t + \text{Ask}_t)}{2}} \qquad \text{for a sell order} \tag{2}$$

where P_{it} is the price at which a retail investor submits the order and Bid_t and Ask_t are the best bid and offer 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 Univariate analysis

Table 2 shows the relationship between nominal stock prices and order aggressiveness. Limit orders are assigned to six price ranges based on the opening price (0–10, 10–20,

[9]Daily market capitalizations come from EUROFIDAI daily stock database.

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 relationship between stock price and order aggressiveness. This dependence between aggressiveness and prices seems to be predominant for non-marketable limit orders. The relationship is 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 types of order will end up being executed under the same conditions. On the contrary, the aggressiveness of non-marketable limit orders has a direct link with the 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 will thus focus on this type of orders in the remainder of the paper. The empirical patterns found for non-marketable limit orders, in Table 2, are consistent with the use of different scales for small numbers than for large numbers. The aggressiveness of 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 priced above 50 euros. This difference is statistically significant.

Obviously, these differences in aggressiveness between small price stocks and large prices 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 on one hand, and categories based on market capitalization (respectively, relative spread) on the other hand. Panel A of Table 3 provides, for each size category, the average order aggressiveness of non-marketable orders in the different price categories. Overall, the relationship 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 the relationship between order aggressiveness and stock price is assessed 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 found in Table 2 is caused by small price stocks and large price stocks having different characteristics. However, these results also indicate that a price effect remains after discriminating by size and liquidity. We show in the next section that the differences in aggressiveness between small price stocks and large price stocks remain when controlling carefully for liquidity or other factors known to influence order aggressiveness.

4 Multivariate analysis

4.1 Model

We use pooled OLS regressions to analyze the relationship between nominal stock price and order aggressiveness, controlling for a number of variables that have been shown in the literature to explain order aggressiveness. We estimate the following regression:

$$\text{AGGRESSIVENESS}_{i,j,t} = \alpha + \sum_{k=1}^{5} \beta_k \text{PRICE CATEGORY}^k_{i,j,t} + \gamma \text{CONTROLS}_{i,j,t} + \epsilon_{i,j,t} \tag{3}$$

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 $\text{PRICE CATEGORY}^k_{i,j,t}$ identify the first five price categories (0–10, 10–20, 20–30, 30–40, and 40–50 euros). Specifically, $\text{PRICE CATEGORY}^k_{i,j,t}$ is equal to 1 if the opening price of stock j is in price category k ($k = 1, \ldots, 5$) on day t and 0 otherwise. Finally, $\text{CONTROLS}_{i,j,t}$ is a set of control variables discussed in section 4.2. The statistical significance reported in the regressions is based on robust standard errors clustered by firm and by day.

4.2 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, Smith, Turnbull et al. (2000); Ranaldo (2004); Bessembinder, Panayides and Venkataraman (2009); Lo and Sapp (2010)). We include the following variables to control for these alternative explanations.

Relative spread: the difference between the best ask and the best bid divided by the midpoint at the time of submission, in percent. Griffiths, Smith, Turnbull 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, Schwartz and Tiwari (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: 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' decision. 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: 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 exceeds opposite-side depth). Following Parlour (1998), we expect a positive relation between order book imbalance and order aggressiveness.

Number of transactions: the number of transactions in the last 30 minutes, in thousands of shares. Bessembinder, Panayides and Venkataraman (2009) findings suggest that traders post more aggressive orders when recent trading activity was important. We expect a positive relation between the number of transactions and the order aggressiveness.

Volatility: the 1-minute realized volatility of the midpoint returns over the last 30 minutes, 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 have posted. 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.

4.3 Results

Table 4 reports the results in the multivariate setting. The two first columns show 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 in 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.

4.4 Additional analysis

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 found 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 day and each firm in our sample, 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 significant. However, the inclusion of controls in Model 2, sharply changes the magnitude and the significance of price dummies. We do not find anymore a relationship between price level and order aggressiveness. This negative result for HFTs is an additional argument that our previous findings on individual investors show the existence of a behavioral bias.

5 Robustness test

5.1 Subsample of stocks with RLP coverage

Among the 334 stocks in our sample, RLPs provide price improvements for only 286 of them. For the other stocks, no RLPs are present and thus, individual investors cannot benefit from the liquidity advantages of the *Best of Book* service. As a consequence, and although there still are some benefits to trading through this service (since it offer lower execution costs), a selection bias may arise. We conduct a robustness test where we consider only stocks where at least one RLP is operating. We perform the main regression on this subsample of stocks. The results appear in Table 6. Our conclusions remain unchanged.

6 Conclusion

Our article provides additional evidence that market participants, and more generally individuals, process small prices and large prices differently. We use a unique database which 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 an existing literature which looks at the influence of stock price level (Birru and Wang, 2016; Roger, Roger and Schatt, 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, Roger and Schatt, 2018; Roger, Bousselmi, Roger et al., 2020). Finally, our paper relates, albeit more loosely, to the literature on the differential processing of prices and returns (Glaser, Iliewa and Weber, 2019; Shue and Townsend, 2019).

References

Angel, J. J. (1997). Tick size, share prices, and stock splits. *Journal of Finance*, 52 (2), 655–681.

Autorité des Marchés Financiers (2017). Study of the behaviour of high-frequency traders on Euronext Paris. Technical report, Autorité des Marchés Financiers.

Baker, H. K. and P. L. Gallagher (1980). Management's view of stock splits. *Financial Management*, 32 (3), 73–77.

Baker, M., R. Greenwood, and J. Wurgler (2009). Catering through nominal share prices. *Journal of Finance*, 64 (6), 2559–2590.

Bessembinder, H., M. Panayides, and K. Venkataraman (2009). Hidden liquidity: An analysis of order exposure strategies in electronic stock markets. *Journal of Financial Economics*, 94 (3), 361 – 383.

Bian, J., K. Chan, D. Shi, and H. Zhou (2017). Do behavioral biases affect order aggressiveness? *Review of Finance*, 22 (3), 1121–1151.

Birru, J. and B. Wang (2016). Nominal price illusion. *Journal of Financial Economics*, 119 (3), 578–598.

Copeland, T. E. (1979). Liquidity changes following stock splits. *The Journal of Finance*, 34 (1), 115–141.

Dehaene, S., V. Izard, E. Spelke, and P. Pica (2008). Log or linear? Distinct intuitions of the number scale in Western and Amazonian indigene cultures. *Science*, 320, 1217–1220.

Dyl, E. A. and W. B. Elliott (2006). The share price puzzle. *Journal of Business*, 79 (4), 2045–2066.

Fernando, C. S., S. Krishnamurthy, and P. A. Spindt (2004). Are share price levels informative? evidence from the ownership, pricing, turnover and performance of ipo firms. *Journal of Financial Markets*, 7 (4), 377–403.

Foucault, T. (1999). Order flow composition and trading costs in a dynamic limit order market. *Journal of Financial Markets*, 2 (2), 99 – 134.

Foucault, T., O. Kadan, and E. Kandel (2005). Limit Order Book as a Market for Liquidity. *The Review of Financial Studies*, 18 (4), 1171–1217.

Glaser, M., Z. Iliewa, and M. Weber (2019). Thinking about prices versus thinking about returns in financial markets. *Journal of Finance*, forthcoming.

Gompers, P. and A. Metrick (2001). Institutional investors and equity prices. *Quarterly Journal of Economics*, 116 (1), 229–259.

Griffiths, M. D., B. F. Smith, D. S. Turnbull, and R. W. White (2000). The costs and determinants of order aggressiveness. *Journal of Financial Economics*, 56 (1), 65 – 88.

Handa, P., R. Schwartz, and A. Tiwari (2003). Quote setting and price formation in an order driven market. *Journal of Financial Markets*, 6 (4), 461 – 489.

Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance*, 64 (4), 1889–1933.

Kumar, A. and C. M. C. Lee (2006). Retail investor sentiment and return comovements. *Journal of Finance*, 61 (5), 2451–2486.

Laski, E. V. and R. S. Siegler (2007). Is 27 a big number? Correlational and causal connections among numerical categorization, number line estimation, and numerical magnitude comparison. *Child Development*, 78 (6), 1723–1743.

Lo, I. and S. G. Sapp (2010). Order aggressiveness and quantity: How are they determined in a limit order market? *Journal of International Financial Markets, Institutions and Money*, 20 (3), 213 – 237.

Millroth, P. and P. Juslin (2015). Prospect evaluation as a function of numeracy and probability denominator. *Cognition*, 138, 1–9.

Mueller, S. M., J. Schiebener, M. Delazer, and M. Brand (2018). Risk approximation in decision making: approximative numeric abilities predict advantageous decisions under objective risk. *Cognitive processing*, 19 (3), 297–315.

Nieder, A. (2005). Counting on neurons: The neurobiology of numerical competence. *Nature Reviews*, 6, 177–190.

Park, I. and S. Cho (2018). The influence of number line estimation precision and numeracy on risky financial decision making. *International Journal of Psychology*, 54, 530–538.

Parlour, C. A. (1998). Price Dynamics in Limit Order Markets. *The Review of Financial Studies*, 11 (4), 789–816.

Perez, M. F. and A. Shkilko (2017). Catering through nominal share prices revisited. *Critical Finance Review*, 6 (1), 43–75.

Peters, E., P. Slovic, D. Västfjäll, and C. K. Mertz (2008). Intuitive numbers guide decisions. *Judgment and Decision Making*, 3 (8), 619–635.

Ranaldo, A. (2004). Order aggressiveness in limit order book markets. *Journal of Financial Markets*, 7 (1), 53 – 74.

Roger, T., W. Bousselmi, P. Roger, and M. Willinger (2020). Number processing and price dynamics: A market experiment. Working paper.

Roger, T., P. Roger, and A. Schatt (2018). Behavioral bias in number processing: Evidence from analysts' expectations. *Journal of Economic Behavior & Organization*, 149, 315–331.

Schley, D. R. and E. Peters (2014). Assessing Economic Value: Symbolic-Number Mappings Predict Risky and Riskless Valuations. *Psychological science*, 25 (3), 753–761.

Schultz, P. (2000). Stock splits, tick size, and sponsorship. *Journal of Finance*, 55 (1), 429–450.

Shue, K. and R. R. Townsend (2019). Can the market multiply and divide? non-proportional thinking in financial markets. Technical report, National Bureau of Economic Research.

Siegler, R. S. and J. E. Opfer (2003). The development of numerical estimation: Evidence for multiple representations of numerical quantity. *Psychological Science*, 14 (3), 237–243.

Viarouge, A., E. Hubbard, S. Dehaene, and J. Sackur (2010). Number line compression and the illusory perception of random numbers. *Experimental Psychology*, 57 (6), 446–454.

Weld, W. C., R. Michaely, R. Thaler, and S. Benartzi (2009). The nominal share price puzzle. *Journal of Economic Perspectives*, 23 (2), 121–142.

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)	6,125
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.

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
$\geq$ 50 €	-0.0090	-0.0157	0.0004
Difference	-0.0173***	-0.0195***	0.0006***
Welch t-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 for a sample of 334 stocks listed on Euronext Paris from March to December 2017. 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. ***, ** and * denote statistical significance of the difference according to the Welch test at the 1%, 5% and 10% level, respectively.

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 t-statistics	-33.7600	-46.9900	-23.6400

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 t-statistics	-65.4300	-66.5000	-37.4800

Panel A reports the average order aggressiveness of non-marketable limit orders for stocks that are sorted on nominal stock price and, respectively, on 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). We consider non-marketable limit orders submitted by retail investors via Retail Member Organizations for a sample of 334 stocks listed on Euronext Paris from March to December 2017. 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 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. ***, ** and * denote statistical significance of the difference according to the Welch test at the 1%, 5% and 10% level, respectively.

Table 4
Regressions of order aggressiveness on price categories

	Model 1	Model 2
Intercept	-1.5699***	-1.3300***
	(0.0785)	(0.0764)
< 10 dummy	-1.9498***	-0.9029***
	(0.3171)	(0.1355)
[10,20[dummy	-0.8530***	-0.5414***
	(0.1575)	(0.1440)
[20,30[dummy	-0.6587***	-0.4289***
	(0.1168)	(0.0991)
[30,40[dummy	-0.4915***	-0.2884***
	(0.0965)	(0.0971)
[40,50[dummy	-0.1775	-0.1443*
	(0.1371)	(0.0832)
Relative spread		-1.2204***
		(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		0.0328
		(0.0431)
Volatility		-0.1815***
		(0.0367)
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 for a sample of 334 stocks listed on Euronext Paris from March 2017 to December 2017. 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 minutes, in thousands of shares (number of transactions); the 1-minute realized volatility of midpoint returns over the last 30 minutes, in percent (volatility). ***, ** and * denote statistical significance at the 1%, 5% and 10% level, based on robust standard errors (in parenthesis) clustered by firm and by day.

Table 5
Regressions of high frequency traders' (HFT) order aggressiveness on price categories

	Model 1	Model 2
Intercept	-0.0607***	0.0139
	(0.0039)	(0.0188)
< 10 dummy	-0.1352**	0.0098
	(0.0572)	(0.0360)
[10,20[dummy	-0.0402***	0.0977
	(0.0091)	(0.0883)
[20,30[dummy	-0.0228**	0.0394
	(0.0114)	(0.0372)
[30,40[dummy	-0.0271*	0.0104
	(0.0163)	(0.0068)
[40,50[dummy	0.0101	0.0055
	(0.0085)	(0.0048)
Relative spread		-1.6330***
		(0.1753)
Same side depth		-0.0148
		(0.0130)
Opposite side depth		-0.0159
		(0.0143)
Order book imbalance		0.0150***
		(0.0042)
Number of transactions		0.0100
		(0.0103)
Volatility		-0.0203
		(0.0276)
Number of observations	9,401,319	9,401,319
Adjusted R-squared	0.49%	6.41%

The table reports parameter estimates and standard errors of pooled OLS regressions of pure-HFT order aggressiveness on price categories for a sample of 334 stocks listed on Euronext Paris from March 2017 to December 2017. 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. 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 minutes, in thousands of shares (number of transactions); the 1-minute realized volatility of midpoint returns over the last 30 minutes, in percent (volatility). ***, ** and * denote statistical significance at the 1%, 5% and 10% level, based on robust standard errors (in parenthesis) clustered by firm and by day.

Table 6
Subsample of stocks with at least one Retail Liquidity Provider

	Model 1	Model 2
Intercept	-1.5701***	-1.3252***
	(0.0794)	(0.0780)
< 10 dummy	-1.7594***	-0.8668***
	(0.3085)	(0.1474)
[10,20[dummy	-0.8139***	-0.5401***
	(0.1654)	(0.1557)
[20,30[dummy	-0.6355***	-0.4397***
	(0.1252)	(0.1004)
[30,40[dummy	-0.4989***	-0.3177***
	(0.1015)	(0.0966)
[40,50[dummy	-0.1746	-0.1565*
	(0.1448)	(0.0867)
Relative spread		-1.2522***
		(0.0824)
Same side depth		-0.0002
		(0.0001)
Opposite side depth		-0.0002*
		(0.0001)
Order book imbalance		0.6086***
		(0.0969)
Number of transactions		0.0377
		(0.0413)
Volatility		-0.1987***
		(0.0449)
Number of observations	2,059,441	2,059,441
Adjusted R-squared	1.21%	4.53%

The table reports parameter estimates and standard errors of pooled OLS regressions of retail order agressiveness on price categories for a subsample of 286 stocks listed on Euronext Paris from March 2017 to December 2017 and for which there is a Retail Liquidity Provider (RLP). 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 minutes, in thousands of shares (number of transactions); the 1-minute realized volatility of midpoint returns over the last 30 minutes, in percent (volatility). ***, ** and * denote statistical significance at the 1%, 5% and 10% level, based on robust standard errors (in parenthesis) clustered by firm and by day.