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Abstract

This paper examines the extent to which individual investors provide liquidity to the stock market, and whether they are compensated for doing so. We show that the ability of aggregate retail order imbalances, contrarian in nature, to predict short-term future returns is significantly enhanced during times of market stress, when market liquidity provisions decline. While a weekly rebalanced portfolio long in stocks purchased and short in stocks sold by retail investors delivers a sizable 19% annualized excess returns over a four factor model from 2002 to 2010, in periods of high uncertainty it delivers up to 40% annualized returns. Despite this high aggregate performance, individual investors do not reap the rewards from liquidity provision because (i) they experience a negative return on the day of their trade, and (ii) they reverse their trades long after the excess returns from liquidity provision are dissipated. Finally, we show that experienced traders tend to do better on both dimensions.

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1. Introduction

What is the contribution of individual investors to the formation of prices and liquidity in financial markets? A longstanding literature has considered them as "noise" traders, in the sense of Black (1986) and Shleifer and Summers (1990), who push prices away from fundamentals and destabilize markets. In contrast to this literature, recent empirical evidence suggest that individual investors' trades provide liquidity to meet demand for immediacy by other market participants (Kaniel et al., 2008, 2012; Kelley and Tetlock, 2013). While retail investors may be less sophisticated than their institutional counterparts, they also face lower agency costs and liquidity constraints relative to institutional investors such as mutual funds (Chevalier and Ellison, 1999; Coval and Stafford, 2007). Retail traders could thus have some ability to act as market makers, especially when institutional liquidity dries up, as was the case during the recent financial crisis.

This paper examines the extent to which individual investors provide liquidity to the stock market, and whether or not they are compensated for doing so. We use a unique dataset obtained from a leading European online broker in personal investing and online trading. This dataset allows us to track the orders of a large sample of individuals over the period running from January 2002 to December 2010. In particular, the data covers the 2008-2009 financial crisis, when the liquidity-provision capacity of traditional market makers was plausibly reduced (Nagel, 2012). We uncover three main findings.

First, individuals' provide liquidity especially at times when conventional liquidity providers are constrained. We begin by showing that in our sample, consistent with recent literature, aggregate retail buy-sell imbalances are contrarian and positively predict the cross-section of stock returns at a horizon of a couple of weeks. A one standard deviation increase in daily order imbalances is associated with an increase in return over two trading weeks of about 15 additional basis points (4% increased annualized return). We then test whether this increase in returns earned by retail investors correspond to compensation for liquidity provision. To do so, we first construct a weekly rebalanced portfolio that goes long in stocks purchased and short in stocks sold by retail investors (the "retail" portfolio). We then compare the returns on this portfolio with time-series variation in the supply of liquidity provided by institutional investors. Recent work, including Adrian et al. (2012), Ang et al. (2011) and Ben-David et al. (2012) suggests that intermediaries are especially constrained in their ability to provide liquidity for high values of the VIX index.[1] We thus simply split our sample into periods of high and low VIX, when the VIX is higher or lower than 20, its 2002-10 median, and contrast the returns on the "retail" portfolio in these two subsamples. We find robust evidence that the rewards to liquidity provision increase sharply in times of high uncertainty. While the "retail" portfolio earns a 19% annualized excess returns over a four factor model from 2002 to 2010, it earns up to 40% annualized returns when traded over the weeks where the VIX is above its sample median. These results indicate that rather than merely adding noise to the market, retail traders do indeed provide liquidity to the stock market, especially when institutional liquidity dries up.

Second, we show that retail investors fail to reap the actual returns from liquidity provision, and provide two explanations for this result. The first one has to do with the price at which retail orders are executed on the day of trading. To benefit from the predictable short-term returns that follow a day of intense imbalances, individual investors need to avoid being picked-off on day 0. To understand why, suppose that institutions holding stock S are hit with liquidity shocks and need to fire sell their shares of S. The price of S will plummet on day 0 and recover in the short-term thereafter. Individuals buying stock S at its lowest on day 0 will fully benefit from the price reversal in the next days. However, those who purchased S *before* its reaches its lowest price experience a negative intra-day return on day 0, which may more than offset the gain from price reversal. Our analysis of order-level data indicates that in our sample, retail investors do get picked off on day 0. The average retail order experiences large and negative returns on this day, so much so that returns on

[1] In support of this hypothesis, Nagel (2012) use the returns to short-term reversal strategies as a proxy for the returns to liquidity provision and finds that they are almost perfectly correlated with the level of the VIX.

day 0 more than offset the rewards from liquidity provision that could arise subsequently. The second reason for the low performance of individual investors in our sample has to do with the speed at which they reverse their trades. Individuals cannot benefit from liquidity provision unless they reverse their trades quickly enough thereafter, before the benefits are dissipated. This is exactly what retail investors in our sample fail to do. The average holding period among retail investors in our sample is above 300 days, while most of the returns from liquidity provision are gone after 20 days. Thus, surprisingly, low trading frequency and specifically slow reversal of trades is one of the reasons why individual investors in our sample underperform. This result contrasts with Odean (1998) or Barber and Odean (2000), who argue that over-trading is responsible for the low performance of retail traders.

Finally, we a take advantage of the richness of our data to document cross-sectional heterogeneity in the returns to liquidity provision. We first sort orders based on the experience of the individuals placing them. We find that highly experienced individuals are much less prone to the picking-off effect. In addition, they also flip their orders much quicker. These two components explain a significant share of their outperformance relative to less experienced traders. We also sort orders based on the average speed at which the individuals who place them usually reverse their trades. We find that "fast" traders are less prone to the picking-off effect, and thus experience higher returns relative to slower traders.

This paper adds to the ongoing debate on the contribution of retail trades to stock market efficiency. A number of papers have found that individual trades positively predict short-term returns. A first body of work has interpreted this as evidence of noise trading pushing prices away from fundamentals. Barber et al. (2009) find that stocks that individual investors are buying (selling) during one week have positive (negative) abnormal returns that week and in the subsequent two weeks. These returns then reverse over the next several months. Although Barber et al. (2009) interpret their results as evidence of noise trading, they are also consistent with individual investors providing liquidity to institutional investors. Hvidkjaer (2008) finds that stocks with a high level of sell-initiated small-trade volume, measured over the prior several months, outperform stocks with a high level of buy-initiated small-trade volume at horizons of two years.[2] Another body of work has associated the short-term predictability of retail trades with liquidity provision. Kaniel et al. (2008) identify individual investor trades using the NYSEs Consolidated Audit Trail Data files, which contains detailed information on all orders executed on the exchange, including a field that identifies whether the order comes from an individual investor. They show that the top decile of stocks heavily bought by individuals outperform those heavily sold by individuals, a result again consistent with retail traders providing liquidity to institutions that require immediacy. Dorn et al. (2008) show that correlated limit orders predict subsequent returns in a manner consistent with executed limit orders receiving compensation for accommodating liquidity demands. Kaniel et al. (2012) also find evidence that stocks purchased by individual investors prior to earnings announcement outperform those that they sell and that compensation for risk-averse liquidity provision accounts for approximately half of this over-performance. Finally, Kelley and Tetlock (2013) argue that retail traders provide liquidity to the market and benefit from the reversal of transitory price movements. Our contribution to this body of work is to two fold. First, we show that the predictability of individual trades increases when the rewards to liquidity provision are high; consistent with them providing liquidity. Second, utilizing our order level data we demonstrate that individuals fail to benefit from their liquidity provision role.

Because we focus on returns at the order level, our results also relate to the literature on individual investors performance.[3] The average household trades in excess of what liquidity and hedging motives would command and loses money in the process (Odean, 1998; Barber and Odean, 2000; Barber et al., 2006; Grinblatt and Keloharju, 2000) especially when going online (Barber and Odean, 2002). This is generally attributed to behavioral biases such

[2]A significant part of small trades are likely due to institutions splitting orders, especially in the later part of the Hvidkjaer (2008) sample. Campbell et al. (2009) finds that trades below $2,000 are more likely to come from institutions than from individuals.

[3]For an extensive review of the performance of individual investors behavior and performance, see Barber and Odean (2011).

as overconfidence or gambling (Statman et al., 2006; Glaser and Weber, 2007; Grinblatt and Keloharju, 2009; French, 2008). A small select group of retail traders however manage to generate absolute performance Barber et al. (2014), with some persistence (Coval et al., 2005). Linnainmaa (2010) finds losses on limit orders and gains on market orders in Finland, for portfolios long (short) in stocks that individuals on aggregate net bought (sold). We add to this body of work by showing that individual investors returns are low because (1) they get picked-off and (2) they fail to reverse their trades soon enough. Retail investors do not trade fast enough to collect the benefits from their liquidity provision.

Our results, which indicate that experienced investors trade at a better price in a given day and reverse their positions quicker contribute to the recent and growing literature on learning dynamics in finance. The fact that investors' own experience shape their future decisions has been shown in the context of IPOs (Kaustia et al., 2008; Chiang et al., 2011), retirement savings decisions (Choi et al., 2009) and mutual funds management (Greenwood and Nagel, 2009). Learning may occur in a variety of ways. Investors may gradually discover their true type by rationally updating their priors in a Bayesian way after each action (Mahani and Bernhardt, 2007; Linnainmaa, 2011). Investors may otherwise update their beliefs in a non Bayesian way as in Gervais and Odean (2001). The performance of retail investors might increase through time due to learning by doing (Nicolosi et al., 2009; Seru et al., 2009). Seru et al. (2009) show that individual investors behavior is consistent with both learning about one's type and learning by doing but that the former is quantitatively more significant than the later. Finally, List (2003), Agarwal et al. (2008) and Kaustia et al. (2008) show in various frameworks that with experience, investment behaviors tend to get closer to what full rationality would command.

The rest of the paper is organized as follows. We present the data in section 2. Section 3 presents the results, and section 4 concludes.

2. Data

We consider a large sample of French retail investors trading between January 2002 and December 2010, provided by a leading European broker in personal investing and online trading. In the past twelve years, this broker accounted for an average 15 percent of online brokers stock trades on Euronext Paris, which collectively represented 14 percent of all trades in the market[4]. This sample is thus fairly representative of the behavior of individual investors directly investing in the French stock market. This data was also used in Foucault et al. (2011), who study the effect of retail investors on the volatility of stock returns.

There are 91,647 investors placing approximately 4.6 million orders in 730 stocks in our sample. For each order, we track the trading exchange identifier (the ISIN), the trading date, the quantity and the amount traded in euros. Given that we do not have the exact timing of the order within the day, we aggregate trades by individual-stock-days. The average trade size in our sample is 7,741 euros. We obtain daily stock returns from EUROFIDAI.[5] In addition to the stock-level data, we obtain the mutual fund trades and positions of these individual investors from the same broker, from 2006 to 2010.

Our sample stands out in a number of ways. First, it includes information at the order level, which allows us to perform detailed analysis of retail trading. Second, it spans a long time period which includes episodes of market stress, such as the recent financial crisis. This makes it possible to contrast the behavior of a large number of retail investors at different points in time, when the returns to liquidity provision vary. Recent work, including Adrian et al. (2012), Ang et al. (2011) and Ben-David et al. (2012) suggest that intermediaries are especially constrained for high levels of the VIX index of implied volatilites of S&P index options. Nagel (2012) uses the returns to short-term reversal strategies as proxies for the returns to liquidity provision. He finds that they are almost perfectly correlated with the

[4]According to "Acsel", the association of French online brokers (see http://www.associationeconomienumerique.fr/) which collects monthly data on online trading.

[5]EUROFIDAI is a research institute funded by the CNRS (French National Center for Scientific Research) whose mission is to develop European stock exchange databases for academic research.

level of the VIX. We thus simply construct a dummy High VIX equals to one if the level of the VIX is above its 2002-10 median. In addition, we also define a Crisis dummy equals to one in the seven months running from September 2008 to April 2009.

In some of the analysis, we adjust returns and cumulative returns for systematic risk. To do so, we estimate the exposure of each of the 730 stocks in the sample to systematic risk factors (Market, Small-minus-big, High-minus-low, and Momentum) over the sample period (2002-2010) at the weekly level. More specifically, we run the following OLS model for each stock in the sample:

$$Ret[t] - r_f = a + b.Mkt_t + c.SMB_t + d.HML_t + e.MOM_t + \epsilon_{it}, \tag{1}$$

where $Ret[t]$ is a given stock's return in week t, and Mkt_t, SMB_t, HML_t and MOM_t are respectively the returns of the Market factor, Small-minus-big, High-minus-low, and Momentum. The estimated coefficients $\hat{b}$, $\hat{c}$, $\hat{d}$ and $\hat{e}$ are then used to define the risk adjusted return on any given stock i in any given period t, $AdjRet[t]$, as the difference between the realized return $Ret[t]$ and its predicted value:

$$AdjRet[t]_i = Ret[t]_i - (\hat{b}_i.Mkt_t + \hat{c}_i.SMB_t + \hat{d}_i.HML_t + \hat{e}_i.MOM_t + r_f) \tag{2}$$

3. Results

3.1. Evidence on liquidity provision

This paper studies the relationship between retail orders and future short-term returns both at the stock-day level and the order level. We start by aggregating individual orders at the stock-day level. Our main measure of imbalances, $Imb[0]$, is similar to the one used in Kelley and Tetlock (2013). It is computed daily as the number of shares bought by retail investors minus the number of shares sold by retail investors divided by shares bought plus shares sold.[6] As in Kelley and Tetlock (2013), we exclude from the sample stock×days with less than five orders. We are left with 91,647 individuals trading 730 stocks from 2002 to 2010, leaving us with 217,511 stock-days. We control for the size of firms with the log of their market capitalisation (Size). We denote as $Ret[x, y]$ the holding period between day x and day y.

Panel A of Table 1 provides summary statistics. The average and median of $Imb[0]$ are very close to zero. The average aggregate volume traded in a stock on a given day is just over 165,000 euros, which represents an average of 2.4% of the total daily volume for these stocks.[7] We first estimate whether retail order imbalance dynamics are consistent with liquidity provision, i.e., if they seem to respond to past liquidity shocks. More specifically, we want to measure the sensitivity of retail imbalances to past returns, controlling for market conditions and stock invariant characteristics. We do so by running the following linear regression:

$$Imb[0]_{it} = \alpha_0 + \alpha_1.Ret[-5,-1]_{it} + \alpha_2.Ret[-26,-6]_{it} + \alpha_3.Size_{it} + \pi_t + \eta_i + \epsilon_{it}, \quad (3)$$

where $Imb[0]_{it}$ is the imbalance of stock i in day t, and $Ret[-5,-1]_{it}$ and $Ret[-26,-6]_{it}$ are the cumulative returns over the past week and the month before it on stock i. We control for the size of firms with the log of their market capitalisation ($Size_{it}$). π_t and η_i are respectively day and stock fixed effects. Standard errors are clustered at the stock level. Results are presented in Table 2. The first specification includes only day fixed effects, while the second adds with stock fixed effects. Consistent with evidence in Kelley and Tetlock (2013) and Kaniel et al. (2008), we find that retail imbalances react strongly to past returns. The estimates are highly statistically significant, and the coefficients are economically large. A one standard deviation decrease in past week's returns, $Ret[-5,-1]_{it}$, leads to an increase of about 7 percentage points in $Imb[0]$, which represents 12% of the

[6] We check below that our results are robust when we use alternative measures.

[7] Our coverage is comparable to Kelley and Tetlock (2013) where retail trades account for 2.3% of total listed (NYSE/Amex/NASDAQ) volume, over a period of 5 years.

sample standard deviation of $Imb[0]$. The estimate is unaffected by the inclusion of stock fixed effects, suggesting that time invariant stock-level characteristics are not responsible for the cross-sectional correlation between retail imbalances and past returns. This pattern of buying and selling in reversal strategies resembles the trading of a market maker who takes opposite positions to the rest of the market, and is overall consistent with the idea that retail trades provide liquidity.

We then turn to the analysis of the returns to liquidity provision. Our regression model for predicting cumulative holding period returns from day x to y is:

$$Ret[x,y]_{it} = \beta_0 + \beta_1.Imb[0] + \beta_2.Ret[-5,-1]_{it} + \beta_3.Ret[-26,-6]_{it} + \beta_4.Size_{it} + \pi_t + \eta_i + \epsilon_{it}, \quad (4)$$

where $Imb[0]_{it}$ is the retail imbalance in stock i in day t, and $Ret[-5,-1]_{it}$ and $Ret[-26,-6]_{it}$ are the cumulative returns over the past week and the past month on stock i. The coefficient of interest is β_1 which measures the sensitivity of future returns to current imbalances from retail orders.

We first run separate regressions for the cumulative returns from day $x = 1$ to day y where y take values from1 to 100. We plot the coefficient along with 95% confidence intervals in Figure 1. The graph shows that stocks heavily purchased by retail investors outperform those that are heavily sold by a significant 25 basis points over the first couple week. This outperformance then gradually dissipates over the next 85 days. We obtain identical results when we perform the same analysis with risk adjusted cumulative returns. We formalize this result in a regression setting by estimating equation 4. The results are presented in Table 3. Columns 1 and 2 present the estimates of specifications including day fixed effects, while Columns 3 and 4 present the results of the same model augmented with stock fixed effects. Column 1 and 3 use x=1 and y=16 days, i.e. these columns look at returns over the next couple weeks following the initial imbalance. Column 2 and 4 use x=17 and y=100. The main finding is that retail imbalances positively predict cumulative returns from day

1 to day 16 (columns 1 and 3). A one standard deviation increase in $Imb[0]$ leads to a 15 basis points increase in cumulative returns over the following couple weeks. These estimates are comparable in magnitudes to those obtained by Kelley and Tetlock (2013). Columns 2 and 4 show that the effect is short-lived, since it is nearly fully reversed after 100 days. As we already noticed in Table 2, the estimates are virtually unaffected by the inclusion of stock fixed effects. Taken together, Table 2 and Table 3 suggest that individual investors provide liquidity by placing contrarian trades and receive a significant compensation in the form of high returns over the couple weeks following their trades. We perform a number of robustness tests to ensure that these results are robust to the proxy we use for imbalances created by retail investors' trades. In particular, we show in Table 4 that the results hold (i) when we standardize $Imb[0]$ (by subtracting its within-stock mean and scaling it by its within-stock standard deviation), (ii) when we use terciles of $Imb[0]$, or (iii) when we define imbalances on stock i as the ratio of buy minus sell orders by retail investors on this stock normalized by the market-wide volume on the stock.

3.2. Retail Investors' Performance and the Demand for Liquidity

As we already emphasized, a natural interpretation of our results in Section 3.1 is that retail investors provide liquidity to the market and receive in exchange higher returns on their trades. An alternative interpretation of the results in Section 3.1 is that the predictive power of retail imbalances result from noisy correlated trading pressure from individuals. To disentangle between these two alternative hypotheses, we simply look at how the sensitivity of retail imbalances to past returns as well as the predictive power of these imbalances on future returns vary with general liquidity conditions in the market. If the predictability of individual imbalances increases when liquidity dries up elsewhere in financial markets, then it is likely that these trades are indeed providing liquidity, rather than pushing prices away from fundamentals.

Recent work, including Adrian et al. (2012), Ang et al. (2011) and Ben-David et al.

(2012) suggest that intermediaries are especially constrained when the VIX index of implied volatilities of S&P index options reaches high levels. Nagel (2012) use the returns to short-term reversal strategies as proxies for the returns to liquidity provision. He finds that they are almost perfectly correlated with the level of the VIX. We thus simply use the level of the VIX as a proxy for the returns to liquidity provision and split our sample into weeks of high and low VIX, where high VIX is defined as a VIX level higher than 20, its 2002-10 median. We simply re-run the analysis of Section 3.1 for each of these two subsamples.

We first estimate whether the sensitivity of retail imbalances to past returns is significantly different in periods of high and low uncertainty, controlling for market conditions and stock invariant characteristics. To do so, we start with model 3 and interact all terms with a dummy equal to 1 on days when the VIX is higher than 20, its 2002-10 median, and zero otherwise. The results are presented in Table 5, Column 1 and 2. The interaction term is positive, small and insignificant. This suggests that the response of individual investors to past returns does not vary with the level of VIX. While this is not proof that retail investors are the residual investors in times of high uncertainty, this suggests that they are probably less constrained in their liquidity provisions than other market participants identified in the literature, since their liquidity provision does not seem to decrease on high VIX days.

As a robustness check, we also use the crisis period as another period in our sample where the returns to liquidity provision are likely to be very high. We thus estimate an augmented version of equation (3), where all the variables are interacted with a Crisis dummy equal to 1 in the seven month running from September 2008 to April 2009, i.e. the core of the financial crisis. The results are presented in Table 5, Column 3 and 4. The interaction of the Crisis dummy and past returns is now positive and significant. This indicates that the sensitivity of retail imbalance to past returns did in fact decrease during the crisis relative to the rest of the sample period, suggesting some decline in their liquidity provision capacity: while a 1% return in the past 5 days lead to a 1.1 percentage point decrease in imbalances at date 0 outside the crisis, it leads only to a decrease of .66 percentage point during the crisis. Note, however, that the sensitivity of retail imbalance to past returns remain negative and statistically significant during the crisis period, albeit smaller. When we throw both interactions (Crisis and VIX) in the regression (columns 5 and 6), the results remain very similar.

We then investigate how the returns following large retail imbalance varies with our two proxies for the returns to liquidity provision. We start with a graphical analysis, based on equation 4. We split the sample into low and high VIX days, where high VIX days happen when the VIX is higher than 20, its 2002-10 median. In each of these subsamples, we run separate regressions of the cumulative returns from day $x = 1$ to day y where y take values 1 to 100 on day 0 retail imbalance, controlling for past weekly and monthly returns, as well as the log of the market capitalization of the stock. We plot the estimated coefficients for $Imb[0]$ at each horizon (1 to 100), along with their 95% confidence intervals in Figure 2. Panel A (resp. panel B) corresponds to days of high VIX (resp. low VIX). Two interesting facts emerge from Figure 2. First, when the VIX is high, retail investors imbalances are followed by a much larger price increase over the next couple weeks than when the VIX is low: stocks heavily purchased by individuals reach 30 basis points in cumulative returns over the next 16 days, while they reach about 15 basis points in cumulative returns in low VIX days. Second, the reversal is much more pronounced in low VIX days than in high VIX days. A potential interpretation of these results is that when uncertainty is high, retail trades provide liquidity and get significantly compensated for it. Conversely, in times of low uncertainty, retail trades are more likely to be picked-off by informed traders and eventually generate negative cumulative returns.

We confirm these results in formal regression tests. We interact all terms in equation 4 with a dummy equal to 1 on days when the VIX is higher than its sample median between 2002 and 2010, and zero otherwise. The results are presented in column 1 and 2 of Table 6. Column 1 use only day fixed effects, while column 2 adds stock fixed effects. Consistent with the intuition obtained from Figure 2, the short-term rewards to individual investors liquidity provision are twice larger in high VIX days relative to low VIX days. A one standard deviation increase in date-0 imbalances leads to a 10 basis points increase in cumulative returns over the following couple weeks in low VIX days while it leads to a 20 basis points increase when the VIX is above its sample median. As we did earlier, we also investigate how the returns earned by stocks experiencing high retail imbalance changed during the Crisis period (Column 3 and 4 of Table 6). We find that the short-term returns to individuals' liquidity provision almost triple in value during the financial crisis: while the sensitivity of three-weeks cumulative returns to retail imbalance is .0024 outside the financial crisis, it is .0075 during the financial crisis.[8]

Altogether, these results provide compelling evidence that the outperformance of stocks heavily purchased by individuals over those heavily sold by individuals amounts to compensation for liquidity provision. Of course, one objection to our interpretation is that during high VIX period, limits to arbitrage increase so that correlated trading by individual investors would be less likely to be arbitraged away by constrained sophisticated arbitrageurs. As a result, the increased predictability during high VIX period would simply be the result of noisy price pressure from individuals and be unrelated to the returns to liquidity provision. However, we find in unreported tests that the autocorrelation of our measure of retail imbalances is significantly lower in high VIX days. This makes this alternative interpretation much less compelling than our hypothesis based on liquidity provision.

These results also emphasize the value of our dataset: because we track individuals for a long period of time, we are able to reconcile apparently contradictory findings from the literature with respect to the reversal of short-term returns. Indeed, while Hvidkjaer (2008) and Barber et al. (2009) found evidence of reversal following short-term returns, Kaniel et al. (2008) and Kelley and Tetlock (2013) found none. Our results suggest that different samples

[8] In a robustness test presented in Table 14, we interact the Crisis and the High VIX dummies with a dummy called SBF120, which takes the value of one for stocks included in the SBF120 index, and zero for the 120 largest stocks not included in the SBF120. We find that most of the additional returns to liquidity provision obtained during the crisis or in times of high volatility are found in stocks included in the SBF120 index. Given that institutions are likely to track the SBF120 index, this is consistent with the idea that individual investors provide liquidity to meet institutional demand for immediacy.

and time periods might explain these differences.

3.3. Portfolio analysis

In this section, we show that portfolios mimicking the trades of individual investors generate significant positive abnormal returns at the weekly horizon. There are several motivations for this. First, we want to check that the effects that we documented in the previous Section are economically meaningful, and in particular, that they are not driven by the smallest trades observed in our sample of individual investors. The portfolio we build aggregate trades across individuals and assets and thus gives a larger weight to stocks heavily traded. Second, we want to make sure that the results are not driven by a particular feature of $Imb[0]$, our measure of retail imbalances. In the analysis that follows, we pool all stocks into a long and a short portfolios, and we therefore abstract from any measure of imbalances. Finally, we want to analyze how the returns of the short-term reversal strategies of individual investors load on systematic risk factors.

We proceed as follows. Each week over the sample period spanning 2002 to 2010, we aggregate individual trades at the stock level. We sort stocks based on their net retail aggregate position into two subsets of stocks sold and stocks purchased. We form a long and a short portfolios by value-weighting the stocks in each of these two subsets. Hence a stock enters in respectively the long and the short portfolio with a weight that reflects the size of the aggregate individual imbalance in that stock in a given week. We rebalance each of the two portfolios at the end of each week. We consider the returns on the long-short portfolio (the "retail" portfolio). More precisely, we regress the returns on the long-short portfolio on a model similar to equation 2. The coefficient of interest here is a, which is an estimate of the weekly returns on the "retail" portfolio, adjusted for exposure to systematic risk. We introduce the risk factors one by one in the model to assess their effects on the estimate of excess returns. The results of the main specification are presented in Panel A of Table 7. The unadjusted return is 26 weekly basis points, which amounts to 15% annualized returns. A CAPM market model (Column 2) generates an alpha of 23 basis points per week, which amounts to an annualized risk adjusted return of 13%. Moving to a Fama French risk model (Column 4) increases the estimates to 33 basis points, an annualized return of 19%. Introducing the Momentum factor (Column 5) in the model does not affect the estimate of alpha.

If these excess returns represent compensation for liquidity provision, then we should find, consistent with the analysis presented above, that these excess returns increase in times of high uncertainty, i.e. when the rewards to liquidity provision increase. We thus split the sample based on the level of the VIX in the last day of the portfolio formation week. We then regress the excess returns on the zero cost "retail" portfolio on the same risk factors as those used in equation 2, but using only these weeks where the level of the VIX is above its sample median. The results are presented in Panel B of Table 7. The unadjusted returns are 52 basis points weekly, a 30% in annualized terms. Adjusting for the exposure to the market increases the estimates to 57 basis points, which amounts to an annualized risk adjusted performance of 34%. Introducing the three other risk factors pushes the returns even further to an impressive annualized return of nearly 40%. In other words, irrespective of the particular risk-adjustment, the excess returns earned by the "retail" portfolio are twice larger in high VIX weeks relative to low VIX weeks. These impressive returns strengthen the conclusion that retail trades provide liquidity to the markets.

Finally, we check whether the effects are stronger if we restrict the sample to stock-weeks when retail imbalances are extreme. We define an imbalance as extreme if this stock-week lies in the top or the bottom tercile of the distribution of the stock's retail imbalances between 2002 and 2010. We then compute the long and short portfolios as described above. Given that the returns to liquidity provision are higher for large retail imbalances, we expect the abnormal returns on this portfolio to be higher than what we obtained using the whole sample. We run the same model and present the results in panel C of Table 7. Unsurprisingly, the results are larger than those obtained in Panel A. A CAPM market model delivers a return of 34 basis points weekly, which amounts to an annualized return of 19%. A four-factor model increases the alpha to 47 basis points weekly, or about 28% annually.

3.4. Order level analysis

The results aggregated at the stock level seem at odds with the results commonly found in the literature that individual investors lose money on average (Odean, 1998; Barber and Odean, 2000; Barber et al., 2006; Grinblatt and Keloharju, 2000), either because they trade too much, or because they pick the losing stocks. In this Section, we attempt to reconcile these results with our findings. We first notice that the fact that the "retail" portfolio earns positive and significant excess returns does not necessarily mean that retail traders earn significant trading profits. In fact, for individual investors to collect the returns from liquidity provision, it needs to be the case that (i) the return on the day of the trade (day 0) should not be lower than the subsequent excess returns, and that (ii) their trades are reversed before the rewards from liquidity provision are dissipated. We exploit the richness of our data to explore the behavior of individual investors along these two dimensions.

For each of the approximately 5 million orders in the sample, we construct the following variables. First, we define the return on day 0, $Ret[0]$ as the difference between the closing price at the end of the day when the order was placed, and the price at which the order was executed during the day. We also define days to reversal as the number of days between the date of an order, and the earliest date at which the order was a least partially reversed.[9] We measure the holding period return as the cumulative return from the time of execution to the close of the earliest date at which the order is partially reversed.[10] For ease of comparison across holding periods, we also compute the internal rate of return of each trade. For most of the analysis, we adjust both the holding period returns and the internal rate of returns

[9]We would obtain similar results by considering the number of days until the position is fully reversed, however our measure is more conservative for the purpose of this study.

[10]For simplicity, we cap the holding period to 500 days. When an order is never reversed in the sample, we cap its holding period to the earliest of (i) the last day of trading in the sample and (ii) the last quotation day of the stock if it delisted.

for exposure to systematic risk, following the procedure described in Section 2. Again, we call $Ret[x,y]$ the cumulative returns obtained from day x to day y. In addition, since we are interested in the heterogeneity in experience across individual investors, we define the cumulative number of orders for a trader i as the total number of orders placed prior to placing a given order.

Summary statistics for the sample at the order level are presented in Table 1. The average order is worth 7,741 euros. There are slightly more purchases than sales in the sample, but purchases are slightly smaller (7,186 euros) than sales (8,342 euros). Turning to our variables of interest, the average holding period is 310 days and the median is 40. This is much longer than the average time at which the returns to liquidity provision are dissipated on average: as is apparent from Figure 1, the cumulative returns following retail order imbalances are only 10 basis points after 30 days and are 0 after 80 days. Additionally, the average return on day zero, $Ret[0]$, is -90 basis points. This is much larger (in absolute value) than the average estimated rewards from liquidity provision (which is at best 25 basis points). Hence the average trade in the sample does not reap the returns to liquidity provision because (1) it is picked-off on day 0 and (2) it is not reversed quickly enough.

Table 1 indicates that the average holding period return is -2.7%, and the average internal return is 4 basis points per day. On a risk adjusted basis, these numbers are respectively -90 basis points, and 3 basis points.[11][12] Table 11 presents the correlations between these variables. The number of days to reversal is negatively related to $Ret[0]$ and the internal rate of return, which are positively correlated. Quickly reversed trades are picked off less, on average. We decompose the holding period return in Table 8. We present the decomposition on both unadjusted and risk-adjusted terms. The loss on day 0, $Ret[0]$, accounts for approximately one third of the negative holding period returns, while the rest comes from

[11] The discrepancy between holding period returns and internal rates of returns comes from the fact that losing positions tend to be held longer, so that their holding period returns are larger in absolute value than the holding period returns of winning positions that are reversed quickly. The internal rate of return rescales returns to the daily horizon, therefore correcting this bias.

[12] The adjusted return on day 0 is computed as the difference between $Ret[0]$ and the stock return predicted by the four factor model presented in equation 2.

$Ret]16, R]$, the returns from day 16 to the reversal of the trade. On a risk adjusted basis, the results are very similar. One of the striking implication of these results is that individuals seem to be losing money because they do not reverse their trades soon enough, i.e., because they do not trade enough.

3.5. Heterogeneous effects

In this Section, we exploit the richness of our dataset to document the heterogeneity in the behavior of individual investors. In particular, we show that certain individual characteristics seem to be associated with a better ability to capture the returns to liquidity provision. The first characteristic we consider is a trader's experience. We sort orders in our sample based on the experience of the trader, measured by the total number of prior orders placed. We expect that experienced individual investors should be less "picked-off" and should reverse their trades quicker. We thus simply compute the average of all our return variables across all deciles of experience. The results are presented in Panel A of Table 9. The average cumulative number of orders placed in the first decile of experience is 12 vs. 3,323 in the highest decile of experience. Experienced traders flip their trades much faster than inexperienced ones. Interestingly, experienced traders also get less picked-off. The difference between the first and the tenth deciles of experience in $Ret[0]$ is an impressive 100 basis points, which is more than half their difference in holding period returns in risk-adjusted terms. Experienced traders have slightly better returns between day 1 and day 16. Their risk adjusted holding period return and internal rate of return are respectively 20 and 10 basis points larger than those of inexperienced investors.

The second characteristic we consider is a traders' average holding period. Precisely, we sort orders in the sample based on the propensity of each trader to quickly reverse its trades. We expect that individuals who have shorter holding periods should be more capable of seizing the returns from liquidity provision. To check whether this is the case, we compute the average holding period of the trader over the sample. We then compute the average of all our return variables across the ten deciles of holding period. The results are presented in Panel B of Table 9. The average cumulative number of orders placed in the first decile of speed to reversals is 33, versus 1,065 in the highest decile of reversals. Traders who usually reverse their positions faster also get less picked-off. The difference between decile 1 and 10 in the average date-0 return, $Ret[0]$, is 35 basis points. The risk adjusted holding period returns and internal rates of returns of traders quickly reversing their trades are respectively 4.5% and 10 basis points higher than those of traders in the bottom decile, and decline in internal rates of return is monotonic.

Taken together, these results do suggest that experience and average holding period are two characteristics associated with higher reward to liquidity provision. In principle, this result could emanate from two different channels. First, it could be that the worst performing types (low experience, long holding periods) exit the sample more frequently. Second, in the case of experience, it could be that individual investors indeed experience some form of learning-by-doing. To get a quantitative sense of these two channels, we run simple regressions of $Ret[0]$ and of the log of the number of days to reversal on vectors of time varying trader characteristics (including the log of the cumulative number of past orders and its square, the log of the size of the account and the log monthly volume traded) and day and stock $\times$ day fixed effects. Most importantly, we add individual fixed effects. If there is any learning-by-doing, the outcome variables should be associated with our measure of experience, the log of the cumulative number of past orders. We present the results in Table 10. The results confirm that experience is strongly positively related to $Ret[0]$, and negatively to the number of days to reversal. Traders with a larger number of past orders are less picked-off and reverse their trades faster. However, the coefficients decrease substantially when we introduce individual fixed effects. This suggests that an important part of the learning occurs via the attrition of our sample, i.e., the survival of the trades which are less picked-off and which reverse their trades more quickly.[13]

[13]Interestingly, larger orders get picked off less and start to get reversed faster.

3.6. Discussion

The results presented in this paper indicates that individual investors provide liquidity to stock markets, and that some of them are compensated for it, especially in periods of high uncertainty such as the 2008-09 financial crisis, when institutional liquidity providers were most constrained. This seems at odds with the view according to which retail investors flee to liquidity during times of financial market stress and thereby amplify the initial stress. Financial newspapers, both in Europe and in the U.S., have reported a massive exodus of small retail investors from the stock market following the financial crisis, with potentially worrisome consequences. According to the Wall Street Journal,[14] in the U.S., "from 2007 through 2009, [retail investors] withdrew money [from mutual funds that invest in U.S. stocks] for three consecutive years", which "marked the first three-year period of withdrawals since 1979-1981".

Using our data, we find that on aggregate, individual investors decreased their exposure to mutual funds. However, they also significantly increased their exposure to equities. As evidenced from Figure 3, the net outflows of individual investors in our sample from equity mutual funds reach 150 million euros from mid-2007 to the first quarter of 2009. In the meantime, inflows into stocks amount to approximately 100 millions over the same period. The results presented in this paper offer a new perspective on this somewhat surprising finding: in the aggregate, individual investors acted as liquidity providers for the rest of the market.

4. Conclusion

This paper examines the extent to which individual investors provide liquidity to the stock market, and whether or not they are compensated for doing so. We start by confirming with our data that aggregate retail buy-sell imbalances are contrarian and positively predict the

[14]See "Small Investors Flee Stocks, Changing Market Dynamics", Wall Street Journal, June 2010.

cross-section of stock returns at a horizon of couple weeks. We then uncover three main findings. First, rewards to liquidity provision increase sharply during the financial crisis of 2008-09, or more generally in times of high uncertainty. Second, individual investors fail to reap the benefits from liquidity provision and this for two reasons: (1) they get picked-off on the day of trading (2) they do not reverse their trades fast enough so that when they close their trades, the returns to liquidity provision are dissipated. Third, we take advantage of the richness of our data to document heterogeneity in the returns to liquidity provision across individuals. We show that experience traders get less picked-off and reverse their trade much faster than less-experienced traders. Overall, these two components explain a significant share of the outperformance of experienced traders relative to less experienced traders.

At least for investors in our sample, it is procrastination that leads to under-performance; not too frequent trading. Finally, our data suggests that during the financial crisis retail investors on aggregate fled from delegation, yet at the same time stepped up to the plate, increased stock holdings and provided liquidity.

References

Adrian, Tobias, Erkko Etula, and Tyler Muir, "Financial intermediaries and the cross-section of asset returns," *Staff Reports*, 2012, *464.*

Agarwal, Sumit, John C. Driscoll, Xavier Gabaix, and David Laibson, "Learning in the Credit Card Market," *NBER Working Paper*, February 2008, (13822).

Ang, Andrew, Sergiy Gorovyy, and Gregory B Van Inwegen, "Hedge fund leverage," *Journal of Financial Economics*, 2011, *102* (1), 102–126.

Barber, Brad M and Terrance Odean, "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *The Journal of Finance*, 2000, *55* (2), 773–806.

_ and _ , "Online Investors: Do the Slow Die First?," *Review of Financial Studies*, 2002, *15* (2), 455–487.

_ and _ , "The behavior of individual investors," *Handbook of the Economics of Finance*, 2011, *2*, 1533–1570.

_ , _ , and Ning Zhu, "Do retail trades move markets?," *Review of Financial Studies*, 2009, *22* (1), 151–186.

_ , Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, "Just How Much Do Individual Investors Lose by Trading?," *Review of Financial Studies*, 2006, *22* (2), 609–632.

Barber, Brad, Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, "The cross-section of speculator skill: Evidence from daytrading," *Journal of Financial Markets*, 2014, *18*, 1–24.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, "Hedge fund stock trading in the financial crisis of 2007–2009," *Review of Financial Studies*, 2012, *25* (1), 1–54.

Black, Fischer, "Noise," *The Journal of finance*, 1986, *41* (3), 529–543.

Campbell, John Y., Tarun Ramadorai, and Allie Schwartz, "Caught on tape: Institutional order flow, stock returns and earnings announcements," *Journal of Financial Economics*, 2009, *92* (1), 66–91.

Chevalier, Judith and Glenn Ellison, "Career Concerns of Mutual Fund Managers," *Quarterly Journal of Economics*, 1999, *114* (2), 389–432.

Chiang, Y M, D Hirshleifer, Y Qian, and A E Sherman, "Do Investors Learn from Experience? Evidence from Frequent IPO Investors," *Review of Financial Studies*, 2011, *24* (5), 1560–1589.

Choi, James J, David Laibson, Brigitte C Madrian, and Andrew Metrick, "Reinforcement Learning and Savings Behavior.," *The Journal of finance*, 2009, *64* (6), 2515–2534.

Coval, Joshua and Erik Stafford, "Asset fire sales (and purchases) in equity markets," *Journal of Financial Economics*, 2007, *86* (2), 479–512.

Coval, Joshua D, David A Hirshleifer, and Tyler Shumway, "Can Individual Investors Beat the Market ? Can Individual Investors Beat the Market ?," *Social Science Research*, 2005, *1001* (04), 1–37.

Dorn, Daniel, Gur Huberman, and Paul Sengmueller, "Correlated trading and returns," *The Journal of Finance*, 2008, *63* (2), 885–920.

Foucault, Thierry, David Sraer, and David J Thesmar, "Individual Investors and Volatility," *Journal of Finance*, 2011, *LXVI* (4), 1369–1406.

French, Kenneth R, "Presidential Address: The Cost of Active Investing," *The Journal of Finance*, 2008, *63* (4), 1537–1573.

Gervais, Simon and Terrance Odean, "Learning to be overconfident," *Review of Financial Studies*, 2001, *14* (1), 1–27.

Glaser, Markus and Martin Weber, "Overconfidence and trading volume," *The Geneva Risk and Insurance Review*, 2007, *32* (1), 1–36.

Greenwood, Robin and Stefan Nagel, "Inexperienced investors and bubbles," *Journal of Financial Economics*, 2009, *93* (2), 239–258.

Grinblatt, Mark and Matti Keloharju, "The investment behavior and performance of various investor types: a study of Finland's unique data set," *Journal of Financial Economics*, 2000, *55* (1), 43–67.

_ **and** _ , "Sensation Seeking, Overconfidence, and Trading Activity," *The Journal of Finance*, 2009, *64* (2), 549–578.

Hvidkjaer, Soeren, "Small trades and the cross-section of stock returns," *Review of Financial Studies*, 2008, *21* (3), 1123–1151.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, "Individual Investor Trading and Stock Returns," *Journal of Finance*, 2008, *63* (1), 273–310.

_ **, Shuming Liu, Gideon Saar, and Sheridan Titman**, "Individual investor trading and return patterns around earnings announcements," *The Journal of Finance*, 2012, *67* (2), 639–680.

Kaustia, Markku, Eeva Alho, and Vesa Puttonen, "How Much Does Expertise Reduce Behavioral Biases? The Case of Anchoring Effects in Stock Return Estimates," *Financial Management*, 2008, *37* (3), 391–412.

Kelley, Eric K and Paul C Tetlock, "How wise are crowds? Insights from retail orders and stock returns," *The Journal of Finance*, 2013, *68* (3), 1229–1265.

Linnainmaa, J T, "Why Do (Some) Households Trade So Much?," *Review of Financial Studies*, 2011, *24* (5), 1630–1666.

Linnainmaa, Juhani T, "Do limit orders alter inferences about investor performance and behavior?," *The Journal of Finance*, 2010, *65* (4), 1473–1506.

List, John A, "Does Market Experience Eliminate Market Anomalies?," *Quarterly Journal of Economics*, 2003, *118* (1), 41–71.

Mahani, Reza and Dan Bernhardt, "Financial Speculators' Underperformance: Learning, Self-Selection, and Endogenous Liquidity," *The Journal of Finance*, 2007, *62* (3), 1313–1340.

Nagel, Stefan, "Evaporating Liquidity," *Review of Financial Studies*, 2012, *25* (7), 2005–2039.

Nicolosi, Gina, Liang Peng, and Ning Zhu, "Do individual investors learn from their trading experience?," *Journal of Financial Markets*, 2009, *12* (2), 317–336.

Odean, Terrance, "Do Investors Trade Too Much?," *SSRN Electronic Journal*, 1998, *89* (5), 1279–1298.

Seru, A, T Shumway, and N Stoffman, "Learning by Trading," *Review of Financial Studies*, 2009, *23* (2), 705–739.

Shleifer, Andrei and Lawrence H Summers, "The noise trader approach to finance," *Journal of Economic perspectives*, 1990, *4* (2), 19–33.

Statman, M, S Thorley, and K Vorkink, "Investor Overconfidence and Trading Volume," *Review of Financial Studies*, 2006, *19* (4), 1531–1565.

5. Graphs

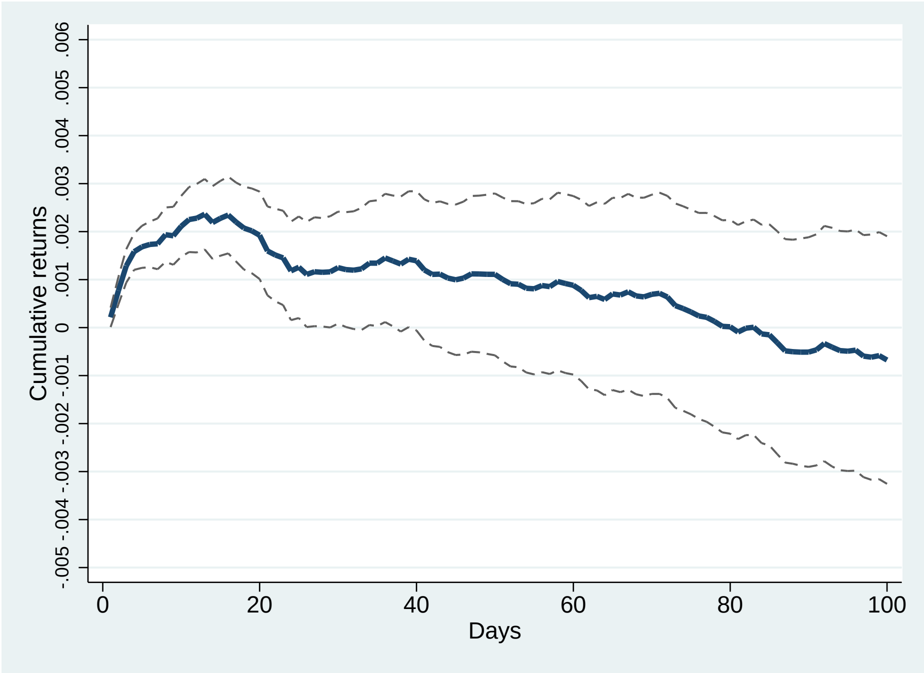
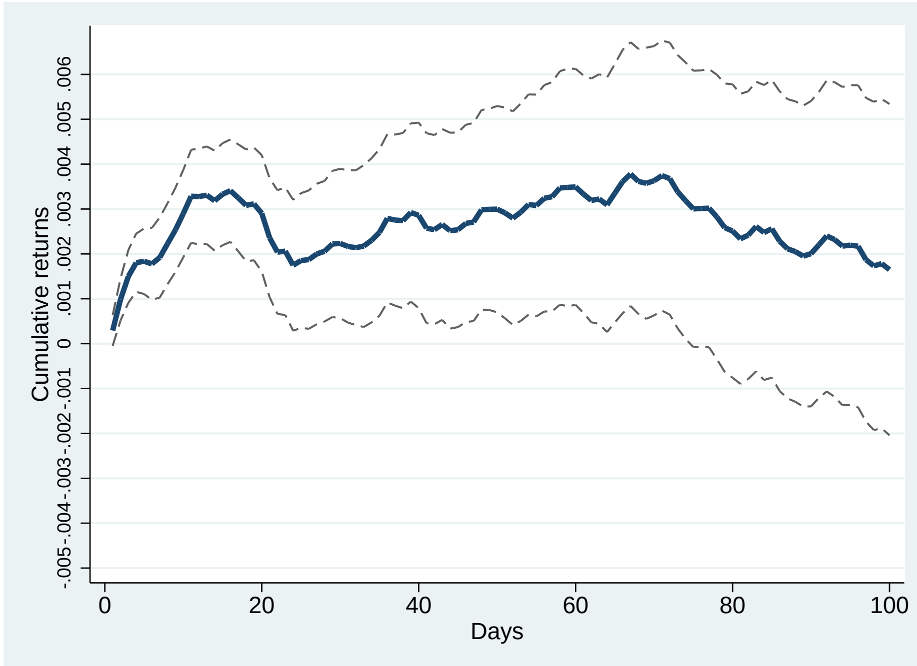
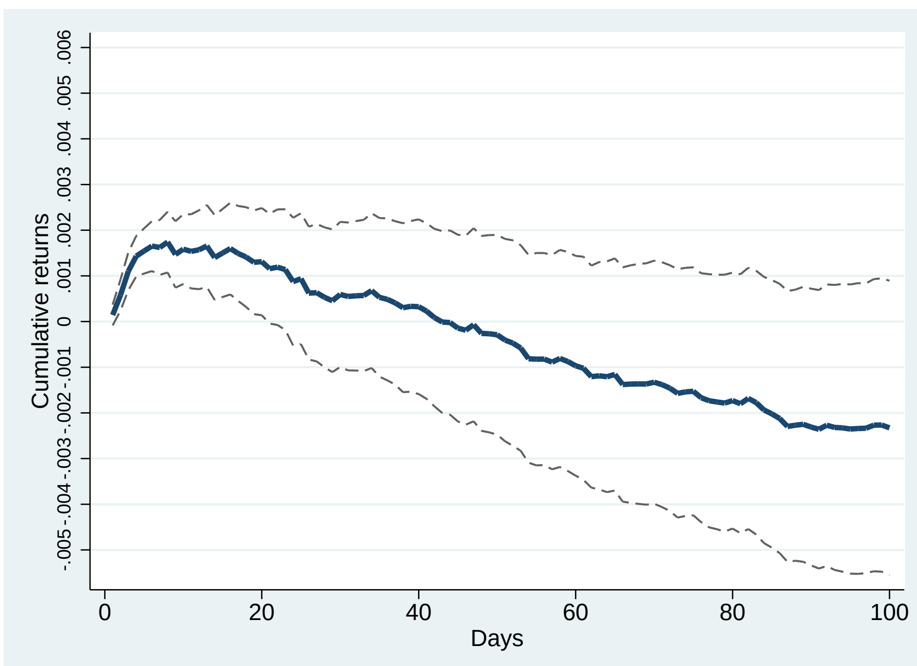


Figure 1: **Predicting returns using retail order imbalances.** This graph plots the coefficient on aggregate retail imbalances, $Imb[0]$, in stock $\times$ day level regressions where the dependent variable is $R[1, x]$, the cumulative return from day 1 to day x (from 1 to 100) following the trading day, and controls include past weekly and monthly returns, as well as market equity (see equation 4). $Imb[0]$ is defined as shares bought minus shares sold divided by shares bought plus shares sold. There are 730 distinct stocks traded between 2002-2010.



Panel A: High VIX days



Panel B: Low VIX days

Figure 2: **Predicting returns using retail order imbalances, high vs. low VIX days.** This graph plots the coefficient on aggregate retail imbalances, $Imb[0]$, in stock $\times$ day level regressions where the dependent variable is $R[1, x]$, the cumulative return from day 1 to day x (from 1 to 100) following the trading day, and controls include past weekly and monthly returns, as well as market equity. $Imb[0]$ is measured using shares bought minus shares sold divided by shares bought plus shares sold. There are 730 distinct stocks traded between 2002-2010. Panel A and B presents the estimates on the subsample of days when the VIX is respectively above and below its 2002-10 median.

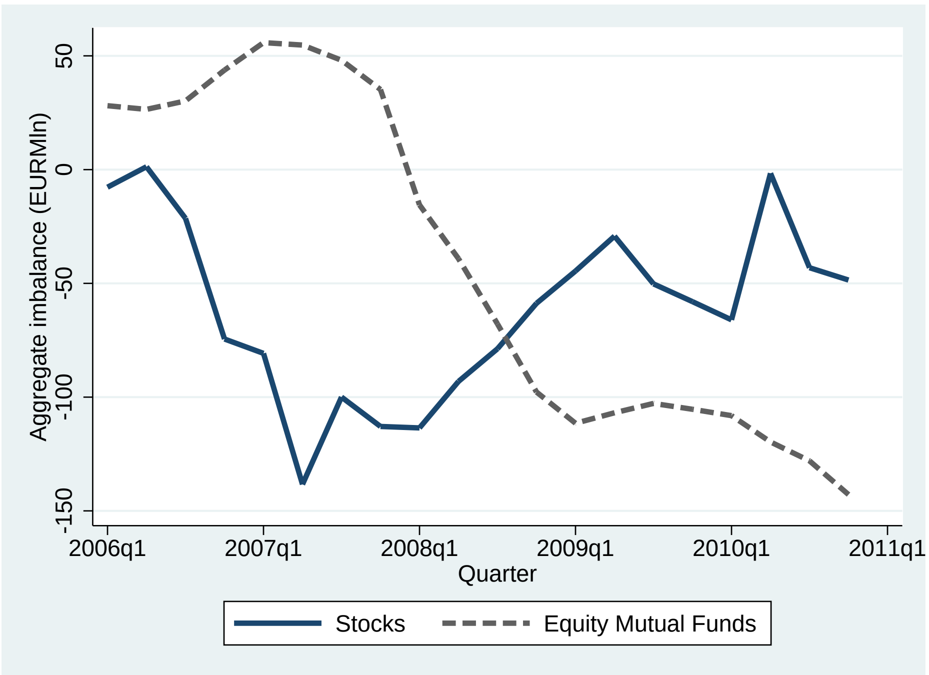


Figure 3: **Equity investment by individual investors during the crisis.** This graph plots the cumulative aggregate net flows into stocks and equity mutual funds from 2006 to 2010, in million euros. The sample includes the trades of the 81,946 investors in our sample who traded during this period.

6. Tables

Table 1: SUMMARY STATISTICS

This table presents summary statistics for the stock × day level sample (Panel A) and the order level sample (Panel B). There are a total of 92,301 traders placing approximately 5 million orders in 730 stocks from 2002 to 2010 in our sample, which leaves us with 217,511 stock-days. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. Retail volume is the absolute value, in euros, of trades in the stock originating from traders in our sample. Share of retail volume is the ratio of the number of shares of the stock traded in our sample divided by the market-wide number of shares traded. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Days to reversal is the number of days from the day the order was placed until the earliest date at which the order is at least partially reversed. Crisis dummy is a dummy taking the value of one in the seven months running from September 2008 and April 2009. High VIX is a dummy taking the value of one if the VIX is above its 2002-10 median.

	Obs.	Mean	Std. dev.	Median
Panel A: Stock×day level statistics				
$Imb[0]$	217511	-0.0034	0.5381	0.0014
Market equity	217511	21.6121	2.0717	21.8274
Retail Volume	217511	165161	362247	54940
Share of retail volume	217480	0.0241	0.0388	0.0073
$Ret[-26, -6]$	217511	0.0116	0.1239	0.0108
$Ret[-5, -1]$	217511	0.0050	0.0646	0.0031
$Ret[1, 16]$	217511	0.0035	0.1001	0.0044
$Ret[17, 100]$	217511	0.0198	0.2336	0.0218
$Ret[0]$	217511	-0.0043	0.0137	-0.0037
Days to reversal	217511	223.8163	381.9827	62.0000
Crisis dummy	217511	0.0618	—	—
High VIX	217511	0.4457	—	—
Panel B: Order level statistics				
Ret	4603607	-0.0269	0.2974	0.0045
$Ret[0]$	4639850	-0.0090	0.0251	-0.0066
AdjRet	4637552	-0.0093	0.2339	0.0034
$AdjRet[0]$	4637552	-0.0066	0.0269	-0.0051
IRR	4534305	0.0004	0.0101	0.0001
$IRR[0]$	4639850	-0.0090	0.0251	-0.0066
AdjIRR	4622152	0.0003	0.0084	0.0001
$AdjIRR[0]$	4637552	-0.0066	0.0269	-0.0051
Log cum. nb. of orders	4639850	5.3528	1.6332	5.4889
Squared log cum. nb. of orders	4639850	31.3194	16.7155	30.1284
Log days to reversal	4639101	3.8015	2.3198	3.6889
Purchase	4639850	0.5196	0.4996	1.0000
Log order size	4639850	7.8978	1.3445	7.8215
Market Equity	4639850	22.3344	1.9291	22.7396
Log mthly volume traded	4639850	2.9508	2.1494	2.9247
Log Account size	4639850	2.5069	1.7928	2.7193
Log nb of months since inception	4637671	4.1298	0.9851	4.3820

Table 2: LIQUIDITY PROVISION

This table presents the results of stock×day level OLS regressions of retail order imbalances on past returns, controls, and day and stock fixed effects. There are 730 distinct stocks traded between 2002-2010. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively.

	Dependent variable: $Imb[0]$	
$Ret[-5, -1]$	-1.03***	-1.05***
	(0.05)	(0.05)
$Ret[-26, -6]$	-0.26***	-0.26***
	(0.02)	(0.02)
Market equity	-0.02***	-0.02***
	(0.00)	(0.01)
Day FE	Yes	Yes
Stock FE	No	Yes
Observations	217511	217511
R^2	0.075	0.090

Table 3: RETURNS TO LIQUIDITY PROVISION

This table presents the results of stock×day level OLS regressions of future returns on retail order imbalances, past returns, controls, and day and stock fixed effects. There are 730 distinct stocks traded between 2002-2010. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively.

	$Ret[1,16]$	$Ret[17,100]$	$Ret[1,16]$	$Ret[17,100]$
$Imb[0]$	0.0027***	-0.0028**	0.0027***	-0.0021**
	(0.0004)	(0.0011)	(0.0004)	(0.0010)
$Ret[-5,-1]$	-0.0383***	0.0410**	-0.0418***	0.0380**
	(0.0080)	(0.0183)	(0.0077)	(0.0175)
$Ret[-26,-6]$	-0.0002	0.0480***	-0.0059	0.0332*
	(0.0069)	(0.0182)	(0.0065)	(0.0183)
Market equity	0.0012***	0.0040**	-0.0253***	-0.1202***
	(0.0004)	(0.0016)	(0.0026)	(0.0129)
Day FE	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	Yes
Observations	217511	217511	217511	217511
R^2	0.362	0.406	0.388	0.496

Table 4: RETURNS TO LIQUIDITY PROVISION - ALTERNATIVE PROXIES

This table presents the results of stock×day level OLS regressions of future returns on retail order imbalances, past returns, controls, and day and stock fixed effects.There are 730 distinct stocks traded between 2002-2010. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively.

	$Ret[1, 16]$	$Ret[17, 100]$	$Ret[1, 16]$	$Ret[17, 100]$
Panel A: $Imb[0]$, normalized				
$Imb[0]$	0.0017***	0.0004	0.0014***	-0.0011**
	(0.0002)	(0.0006)	(0.0002)	(0.0006)
$Ret[-5, -1]$	-0.0379***	0.0447**	-0.0420***	0.0381**
	(0.0080)	(0.0182)	(0.0077)	(0.0174)
$Ret[-26, -6]$	-0.0002	0.0489***	-0.0059	0.0332*
	(0.0069)	(0.0181)	(0.0065)	(0.0183)
Market equity	0.0011***	0.0041***	-0.0253***	-0.1202***
	(0.0004)	(0.0016)	(0.0026)	(0.0129)
Day FE	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	Yes
Observations	217483	217483	217483	217483
R^2	0.362	0.406	0.388	0.496
Panel B: Buy-Sell over market wide volume, normalized				
Normalized imbalances	0.0010***	0.0003	0.0008***	-0.0008
	(0.0002)	(0.0005)	(0.0002)	(0.0005)
$Ret[-5, -1]$	-0.0401***	0.0442**	-0.0438***	0.0392**
	(0.0081)	(0.0181)	(0.0077)	(0.0174)
$Ret[-26, -6]$	-0.0007	0.0488***	-0.0064	0.0336*
	(0.0069)	(0.0181)	(0.0065)	(0.0182)
Market equity	0.0011***	0.0041***	-0.0253***	-0.1202***
	(0.0004)	(0.0016)	(0.0026)	(0.0129)
Day FE	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	Yes
Observations	217458	217458	217458	217458
R^2	0.362	0.406	0.388	0.495
Panel C: Tertiles of within stock $Imb[0]$				
Medium $Imb[0]$	0.0017***	-0.0012	0.0014***	-0.0024*
	(0.0005)	(0.0014)	(0.0005)	(0.0014)
Large $Imb[0]$	0.0037***	0.0008	0.0030***	-0.0024*
	(0.0006)	(0.0013)	(0.0005)	(0.0012)
$Ret[-5, -1]$	-0.0384***	0.0447**	-0.0424***	0.0387**
	(0.0080)	(0.0182)	(0.0076)	(0.0174)
$Ret[-26, -6]$	-0.0003	0.0489***	-0.0061	0.0334*
	(0.0069)	(0.0181)	(0.0065)	(0.0183)
Market equity	0.0011***	0.0041***	-0.0253***	-0.1202***
	(0.0004)	(0.0016)	(0.0026)	(0.0129)
Day FE	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	Yes
Observations	217511	217511	217511	217511
R^2	0.362	0.406	0.388	0.496

Table 5: LIQUIDITY PROVISION AND THE CRISIS

This table presents the results of stock×day level OLS regressions of retail order imbalances on past returns, controls, and day and stock fixed effects. There are 730 stocks traded from 2002 to 2010 in our sample. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Crisis dummy is a dummy taking the value of one in the seven months running from September 2008 and April 2009. High VIX is a dummy taking the value of one if the VIX is above its 2002-10 median. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively.

	Dependent variable: $Imb[0]$					
High VIX × $Ret[-5,-1]$	0.04	0.09			-0.05	0.00
	(0.08)	(0.08)			(0.08)	(0.08)
High VIX × $Ret[-26,-6]$	-0.02	-0.01			-0.05	-0.04
	(0.03)	(0.03)			(0.03)	(0.03)
Crisis × $Ret[-5,-1]$			0.41***	0.44***	0.45***	0.44***
			(0.09)	(0.09)	(0.09)	(0.09)
Crisis × $Ret[-26,-6]$			0.13***	0.14***	0.16***	0.17***
			(0.05)	(0.04)	(0.05)	(0.04)
$Ret[-5,-1]$	-1.06***	-1.11***	-1.08***	-1.10***	-1.06***	-1.11***
	(0.08)	(0.08)	(0.06)	(0.06)	(0.08)	(0.08)
$Ret[-26,-6]$	-0.25***	-0.26***	-0.27***	-0.27***	-0.25***	-0.26***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
High VIX × Market equity	0.01***	0.01***			0.01***	0.01***
	(0.00)	(0.00)			(0.00)	(0.00)
Crisis × Market equity			0.01***	0.01***	0.01*	0.01*
			(0.00)	(0.00)	(0.00)	(0.00)
Market equity	-0.02***	-0.03***	-0.02***	-0.02***	-0.02***	-0.03***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes	No	Yes
Observations	217511	217511	217511	217511	217511	217511
R^2	0.076	0.090	0.076	0.090	0.076	0.090

Table 6: RETURNS TO LIQUIDITY PROVISION AND THE CRISIS

This table presents the results of stock×day level OLS regressions of future returns on retail order imbalances, past returns, controls, and day and stock fixed effects.There are 730 stocks traded from 2002 to 2010 in our sample. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Crisis dummy is a dummy taking the value of one in the seven months running from September 2008 and April 2009. High VIX is a dummy taking the value of one if the VIX is above its 2002-10 median. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively

	Dependent variable: $Ret[1, 16]$					
High VIX × $Imb[0]$	0.0020**	0.0016**			0.0013	0.0010
	(0.0008)	(0.0008)			(0.0008)	(0.0008)
Crisis × $Imb[0]$			0.0062***	0.0051**	0.0055**	0.0046**
			(0.0021)	(0.0021)	(0.0022)	(0.0021)
$Imb[0]$	0.0018***	0.0019***	0.0023***	0.0024***	0.0018***	0.0019***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
High VIX × $Ret[-5, -1]$	-0.0521***	-0.0394***			-0.0511***	-0.0413***
	(0.0146)	(0.0143)			(0.0151)	(0.0150)
High VIX × $Ret[-26, -6]$	-0.0391***	-0.0318***			-0.0401***	-0.0366***
	(0.0121)	(0.0117)			(0.0122)	(0.0118)
Crisis × $Ret[-5, -1]$			-0.0302	-0.0125	-0.0042	0.0085
			(0.0283)	(0.0279)	(0.0295)	(0.0293)
Crisis × $Ret[-26, -6]$			-0.0142	0.0065	0.0063	0.0251
			(0.0277)	(0.0280)	(0.0283)	(0.0287)
$Ret[-5, -1]$	-0.0095	-0.0198**	-0.0347***	-0.0404***	-0.0095	-0.0199**
	(0.0107)	(0.0098)	(0.0084)	(0.0080)	(0.0107)	(0.0098)
$Ret[-26, -6]$	0.0207**	0.0113	0.0012	-0.0068	0.0207**	0.0113
	(0.0092)	(0.0084)	(0.0071)	(0.0065)	(0.0092)	(0.0083)
High VIX × Market equity	0.0010*	0.0022***			0.0011*	0.0020***
	(0.0005)	(0.0006)			(0.0005)	(0.0006)
Crisis × Market equity			0.0000	0.0023	-0.0007	0.0012
			(0.0015)	(0.0015)	(0.0015)	(0.0015)
Market equity	0.0008*	-0.0266***	0.0012***	-0.0256***	0.0008*	-0.0267***
	(0.0005)	(0.0026)	(0.0004)	(0.0025)	(0.0005)	(0.0026)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes	No	Yes
Observations	217511	217511	217511	217511	217511	217511
R^2	0.363	0.389	0.362	0.389	0.363	0.389

Table 7: WEEKLY REBALANCED PORTFOLIO RETURNS

This table presents the excess returns (Alpha) on a weekly rebalanced portfolio long in the (value-weighted) stocks purchased and short in the (value-weighted) stocks sold by retail investors. Each week over the sample period running from 2002 to 2010, we aggregate individual trades at the stock level. We sort stocks based on their net retail aggregate position into two subsets of stocks sold and stocks purchased. We form a long and a short portfolios by value-weighting the stocks in each of these two subsets. We rebalance each of the two portfolios at the end of each week. The weekly returns on the long-short portfolio are regressed on the weekly returns on the Market, Small-minus-Big, High-minus-Law and Momentum factors. Panel A presents the results for the whole sample; Panel B restricts the sample to weeks when the VIX is above its 2002-10; Panel C restrict the sample to stock-weeks with extreme retail imbalances. ***,**, and * indicate significance at the 1, 5 and 10% respectively.

Panel A: All stock-weeks, all orders

Alpha	0.0026**	0.0023**	0.0029***	0.0033***	0.0033***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Market		0.3711***	0.2673***	0.2400***	0.2276***
		(0.0656)	(0.0691)	(0.0740)	(0.0784)
SMB			-0.2008***	-0.1925***	-0.1893***
			(0.0480)	(0.0487)	(0.0492)
HML				-0.0754	-0.0618
				(0.0731)	(0.0784)
Momentum					-0.0280
					(0.0579)
Observations	467	467	467	467	467
R^2	0.000	0.064	0.098	0.100	0.101

Panel C: High VIX weeks, all orders

Alpha	0.0052***	0.0058***	0.0059***	0.0064***	0.0064***
	(0.0019)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Market		0.4197***	0.2670***	0.2130*	0.1962
		(0.0909)	(0.0984)	(0.1102)	(0.1223)
SMB			-0.2378***	-0.2291***	-0.2263***
			(0.0665)	(0.0669)	(0.0676)
HML				-0.1102	-0.0978
				(0.1013)	(0.1086)
Momentum					-0.0265
					(0.0830)
Observations	234	234	234	234	234
R^2	0.000	0.084	0.132	0.137	0.137

Panel C: All stock-weeks, extreme imbalances

Alpha	0.0037***	0.0034***	0.0042***	0.0047***	0.0047***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Market		0.3819***	0.2488***	0.2073**	0.1925**
		(0.0731)	(0.0764)	(0.0818)	(0.0867)
SMB			-0.2576***	-0.2449***	-0.2412***
			(0.0531)	(0.0538)	(0.0543)
HML				-0.1145	-0.0984
				(0.0808)	(0.0867)
Momentum					-0.0333
					(0.0639)
Observations	467	467	467	467	467
R^2	0.000	0.056	0.101	0.105	0.105

Table 8: DECOMPOSITION OF RETURNS

This table presents the decomposition of retail traders returns between the return on day 0 , the returns between day 1 and 16 and the returns between day 16 after the date of the order and the date R or reversal. $Ret[x,y]$ and $AdjRet[x,y]$ are respectively the raw and the risk adjusted (four factor model) cumulative returns from day x to day y. $IRR[x,y]$ and $AdjIRR[x,y]$ are respectively the raw and the risk adjusted (four factor model) internal rate of return from day x to day y. Days to reversal is the number of days from the day the order was placed until the earliest date at which the order is at least partially reversed.

	Mean	p25	p50	p750
Days to reversal	310	7	40	346
Raw holding period returns				
Ret	-0.0269	-0.0951	0.0045	0.0775
$Ret[0]$	-0.0090	-0.0166	-0.0066	0.0011
$Ret[0,16]$	-0.0094	-0.0651	-0.0082	0.0472
$Ret[1,16]$	-0.0004	-0.0546	-0.0000	0.0539
$Ret[1,R]$	-0.0171	-0.0838	0.0093	0.0841
$Ret]16,R]$	-0.0268	-0.1663	0.0067	0.1359
Risk adjusted holding period returns (four factor model)				
AdjRet	-0.0093	-0.0666	0.0034	0.0660
$AdjRet[0]$	-0.0066	-0.0169	-0.0051	0.0059
$AdjRet[0,16]$	-0.0062	-0.0502	-0.0052	0.0388
$AdjRet[1,16]$	0.0004	-0.0415	0.0005	0.0424
$AdjRet[1,R]$	-0.0026	-0.0565	0.0062	0.0680
$AdjRet]16,R]$	-0.0053	-0.1067	0.0083	0.1162
Raw internal rates of returns				
IRR	0.0004	-0.0017	0.0001	0.0021
$IRR[0]$	-0.0090	-0.0166	-0.0066	0.0011
$IRR[0,16]$	-0.0009	-0.0039	-0.0005	0.0027
$IRR[1,16]$	-0.0003	-0.0035	-0.0000	0.0033
$IRR[1,R]$	0.0014	-0.0008	-0.0000	0.0013
$IRR]16,R]$	0.0003	-0.0011	0.0001	0.0011
Risk adjusted internal rates of returns (four factor model)				
AdjIRR	0.0003	-0.0014	0.0001	0.0015
$AdjIRR[0]$	-0.0066	-0.0169	-0.0051	0.0059
$AdjIRR[0,16]$	-0.0006	-0.0030	-0.0003	0.0022
$AdjIRR[1,16]$	-0.0001	-0.0026	0.0000	0.0026
$AdjIRR[1,R]$	0.0008	-0.0007	0.0000	0.0009
$AdjIRR]16,R]$	0.0003	-0.0008	0.0001	0.0009

Table 9: HETEROGENEITY IN RETURNS

This table presents the heterogeneity in returns across investor types. To construct panel A, we sort orders in our sample based on the experience of the trader, measured with the total number of prior orders placed.We compute the average of all our return variables for all deciles of experience. In panel B, we sort orders in the sample based on the propensity of each trader to quickly flip their positions. We compute the average holding period of the trader. We then compute the average of all our return variables for all deciles of average days to reversal. $Ret[x,y]$ and $AdjRet[x,y]$ are respectively the raw and the risk adjusted (four factor model) cumulative returns from day x to day y. $IRR[x,y]$ and $AdjIRR[x,y]$ are respectively the raw and the risk adjusted (four factor model) internal rate of return from day x to day y. Days to reversal is the number of days from the day the order was placed until the earliest date at which the order is at least partially reversed. ***,**, and * indicate that differences are significant at the 1, 5 and 10% respectively.

PANEL A: SORTED BY EXPERIENCE

Decile of cum.	Nb. of	Cum. nb.	Days to	Raw				Risk adjusted			
nb. of orders	orders	of orders	reversal	$Ret[0]$	$Ret[1,16]$	Ret	IRR	$AdjRet[0]$	$AdjRet[1,16]$	$AdjRet$	$AdjIRR$
1	462019	12	652	-0.0169	-0.0011	-0.0436	0.0002	-0.0150	0.0007	-0.0094	0.0000
2	468814	41	515	-0.0114	-0.0010	-0.0327	0.0003	-0.0090	0.0002	-0.0097	0.0001
3	452279	79	429	-0.0097	-0.0009	-0.0307	0.0003	-0.0074	0.0003	-0.0112	0.0001
4	460676	129	364	-0.0089	-0.0004	-0.0299	0.0004	-0.0066	0.0003	-0.0104	0.0002
5	458042	198	308	-0.0083	-0.0004	-0.0280	0.0004	-0.0060	0.0003	-0.0091	0.0002
6	461210	294	259	-0.0078	-0.0005	-0.0256	0.0004	-0.0055	0.0004	-0.0097	0.0003
7	460452	436	213	-0.0074	-0.0002	-0.0240	0.0005	-0.0051	0.0004	-0.0091	0.0004
8	459786	665	167	-0.0069	0.0000	-0.0216	0.0005	-0.0044	0.0004	-0.0086	0.0005
9	460308	1102	126	-0.0064	0.0001	-0.0175	0.0005	-0.0038	0.0004	-0.0083	0.0005
10	460021	3323	79	-0.0066	0.0006	-0.0151	0.0006	-0.0036	0.0009	-0.0070	0.0007
ALL	4639850	632	310	-0.0090	-0.0004	-0.0269	0.0004	-0.0066	0.0004	-0.0093	0.0003
TEST 9+10 vs 1+2		3296.257***	-503.906***	0.008***	0.002***	0.023***	0.000***	0.008***	0.000***	0.003***	0.001***
TEST 10 vs 1		3310.952***	-572.647***	0.010***	0.002***	0.028***	0.000***	0.011***	0.000	0.002***	0.001***

PANEL B: SORTED BY DAYS TO REVERSAL

Decile of days	Nb. of	Nb. of	Cum. nb.	Days to	Raw				Risk adjusted			
to reversal	traders	orders	of orders	reversal	$Ret[0]$	$Ret[1,16]$	Ret	IRR	$AdjRet[0]$	$AdjRet[1,16]$	$AdjRet$	$AdjIRR$
10	9129	18573	32.6504	1985.683	-0.0419	-0.0048	-0.1946	-0.0005	-0.0400	-0.0023	-0.0522	-0.0004
9	9189	33847	36.3366	1539.172	-0.0309	-0.0049	-0.2247	-0.0007	-0.0288	0.0024	-0.0078	-0.0003
8	9165	53599	53.7651	1241.095	-0.0230	-0.0058	-0.1074	-0.0003	-0.0209	0.0016	-0.0108	-0.0002
7	9175	81995	67.2277	1027.953	-0.0181	-0.0054	-0.0398	-0.0001	-0.0157	0.0007	-0.0126	-0.0002
6	9165	134651	93.6357	857.7832	-0.0148	-0.0030	-0.0287	0.0000	-0.0125	-0.0001	-0.0095	-0.0001
5	9164	213725	96.0123	705.6246	-0.0129	-0.0012	-0.0323	0.0001	-0.0109	0.0004	-0.0122	-0.0001
4	9165	326482	135.1017	565.0345	-0.0112	-0.0010	-0.0298	0.0002	-0.0092	0.0003	-0.0094	0.0000
3	9165	523789	188.5329	426.7355	-0.0101	-0.0004	-0.0310	0.0003	-0.0082	0.0004	-0.0125	0.0000
2	9165	960769	315.2298	279.6747	-0.0086	-0.0001	-0.0282	0.0004	-0.0066	0.0004	-0.0109	0.0002
1	9165	2292420	1064.907	110.8118	-0.0066	0.0001	-0.0177	0.0006	-0.0039	0.0004	-0.0071	0.0005
ALL	91647	4639850	631.5494	309.6692	-0.0090	-0.0004	-0.0269	0.0004	-0.0066	0.0004	-0.0093	0.0003
TEST 1 vs 10			1032.256***	-1874.871***	0.035***	0.005***	0.177***	0.001***	0.036***	0.003***	0.045***	0.001***
TEST 1+2 vs 9+10			810.853***	-1825.001***	0.035***	0.005***	0.174***	0.001***	0.035***	0.003***	0.044***	0.001***

Table 10: PICKING-OFF EFFECT AND TIME TO REVERSAL WITHIN INDIVIDUAL
This table presents the results of order level OLS regressions of the return on day 0, $Ret[0]$ and the number of days to reversal on vectors of time varying order characteristics, trader characteristics, and day, trader and stock $\times$ day fixed effects. The dependent variable, $Ret[0]$, is computed as the percentage change from the execution price to the closing price on the day the order is placed. Days to reversal is the number of days from the day the order was placed until the earliest date at which the order is at least partially reversed. Purchase is a dummy equal to one if the order is a purchase and zero if it is a sale. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively.

	Panel A: Log nb. of days to reversal			
Log cum. nb. of orders	-0.1093***	-0.0852***	-0.0405**	-0.0418**
	(0.021)	(0.022)	(0.017)	(0.016)
Squared log cum. nb. of orders	-0.0184***	-0.0208***	0.0232***	0.0236***
	(0.002)	(0.002)	(0.002)	(0.002)
Log mthly volume traded	-0.2521***	-0.2458***	-0.1006***	-0.0991***
	(0.004)	(0.004)	(0.002)	(0.002)
Log Account size	0.2174***	0.1847***	0.0252***	0.0245***
	(0.007)	(0.005)	(0.002)	(0.002)
Purchase	-1.1840***	-1.1799***	-1.2068***	-1.2098***
	(0.041)	(0.043)	(0.041)	(0.044)
Log order size	-0.2466***	-0.2177***	-0.2923***	-0.2805***
	(0.012)	(0.010)	(0.008)	(0.005)
Day FE	Yes	No	Yes	No
Stock $\times$ Day FE	No	Yes	No	Yes
Trader FE	No	No	Yes	Yes
Observations	4639101	4639101	4639101	4639101
R^2	0.331	0.404	0.461	0.516
	Panel B: $Ret[0]$			
Log cum. nb. of orders	0.0035***	0.0037***	0.0010***	0.0009***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared log cum. nb. of orders	-0.0002***	-0.0002***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Log mthly volume traded	-0.0006***	-0.0007***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Log Account size	0.0004***	0.0003***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Purchase	0.0024***	0.0024***	0.0015***	0.0016***
	(0.000)	(0.000)	(0.000)	(0.000)
Log order size	0.0050***	0.0052***	0.0050***	0.0054***
	(0.000)	(0.000)	(0.000)	(0.000)
Day FE	Yes	No	Yes	No
Stock $\times$ Day FE	No	Yes	No	Yes
Trader FE	No	No	Yes	Yes
Observations	4639850	4639850	4639850	4639850
R^2	0.096	0.206	0.182	0.285

7. Robustness tables

Table 11: CORRELATIONS
This table presents the correlations between variables in the order level sample. There are a total of 92,301 traders placing approximately 5 million orders in 730 stocks from 2002 to 2010 in our sample, which leaves us with 217,511 stock-days. HPR is the holding period return of any given order. $HPR[0]$ is the difference between the closing price on the day of the order and the execution price. Days to reversal is the number of days from the day the order was placed until the earliest date at which the order is at least partially reversed. Panel A presents the correlations based on raw holding period returns, while panel B presents those correlations based on risk adjusted holding period returns.

Panel A: Raw holding period returns

	Ret	$Ret[0]$	Days to reversal
Ret	1		
$Ret[0]$	.103***	1	
Days to reversal	-.197***	-.117***	1

Panel B: Risk adjusted holding periodreturns

All orders

	AdjHPR	$HPR[0]$	Days to reversal
AdjHPR	1		
$AdjHPR[0]$	.101***	1	
Days to reversal	-.0322***	-.118***	1

Table 12: RETURNS TO LIQUIDITY PROVISION - ALTERNATIVE CLUSTERING

This table presents the results of stock×day level OLS regressions of future returns on retail order imbalances, past returns, controls, and day and stock fixed effects.There are 730 distinct stocks traded between 2002-2010. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. In columns 1 and 2, standard errors are clustered by day. In columns 3 and 4, they are clustered two ways, by stock and day. ***,**, and * indicate significance at the 1, 5 and 10% respectively.

	$Ret[1, 16]$	$Ret[17, 100]$	$Ret[1, 16]$	$Ret[17, 100]$
$Imb[0]$	0.0027***	-0.0028***	0.0027***	-0.0028**
	(0.0004)	(0.0008)	(0.0005)	(0.0011)
$Ret[-5, -1]$	-0.0383***	0.0410***	-0.0383***	0.0410**
	(0.0070)	(0.0144)	(0.0095)	(0.0208)
$Ret[-26, -6]$	-0.0002	0.0480***	-0.0002	0.0480**
	(0.0044)	(0.0085)	(0.0078)	(0.0192)
Market equity	0.0012***	0.0040***	0.0012***	0.0040**
	(0.0002)	(0.0004)	(0.0004)	(0.0016)
Cluster	Day	Day	Day and Stock	Day and Stock
Day FE	Yes	Yes	Yes	Yes
Observations	217511	217511	217511	217511
R^2	0.362	0.406	0.002	0.003

Table 13: RETURNS TO LIQUIDITY PROVISION AND TRADING VOLUME

This table presents the results of stock×day level OLS regressions of future returns on retail order imbalances, past returns, controls, and day and stock fixed effects. There are 730 stocks traded from 2002 to 2010 in our sample. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalisation of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Days to reversal is the number of days from the day the order was placed until the earliest date at which the order is at least partially reversed. Crisis dummy is a dummy taking the value of one in the seven months running from September 2008 and April 2009. High VIX is a dummy taking the value of one if the VIX is above its 2002-10 median. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively

	$Ret[1,16]$	$Ret[17,100]$	$Ret[1,16]$	$Ret[17,100]$
	Panel A: high vs. low market wide volume			
$Imb[0]$	0.0019***	-0.0052***	0.0020***	-0.0034**
	(0.0006)	(0.0015)	(0.0006)	(0.0013)
High vol × $Imb[0]$	0.0019**	0.0055**	0.0016*	0.0029
	(0.0009)	(0.0023)	(0.0009)	(0.0021)
High vol	-0.0026*	-0.0158**	0.0010	-0.0112
	(0.0014)	(0.0063)	(0.0016)	(0.0081)
$Ret[-5,-1]$	-0.0414***	0.0417**	-0.0455***	0.0380**
	(0.0079)	(0.0184)	(0.0077)	(0.0176)
$Ret[-26,-6]$	0.0002	0.0471***	-0.0056	0.0325*
	(0.0068)	(0.0178)	(0.0065)	(0.0181)
Market equity	0.0017***	0.0069***	-0.0252***	-0.1185***
	(0.0005)	(0.0020)	(0.0026)	(0.0129)
Day FE	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	Yes
Observations	217511	217511	217511	217511
R^2	0.363	0.410	0.388	0.496
	Panel B: high vs. low *within firm* market wide volume			
$Imb[0]$	0.0029***	-0.0019	0.0026***	-0.0023*
	(0.0006)	(0.0014)	(0.0006)	(0.0013)
High vol × $Imb[0]$	-0.0004	-0.0016	0.0001	0.0005
	(0.0008)	(0.0019)	(0.0008)	(0.0017)
High vol	-0.0057***	-0.0305***	0.0003	-0.0028
	(0.0009)	(0.0040)	(0.0009)	(0.0033)
$Ret[-5,-1]$	-0.0356***	0.0559***	-0.0419***	0.0392**
	(0.0081)	(0.0188)	(0.0076)	(0.0175)
$Ret[-26,-6]$	0.0006	0.0525***	-0.0059	0.0334*
	(0.0070)	(0.0181)	(0.0065)	(0.0183)
Market equity	0.0013***	0.0047***	-0.0254***	-0.1193***
	(0.0004)	(0.0016)	(0.0026)	(0.0133)
Day FE	Yes	Yes	Yes	Yes
Stock FE	No	No	Yes	Yes
Observations	217511	217511	217511	217511
R^2	0.363	0.410	0.388	0.496

Table 14: RETURNS TO LIQUIDITY PROVISION AND THE CRISIS, CONDITIONAL ON INDEX INCLUSION

This table presents the results of a specification similar to the one which results are presented in Table 6, with an additional term, SBF120. SBF120 takes the value of one for stocks included in the SBF120 index, and zero for the 120 largest stocks not included in the SBF120. $Imb[0]$ is our measure of retail imbalances, defined for a stock-day as the number of shares purchased minus sold over the number of shares purchased plus sold. Market equity is the log of the market capitalization of the stock. $Ret[x, y]$ is the cumulative holding period return from day x to day y. Crisis dummy is a dummy taking the value of one in the seven months running from September 2008 and April 2009. High VIX is a dummy taking the value of one if the VIX is above its 2002-10 median. Standard errors are corrected for clustering at the stock level and are presented in parenthesis. ***,**, and * indicate significance at the 1, 5 and 10% respectively

	Dependent variable: $Ret[1, 16]$			
SBF120 × High VIX × $Imb[0]$	0.0028*	0.0029*		
	(0.0017)	(0.0017)		
High VIX × $Imb[0]$	0.0008	0.0007		
	(0.0013)	(0.0013)		
SBF120 × Crisis × $Imb[0]$			0.0088*	0.0092**
			(0.0046)	(0.0045)
Crisis × $Imb[0]$			0.0020	0.0010
			(0.0040)	(0.0038)
SBF120 × $Imb[0]$	-0.0000	-0.0001	0.0008	0.0007
	(0.0010)	(0.0010)	(0.0010)	(0.0009)
$Imb[0]$	0.0013*	0.0015*	0.0015**	0.0017**
	(0.0008)	(0.0008)	(0.0007)	(0.0007)
SBF120	0.0218	0.0487	0.0264	0.0522
	(0.0436)	(0.1252)	(0.0439)	(0.1253)
Controls	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes
Observations	168305	168305	168305	168305
R^2	0.419	0.437	0.419	0.437

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