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Full length article

Individual investors’ trading behavior in Moscow Exchange and the COVID-19 crisis

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ABSTRACT

This article presents the first study of Russian individual investors’ aggregate equity trading behavior using novel data from Moscow Exchange, with a focus on the COVID-19 episode. Aggregate Russian individual bought the dip during the COVID crash in March–April 2020. While this can be accounted for by their regular contrarian trading traits, they remained as net buyers until the market fully recovered, a sign of sophistication in striking contrast to views that characterized individual investors as noise traders. Our analysis suggests that this outcome was driven by a combination of regular contrarian traits and a unique positive shock to individual investor demand for equities, with weaker evidence of exploiting a negative bubble.

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1. Introduction

The COVID-19 episode has brought about a notable increase of individual investor presence in stock markets globally. As of early 2021, individual investors have become recognized as a market-driving force, 1 entailing renewed research focus on individual investors’ aggregate trading behavior and their role in stock market dynamics. Also, the process by which individual investor participation in stock markets has accelerated during the COVID-19 episode warrants to be documented and analyzed.

Existing studies analyzing individual investors’ trading behavior in stock markets are confined to either a few countries which provide complete data by investor type (e.g., Korea, Taiwan, Thailand, Finland) or to limited samples from one brokerage house in western countries. 2 In particular, Russia, or Moscow Exchange (MOEX), an important market that ranks around 20s among the world stock markets, 3 has been absent in this literature; and, very little is known about the trading behavior of Russian individual investors. Given the documented cultural influences on stock market trading (e.g., Ashraf, 2021), out-of-sample evidence from other countries is needed to generalize the patterns found in previous studies on a limited number of countries.

It is important to distinguish individual investors’ aggregate trading behavior from analyses of retail accounts at brokerage houses. The latter can provide statistical evidence of retail traders’ traits; however, nationwide trading of the aggregate individual investor, more of interest as a parameter within the financial system, can be dominated by a smaller number of large individual traders, displaying potentially different behavior. 4 Hence, nationwide data of investor types’ aggregate trading are important for an understanding of systemic events. Such data, however, are rare globally.

This article presents the first study of Russian individual investors’ aggregate trading behavior using novel weekly data from MOEX. First, we provide a descriptive documentary of individual investors’ aggregate trading and performance during the COVID-19 episode. The aggregate Russian individual investor bought

1 Several significant price events in financial markets have been attributed to individual investor crowds: a short-squeeze in several small-cap US stocks, a (failed) run on silver, outperformance of IPOs and small-cap stocks in emerging markets.
2 For studies using complete data from one country, see Barber and Odean (2000), Ulku and Weber (2013), Eom et al. (2019) and Omidshenken and Ulku (2020) on Asian markets, and Grinblatt and Keloharju (2000) on Finland. For seminal work using transactions data from one broker, see Barber and Odean (2000); and for a recent example, Ortmann et al. (2020).
3 According to World Federation of Exchanges statistics, MOEX was globally ranked 21st by market capitalization and 25th by traded value (electronic order book) in 2019.
4 For example, Griffin et al. (2011) show that the 1999–2000 tech-bubble was mainly driven by institutional investors, against media reports which attribute it to individual investors citing evidence from retail accounts.
the dip during the crash in March–April 2020, in unprecedented amounts. Such buying can be accounted for by individual investors’ regular contrarian trading documented in other markets (e.g., Kaniel et al., 2008; Barrot et al., 2016; Onishchenko and Ulkū, 2020), which we confirm on Russian data using a vector autoregression (VAR) analysis. However, the aggregate Russian individual investor made a key exception to contrarianism by remaining as net buyers, instead of contrarian profit-taking, until the market fully recovered. This pattern resulted in a significant wealth transfer to individual investors from other market participants (foreign and domestic institutional investors). Such evidence of sophistication sharply contrasts with the conventional wisdom of treating individual investors as noise traders in the literature (see, for example Barber and Odean, 2009; Choi and Choi, 2020).

To investigate drivers of this superior outcome during the COVID episode, we provide a comparison of Russian individual investors’ trading behavior before and during the COVID-19 crisis. Our VAR impulse responses confirm a similar pattern of contrarian trading by individual investors both before and during the COVID-19 period, suggesting that contrarianism may be a universal individual investor trait. Market returns following shocks to individual investors’ net trading are insignificant, indicating neither forecast ability nor a systematic bias; the same outcome was also in place during the COVID period. Thus, we do not detect notable differences in terms of the dynamic interaction between market returns and trading flows, suggesting that individual investor trading behavior remained essentially the same over the COVID episode. Another feature of investor types’ net trading documented in the literature is persistence (continued net trading in the same direction). VAR impulse responses indicate a prolonged persistence at longer lags during the COVID period. This can be interpreted as a symptom of a trend of inflows, also evident in summary statistics, representing a positive shock to individual investor demand for equities specific to the COVID period.

The COVID period was unique in terms of creating circumstances for a positive shock to individual investor demand for equities: Interest rates in Russia, as in the rest of the world, were lowered to unprecedented low levels, and lockdowns provided excess free time to professional individuals to monitor and trade stock markets, along with a flood of online trading tools. The outcome of this combination is also confirmed by the statistics of individual investor account openings. Thus, a coincidence of the strong V-shaped rebound with a unique positive shock to aggregate individual investor demand sustained persistent inflows and dominated contrarian profit-taking during the rebound. Contrarian buying during the sell-off, followed by this positive shock during the rebound, appears as the driver of this apparently sophisticated aggregate trading outcome.

Stock prices formed a negative bubble during the COVID crash in March–April 2020 which can be considered an example of overreaction.5 Bubble episodes offer unique tests to assess investor sophistication. Despite ample theoretical and experimental work on bubbles, empirical studies of investor types’ aggregate trading during actual bubbles are scarce, Griffin et al. (2011) being the only seminal work. Negative bubbles are an important component of this literature (see Goetzman and Kim, 2018). Hence, Russian data covering the COVID-episode offers an insightful assessment of individual investor sophistication during a notable overreaction episode. In this respect, we test whether correctly identifying and exploiting a negative bubble in stock prices was a driver of individual investors’ trading in this episode, which, to our knowledge, is the first analysis of individual investors’ role in a negative bubble.6 Results indicate a marginally-insignificant increase in individual investor net buying during the negative bubble. The COVID-period effect, capturing a unique positive shock to individual investor demand for equities, is more significant. Thus, evidence of sophistication of Russian aggregate individual investor in exploiting a negative bubble is modest, yet notably different from the findings of the existing literature reviewed in Section 2.

The contribution of this study to the literature lies in providing new evidence on novel data and addressing the links between investor types’ traits, their aggregate trading performance and the special circumstances of a negative bubble episode. An additional contribution is the first use of the mixed-frequency VAR model of Ghysels (2016) in the context of the interaction between stock returns and trading flows.

Section 2 provides a review of the background literature. Data are described in Section 3 along with additional statistics on individual investors’ role in Russia’s stock market. Section 4 presents a graphical analysis of individual investors’ cumulative aggregate trading during the COVID episode. A time-series analysis of the return–flow dynamics with comparisons of the pre-COVID and COVID periods is in Section 5. Section 6 summarizes the conclusions. In the Appendix, we present a mixed-frequency VAR analysis to explore the additional information contained in the interaction between daily returns and weekly flows.

2. Background

While part of the literature tends to characterize individual investors as noise traders vulnerable to psychological biases (e.g., Barber and Odean, 2009; Choi and Choi, 2020), a comprehensive literature on investor types’ trading provides rich granularity on individual investors’ trading behavior and performance. These studies can be located with respect to two polar categories based on the data employed: (i) Micro studies using data on each trade (e.g., Griffin J. Harris and Topaloglu, 2003); usually such data are available for a limited portion of the market (e.g., one brokerage house) and/or for a short sample period. (ii) Marketwide studies using complete (covering all trades) aggregate data from a country’s centralized exchange (e.g., Ulkū and Weber, 2013). While the former allows matching trades with stock-level intraday data and tracking characteristics of specific individual traders, the latter allows time-series analysis of aggregate trading and offers a macro view of investor types’ role within the financial system. There are hybrid studies possessing both elements (e.g., Grinblatt and Keloharju, 2000; Leung et al., 2014, using Finland data). Our study belongs strictly to the second polar category.

Scarcity of daily or weekly data has limited the progress in this path of literature and shaped the way research questions are addressed. For example, recent studies on the US individual investors are limited to a short proprietary sample provided by the NYSE (Kaniel et al., 2008, 2012) — raising questions about out-of-sample validity — or attempts to infer retail trading from statistical approximations (Boehmer et al., 2021) — needing checks for validity on actual data. In contrast, several Asian exchanges have made available long time-series of exact and complete daily aggregate trading data by investor types, enabling researchers to generate concrete evidence (e.g., Kamesaka et al., 2003; Chiang

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5 A negative bubble is a substantial and temporary (but persisting for sufficient time to be exploited) downside deviation of asset prices from their fundamental values (see Goetzman and Kim, 2018). The term was first used by Shiller (2000).

6 There is a literature on individual investor trading in response to terror events and natural disasters, which are potential triggers of negative bubbles. However, the focus of those studies (reviewed in Section 2) is different.
et al., 2012; Phansatan et al., 2012; Ülkü and Weber, 2013; Ikiçleri et al., 2019; Onischenko and Ülkü, 2020). However, the fact that most of the existing literature is confined to Asian data leaves a gap regarding whether the findings on Asian markets are representative of investors from other national cultures. In particular, east Asian individuals have been reported to have stronger belief in mean reversion (Arkes et al., 2010), which raises the question of whether the strong evidence of contrarian trading by individual investors might be specific to the Asian culture. Aggravatingly, the main dataset immediately available to study US individual investor behavior during the COVID-19 episode is Robinhood tracker data that provides merely the number of Robinhood clients holding each stock, a quite rough proxy (see Welch, 2020; Pagano et al., 2021). Therefore, a novel dataset from Russia is promising to enrich our understanding of individual investor trading behavior in stock markets, particularly under the unique circumstances of the COVID episode.

Existing research has established the following stylized facts about individual investor trading:

(i) Contrarian trading: Individual investors’ aggregate net trading is negatively related to contemporaneous and past returns. This has been documented both on the cross-sectional dimension based on net buying (selling) of winner (loser) stocks (Kaniel et al., 2008; Onisichenko and Ülkü, 2020) and on the time-series dimension based on negative impulse responses of marketwide net individual trading flows to market return shocks in VARs (Ülkü and Weber, 2013). Individual investors’ contrarian trading has been regarded as implicit liquidity provision to institutional price pressure, yielding positive returns on average (Kaniel et al., 2008; Barrot et al., 2016), but also potentially slowing down incorporation of new information (Kaniel et al., 2012; Eom et al., 2019). Regarding the driver of this contrarian trait, one argument is that individual investors tend to place ‘out-of-money’ limit orders, which leads to endogenous contrarian trading driven by institutional liquidity consumption, involving an adverse selection process (Linnainmaa, 2010). This should be relevant specifically for the negative relationship with contemporaneous returns. Behavioral drivers such as the disposition effect and a belief in mean reversion (e.g., gambler’s fallacy) can also drive the negative relationship with past returns. Onisichenko and Ülkü (2020) summarize all these effects under a single concept: “uninformed attempt to buy low and sell high using recent prices as heuristic reference points”.

(ii) Attention-driven speculative positive-feedback buying: Despite evidence of aggregate contrarian trading, individual investors have also been associated with speculative positive feedback trading. For example, Kamesaka et al. (2003) report positive feedback trading by both foreign institutions and local individual investors in Japan, and characterize the former as information-based and the latter as behavioral-based. Speculative buying frenzies that involve an element of positive feedback trading and herding are often attributed to individual investors in financial media and in some academic research; for example, Wang et al. (2017) document underperformance following high volume of stocks dominated by individual investors in the Chinese stock market. These seemingly conflicting arguments regarding whether individual investors are positive or negative feedback traders have been reconciled by Onischenko and Ülkü (2020) who show that individual investors are contrarian in institutional investor habitat (i.e., large-cap stocks) and exhibit attention-driven speculative positive-feedback buying (as established by Barber and Odean, 2008) in the small-cap segment.

While individual investors’ gambler-like trading in small-cap stocks attracts more attention in media, their marketwide aggregate trading is dominated by the much larger quantities in large-cap stocks. Consequently, studies on Asian markets consistently report strong aggregate contrarian trading by individual investors. Welch (2020) studying the Robinhood data concludes that individual investor portfolios are not much different from the market portfolio. Since our study involves marketwide-aggregated data, our results should be dominated by and represent individual investors’ aggregate trading in the market portfolio. This is different from studies using micro data on retail investors, whose samples are dominated by a large number of small investors but representing only a small portion of the aggregate individual investor.

The above-portrayed literature deals with regular trading traits of individual investors and the effect of these traits on their performance. Two related branches focus on trading behavior during extreme events such as bubble episodes or negative shocks such as natural disasters and terror attacks. On bubble episodes, the prominent, and to our knowledge the only, study is by Griffin et al. (2011), who investigate investor types’ roles during the tech-bubble. Consistent with the above-stated argument regarding the importance of the aggregate versus micro-level evidence, they find that, despite reports of buying frenzies by individual investors in the media, it was rather institutional investors who mainly drove the tech bubble.

COVID-19 led to a negative bubble, as identified ex post from the significant decline followed by complete rebound which unfolded without removal of the factors that caused the decline.7 Like most other negative bubbles, it was caused by a negatively-perceived unexpected event, leading to a shock to risk aversion. Studies of investor behavior following terror attacks and natural disasters report de-risking and reduction in activities by individual investors (Wang and Young, 2020; Hasso et al., 2020; Bourdeau-Brien and Kryzanowski, 2020). Also, conventional wisdom tends to associate individual investors with panic-selling. What makes this episode interesting is that, in sharp contrast, we document a significant increase in individual investor risk-taking in the stock market following the outbreak of COVID-19.

3. Data

MOEX started publishing weekly individual investor net trading flows data from the beginning of 2018. Data are derived from all individual investors’ transactions in all listed stocks in the centralized exchange, hence precise. Reported time-series refers to weekly net trading imbalance; i.e., marketwide-aggregated purchases minus sales by domestic individual investors. Our sample period spans from the beginning of 2018 to the end of January 2021. This time span allows us to first establish regular trading behavior between January 2018 and February 2020 and then examine COVID-period differences.

In the empirical analysis, we employ net flows normalized by market capitalization, denoted $F$, and MOEX Russia index (MIX) returns, denoted $R$ and computed as the first difference of log index levels.8 Descriptive statistics are presented in Table 1. ADF tests confirm that both variables, $F$ and $R$, are stationary, suitable for VAR estimation.

As this is the first study of Russian individual investors, we provide general information on Russian individual investors’ role in MOEX based on statistics we garnered from MOEX bulletins and Bank of Russia reports.9 MOEX is the main centralized stock

7 Given the difficulties in identifying bubbles (see Gürkaynak, 2008), most recent studies (e.g., Greenwood et al., 2019 and, particularly Goetzman and Kim, 2010, on negative bubbles) rely on ex-post evaluation of stock price behavior.
8 MOEX Russia index, which comprises 50 stocks, and the MOEX Broad Market index, which comprises 100 stocks, yield identical results. Both indices are free-float capitalization-weighted, and their weekly return correlation is 0.9994. Moreover, their total returns over our sample period are 48.88% and 48.46%, respectively, indicating no differential cumulative performance.
9 Some of the statistics can be found at https://www.moex.com/756 and https://cbr.ru/Collection/Collection/File/32069/review_secru_2h.zip.
exchange in Russia. Fig. 1 indicates that MOEX has experienced significant growth in the number of individual investors after 2017, yet the rate of growth sharply accelerated in 2020.

**Individual Investment Accounts (IIA)** introduced in 2015 with favorable taxation rules have been a main driver of the pre-COVID growth: To channel household savings into companies in Russia, the Tax Code was amended in 2015 to allow tax base reductions or capital gains tax exemption. IIAs have become popular; as of November 2020, the number of IIAs has reached 3.2 million and the value of assets in IIAs is more than 285 billion Rubles. Yet, an acceleration in 2020 has occurred following the outbreak of the COVID-19 pandemic, possibly helped by substantial monetary easing and excess free time available to working individuals due to lockdowns. The number of active IIAs (at least one transaction during the year) has grown from 163,000 in 2018, to 305,000 in 2019, and further to 689,000 in 2020. Further statistics reported by Bank of Russia confirm that the ratio of active to total IIAs also jumped in 2020.

During our sample period, local individual investors’ average share in MOEX total trading value is 37.5% (monthly averages ranged between 31% and 46.4%). The largest share in the total trading value is accounted for by foreign investors (predominantly institutional) with a sample period average of 48.7%. Domestic institutions have a relatively minor, and decreasing, presence, with dealers accounting for 7.7% of the trading value, legal entities/institutional asset managers (i.e., funds) 1.7%. A comparison of investor types’ share in traded value in 2013, 2019 and 2020, tabulated in Panel A of Table 2, suggests a notable increase in individual investors’ presence during the COVID period.

Available data on Russian individual investors’ holdings of stocks are summarized in Panel B of Table 2. Individual investor holdings’ share in free-float market capitalization is smaller compared with their share in trading value. It rose from 8.3% at the end of 2019 to 9.4% at the end of 2020. Despite this increase, the share of Russian stocks within aggregate individual investors’ portfolio has decreased during the same period (i.e., the growth rate of individual investors’ holdings of other assets is much higher, see full statistics from the second link provided in footnote 10). The latter can be interpreted to suggest that the recent increase in Russian individual investors’ demand for equities is likely driven by an increase in funds available for investments rather than by a shift in their risk preferences. One likely explanation is that monetary expansion ended up at households’ hands channeled into financial assets.

Further statistics in Panel C on the size decomposition of brokerage accounts compiled from selected largest brokerage houses (available as of the end of the third quarter of 2020) suggest a high concentration: Accounts greater than 10 million Ruble in value constitute about 1% of the total number of accounts (down from 1.4% at the end of 2019) but 64% of the value of equity held (down from 65.2% at the end of 2019). Thus, it is reasonable to assume that aggregate individual trading is dominated by wealthy individuals; however, absent data on each category’s frequency of trading, we are unable to verify this with certainty.

During the first three quarters of 2020, the share (within the total value of assets held at Russian brokers) of all account sizes smaller than 10 million Ruble increased at the expense of the largest size category. In terms of the number of accounts, the share of the smallest category (< 10,000 Ruble) had a large jump. A decomposition by age, reported in Panel D, suggests that the share of the young working age categories has notably increased during the first three quarters of 2020.

**4. A description of Russian individual investors’ aggregate trading during the COVID crisis**

Fig. 2 depicts the cumulative net marketwide flows of Russian individual investors against the MOEX-Russia index throughout our sample period. While cumulative net flows of individual investors were already trending up during 2019, the COVID crash in March 2020 attracted significant above-trend net buying. This behavior is in sharp contrast to the findings of increased risk-aversion following natural disasters and terror events in studies mentioned above. Based on the statistics reported in Panel A of Table 2, MOEX market participants can be roughly partitioned into individuals versus foreign and domestic institutions, and the latter group’s aggregate net flows would be the mirror image of that of individual investors, implying significant net selling by them. This coincides with large net selling by foreign investors in other emerging stock markets and outflows from emerging market equity funds during the same period. 14

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**Table 1**

| Variable | Mean | St. Dev. | Skewness | Kurtosis | ADF test |
|----------|------|----------|----------|----------|----------|
| Weekly Net Flows (bln Ruble) | 2.568 | 12.330 | 1.71 | 16.65 | 4.98* |
| pre-COVID period | 0.951 | 5.808 | 1.84 | 12.35 | 10.86* |
| COVID period | 6.156 | 20.041 | 0.0027 | 0.0261 | 1.71 | 16.65 |
| F | 0.0000595 | 0.0002708 | -1.71 | 16.65 | 4.98* |
| R | 0.0027 | 0.0261 | -1.84 | 13.35 | -10.86* |

This table provides summary statistics of the variables used in the empirical analysis. n = 161 weeks (pre-COVID period 111 weeks; COVID period 50 weeks). ADF test refers to the Augmented Dickey-Fuller unit root test statistic.

* Denotes rejection of ‘H0: unit root’ at the 1% level of significance.

**The negative skewness and high kurtosis in F are driven by a large outflow in week ending 13 November 2020, apparently a concentrated profit-taking in response to sharp rebound after the US election despite signs of a second wave in COVID cases starting. This large negative outflow amid persistent positive average inflows during the COVID period naturally leads to negative skewness.**

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**Note:**

10 MOEX hosts trading in equities, bonds, derivatives, currencies, money market instruments, and commodities. According to the World Federation of Exchanges, MOEX was ranked 21st globally by market capitalization and 25th by trading value (electronic order book) in 2019. Market capitalization has grown from 38651 billion Rubles in the first quarter of 2018 to 45053 billion Rubles in the third quarter of 2020.

11 IIA is a special brokerage or asset management account with newly introduced tax benefits aiming at stimulating households’ equity investments. Hence, the term in this paragraph should be differentiated from the number of total individual investor accounts reported in Fig. 1. See [https://www.moex.com/ir1597](https://www.moex.com/ir1597) for details.

12 Bank of Russia lowered the policy rate from 6.00% in February to 4.25% through July 2020.

13 Also, other data indicate that individual investors’ total assets held at Russian intermediaries grew by 19.6% during the first three quarters of 2020, with most of the increase coming during the third quarter.

14 Authors’ compiled data from the stock exchanges of Japan, Korea, Taiwan, Thailand and Turkey indicates significant net selling by foreign investors in each of these markets during the same period. According to global fund flows data published by EPFR (available on Bloomberg), global emerging market equity funds faced US$ 25.5 billion of redemptions between 19 February and 22 April 2020.
Notice that, in addition to a positive inflow trend, a negative relationship between market returns and individual investor net flows (indicated by opposite-direction fluctuations of the index and cumulative net flow lines) started to emerge from late 2018 onwards. However, during the recovery between April and July 2020, individual investors were not contrarian net sellers; rather, they continued to be net buyers. They again bought in large net amounts during the August–October dip, which completely recovered in November. These observations provide evidence of sophisticated trading, in striking contrast to views that characterized individual investors as noise traders.

How can we account for this outcome? One possibility is a shock to net individual investor demand for equities, indicated by an acceleration of the inflows trend, driven by unprecedented monetary easing and free time to engage in stock
markets, that coincided with the V-shaped rebound in stock markets worldwide.

This coincidence, whether it is a peculiarity of this episode or an outcome of individual investors’ sophistication, has led to a significant transfer of wealth. The incremental gains of individual investors that result from their above documented aggregate trading imply equal amount of losses by foreign and domestic institutional investors, which constitute the rest of the market. (The gains and losses referred to here are in the sense of opportunity cost with respect to status quo if no net trading took place). A rough estimate of the incremental effect of individual investors’ trading on their wealth can be obtained via the following performance metric:

\[
PM = \sum_{t=1}^{T} \left( \sum_{i=1}^{p} F_{t, i}\right) R_{t}
\]

(1)

where \( T \) is the final week in the measurement period. To capture in the \( PM \) statistic the effect of the divergent trading between individual investors and the rest of the market during the COVID period containing the negative bubble and rebound, we set 21 February 2020 as week 1 and the end of November 2020 as \( T \). The resulting \( PM \) estimate suggests that about Ruble 38.5 billion worth of wealth has been transferred to individual investors from the foreign and domestic institutional investors as a result of the trading during the 9-month COVID period.\(^\text{15}\)

Previous literature already documented that individual investors’ contrarian trading is profitable on average as an implicit form of liquidity provision to aggressive trading by institutions (Kaniel et al., 2008; Barrot et al., 2016; Onishchenko and Ülkü, 2020), and in Fig. 2 signs of contrarian trading are evident starting from the end of 2018. Thus, one possibility is that individual investors’ contrarian trading was a regular trait, already profitable even before COVID. A comparison would therefore shed light on whether the COVID-period represents an unusual performance by the aggregate Russian individual investor: During the 26-month pre-COVID period individual investors’ \( PM \) estimate is at Ruble 15 billion (adjusted per footnote 16), in line with gains from regular contrarian trading documented in earlier studies. Yet, the Ruble 38.5 billion gain during the 9-month COVID period is substantially higher than the 15 billion gain during the 26-month pre-COVID period, indicating that the COVID episode is associated with unprecedented outcomes for individual investors.

5. Analysis of Russian individual investors’ trading behavior before and during the COVID crisis

5.1. Methodology

To analyze the dynamic interaction between stock market returns and Russian individual investors’ aggregate net trading, we employ a structural vector autoregression (SVAR) model at the weekly frequency.\(^\text{16}\) Our baseline VAR model takes the following form:

\[
F_t = \omega_1 + \sum_{i=1}^{p} \psi_i F_{t-i} + \sum_{i=1}^{p} \theta_i R_{t-i} + \varepsilon_{1,t},
\]

\[
R_t = \omega_2 + \sum_{i=1}^{p} \gamma_i F_{t-i} + \sum_{i=1}^{p} \lambda_i R_{t-i} + \varepsilon_{2,t}.
\]

(2)

where the optimal lag length of \( p = 3 \) is used as indicated by the Akaike information criterion. The contemporaneous relation is identified via a Cholesky procedure where \( \varepsilon_{2,t} \) is assumed to affect \( \varepsilon_{1,t} \) and not vice versa. This assumption is justified as returns are also driven by exogenous factors such as news arrivals and institutional trading’s price impact, whereas individual investors’ negative contemporaneous relationship with returns (estimated at \( -0.612 \) over our sample period) implies that their trading is endogenous and rules out alternative orderings.\(^\text{17}\)

\(^{15}\) The \( PM \) formula in Eq. (1) is a rough approximation as it assumes that individual investors’ weekly net trading is executed in the same composition as the index portfolio and at the weekly closing level. For the latter, we make an adjustment by assuming that individual investors’ net trading is executed at the average of daily closing index levels. Ruble 38.5 billion is the adjusted figure. The figure before the adjustment was Ruble 46 billion.

\(^{16}\) The null of no cointegrating vector could not be rejected by the Johansen trace test.

\(^{17}\) In the return–flow interaction, there are three possibilities: (1) flows cause returns – price impact – can only lead to a positive relation. (2) returns cause flows – feedback trading – can be positive or negative. (3) news effect that drives both flows and returns simultaneously; it induces only positive relations. Thus, the only possibility of a negative contemporaneous relationship between flows and returns can arise if either investors respond to returns in a contrarian manner or their out-of-money limit orders are filled as a result of price changes, both of which imply that trading flows are endogenous.
Available weekly data causes some loss of granularity compared with daily data. As a result of this, both feedback trading with respect to previous days’ returns and the true contemporaneous relationship resulting from institutional consumption of individuals’ out-of-money limit orders per Linnainmaa (2010) will be captured by the weekly contemporaneous relationship. In other words, what would be identified as feedback trading under daily data is included in the contemporaneous relationship here. Therefore, the contemporaneous relation, identified though the other words, what would be identified as feedback trading under will be captured by the weekly contemporaneous relationship. In individuals’ out-of-money limit orders per Linnainmaa (2010) raneous relationship resulting from institutional consumption of pared with daily data. As a result of this, both feedback trading

1.75% whereas it was 4.25% during the COVID period; about 2.42 times. Hence, the cumulative impulse response to a 1-standard deviation (sd) shock to returns in Fig. 3. Negative impulse response coefficients imply contrarian trading. As discussed above, a negative contemporaneous impulse response coefficient (week 0) can reflect both endogenous contrarian trading driven by institutional investors’ hitting individual investors’ out-of-money limit order limits as well as negative feedback trading with respect to previous day’s returns or even previous hours’ returns on the same day.

The contemporaneous response is significantly negative in both pre-COVID and COVID periods, indicating contrarian aggregate trading. The bulk of the cumulative impulse response comes from the contemporaneous week. This significant negative contemporaneous relationship is consistent with the strong results on Asian markets. Thus, the results from Russia add confidence to the conclusion that contrarian trading is a universal trait of individual investors.

As the rest of the MOEX participants’ aggregate net flows are a mirror image of those of individual investors, this result implies a significant positive contemporaneous relationship for foreign and domestic institutions. This is again consistent with the institutional price impact documented in most other stock markets.

Regarding lagged relationships, during the first three weeks following the shock, individual investors tended to reverse about 1/5 of their contemporaneous negative (i.e., contrarian) response in the pre-COVID period (e.g., following buying a dip in week 0, they sold back 1/5 of it in the next 3 weeks). During the COVID period, however, individual investors retained their contrarian response (by continuing contrarian trading in week 1 and reversing only that part afterwards). This appears as the main difference between pre-COVID and COVID periods. In Section 5.3, we formally test the statistical significance of potential differences in individual investors’ feedback trading behavior in the COVID period employing dummy variable models.

Returning back to the contemporaneous relationship between market returns and individual investors’ trading, we use a MIDAS regression to find out whether the negative weekly relation is mainly driven by feedback trading with respect to previous days’ returns. Let $R_k$ denote daily returns for each day of the week, where $k = 1, 2, ..., m$ is the number of high-frequency (daily) observations within one low-frequency period (week) of the variable $F$ (i.e., $R^i$ is the Monday returns,..., $R^5$ is the Friday returns) with $m = 5$. Adapting Andreou et al.’s (2010) proposed specification to our case, we estimate:

$$F_t = \omega + \sum_{j=1}^{p} \phi_j F_{t-j} + \sum_{j=0}^{m} \sum_{k=1}^{m} \theta_{jk} R^k_{t-j} + \epsilon_t \quad (3)$$

If negative feedback trading with respect to previous day’s return is a significant component of the weekly contemporaneous relationship between $F$ and $R$, $\theta_{jk}^0$ would be expected to be significantly smaller in absolute value (as feedback trading with respect to Friday returns is not included in the current week’s $F$). The estimated $\theta_{jk}^0$ coefficients are tabulated below with Newey–West $t$-statistics in parentheses:

$$R^1 \quad R^2 \quad R^3 \quad R^4 \quad R^5$$

$$(-6.02) \quad (-3.36) \quad (-5.10) \quad (-4.70) \quad (-5.04)$$

To the contrary of what would be expected if feedback trading with respect to previous days’ returns dictated the weekly contemporaneous relationship, the Friday coefficient is the largest in absolute value. Hence, it is difficult to argue that feedback trading with respect to previous day’s return is the dominant driver of the weekly contemporaneous relationship between $F$ and $R$. (Of course, this does not completely rule out feedback trading with respect to previous days’ returns). The daily contemporaneous relationship is likely the dominant driver, and it in turn can be driven by a combination of institutional consumption of individuals’ out-of-money limit orders per Linnainmaa (2010) and intraday negative feedback trading.

18 A narrower COVID-period definition (24 February 2020 to the end of June 2020) yields qualitatively identical results.
19 The absolute size of the coefficient during the COVID period is about three times as large as that in the pre-COVID period. However, one needs to adjust for different shock sizes: in the pre-COVID period 1-sd return shock was about 1.75% whereas it was 4.25% during the COVID period; about 2.42 times. Hence, a large part, albeit not all, of the increase in the size of the contemporaneous negative response is attributable to the size of the shock.
20 During the COVID period, the confidence band widens. This should be explained by relatively more volatile market conditions resulting in higher standard errors and the shorter sample period. The size of the coefficients is rather much larger during the COVID period.
21 We have also applied Chow and CUSUM tests for the VAR system. Except for one version of the Chow test, which yielded a borderline significant break-point, the results suggested no significant change (available from the authors). Some break-point searches rather signaled a break around mid-2018, which probably captures new individual investors’ attraction to the stock market following the tax incentive.
5.2.2. Russian individual investors’ forecast ability

Information content/forecast ability of individual investors’ trading is analyzed by simulating returns’ cumulative impulse response to a 1-sd shock to net flows in Fig. 4. Future returns following a shock to individual investors’ net flows are insignificant (albeit negative) in both the pre-COVID and COVID periods, indicating that individual investors’ aggregate net trading neither contains forecast ability nor displays significant symptoms of a systematic bias. This result suggests that individual investors’ ability to predict future returns was no different in the COVID period. Hence, the above documented successful outcome cannot be explained by a COVID-period improvement in their forecast abilities.

5.2.2. Persistence of Russian individual investors’ aggregate net trading

Persistence of individual investors’ net aggregate trading is analyzed by simulating net flows’ cumulative impulse response to a 1-sd shock to net flows in Fig. 5. There is evidence of persistence in both the pre-COVID and the COVID period. However, the shape of the persistence differs: in the pre-COVID period a 1-sd shock is followed by further net trading in the same direction by about 50% of the initial shock over the next 2–3 weeks followed by stabilization, whereas in the COVID period prolonged continuation exceeding 80% of the size of the initial shock is observed up to week 7. This can be a symptom of an increase in individual investor demand for equities in the COVID period (investigated below in Section 5.3).

Notice that in the pre-COVID period a 1-sd net flow shock was about 0.00009 whereas it was 0.00037 during the COVID period.
5.3. Tests of differences in Russian individual investors’ trading behavior during the COVID-period

To formally test whether Russian individual investors’ trading behavior significantly differed during the COVID period, we create a dummy variable $D_t$ that takes the value of 1 during the COVID period defined above and 0 otherwise, and estimate a modified $F$-equation\(^{22}\):

$$F_t = \omega + \omega' D_t + \psi \sum_{i=1}^{p} F_{t-i} + \psi' \sum_{i=1}^{p} D_{t-i} F_{t-i} + \lambda R_t + \lambda' R_tD_t$$

$$+ \theta \sum_{i=1}^{p} R_{t-i} + \theta' \sum_{i=1}^{p} D_{t-i} R_{t-i} + \epsilon_{1,t} \quad (4)$$

Note that, to be able to report COVID-period differences in single statistics, the coefficients are assigned to the sums of lag terms in Eq. (4) instead of each individual lag. By doing so, we effectivly represent near-past returns and near-past net flows in single transformed variables. Both alternative versions lead to qualitatively identical conclusions\(^{23}\); Eq. (4) is preferred only to keep reporting manageable in crowded regression models.

Parameters of interest are $\omega$, $\psi$, $\lambda$, and $\theta$, which will indicate, respectively, whether during the COVID-period: (i) mean net flows differed after controlling for the return–flow dynamic interaction, i.e., an exogeneous shock to individual investor demand for equities occurred; (ii) the persistence of net flows, which can be interpreted as a measure of herding, differed; (iii) individual investors responded differently to contemporaneous returns and (iv) to past returns. Results are presented in the second block of Table 3. The first block on the left presents the results for the baseline model without the dummy, but with lags summed as in Eq. (4), to show that this specification yields similar results as our standard VAR model.

Estimated Newey–West $t$-statistics in the second block, $t(\psi') = -0.41$, $t(\lambda') = -0.35$ and $t(\theta') = -0.02$, indicate that differences in individual investors’ trading behavior (persistence

with respect to past net flows and response to contemporaneous and past returns, respectively) during the COVID period are not statistically significant. Hence, our conclusion from the impulse response functions (that Russian individual investor trading behavior remained similar during the COVID period) is confirmed. Any exogeneous shocks to individual investor demand for equities would be captured by the $\omega$-coefficient. The positive $\omega$ implies a substantial increase in mean net inflows, which however is marginally insignificant with a Newey–West $t = 1.63$.

Investor response to positive and negative returns may differ. Omission of a potential nonlinearity in investor response to positive and negative returns may amount to a misspecification and lead to noninformative coefficient estimates. Hence, we estimate a nonlinear version. For this purpose, we create a dummy variable, $N_t$, that takes the value of 1 when $R_t < 0$ and 0 otherwise. The third block in Table 3 provides the results for the baseline nonlinear model, i.e.:

$$F_t = \omega + \psi \sum_{i=1}^{p} F_{t-i} + \lambda R_t + \lambda' R_tD_t + \theta \sum_{i=1}^{p} R_{t-i} + \theta' \sum_{i=1}^{p} N_{t-i} R_{t-i} + \epsilon_{1,t}$$

(5)

It indicates significant nonlinearity: individual investors are more contrarian to positive contemporaneous returns than to negative ones. In other words, selling on market increases is a more immediate tendency compared with buying dips. This is an intuitive result given the expected immediate effect of negative returns on risk tolerance and the well-known disposition effect. With respect to past weeks’ returns, however, we observe an opposite result: individual investors are more contrarian to negative past returns than to positive ones. This indicates that the effect of negative returns on risk tolerance dissipates over time, and motivation to exploit the opportunity to buy cheaper starts to dominate. With respect to positive past returns, individual investors do positive-feedback-trade.

A visual inspection of Fig. 2 above suggests that the aggregate individual investor skipped contrarian profit taking specifically during the rebound from the COVID crash. This warrants a formal statistical test to find out whether it can be explained in terms of the nonlinearity during the COVID-period, i.e., a higher (lower) propensity to buy dips (sell rebounds), formally captured by the interaction of the two dummies $D$ and $N$. For this purpose, we estimate:

$$F_t = \omega + \omega D_t + \psi \sum_{i=1}^{p} F_{t-i} + \psi' \sum_{i=1}^{p} D_{t-i} F_{t-i} + \lambda R_t + \lambda' R_tD_t \quad (6)$$

The $R$-equation is suppressed for brevity as the focus here is on the $F$-equation. FGLS estimation of the full VAR system yields qualitatively identical results, while reported results are from Newey–West estimation of the single equation.

An equivalent statistic can be generated from a model with three lagged terms by summing the coefficients of each lag and applying an $F$-test for the sum. Conclusions are qualitatively identical either way.
investors responded to COVID news in a rational manner. Fears and a rational positive response to news arrivals. Accordingly, individual investors responded to COVID news in a rational manner. Individual driven by two components: a contrarian response driven by behavioral effects and a rational positive response to news arrivals. Accordingly, individual investors responded to COVID news in a rational manner.

Fig. 5. Market returns’ impulse response to a 1-sd shock to individual investor net flows. This figure depicts the impulse response of individual investor net flows to a 1-sd shock in itself (denoted as Indiv → Indiv). All other explanations are the same as in Fig. 2. The size of the net flow shock can be gauged from the contemporaneous coefficient of the Indiv → Indiv impulse response function.

\[ + \lambda'' R_{t} N_{t} + \lambda''' R_{t} D_{t} N_{t} + \theta \sum_{i=1}^{p} R_{t-i} + \theta' \sum_{i=1}^{p} D_{t-i} R_{t-i} \]

\[ + \theta'' \sum_{i=1}^{p} R_{t-i} N_{t-i} + \theta''' \sum_{i=1}^{p} D_{t-i} R_{t-i} N_{t-i} + \epsilon_{1,t} \] (6)

where parameters of interest, \( \lambda'' \) and \( \lambda''' \), will indicate whether individual investors’ response specifically to negative returns differed during the COVID period. Results are in the fourth block of Table 3 (under ’Eq.(6)’).

The significantly negative \( \lambda \) with estimated Newey–West \( t = -2.63 \) suggests that individual investors were more contrarian with respect to positive contemporaneous returns during the COVID period. On the other hand, the significantly positive \( \lambda'' \) with estimated Newey–West \( t = 3.19 \) suggests that individual investors were much less contrarian with respect to negative contemporaneous returns during the COVID period. In fact, the significance of \( \lambda'' \) in the baseline result (block 3) disappears once we control for COVID-period effects, suggesting that the observed differential impact of negative returns is mainly driven by the COVID period. These results contrast the above-stated impression from the visual inspection of Fig. 2, and can be interpreted as evidence of increased risk aversion caused by COVID news, which drove negative returns during this period and were salient to individual investors. \(^{24}\) Such increase in risk aversion (adding to the urge to take profits) can also explain the more-contrarian response to positive returns during the COVID period. This increase in risk aversion is consistent with the findings of studies of natural disasters and terror events, reviewed in Section 2: Russian individual investor behavior in response to disasters was no different during the COVID episode. Then, what is the nuance behind the observed increase in individual investors’ inflows in stock market? The next two paragraphs below provide the answer.

Part of the answer lies in individual investors’ response to past positive and negative returns. Albeit statistically insignificant, the size of the coefficients suggests that during the COVID period individual investors were more contrarian to negative past returns (negative \( \theta'' \)) and less contrarian to positive past returns (positive \( \theta' \)) compared with pre-COVID period (i.e., a tendency of more buying resumed in either case). This is the only result consistent with the visual impression from Fig. 2, albeit a statistically weak one.

Importantly, the significance of \( \psi \) (\( t = 2.84 \) in the baseline nonlinear model) disappears once the COVID period intercept is controlled for in Eq. (6). The decrease is not captured by the \( \psi \) term, indicating no change in the dynamic persistence. Instead, \( \omega' \) has now become highly significant, once the nonlinearity in the return–flow dynamics is controlled for. That is, COVID-period differences leading to significant net buying are mainly captured by the intercept term. Hence, in a model which fully accounts the nonlinearity in the dynamic interaction, it becomes clear that the main difference in the COVID-period is in the intercept term, representing an exogenous shock to net inflows of individual investors. This can be interpreted to indicate an exogenous positive shock to individual investor demand for equities during the COVID period, outside the dynamics of the return–flow interaction. This result also favors a positive shock to individual investor demand for equities over an alternative of increased herding.

One possibility is that Russian individual investors may have acted with a potential motivation of exploiting a negative bubble, a nonlinear form of response to stock price information rather than an exogenous increase. An inspection of Fig. 2 also suggests a negative bubble was formed during the sell-off in March–April. Following the practice in the recent empirical literature on bubbles, in particular Goetzman and Kim (2018) on negative bubbles, we define the negative bubble period based on ex post price action\(^{25}\) and create a negative-bubble dummy variable, \( B_{t} \), which takes the value of 1 when the MOEX index was below its January–February 2020 pre-COVID average value by 20% or more and 0 otherwise.\(^ {26}\) Then, we add \( B_{t} \) into Eq. (6), in order to test whether exploiting this negative bubble was a motivation behind Russian individual investors’ net buying during the COVID period after controlling for all other relevant terms.

\(^{24}\) Onischenko and Ulku (2020) characterize individual investor trading driven by two components: a contrarian response driven by behavioral effects and a rational positive response to news arrivals. Accordingly, individual investors responded to COVID news in a rational manner.

\(^{25}\) We follow the criterion identified ex post by an eventual reversion of the index to the initial level without arrival of unpredictable news. See Gürkaynak (2008) who concludes that “cointegration detection of asset price bubbles cannot be achieved with a satisfactory degree of certainty”.

\(^{26}\) There is no formal guideline in the literature on how a specific bubble territory should be defined. Goetzman and Kim (2018) experiment with many different thresholds (of the size of a crash in stock indices), obtain different samples based on each threshold and report a reasonable one of them as their baseline results. With only one event at hand, the 20% threshold had to be determined simply based on intuition. We tested many nearby alternatives (between –14% and –22%). All of them yield similar conclusions. Thresholds stricter than –22% lead to a too small number of weeks identified as negative-bubble levels, hence not preferred.
The result is reported in the last block of Table 3. The $B_i$ coefficient is positive, however its Newey–West $t$-statistic is marginally insignificant at 1.58, and the size of its coefficient is slightly smaller than the COVID-dummy’s coefficient. (Notice that when $B_i$ and $D_i$ are jointly included in the regression, they compete against each other to capture the increase in mean net flows from the pre-COVID period). These results suggest some signs of Russian individual investors acting with a motivation to exploit the negative bubble, yet the COVID period effects on individual investor inflows were a stronger driver. Note also that adding the negative bubble dummy did not alter any of the results for the other parameters.

Recall that the negative bubble occurred before workers adopted a work-from-home life style and Bank of Russia started to cut interest rate in response to COVID (the first 50 bp cut came on 27 April 2020, followed by 100 bp and 25 bp cuts on 22 June and 27 July, respectively). The results suggest the exogenous positive shock to individual investor demand for equities possibly driven by these two effects was more significant.

6. Conclusions

In the first study of Russian individual investors’ aggregate trading behavior, we document that a key individual investor trait found in other countries, contrarian trading, generalizes to Russian individual investors.

Russian individual investors bought the dip during the COVID crash in March–April 2020. Given that individual investors account for 38% of the trading value in the Russian stock market, foreign and domestic institutional investors, which account for the rest of the trading, evidently sold the dip. While individual investors’ buying the dip can be explained by their regular contrarian traits, the aggregate Russian individual remained as net buyers to fully ride the rebound whereas contrarian profit taking would be expected to lead to net selling. This pattern of net aggregate trading, which yielded the aggregate Russian individual investor a substantial wealth gain, sharply contrasts with previous claims about individual investors’ lack of sophistication.

Our analysis reveals that this outcome was driven by a unique sequence in this episode: first, regular contrarian traits led individual investors to buy the dip during the crash, and at that point there is some evidence of a sophisticated motivation to exploit the negative bubble; then a unique positive shock to individual investor demand for equities, which coincided with the rebound, kept the aggregate individual investor as net buyers, to fully exploit the rebound. This positive shock is likely an outcome of a unique combination of unprecedented monetary easing and the lockdowns providing professionals free time to access and trade stock markets.

While partly attributed to the peculiarities of this episode, the aggregate Russian individual investor’s sophisticated trading documented in this article is significant enough to change the way individual investors are viewed in the literature. This is best seen by comparing to Chiang et al.’s (2012) conclusion that domestic individual investors have an edge in investment performance over the other investor types when the market was near equilibrium, however they perform poorly when the market departed substantially from equilibrium. (This is because contrarian trading, driven by an uninformed attempt to buy low and sell high, typically earns small profits during fluctuations within a stable band, however when large price moves occur, individual investors’ failure to predict the size of the move leads to losses). The behavior of Russian individual investors documented in this article provides the first example of their sophistication during a major departure from equilibrium.

Potential limitations of this study are as follows. The aggregate nature of our data without a breakdown per stock may cloud important nuances in trading performance. Yet, the highly concentrated nature of the Russian stock market leaves little potential for aggregate trading values to be driven by anything other than the market portfolio. Secondly, absence of a further breakdown of individual investor trading into big/experienced versus retail/inexperienced limits our ability to locate the source of the observed performance outcomes. Lastly, as the data has recently started to be compiled, our sample period is relatively short. Hence, it will be worthwhile to reassess Russian individual investors’ sophistication in the future when much more data are accumulated.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Mixed-frequency vector autoregression (MFVAR) analysis

MFVAR allows use of time-series variables with different frequencies in the same VAR system, while in conventional VARs all variables are aggregated to a common lower frequency of the available data. The latter results in loss of the information in the variable that is available in higher frequency. In this section, we present the first application of the MFVAR method to the literature on the return–trading flow interaction in financial markets. Because this analysis has a separate theme from the main body of this paper, we present it as an Appendix.

In our case, the frequencies are weekly (low) and daily (high). Let $m \in \mathbb{Z}^+$ be the number of high-frequency data points in one low-frequency period. In our case, $m = 5$. For $j = 1, \ldots, m$ we define $m$ high-frequency variables ($R$) at time $\tau_l$ and sub-period $j$ as $R_{lj} (\tau_l, j)$. Similarly, $F_{lj} (\tau_l)$ signifies the value of the low-frequency variable in period $\tau_l$. To construct the MFVAR model, we need to stack the high and low-frequency variables in the mixed-frequency vector $X_M$:

$$X_M (\tau_l) = \begin{bmatrix} R_{l1} (1, \tau_l) & R_{l2} (2, \tau_l) & \cdots & R_{lM} (m, \tau_l) & F_{l1} (\tau_l) \end{bmatrix}$$

(A.1)

Utilizing Assumption 4.1 of Ghysels (2016), the MFVAR model can be written as:

$$X_M (\tau_l) = \delta_{M, 0} + \sum_{i=1}^{km} \delta_{M, i} X_M (\tau_l - i) + \varepsilon_M (\tau_l) \quad \text{with} \quad \varepsilon_M (\tau_l) \sim N (0, \Sigma)$$

(A.2)

For each $l = \{R_1, \ldots, R_m, F\}$, the parameters $\delta_{M, 0,i}$ is the intercept coefficient of each equation; and, for each $j, l = \{R_1, \ldots, R_m, F\}$ and $i = \{1, \ldots, km\}$, $\delta_{M, i,j}$ is the slope coefficient of the equation for the variable $l$ and the regressor $\text{thlag}$ of the variable $j$. We also define $\Sigma_{M}$ as the variance–covariance matrix of the reduced form error term in the mixed frequency VAR equations, which is used in deriving impulse response functions. Following Ghysels (2016), high-frequency variables are assumed to affect the low-frequency variable contemporaneously, and not vice versa.

MFVAR can be estimated via standard methods. The main difference between the MFVAR and the standard VAR models is that the MFVAR stacks the variables with different frequencies based on Ghysels’ (2016) Assumption 4.1. Thus, each of our depicted results consists of five impulse response functions shown in Figs. A.1 and A.2 where $R1$ represents Monday returns, $R2$...
Mixed-frequency impulse responses of weekly individual investor net flows to shocks in daily returns. Each graph represents the low-frequency variable $F$ (or Indiv)'s impulse response to a shock in each of the high-frequency variables $R_j$ with $j = 1, 2, ..., 5$. All other explanations are the same as before.

Mixed-frequency impulse responses of daily returns to shocks in weekly individual investor net flows. Each graph represents each of the high-frequency variable $R_j$'s impulse response to a shock in the low-frequency variable $F$ (Indiv). Thus, the first row presents Indiv $\rightarrow$ R1 impulse responses, followed by Indiv $\rightarrow$ R2 in the second row, Indiv $\rightarrow$ R3 in the third row, Indiv $\rightarrow$ R4 in the fourth row and Indiv $\rightarrow$ R5 in the last row. All other explanations are the same as before.

Tuesday returns, ...., and R5 Friday returns, while F remains weekly net flows as before.

The main benefit from employing an MFVAR model is that it allows us to uncover potential periodic relations between the low-frequency variable and each period of the high-frequency variable. As such, it offers a novel connection between the VAR models and periodic models (Ghysels, 2016).

Accordingly, $R_k \rightarrow F$ impulse responses will help us uncover if individual investors' weekly net flows respond differently to market returns by each specific day of the week. Results in Fig. A.1 point to visible differences across $R_k$, which confirms the efficacy of the MFVAR method. Individual investors remain most contrarian to Friday returns, whereas they reverse in subsequent weeks their initial contrarian response to Tuesday and Wednesday returns.

Results in Fig. A.2 help us uncover if individual investors' weekly net flows have differential ability to forecast future returns by each specific day of the week. Individual investors' weekly net flows positively predict market returns on Mondays of the next three weeks, and negatively predict returns of the other days in future weeks (especially significant for Wednesdays). A possible interpretation of the positive predictability of Monday returns, which consistently holds in both pre-COVID and COVID periods (subperiod results available from the authors), is along the lines of the hypothesis proposed by Ülkü and Andonov (2016): on Mondays institutional investors are relatively inactive such that individual investors' share in trading value increases, which makes institutional price pressure most likely be reversed on the following Mondays. Thus, individual investors' contrarian trading against institutional price pressure positively predicts returns over the Mondays of the coming weeks.

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