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COVID caused a negative bubble. Who profited? Who lost? How stock markets changed?

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ABSTRACT

Compiling a unique, worldwide collection of trading data, we analyze investor types' aggregate trading in stock markets throughout the COVID-19 episode, to assess investor types' role in a worldwide negative bubble and their degree of sophistication in responding to it. Individual investors were the main buyers and consequently the winners during the rebound. Foreign institutional investors exited host markets; some domestic institutions exploited the negative bubble by well-timed buying. In US index futures, asset managers heavily sold into crash; dealers profited from the rebound. Individual investors' buying was driven by their contrarian behavioral traits and a unique positive shock to retail investor demand for self-serviced investing in stocks, driven by work-from-home practices and unprecedented stimulus. This shock has changed the participant composition of world stock markets. Overall, the COVID-19 episode has many unique aspects that cannot be accounted for under existing theories.

1. Introduction

Despite a vast literature on and renewed interest in stock price bubbles (e.g., Greenwood et al., 2019), little is known regarding investor types' trading behavior in actual bubbles. Existing literature on investor behavior in bubbles relies on experimental evidence (e.g., Weitzel et al., 2020); the only study of investor types' trading in an actual marketwide bubble is Griffin et al. (2011) on the 2000–2001 tech bubble.[1] Negative bubbles, i.e., substantial dips followed by full rebounds (see Goetzman and Kim, 2018),[2] constitute a subset of the bubble phenomenon, with even more scarce evidence regarding which investor types foment and which ones exploit them.[3] Typically driven by overreaction, negative bubbles lead to significant wealth transfers and offer natural experiments to assess investor sophistication.

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[1] A limited literature using broker-level data and focusing on narrower bubbles is also emerging: Gong et al. (2017), Li et al. (2021).

[2] The term 'negative bubble' was first used by Shiller (2000). He interprets 1929 and 1987-Black Monday crashes as negative bubbles.

[3] Hoopes et al. (2016) use tax return data to identify who sold during the 2008–09 crisis. There are also studies examining investor response to terror events and natural disasters, which are potential triggers of negative bubbles (e.g., Wang and Young, 2020; Bourdeau-Brien and Kryzanowski, 2020).

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With the outbreak of the COVID-19 pandemic (COVID hereafter), world stock markets formed a negative bubble, which, as we show below, led to substantial wealth transfers among investor types. This episode presents an interesting opportunity to identify investor types' roles during a remarkable worldwide negative bubble. While the return behavior of financial instruments during the COVID period has been extensively investigated, research on investor types' trading behavior is quite limited[4]; a broad worldwide picture of investor types' aggregate trading during the COVID episode is still missing.

This article provides the first comprehensive documenting of investor types' trading in an actual worldwide negative bubble. As a counterpart of Griffin et al. (2011), we follow a similar exposition, starting with presenting descriptive evidence to answer the following questions: who sold into the COVID crash in March–April 2020; who bought the dip; who contributed to and benefited from the subsequent rebound; how investor types' aggregate trading affected their wealth? This is followed by an inquiry into what factors drove their reaction and the implications regarding investor types' sophistication. We also document a change in the investor-type structure of stock markets, a substantial increase in individual investor presence, brought about by COVID. Finally, we discover a new pattern, asymmetric negative feedback trading by individual investors, whose increased role in stock market dynamics is likely to endure going forward.

Our primary contribution is compiling a unique collection of worldwide trading data disaggregated by investor type, to enable a generalizable analysis of investor trading around a worldwide negative bubble. Our dataset comprises a combination of precise daily or weekly data from all major international (mostly East Asian) stock exchanges that provide such data and available proxies from the US. The latter includes weekly trader positions in equity index futures and *Robinhood* client numbers for each stock.

Available data point to a worldwide pattern: Individual investors were the main buyers during the COVID episode in every country analyzed. Foreign institutional investors heavily sold and indiscriminately exited host markets, in line with the 'when in peril, retrench' phenomenon suggested by Broner et al. (2006). Some domestic institutional investors exploited the negative bubble with well-timed buying. In the US index futures, asset managers heavily sold into the crash in March 2020. Their net selling was absorbed by individual investors and dealers. Dealers successfully captured the rebound with sophisticated timing.

Retail individual investor interest, as proxied by the number of *Robinhood* clients holding S&P500 stocks and further corroborated by individual investor statistics from many countries, displayed a sharp acceleration, literally an explosion, during the COVID period. Timing of this retail investor demand shock coincided with, and enabled them to capitalize on, the rebound and the subsequent prolonged uptrend.

Our estimates of the incremental effect of investor types' trading on their wealth during the COVID episode indicate significant wealth transfers. In the US index futures, dealers profited from sophisticated timing at the expense of asset managers. In international markets, individuals and domestic institutions were the main winners at the expense of foreign institutions. The aggregate individual investor's winner status on a global basis in this episode is in stark contrast to previous characterizations of individual investors as noise traders (Schmeling, 2007; Barber et al., 2009; Chang et al., 2015; Choi et al., 2020).

Griffin et al. (2011) find that it was institutional investors who both drove and burst the tech bubble (against media reports pointing to individual investors) and the burst was associated with a coordinated pivoting by institutions while individuals initially continued buying. The COVID episode is similar in that institutions drove the negative bubble, but differs in that the aggregate individual investor was the main profiter, and the correction was not associated with a coordinated pivoting by institutions. The latter suggests that the COVID negative bubble cannot be accounted for by theories of delayed arbitrage due to arbitrageurs' synchronization problem (Abreu and Brunnermeier, 2002, 2003).

Next, we explore drivers of investor types' trading during the COVİD episode, in particular, how individual investors' net buying led to superior performance and what drove foreign institutional investors' sustained selling. Individual investors' buying during the crash is consistent with their previously-documented contrarian trading behavior (Griffin et al., 2003; Kaniel et al., 2008),[5] but contradicts with increased risk aversion following catastrophic events documented in numerous studies (Wang and Young, 2020; Bourdeau-Brien and Kryzanowski, 2020; Hasso et al., 2020) and findings of a high (low) level of sophistication of institutional (individual) investors in reacting to transient negative news (Carpentier and Suret, 2021). We find that individual investors' buying was driven by a sequence of their usual contrarian trading behavior followed by a unique positive shock to retail investor demand for equities. Contrarian behavior is further confirmed in stock selection: individual investor buying was concentrated in COVID-vulnerable stocks, as opposed to COVID-beneficiary stocks. The positive shock was probably due to a unique combination of excessive worldwide monetary easing, fiscal stimulus and ample free time to trade stocks due to lockdowns and a new work-from-home lifestyle. The lucky coincidence of this sequence with a V-shaped rebound led to a peculiar outcome and helped individual investors exploit the specific term structure of risk premia documented by Berkman and Malloch (2023).

Japanese data reveal that cash versus margin trading was also a driver of individual investor behavior: margin traders failed to buy the dip during the COVID crash, but later benefited from the prolonged rebound, while cash traders successfully picked the bottom but

[4] Bing and Ma (2021) and Zhang et al. (2021) study foreign and domestic institutional investors' trading in China using limited proxies (Chinese stock markets do not provide exact daily trading data). Djalilov and Ülkü (2021) cover individual investors in Russia, while Naik et al., 2022 cover institutional investors in India.

[5] What drives their contrarian trait? One argument is that individual investors tend to place 'out-of-money' limit orders, which leads to endogenous contrarian trading elicited by institutional liquidity consumption (Linnainmaa, 2010). This could explain specifically the contemporaneous negative relationship between their net trading and returns. Behavioral drivers such as the disposition effect, belief in mean reversion (e.g., gambler's fallacy) can also drive the negative relationship with past returns. Onishchenko and Ülkü (2022) summarize all these effects under a single concept: "uninformed attempt to buy low and sell high using recent prices as heuristic reference points".

exited early.

Further analysis to identify skill in exploiting a negative bubble (and to distinguish it from an exogenous positive shock to individual investor demand for equities) suggests that some domestic institutions may have acted specifically to exploit the negative bubble in March–April 2020. There is some weak evidence that individual investors also exploited the negative bubble. Yet, a positive shock to individual investor demand is much more significant statistically, implying that a lucky coincidence was a main driver of individual investors' success in this episode.

Foreign institutions' exit from host markets and asset managers' heavy selling of US equity index futures into the crash in March 2020 were, at least partly, driven by client outflows. Significant outflows from equity funds clustered in March 2020. The aggregate household, who rushed into equities, sold equity funds; implying a sharp divergence between fund clients' and self-serviced individual investors' behavior. We conjecture that excess free time due to lockdowns and a new work-from-home lifestyle induced individual investors to shift from delegated investment management toward self-servicing. Data from subsequent periods shows that fund clients returned back later after the full rebound when markets headed to new highs. Thus, aggregate fund client flows displayed poor timing, consistent with the 'dumb money' tag proposed by Akbaş et al. (2015).

The notable increase of individual investor presence in stock markets during the COVID period has prompted renewed interest in individual investors' aggregate trading behavior.[6] While individual investors have been associated with buying frenzies, our results confirm that contrarian trading is the dominant behavior of the aggregate individual. Such contrarian trading yielded profits by counteracting institutional selling pressure during the COVID crash, as it did during the 2008–09 crisis (Barrot et al., 2016). The contrarianism of the aggregate individual investor once again served as a stabilizer.

Last but not least, we uncover a pervasive asymmetry in individual investor reaction to positive and negative returns: Contemporaneously, they are less contrarian to negative returns than to positive ones. With respect to previous days' returns, however, they are more contrarian to negative returns. In other words, contrarian dip-buying intensifies with a lag. This asymmetry is present in the full sample, but dominates market behavior under easy money conditions with an influx of individual investor money and characterizes rebounds seen following every sell-off during the post-COVID period.

This article is structured to provide a complete picture of trading behavior during the COVID episode, to serve as a reference point for future deeper analysis of the specifics. Section 2 describes trading data brought together in this study. Section 3 provides a graphical documentary of investor types' aggregate trading during the COVID episode, and estimates the incremental effect of their trading on their wealth. Section 4 analyzes drivers of investor types' trading. Section 5 summarizes the conclusions.

2. Investor trading data

We use all available trading data disaggregated by investor type from around the world excluding small frontier markets. In the existing literature, lack of data has constrained the task of deriving a clear picture of investor types' role in actual bubbles. To identify investor types' aggregate role in a bubble, complete and exact market-wide data from centralized electronic records of all transactions are needed, as opposed to limited samples from one brokerage house or proxies derived under assumptions.

Such exact and complete data are provided by only few stock exchanges. Among them, Korea (KRX) offers the world's most comprehensive daily trading dataset by investor type, along with a breakdown of domestic institutional investors, which helps distinguish motivations behind institutional investors' trading. Taiwan (TWSE) and Thailand (SET) also publish precise daily data of investor types' trading. Japan (JPX) offers weekly data from electronic surveys, with a breakdown of domestic institutions.

As cultural factors might influence investor behavior, evidence from outside East Asia is needed for generalizing results. In particular, east Asian individuals are reported to have a stronger belief in mean reversion (Shu et al., 2005; Arkes et al., 2010), which may have driven findings of contrarian trading by individuals in the literature. Serving this purpose, we use novel data from Borsa Istanbul, Turkiye (BIST) and Pakistan Stock Exchange (PSX), both for the first time in the literature. BIST is highly correlated with, and share similar participants as, the European stock markets. We also obtain weekly data of individual investor trading from Russia (MOEX).[7] Our sample countries represent a range of Hofstede individualism scores,[8] ranging from as low as 14 for Pakistan,18 for S. Korea and 20 for Thailand to 37 for Turkiye, 39 for Russia, 46 for Japan and 91 for the US.

In these datasets, three main investor types are identified: individuals, domestic institutions and foreign investors (predominantly institutional),[9] which we denote as *Indiv*, *Inst* and *For*, respectively. Our data comprises daily values (in home currency) of each investor types' marketwide-aggregated purchases and sales. We compute the daily net trading flow of each investor type (F_t^m) as purchases minus sales by investor type m on day t, normalized by current free-float market capitalization. Thus, F_t^m represents the size of net trading as a proportion of the value of outstanding shares.

In the US, no complete records of investor types' trading are kept, and the fragmented structure of the US stock market precludes compiling such data. We utilize two data sources to obtain at least a partial picture of investor types' trading in the US: *i*) Weekly long/short positions in equity index futures from the weekly *Traders in Financial Futures* survey by the US Commodity Futures Trading

[6] Several price events, such as short-squeezes in meme-stocks, have been attributed to individual investor crowds.

[7] Mirror image of individual investors' trading can be taken to represent domestic and foreign institutions combined. Russia data starts from January 2018.

[8] Individualism has been suggested as a driver of financial behavior; e.g., Foley et al. (2022).

[9] Wherever a break-down of foreign individual and institutional investors is available, we leave out foreign individuals which constitute a negligible proportion of total traded value (< 0.0008 in Japan, < 0.002 in Turkiye, < 0.007 in Pakistan).

Commission (CFTC), *ii*) Investor positions from retail broker *Robinhood* tracker data. CFTC data classifies open interest positions held by five categories: asset managers (AM), leveraged funds (i.e., hedge funds, HF), dealer/intermediary (DL), other reportables (OR) and non-reportables (NR). NR is a residual category that contains all smaller non-reporting traders, presumably dominated by individual investors.[10] *Robinhood* data reports the number of clients holding each particular stock. As such, it is more an indicator of the popular interest of retail investors,[11] while NR in CFTC data quantifies relatively more-experienced and large-sized individuals' trading. Consistent with this, we find that *Robinhood* flows are positively correlated with the individual investor sentiment reported by AAII (American Association of Individual Investors) while NR is uncorrelated (see in Section 4).

Proxies for F_t^m in the US data are as follows: For the CFTC data, weekly net position changes, computed as the number of S&P500 index (ES) futures contracts normalized by open interest. For *Robinhood* data, daily changes in the number of clients holding S&P500 index constituent stocks (*dRH*); we also replicate for SPY and VOO (most popular S&P500 index-tracking ETFs) and for portfolios of COVID-beneficiary and COVID-vulnerable stocks.

Robinhood data are available per stock. We also employ stock-level data from Korea and Turkiye. Stock-level data enables us to perform a difference-in-difference analysis of stock selection behavior in response to the COVID news.

Our sample period ends in mid-November 2020; thus, it covers the period in which the rebound was completed without the actual reopening of the economy (i.e., the negative bubble was corrected solely on expectations) and excludes the effect of the Biden-era extra stimulus, so that the analysis of trading in relation to the negative bubble is not distorted by subsequent news. We employ a pre-COVID period, defined as 4.January.2010–21.February.2020, as a benchmark of regular trading behavior. 24.February.2020–20. November.2020 is designated as the COVID period. (24.February is when selling in stock markets began upon early signs of COVID. Even though COVID attracted public attention in March, it is imperative to monitor trading from when smart money may have started to act). *Robinhood* data are available from 3.May.2018 to 13.August.2020. A brief description of the data and summary statistics are in Appendix Table A.1. A practical glimpse of investor types' trading is provided in Table 1 with statistics using net trading normalized by total traded value.

Auxiliary data: To address specific questions about drivers of investor behavior, we also employ the following sets of data:

i) Individual investor statistics: based on a worldwide search, we employ all centralized/nationwide statistics on individual investor account openings and demographics available as of the time of writing this paper. For the US, we employ statistics from a leading online discount broker.
ii) Weekly data on client flows toward mutual funds, reported by three different sources: *EPFR*, *Refinitiv-Lipper* and *Investment Company Institute* (*ICI*, monthly).
iii) Weekly (American Association of Individual Investors) AAII individual investor sentiment survey.

3. Investor types' aggregate trading during the COVID-19 episode

3.1. A graphical documentary of cumulative trading around the COVID period

In this section, we address the following questions, which naturally involve descriptive evidence: Who sold into the COVID negative bubble? Who bought the dip in late March – early April 2020? Who drove and/or benefited from the subsequent rebound? These questions are collectively and concisely answered by graphs in Fig. 1, which plot the stock market index levels along with cumulative net trading by main investor types (i.e., accumulated F_t^m) from the end of 2019 to November 2020 in KRX (Korea), TWSE (Taiwan), SET (Thailand), BIST (Turkiye), JPX (Japan), MOEX (Russia) and PSX (Pakistan), respectively. These graphs provide a complete broad glimpse of how investor types responded to the COVID negative bubble.

First, identify the negative bubble in main stock indices (the black line) in all graphs. As Gürkaynak (2008) concludes, "econometric detection of asset price bubbles cannot be achieved with a satisfactory degree of certainty". Two approaches to identifying bubbles are based either solely on price pattern or on deviation from fundamentals. In the former approach, full rebound following a substantial crash, especially if the rebound unfolded in the absence of news surprises, is taken as ex-post evidence of a negative bubble. Based on this definition, the black lines show that every stock market in our sample had a negative bubble.[12]

Regarding investor behavior with respect to the negative bubble, in all countries a common pattern emerges: Individual investors' cumulative net buying started to rise with the outbreak of COVID, accelerated during the crash in March–April 2020 and kept rising during the rebound. Foreign investors started to sell with the outbreak and continued selling during the rebound. Their selling was indiscriminate: for example, they sold Taiwan stocks despite the country's success in containing the pandemic, although the US, the main source of equity portfolio flows, suffered the most. Domestic institutions were net buyers, notably in Thailand, Turkiye, Pakistan and Japan, albeit in relatively small sizes; the main offset to foreign selling was provided by individual investors.

Panel A of Fig. 2 plots cumulative net trading by subcategories of domestic institutions in Korea. Korean pension funds successfully

[10] See https://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm for further information. Our data is retrieved from the 'Traders in Financial Futures' section.

[11] See Welch (2020) and Pagano et al. (2021) for concurrent studies of *Robinhood* data.

[12] While one may argue that the strong response of the monetary policy was a surprise, strong policy support in response to natural disasters, especially in the case of a global pandemic, was a sure thing. Below we also provide an assessment regarding the second approach (deviation from fundamentals) looking at the price behavior of COVID-beneficiary stocks.

Table 1
Descriptive statistics of net trading by investor types as a proportion of trading volume.

Country	Variable	Pre-COVID period: Mean	Median	St.Dev.	COVID period: Mean	Median	St.Dev.
			4 Jan 2010–21 Feb 2020			24 Feb - 20 Nov 2020	
Korea	*Indiv*	−0.0041	−0.0015	0.0447	0.0169	0.0164	0.0454
	Inst	0.0002	−0.0014	0.0420	−0.0050	−0.0074	0.0300
	For	0.0034	0.0031	0.0455	−0.0130	−0.0064	0.0340
			4 Jan 2010–21 Feb 2020			24 Feb - 20 Nov 2020	
Taiwan	*Indiv*	−0.0017	−0.0078	0.0760	0.0165	0.0111	0.0733
	Inst	−0.0012	−0.0012	0.0062	0.0011	0.0012	0.0050
	For	0.0041	0.0090	0.0691	−0.0138	−0.0072	0.0641
			4 Jan 2010–21 Feb 2020			24 Feb - 20 Nov 2020	
Thailand	*Indiv*	0.0008	0.0008	0.0591	0.0178	0.0193	0.0478
	Inst	0.0052	0.0046	0.0398	0.0044	0.0051	0.0393
	For	−0.0061	−0.0056	0.0494	−0.0228	−0.0219	0.0324
			4 Jan 2010–21 Feb 2020			24 Feb - 30 Oct 2020	
Turkiye	*Indiv*	−0.0004	0.0001	0.0202	0.0042	0.0035	0.0111
	Inst	0.0000	0.0004	0.0103	0.0015	0.0006	0.0089
	For	0.0004	−0.0004	0.0200	−0.0057	−0.0044	0.0079
			24 Jan - 21 Feb 2020			24 Feb - 20 Nov 2020	
Pakistan	*Indiv*	0.0030	0.0101	0.0318	0.0100	0.0088	0.0429
	Inst	0.0437	0.0432	0.0452	0.0288	0.0258	0.0499
	For	−0.0453	−0.0370	0.0474	−0.0395	−0.0308	0.0403
			3 Jan 2011–21 Feb 2020			24 Feb - 20 Nov 2020	
Japan	*Indiv*	−0.0023	−0.0028	0.0081	−0.0003	0.0009	0.0076
	Inst	0.0037	0.0031	0.0089	0.0042	0.0036	0.0078
	For	−0.0013	−0.0021	0.0108	−0.0034	−0.0031	0.0096
			2 Jan 2018–21 Feb 2020			24 Feb - 20 Nov 2020	
Russia	*Indiv*	0.0037	0.0031	0.0252	0.0160	0.0221	0.0420
			3 May 2018–21 Feb 2020			24 Feb - 13 Aug 2020	
US *Robinhood*	*dRH*	0.0000014	0.0000013	0.0000021	0.0000141	0.0000130	0.0000098
			4 Jan 2010–18 Feb 2020			19 Feb - 17 Nov 2020	
	NR	0.0003	0.0004	0.0082	−0.0007	0.0007	0.0122
US CFTC	AM	0.0001	0.0004	0.0098	−0.0004	0.0000	0.0091
	DL	−0.0002	−0.0005	0.0088	0.0019	−0.0006	0.0131
	HF	−0.0003	−0.0001	0.0104	−0.0003	−0.0008	0.0074

Indiv, Inst and *For* stand for net trading of individual, domestic institutional and foreign investors, respectively, as a proportion of total traded value of the equity market. For the US *Robinhood* data, net trading is approximated by the daily change in the number of investors holding S&P500 stocks (*dRH*). For the US CFTC data, net trading is approximated by the net change in futures position (NR = Nonreportables, comprising mainly individual investors, AM = Asset Managers, DL = Dealers, HF=Hedge Funds. CFTC weeks start on Wednesday and end on Tuesday).

executed a well-timed contrarian strategy and took profits after the rebound. Other domestic institution subcategories' trading during the COVID is trivial.[13] Pension funds, which have sufficiently long horizons free of the threat of client mass-redemptions, were able to implement a successfully-timed strategy to exploit the negative bubble. One possibility is that pension fund clients switched to equity funds and drove this shift. (No data are available to examine this possibility). However, mutual funds and ETFs ('Investment Trusts') were rather net sellers. Redeemability seems to account for the difference between pension funds' and investment trusts' trading, as nonredeemable pension fund clients may have switched to equity funds, while mutual fund clients took their money to self-invest.

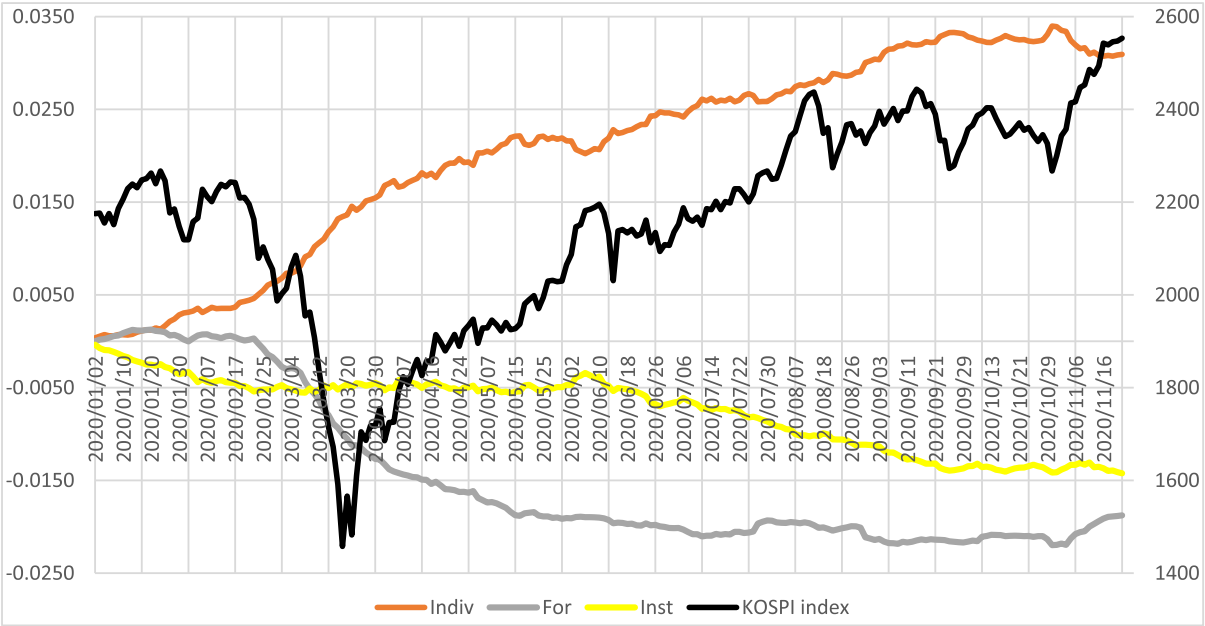
Trading behavior of hedge funds, often called 'smart money', has been a focus of interest in the literature; for example, Akbaş et al. (2015) find that hedge fund flows tend to attenuate anomalies. Korean hedge funds, however, played little role during the COVID episode, and rather, by selling into rebound they counteracted the correction from the negative bubble. (Below, we revisit this issue when discussing US hedge funds' index futures trading).

Panel B of Fig. 2 provides a selected breakdown from Japan and yields the following observations:

i) Japanese trust banks (a special type of investment banks providing custody services for clients) started net-buying around the bottom of the negative-bubble and fully exploited the rebound, indicative of a sophisticated strategy.
ii) Foreign individuals' trading was totally different from that of foreign institutions: foreign individuals exploited the negative bubble just like domestic individuals. This result is further reinforced on the other markets that provide a breakdown of foreign individuals versus institutions: Fig. OA.2 in Supplementary Material 2 shows that in Turkiye foreign individuals were net buyers in sharp contrast to foreign institutions.

[13] Brokers/dealers (named 'Financial Investment' by KRX) engaged in heavy selling throughout 2020, which appears to have a component unrelated to the COVID crisis. This heavy selling offsets pension funds' well-timed buying in the aggregated domestic institution trading.

Panel A. Korea



Panel B. Taiwan

Prop: designated dealers' speculative trading on their own account. *Hedge*: designated dealers' trading to hedge market-making activities.

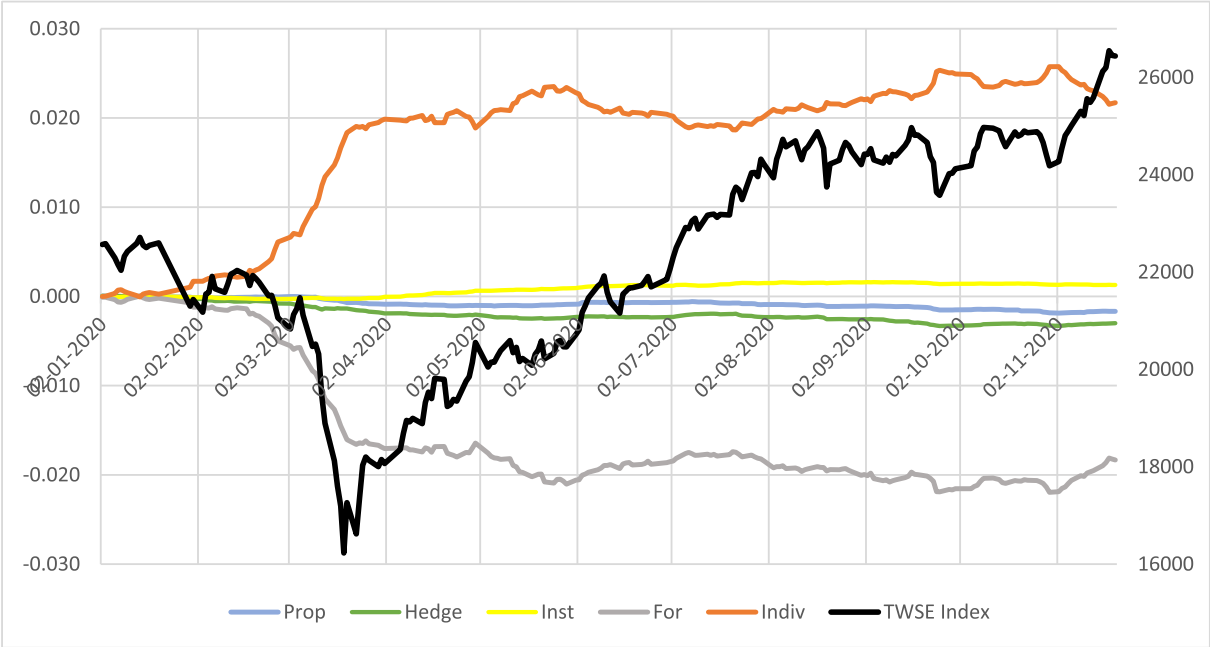
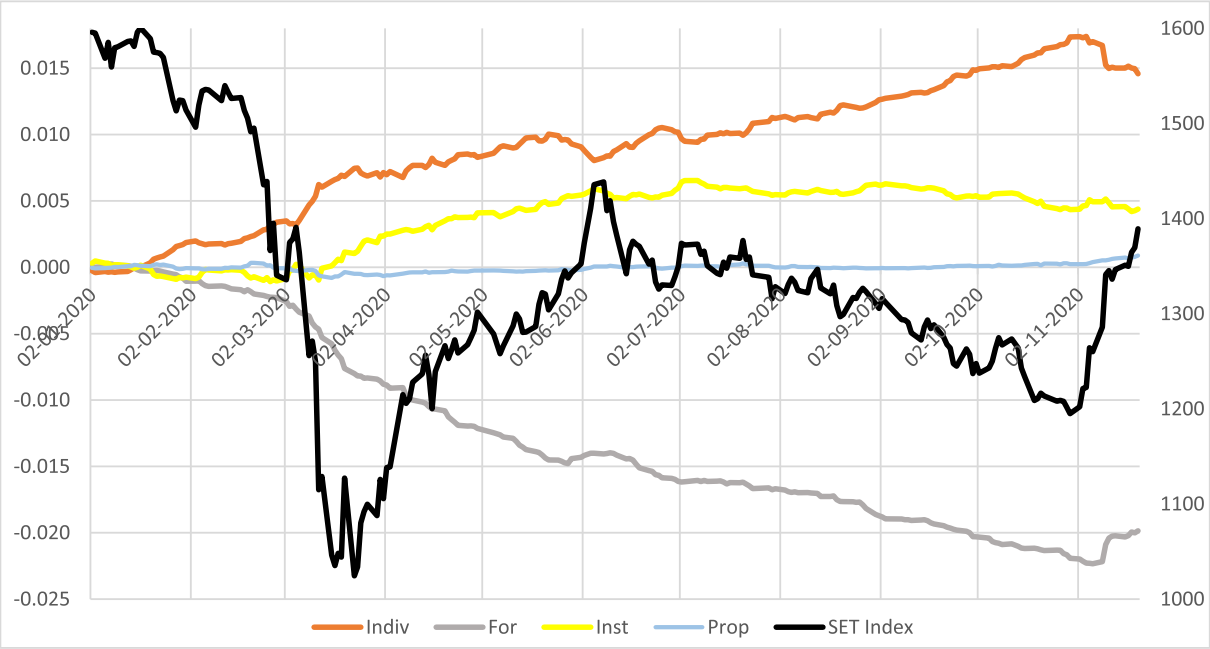


Fig. 1. Main investor types' cumulative net trading during the COVID episode.
Investor types' cumulative net trading as a proportion of market capitalization are on the left-vertical axis (set to zero at the beginning of 2020). *Indiv*: domestic individuals, *For*: foreign investors, *Inst*: domestic institutions. In all graphs below consistently: orange represents individuals; yellow represents domestic institutions; grey represents foreign investors. An increase (decrease) implies net buying (selling) on the day it occurs. Market-index values (black curve) are on the right-vertical axis.

Panel C. Thailand

Prop: member brokers trading on their own account.



Panel D. Borsa Istanbul (Turkiye)

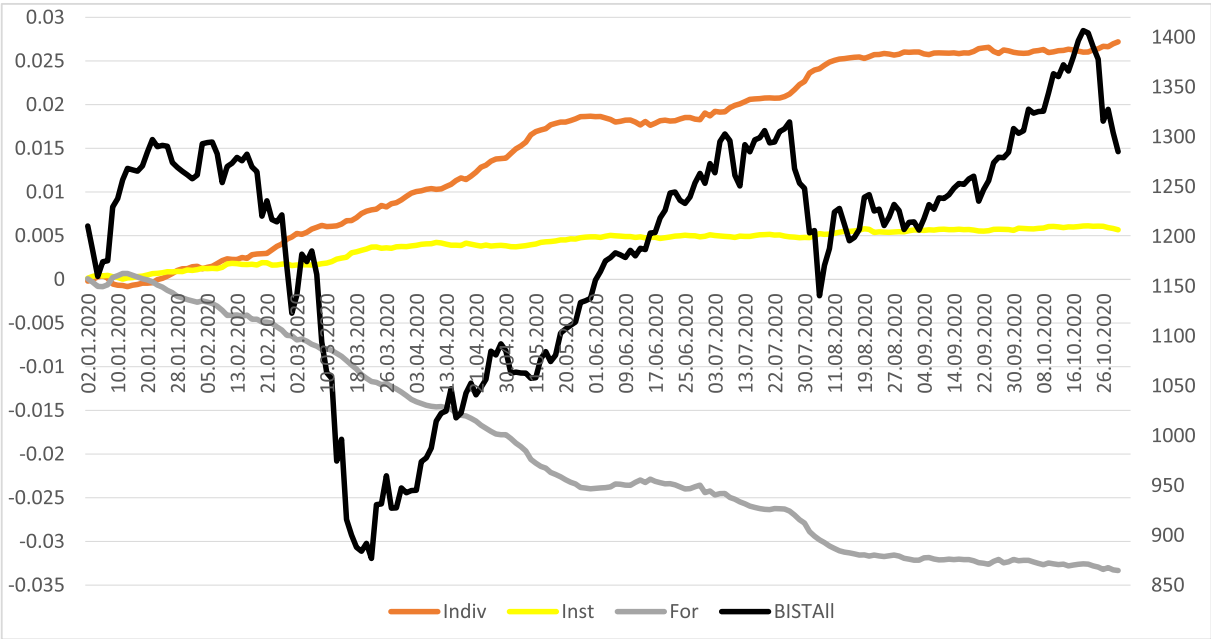
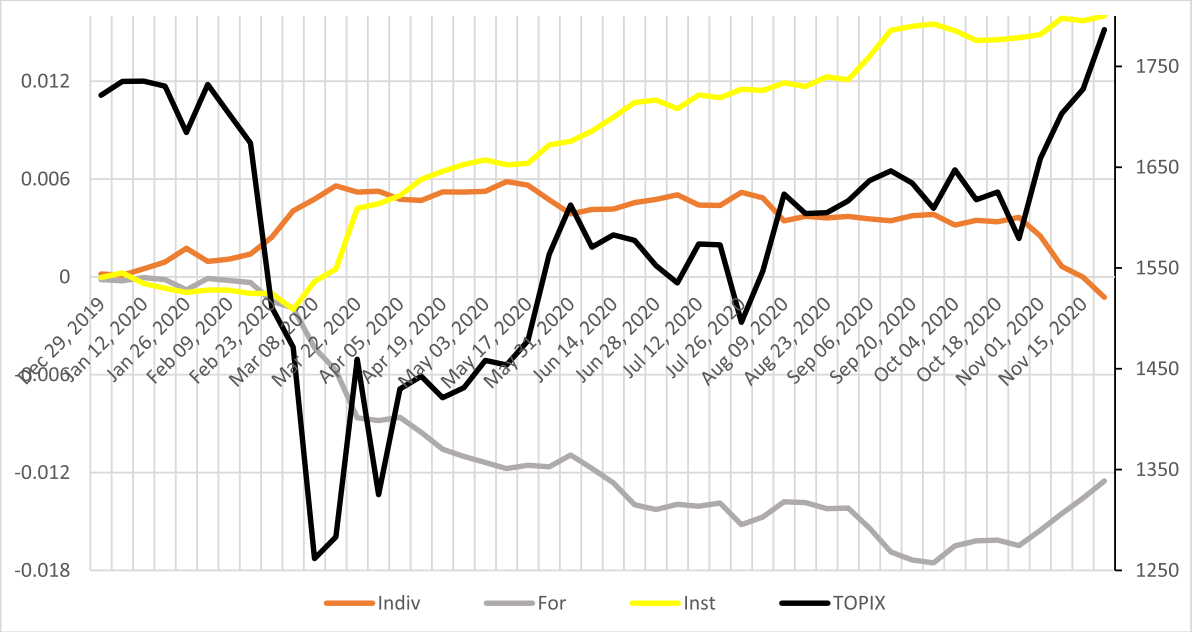


Fig. 1. (*continued*).

Panel E. Japan (derived from weekly data)



Panel F. Russia (derived from weekly data)

Data are available for only individual investors. The mirror image of individual investors roughly represents foreign and domestic institutional investors combined.

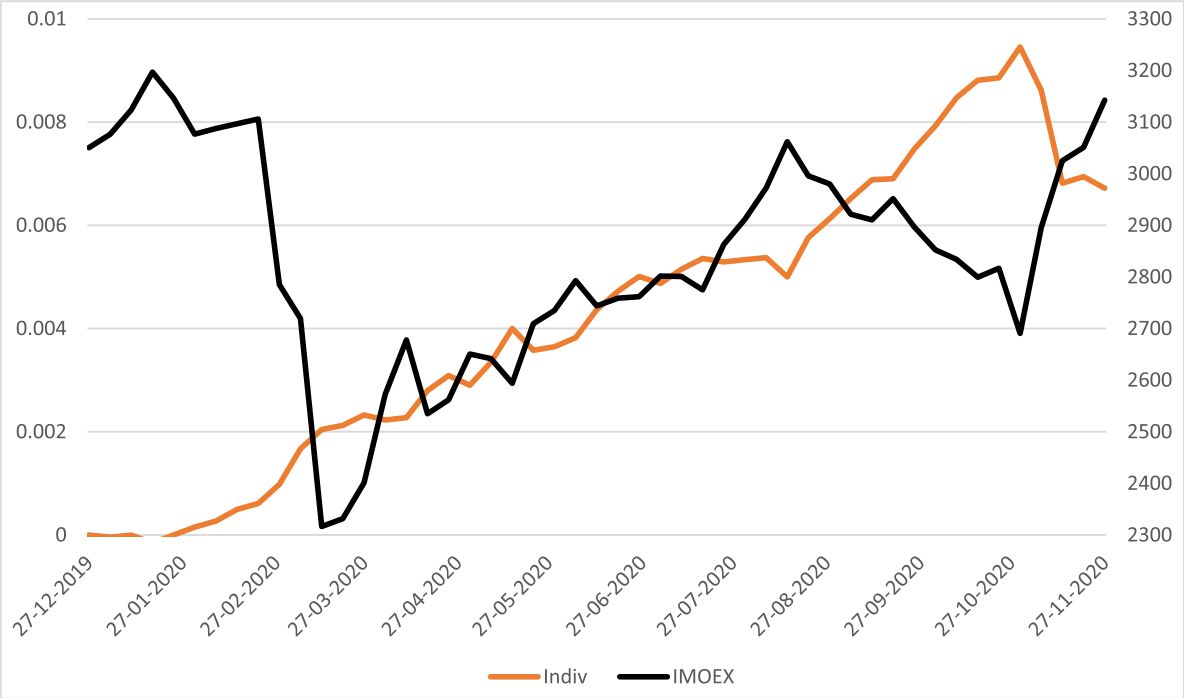


Fig. 1. (*continued*).

Panel G. Pakistan

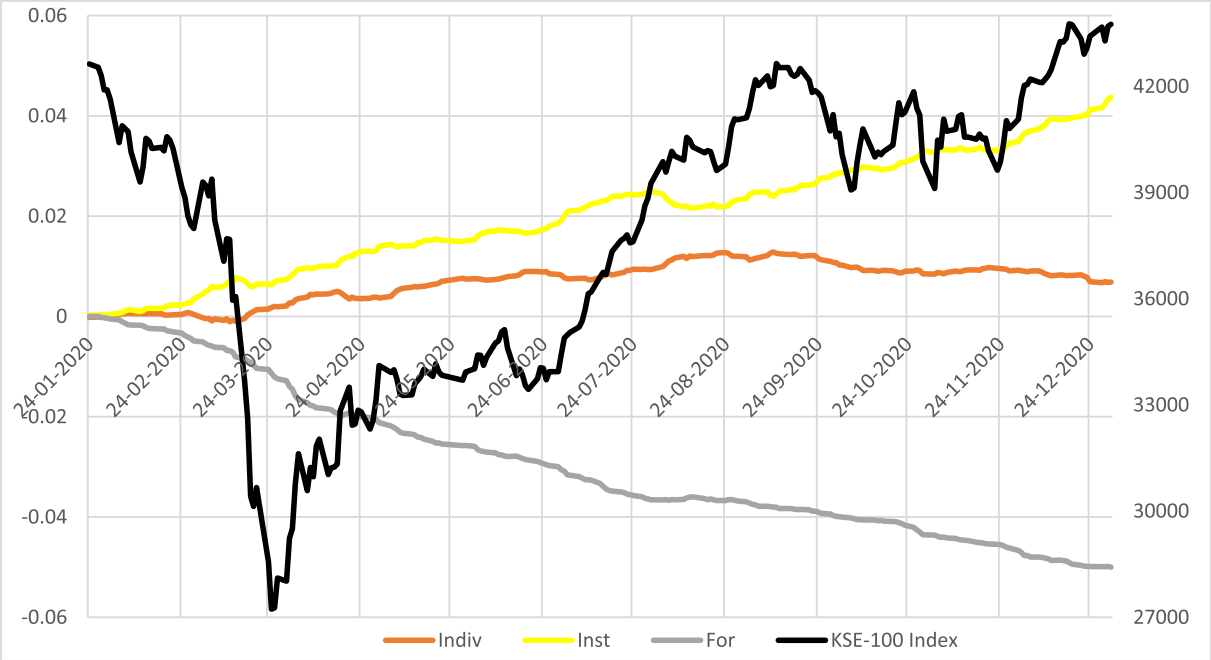


Fig. 1. (*continued*).

iii) A breakdown of cash versus margin trading of individual investors indicates sharp differences in trading behavior: Cash investors pursued a contrarian strategy; were significant net buyers at the bottom of the negative bubble; and then sold during the rebound. They did not fully exploit the rebound and their cumulative net trading turned into deeply negative when the rebound was completed. On the other hand, margin traders initially bought at the beginning of the sell-off, which they had to reverse around the bottom and the first leg of the rebound[14]; then during the recovery they gradually built-up net purchases again. Thus, cash investors' early exit during the rebound offset their profits from successfully picking the bottom of the negative bubble, while margin investors missed out on picking the bottom and rather joined at the later stages of the rebound.

Existing literature on cash versus margin traders' behavior is limited. Shu et al. (2005) find that margin traders in Taiwan display muted disposition effect, consistent with our observation on Japan. We also observe that margin traders' forced selling during a crash can reduce the measured disposition effect.

As to the US, cumulative S&P500 futures position changes in Fig. 3 indicate that asset managers sold into the crash in March 2020 and did not contribute to the early stages of the rebound, which they joined at much later stages. Nonreportables, which contain individual investors, were the most net buyers in the early weeks of the crash in March; they reduced part of their long positions with a poor timing at the bottom of the crash (likely, another case of forced selling due to futures leverage), and kept remaining long positions through the first leg of the rebound. Dealers were the most net buyers at the bottom of the negative bubble as well as during early stages of the rebound. They started reducing long positions only after fully exploiting the rebound. Hedge funds were minor net buyers during the crash, and minor net sellers (buyers) in early (late) stages of the rebound. Similar to Korean hedge funds, US hedge funds' index futures trading during the COVID episode is relatively insignificant.

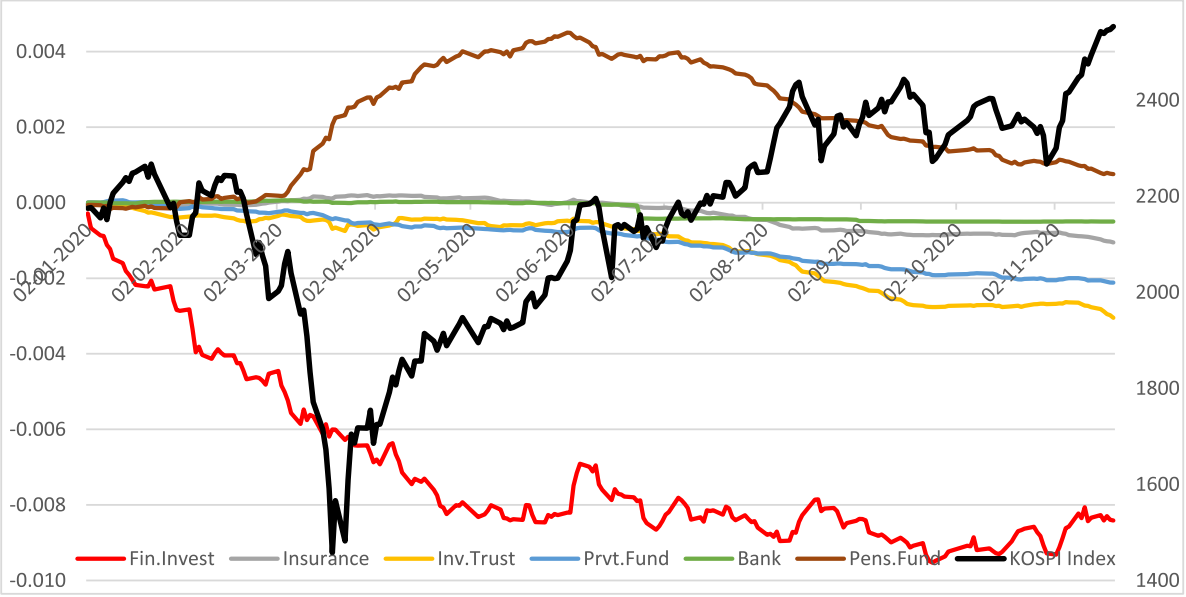
Results for Nasdaq and Russell-2000 index futures (NQ and RTY, respectively) are broadly similar: Dealers' sophisticated contrarian buying is particularly notable in RTY (presented in Supplementary Material 1, Fig. A1), which contains smaller stocks vulnerable to the pandemic. As the literature on CFTC investor types' ability to exploit market dislocations is scarce, our finding opens up a potential pattern, Dealers' sophisticated timing, for further investigation.

Aggregated number of *Robinhood* clients holding S&P500 index-constituent stocks in Fig. 4 displayed a sharp acceleration starting with the crash in March. Graphs of the number of *Robinhood* clients holding SPY and VOO ETFs (Fig. A.2 in Supplementary Material 1) are similar. Notice that the previous market dip in December 2018 did not trigger a similar acceleration in the number of *Robinhood* clients, suggesting that the unique jump in the COVID period cannot be explained by contrarian trading alone. This provides the first evidence that the lockdowns combined with monetary easing had a unique effect on individual investor participation, which in Section 4 we identify as a unique exogenous positive shock to retail investor demand for equities.

[14] Foley et al. (2021) identify raised margin requirements as a potential driver of forced selling.

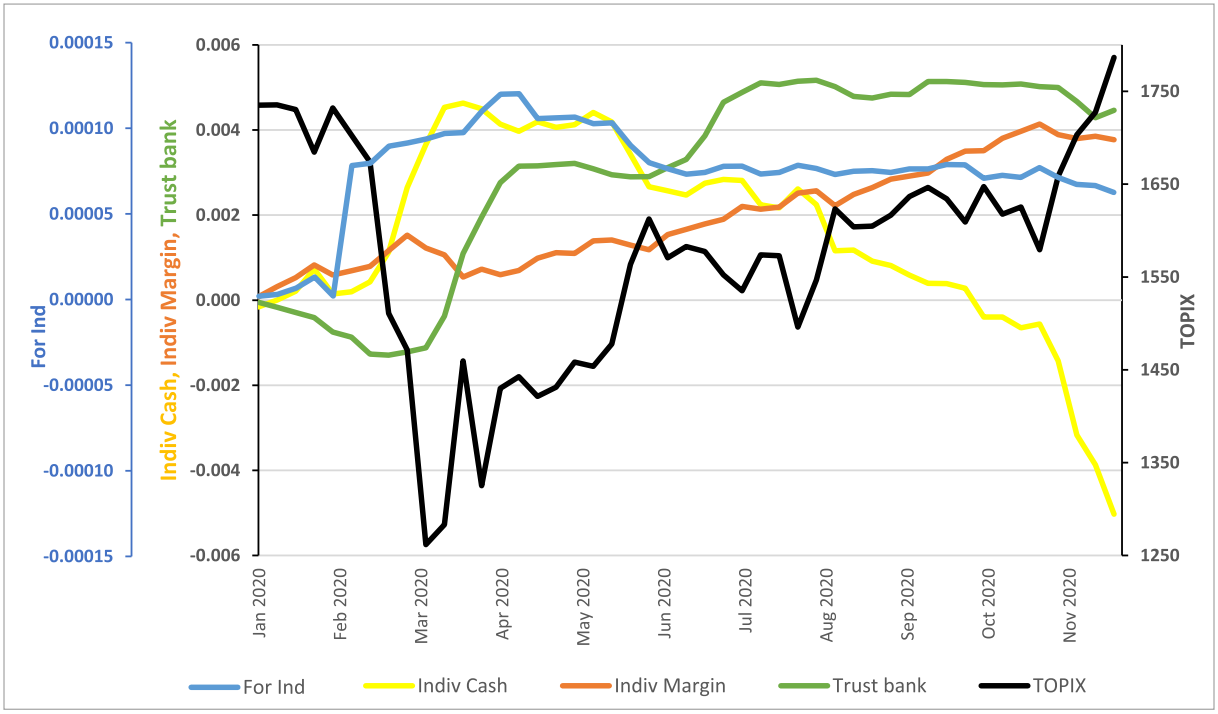
Panel A. Korea

Fin.Invest: brokers/dealers, *Insurance*: insurance companies, *Inv.Trust*: mutual funds, *Prvt.Funds*: hedge funds, *Bank*: Banks' trading for their portfolio, *Pens.Fund*: pension funds.



Panel B. Japan (weekly, selected subcategories)

Japanese data offers unique breakdowns: foreign institutions versus foreign individuals (*ForInd*), individual investors' cash versus margin trading (*IndivCash* and *IndivMargin* respectively). A subcategory of domestic institutions is *Trust bank*s which are a special type of bank in Japan offering custody services by acting as a trustee in transactions including asset management. This panel plots the cumulative trading of these subcategories of interest.



(caption on next page)

Fig. 2. Cumulative net trading by subcategories of domestic institutions during the COVID episode.

To summarize, individual investors were net buyers during the COVID episode and rode the rebound. Asset managers in the US sold the dip. Foreign institutional investors in host markets not only sold the dip but also continued selling during the rebound. Some domestic institutions and Dealers in the US futures undertook well-timed buying to exploit the negative bubble.

3.2. *The effect of investor types' trading during the COVID period on their wealth*

The accumulated net trading of investor types at each point in time, the variable in the above graphs, can be used to obtain an estimate of the monetary value of the incremental effect of investor types' trading on their wealth from that point onwards. This incremental effect is measured in comparison with the status quo alternative where they did not trade. Based on this, we construct a performance metric (*PM*):

$$PM = \sum_{t=1}^{T}\left(\sum_{t=1}^{t-1} F_t\right) R_t \tag{1}$$

where R_t is the return of the market index, T is the final day in the sample period and 24 February 2020 is set as $t = 1$. The performance metric in Eq.(1) is a rough approximation as it assumes that investor types' net trading is executed in the same composition as the index portfolio (this assumption is certainly true for the S&P500 index futures) and at the closing index level (this effect becomes significant whenever weekly data is used, in which case we make an adjustment by using average daily data).

The resulting estimates, converted into US dollars at the average exchange rate of the period, are reported in Table 2. The main message is that individual investors' trading during the COVID period had an economically significant positive incremental effect on their wealth, at the expense of foreign investors. In many countries, domestic institutional investors also made significant incremental gains as a result of their trading. Subcategories, for which we detected interesting trading patterns above, end up with notable performance outcomes (not in the table): In Korea, pension funds had a significant gain of $ 1.457 bln. In Japan, trust banks gained $ 2.61 bln.

The breakdown of Japanese individuals as cash versus margin traders (not in the table) provides an interesting observation: Cash traders successfully exploiting the negative bubble had a peak profit at $599 million in June 2020 when margin traders, forced to sell during the crash, were losing money. Margin traders' loss hit a maximum in August 2020 at −$639 million and then started to recover. By the third week of November, margin traders reached a profit of $220 million while cash traders moved into a loss of $ −406 million due to early exiting, missing a large portion of the rebound. (Table 2 reports cumulative profits/losses as of the end of our sample period. Figures depicting the evolution of these profits over time are available upon request.) Japanese aggregate individual investor's

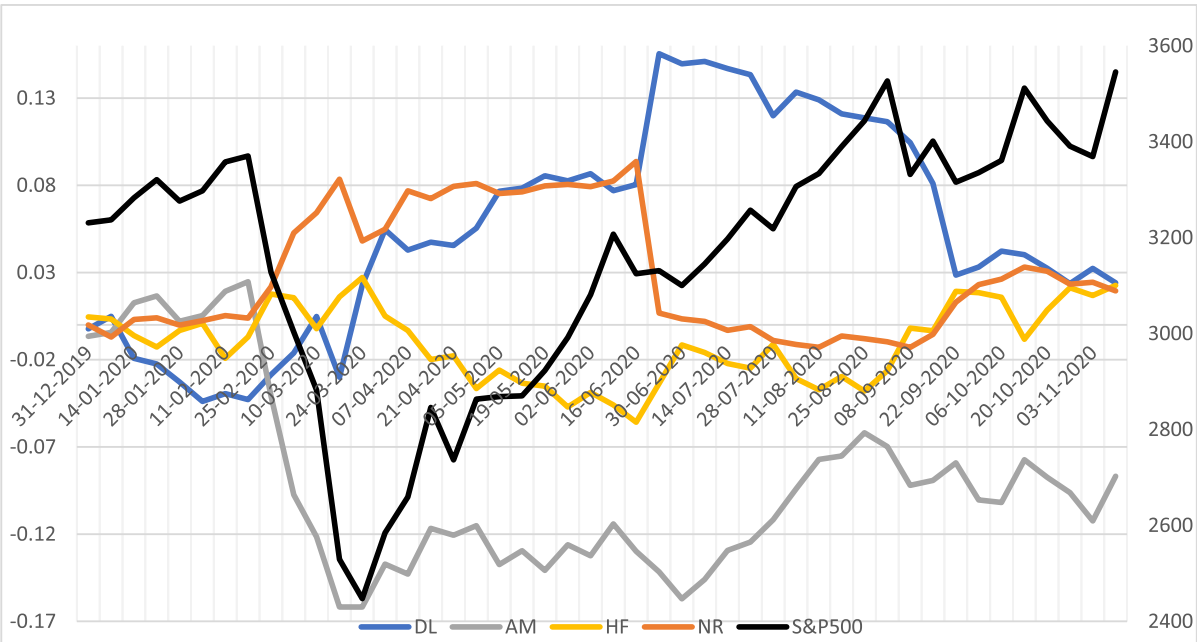


Fig. 3. Investor types' positioning in S&P500 *E*-mini index futures during the COVID episode.
Investor categories' cumulative net position changes as a proportion of total open interest are on the left-vertical axis. S&P500 index values are on the right-vertical axis. DL: Dealers, AM: Asset managers, HF: Hedge funds, NR: Nonreportables (dominated by individual investors).

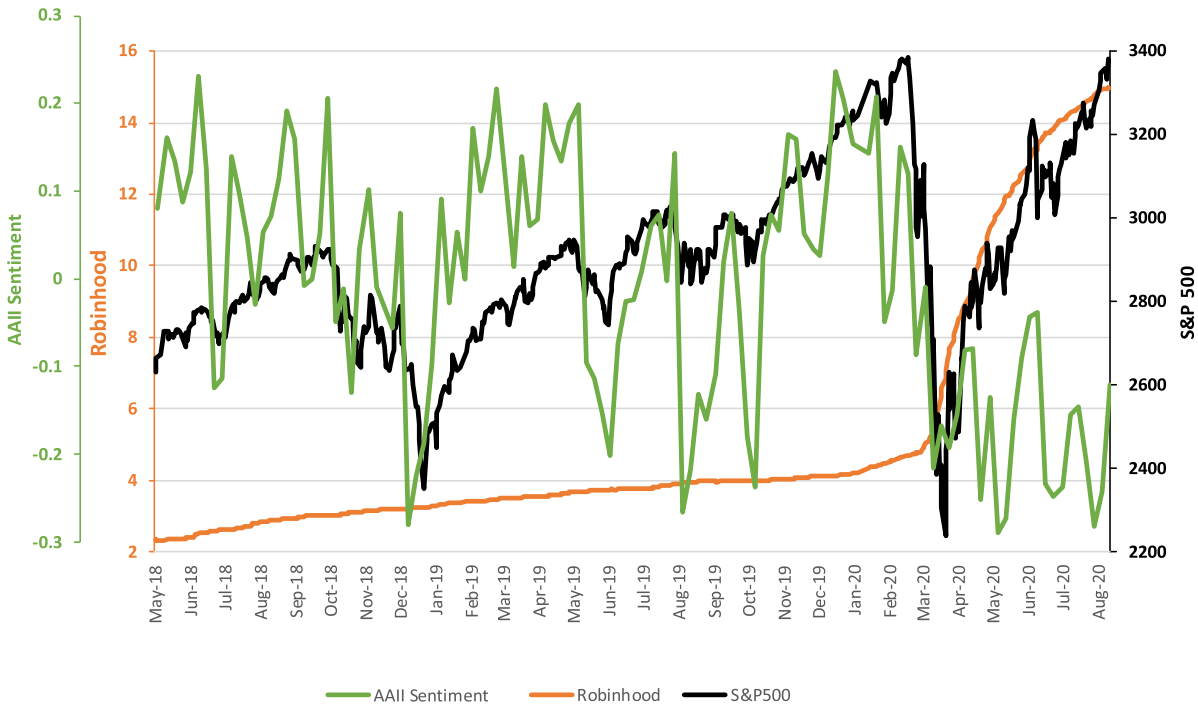


Fig. 4. Number of *Robinhood* clients holding S&P500 stocks during the COVID episode.
Aggregated number (in millions) of Robinhood clients holding S&P500 index constituent stocks is on the left-orange axis. S&P500 index levels are on the right axis. A bullishness indicator derived from AAII individual investor sentiment surveys (% bullish minus % bearish) is on the left-green axis (referred to in Section 4.2). To illustrate the pre-COVID period trend, this graph covers all available Robinhood data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Incremental effect of investor types' trading on their wealth during the COVID period.

	Indiv	Inst	For	Prop.
Korea	8.934	−1.191	−8.470	–
Taiwan	7.53	0.538	−6.856	−0.451
Thailand	0.694	0.302	−1.000	0.005
Turkey	0.653	0.168	−0.833	–
Pakistan	0.030	0.067	−0.100	–
Japan	−0.186	7.870	−6.672	5.944
Russia	0.550	–	–	–
	DL	AM	HF	NR
US CFTC	30.242	−18.731	−0.803	−2.065

Estimates are obtained using the performance metric in Eq.(1). Reported figures are in billion US dollars, computed in local currency and converted to US$ at the period-end exchange rate.

cumulative incremental profit thus peaked earlier at $ 0.297 billion before falling to $ − 0.186 billion reported in Table 2.

In the US index futures, the clear winners are Dealers with an incremental profit above $30 billion. Individual investors, as represented by NR, did not manage to profit from their contrarian trading: they initially suffered sharp losses buying at the beginning of the crash, which they just recovered during the first wave of the rebound; but they closed long positions in June to miss the rest of the rebound. Main losers were asset managers, who sold into the crash and bought back only in late stages of the rebound.

3.3. Has the investor-type structure of stock markets changed during the COVID episode?

In Table 3, we compare investor types' share in total traded value as of the last month in our sample period with the same month of the previous year; i.e., an October 2019 versus October.[15]

[15] Comparisons using earlier months (September, August) yield similar outcomes.

Table 3
Investor types' share in total traded value.

	Oct - 2019			Oct - 2020			
Market	*Indiv*	*Inst*	*For*	*Indiv*	*Inst*	*For*	*t* (*dif*)
Korea	0.470	0.222	0.297	0.643	0.179	0.166	7.24
Taiwan	0.664	0.060	0.276	0.665	0.048	0.287	0.13
Thailand	0.320	0.273	0.406	0.410	0.222	0.368	6.33
Turkey	0.645	0.067	0.286	0.746	0.047	0.206	9.83
Japan	0.134	0.252	0.614	0.175	0.211	0.614	4.04
Russia	0.360	0.149	0.491	0.417	0.114	0.469	3.26

	Oct - 2019				Oct - 2020				
	DL	AM	HF	NR	DL	AM	HF	NR	*t* (*dif*)
US - CFTC	0.185	0.458	0.121	0.138	0.184	0.425	0.135	0.147	1.04

This table compares proportions of traded value accounted for by each main investor type, derived from our complete trading flows data, in October.2019 versus October.2020. (For the US CFTC, share of each investor type in total non-spreading long and short positions). *t* (*dif*) is a *t*-statistic that tests the null-hypothesis that individual investors' share in October 2020 was equal to that in October 2019.

In all countries with two exceptions, significant increases in individual investors' share in traded value are observed.[16] Thus, the participant composition of world equity markets has changed over the COVID period such that the share of individual investors has increased notably, consistent with anecdotal reports.

3.4. Investor trading in COVID-vulnerable versus COVID-beneficiary stocks

Stock-level data, available from the US *Robinhood* and two countries in our sample (Korea and Turkiye), allow us to contrast investor types' trading behavior in COVID-vulnerable and COVID-beneficiary stocks, in order to gain insight as to the underlying motivations of individual investors' trading. For this purpose, we form equal-weighted portfolios of COVID-vulnerable stocks (airlines, hotels, cruise lines, restaurant chains, oil drillers, refineries, etc.) and COVID-beneficiary stocks (online retailers, telecommunication, remote-work technologies, health services, pharma, some IT services and home entertainment businesses). Where possible, our selection of COVID-vulnerable and COVID-beneficiary stocks is based on direct knowledge of the company's products (e.g., Zoom, Moderna); where such information is ambiguous, we have sought additional confirmation from price action.[17] This procedure yields the following numbers of COVID-vulnerable versus COVID-beneficiary stocks, respectively, in each market: 20 versus 55 stocks for the US, 15 versus 27 for Korea, and 8 versus 7 for Turkiye.

Panel A of Fig. 5 plots accumulated changes in the number of *Robinhood* clients holding stocks included in these portfolios against the cumulative returns of these portfolios. The message from Panel A is twofold: First, during the crash in March 2020, even COVID-beneficiary stocks experienced significant initial price declines, in negative relation with their future fundamentals. This validates arguments for a negative bubble based on deviations from fundamentals (the second approach to bubble detection).

Second, retail investor buying interest in COVID-vulnerable stocks with negative fundamentals was much stronger than that in COVID-beneficiary stocks during the March–June period. The graphs clearly indicate that the divergence was triggered by the COVID outbreak. This difference can be explained by behavioral biases of individual investors: contrarian trading, belief in mean reversion, and attention-driven buying (Barber and Odean, 2008). In particular, drastic events make the most-severely affected stocks attention-grabbing, attracting individual investor attention and triggering buying behavior, providing fresh case-based evidence consistent with Barber and Odean (2008) theory. COVID-vulnerable stocks' continued underperformance during the next 3–6 months supports a behavioral bias interpretation, given that retail investor buying in COVID-vulnerable stocks flattened before a relative rebound. Yet, a longer-horizon play for the anticipated eventual full recovery cannot be ruled out.

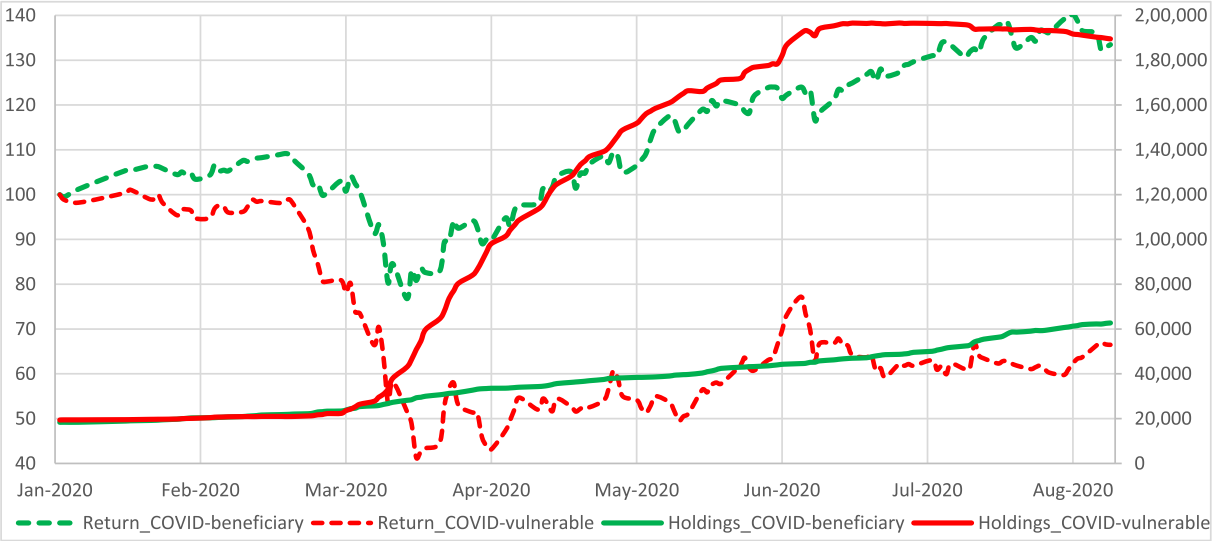
Panel B of Fig. 5 plots individual investors' cumulative net trading in COVID-vulnerable and COVID-beneficiary stocks in Korea and Turkiye. The outcome is similar: Consistent with our first conclusion on the US stock market, COVID-beneficiary stocks also experienced significant initial price declines, validating a negative bubble interpretation. Consistent with our second conclusion based on *Robinhood* investors, net individual investor buying in COVID-vulnerable stocks was much stronger than in COVID-beneficiary stocks

[16] The two exceptions are Taiwan, where individual investors were already dominant with the number of investment accounts at around 40% of the population, and the US index futures where the NR category representing large, experienced individual futures traders was barely affected by the influx of the COVID-generation.

[17] To be included in the COVID-vulnerable (−beneficiary) portfolio, a stock must have significant negative (positive) market-adjusted return during the 24.February – 31.March 2020 period. We also restrict the selection to the constituents of the S&P500, KOSPI-200 and BIST-100 index, respectively, unless news about the firm's product made the stock of special interest for traders during the COVİD period.

Panel A. Robinhood client holdings in COVID-vulnerable and COVID-beneficiary stocks

Number of *Robinhood* clients holding stocks included in these portfolios is plotted in solid lines (averaged across stocks, right-vertical axis). As two portfolios contain different number of stocks, average count across stocks is comparable.



Panel B. Individual investors' net trading in COVID-vulnerable and COVID-beneficiary stocks

Cumulative net trading of individual investors, *Indiv*, in these portfolios, expressed as a proportion of market capitalization, is plotted in solid lines (averaged across stocks, right-vertical axis). Cumulative net trading of domestic and foreign institutional investors are not included in order to keep the graph tractable, but their sum can be inferred as the mirror image of individual investors' cumulative net trading.

Korea

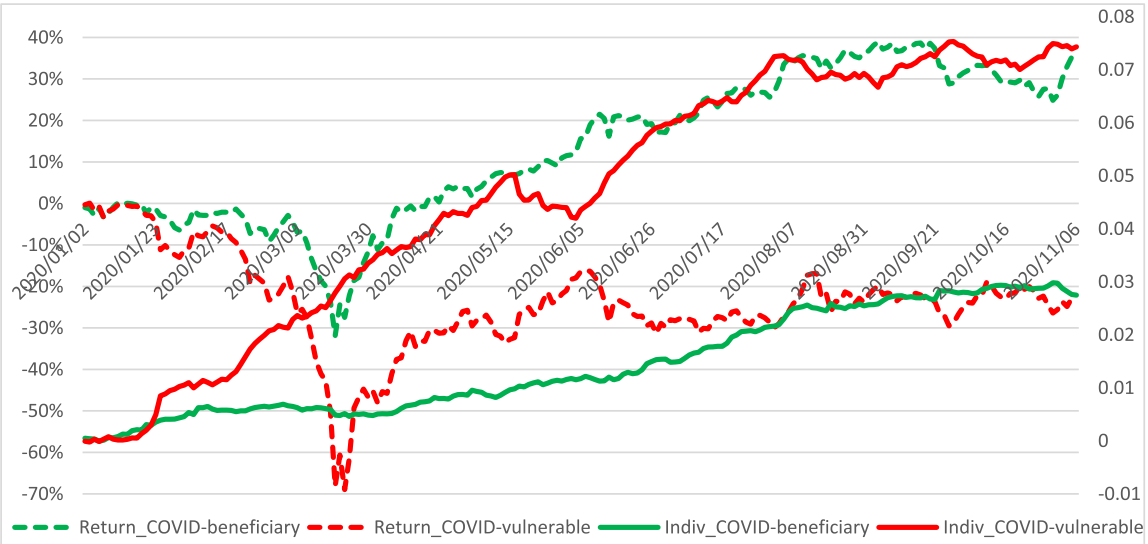


Fig. 5. Investor trading in COVID-vulnerable and COVID-beneficiary stocks.
In each market, equal-weighted portfolios of COVID-vulnerable and COVID-beneficiary stocks are constructed and their return indexes are set to 100 at the beginning of 2020 (red and green dashed lines, respectively; left-vertical axis).

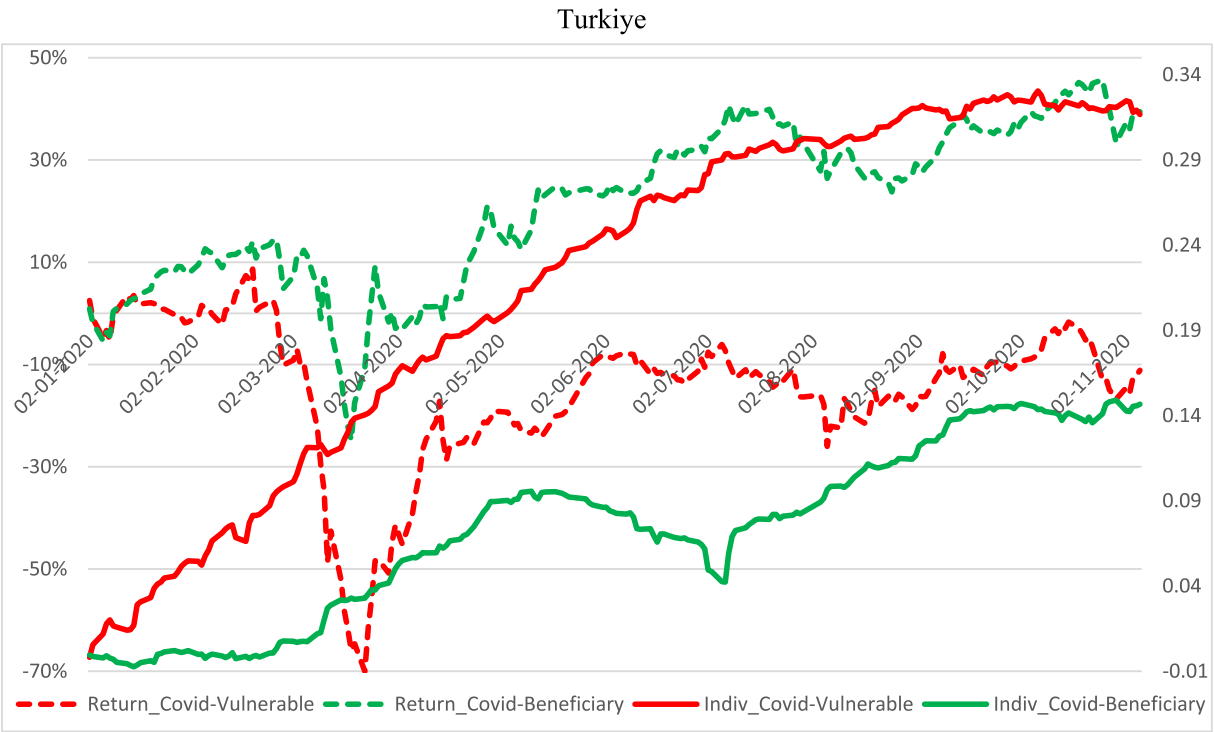


Fig. 5. (*continued*).

in both countries.

It is interesting to note that the divergence in individual investors' net trading in the two portfolios started early in both Korea and Turkiye.[18] In both markets as well as the US, the divergence in cumulative returns started during the second half of January, but remained minor until the last week of February. As a result, a notable part of individual investor net buying in COVID-vulnerable stocks was performed before the global crash in March. It seems that small price concessions lured individual investors before the crash. This particular point lends additional support to behavioral drivers of individual investors' trading.

The cumulative net trading of domestic and foreign institutions (not included in order to keep the graphs tractable; their sum is the mirror image of individual investors) indicates strong net selling of COVID-vulnerable stocks and flat to mild selling of COVID-beneficiary stocks in both Korea and Turkiye. This suggests that institutional investors responded to information besides the pressure of outflows.

4. Understanding drivers of investor trading behavior during the COVID period

We now investigate drivers of investor types' significant trading that resulted in wealth transfers portrayed above. Candidate explanations are differences in sophistication (i.e., successfully exploiting versus joining a negative bubble), a coincidence of the price dynamics of the episode with behavioral (e.g., feedback trading) traits, or a unique shock to investor types' demand for equities. In this section, we distinguish potential explanations using available data and tools by utilizing an empirical setup that accommodates well-known time-series properties of trading flows (i.e., persistence) and their interaction with returns (i.e., feedback trading).

Within a model that fully accounts for these patterns, nonlinear responses to negative bubble levels or exogenous shocks to investor types' demand for equities can be identified by differential intercept terms. For this purpose, we create two dummy variables: *i*) an ex-post identified COVID negative bubble dummy, B_t, which takes the value of 1 when the market index is a certain percentage below its average value during the two months before COVID hit and 0 otherwise. *ii*) a COVID-period dummy, C_t, which takes the value of 1 after the first lockdown took effect in the respective country and 0 before, to capture the period in which individuals started to adapt to a new lifestyle with free time to monitor and trade stock markets.

[18] It is possible to attribute the early divergence in Korea to its geographical proximity to China which experienced an initial wave ahead of the rest of the world, while in Turkiye domestic individual investor buying seems to be driven by the domestic low interest rate policy coincident with foreign investor selling.

4.1. Any skills of identifying a negative bubble?

While aforementioned studies of investor behavior following transient catastrophic events find de-risking and a reduction in trading activities, negative bubbles discussed by Shiller (2000) and Goetzman and Kim (2018) imply that such events offer highly profitable opportunities in excess of rational risk premiums. Hence, transient catastrophic events offer unique assessments of investor sophistication (studies linking investor response during such events to the degree of sophistication are common, e.g., Carpentier and Suret, 2021).

To find out whether the negative-bubble levels hit during the COVID crash in March 2020 had a nonlinear association with investor types' net trading, we test the significance of the negative-bubble dummy B_t in each investor type's augmented net trading (F_t^m) equation.

$$F_t^m = \omega + \omega' B_t + \sum\nolimits_{i=1}^{k} \rho_i F_{t-i}^m + \lambda R_t + \sum\nolimits_{i=1}^{k} \theta_i R_{t-i} + \varepsilon_{1,t} \tag{2}$$

where R_t is the market index return and $k = 5$ with daily data and $k = 1$ with weekly data (further lags turn out insignificant). Eq.(2) controls for autocorrelation in net trading (captured by ρ coefficients) and net trading's response to contemporaneous and past returns (captured by λ and θ coefficients, respectively). Where an investor types' net trading is highly positively-correlated with contemporaneous returns (which is the case for foreign investors and in some markets for domestic institutions) raising the possibility of price impact driving returns, we also estimate an alternative version of Eq.(2) excluding the λR_t term, to address the simultaneity between returns and trading flows. This provides a view on the possibility that inappropriately controlling for returns driven by the price impact of an investor type's trading interferes with the measured significance of the other terms in Eq.(2).

A significantly positive ω' coefficient in Eq.(2) would imply skill in identifying and exploiting the COVID negative bubble (i.e., significant net buying at negative-bubble levels after controlling for net trading's regular interaction with returns). A significantly negative ω', on the other hand, would imply fomenting (i.e., selling into) a negative bubble. Hereby, we introduce an asymmetric version of a negative-bubble dummy, taking into account a potential asymmetry in perceived risk: In a V-pattern, the perceived risk can be higher on the left wing during the sell-off than at the same level on the right wing during the rebound. Hence, perceived-risk-adjusted expected returns by which a rational investor would identify a negative bubble level might differ at the same index level on the left and right wings of the V-pattern. To our knowledge, this study is the first to incorporate such asymmetry. The plain version of B_t takes the value of 1 when the index is 20σ below its 23.Dec.2019–21.Feb.2020 average value, where σ is the pre-COVID standard deviation of daily returns.[19] The asymmetric version uses a threshold of 22σ on the left wing and 18σ on the right wing (reasonable variation of these parameters yields similar results).

Table 4 reports results from estimating Eq.(2) using the asymmetric version of B_t.[20] The first B column on the left reports the estimated coefficient of the COVID negative-bubble dummy before controlling for F's interaction with returns; i.e., excluding the terms with λ and θ in Eq.(2). If this B-coefficient loses its significance in the augmented Eq.(2) on the right block, it would imply that the investor type's response to the negative bubble can in fact be accounted for by its regular feedback trading traits.

The most-left column suggests that B-coefficients before controlling for the interaction with returns are significantly positive for domestic individuals and domestic institutions, and significantly negative for foreign investors in most cases. In others, they are marginally insignificant with similar signs. (Weaker result for NR in US CFTC data can be due to forced selling of long positions in margined futures accounts during the sharp sell-off). Thus, before controlling for trading styles, domestic investors appear to have exploited/counteracted the COVID negative bubble while foreign/institutional investors fomented it.

In the center-right large block, B-coefficients are significantly or marginally-insignificantly positive for domestic individuals and domestic institutions and negative for foreign investors. Significance levels are reduced compared with the first column for individuals in Thailand and Turkiye, for domestic institutions in Taiwan, for pension funds in Korea and for DL and NR in the US equity futures, indicating that regular contrarian traits helped these investor types exploit the negative bubble. For domestic institutions in Turkiye, who have no significant regular contemporaneous contrarian trading behavior, the B-coefficient rather gains significance after controlling for interaction with returns, indicating that their trading may have particularly aimed at exploiting the negative bubble. In the last column, excluding the contemporaneous return (i.e., the λR_t term) in the F equation strengthens the significance of foreign investors' selling into the negative bubble in smaller markets such as Thailand and Turkiye where foreign investors' price impact is expected to drive returns.

In summary, the above results provide moderate evidence that domestic individual and institutional investors exploited the negative bubble in March–April 2020 and foreign institutional investors were sellers at negative-bubble levels. They also suggest that regular contrarian trading traits helped some investor types to exploit the negative bubble. As a side note, significant *F-lag* coefficients confirm the well-known persistence in investor types' trading, while significant R and *R-lag* coefficients confirm positive feedback trading by foreign investors and negative feedback trading by individuals.[21]

[19] 20 is a parameter set such that a sufficiently long time-span during which a substantially cheaper index level could be exploited for buying. There is no existing guidance regarding what this number should be; Goetzman and Kim (2018) experiment with a range of threshold levels on historical data to yield a desirable sample size of negative bubble cases.

[20] Results using the plain version are similar with weaker significance levels in several cases.

[21] Results remain robust using a generalized method of moments (GMM) estimation which offers alternative ways of dealing with the simultaneity between flows and returns, and heteroskedasticity.

Table 4
Significance of the COVID negative bubble in driving investor types' trading.

Market	Investor type	*B*	*R*	*R* lag	*F* lag	*B*	*B* (alt.)
Korea	Domestic Individual	0.650	-0.625	0.037	0.242	0.972	
		(2.44)*	(−13.16)	(1.04)	(8.26)	(2.46)*	
	Domestic Institutions	0.008	0.222	-0.207	0.253	-0.200	-0.085
		(0.04)	(6.60)	(-7.07)	(9.56)	(-0.50)	(−0.18)
	Foreign	-0.287	0.458	0.140	0.351	-0.712	-0.452
		(-1.85)	(12.00)	(4.49)	(13.40)	(-1.41)	(−1.42)
Taiwan	Domestic Individual	0.235	-0.680	-0.016	0.391	0.422	
		(1.42)	(−18.83)	(−0.64)	(22.03)	(1.69)	
	Domestic Institutions	0.686	0.392	-0.097	0.353	0.538	0.612
		(3.65)**	(15.12)	(−3.62)	(13.09)	(2.61)*	(2.35)*
	Foreign	-0.174	0.621	0.029	0.423	-0.348	-0.214
		(−1.05)	(18.14)	(1.09)	(25.56)	−1.49	(−1.52)
Thailand	Domestic Individual	0.160	-0.614	-0.019	0.198	0.189	
		(1.16)	(−14.93)	(−0.49)	(4.80)	(0.52)	
	Domestic Institutions	0.713	0.497	-0.262	0.228	0.451	0.476
		(2.98)*	(17.93)	(−8.81)	(11.14)	(2.05)*	(2.07)*
	Foreign	-0.400	0.253	0.122	0.362	-0.445	-0.428
		(−2.13)*	(6.86)	(4.03)	(9.67)	(−1.68)	(−2.47)*
Turkiye	Domestic Individual	0.519	-0.675	-0.014	0.131	0.602	
		(4.20)**	(−17.64)	(−0.72)	(5.05)	(2.18)*	
	Domestic Institutions	0.393	-0.032	-0.163	0.108	0.361	
		(1.68)	(−1.17)	(−6.76)	(4.96)	(2.82)**	
	Foreign Inst.	-0.525	0.648	0.038	0.196	-0.628	-0.552
		(−3.10)**	(18.46)	(1.28)	(8.44)	(−2.99)**	(−3.23)**
Japan	Domestic Individual	0.249	-0.689	-0.083	0.142	0.286	
		(3.10)**	(−9.65)	(−1.30)	(2.06)	(0.76)	
	Domestic Institutions	0.519	0.19	-0.10	0.49	0.49	0.489
		(1.40)	(2.73)	(-2.04)	(10.17)	(1.34)	(1.38)
	Foreign Inst.	-0.483	0.409	-0.020	0.398	-0.498	-0.473
		(−1.94)	(5.26)	(−0.33)	(6.38)	(−1.75)	(-1.83)
Russia	Domestic Individual	0.527	-0.586	-0.027	0.118	0.408	
		(1.61)	(−3.89)	(-0.27)	(1.08)	(2.14)*	
US - CFTC	NR	0.082	-0.149	-0.012	-0.053	-0.001	
		(0.46)	(-3.10)	(-1.42)	(-2.63)	(-0.08)	
	AM	0.081	0.613	0.08	-0.04	0.433	0.106
		(0.00)	(11.13)	(0.92)	(-0.91)	(0.25)	(0.13)
	HF	-0.23	-0.297	0.041	-0.158	-0.357	
		(-1.35)	(−5.60)	(1.32)	(-3.99)	(-2.07)*	
	DL	0.505	-0.086	-0.167	0.055	0.384	
		(2.46)*	(-1.42)	(-2.63)	(0.32)	(1.73)	
US	Robinhood client #	0.548	-0.016	-0.086	0.808	0.439	
		(1.34)	(−0.31)	(−1.51)	(16.05)	(1.29)	

The dependent variable is F_t^m. All variables (except the dummy *B*) are standardized to have mean = 0 and st.dev. = 1, such that estimated coefficients are comparable across investor types and countries. The first column on the left reports *B*'s coefficient in a univariate regression controlling for only autocorrelation in *F*. The main middle block reports full estimation of Eq.(2). The most-right column reports estimation of *B* in an alternative version of Eq.(2) which excludes the contemporaneous return *R* (only for those investor types whose net trading is significantly positively correlated with contemporaneous returns). To keep reporting concise, sum of lag coefficients are reported in single statistics: $R\text{-}lag = \sum_{i=1}^{k}\theta_i$ is an indicator of feedback trading and $F\text{-}lag = \sum_{i=1}^{k}\rho_i$ is an indicator of flow persistence. Newey-West *t*-statistics are in parentheses. *(**) denotes statistical significance of the *B*-coefficient at the 5%(1%) level.

Any coincidence of aggregate trading with the direction of the market return may potentially drive the above inference regarding sophistication based on a single event. In such cases, additional granularity from the cross-section of net-trading and returns provides a robustness check. *Robinhood* data enable a cross-sectional analysis of whether retail investors' stock selection when buying during the negative bubble had any predictive value for the cross-section of stock returns during the rebound. For this purpose, we define the following variables for all S&P500 index constituent stocks:

$$F0_i = \%\text{change in the number of } \textit{Robinhood} \text{ investors holding stock } i \text{ during the negative} - \text{bubble period}$$

$$R0_i = \text{return of stock } i \text{ over the negative} - \text{bubble period.}$$

$$R1_i = \text{return of stock } i \text{ over the rebound period}$$

where the negative-bubble period is defined as 11.March–17.April 2020 and the rebound period as 17.April–13.August 2020 (13. August is the last day *Robinhood* data are available). To assess predictive ability, we run the following cross-sectional regression:

$$R1_i = \alpha + \psi F0_i + \varphi R0_i + \varepsilon_i \tag{3}$$

Results are reported in Table 5.

The univariate regression in the first row suggests that retail investors' stock selection during the negative-bubble period has statistically-significant predictive ability for the cross-section of stock returns during the rebound period. The second row, controlling for returns during the negative-bubble period, suggests that part of this predictive ability might be owing to contrarian trading: bubble-period returns negatively predict rebound-period returns and this control wipes out a large part of the statistical significance of retail investors' predictive ability. In the third row, we run a regression of *F0* on *R0* to characterize retail investors' stock selection. The result confirms significant contrarianism, where the negative cross-sectional relation with returns explains 19.5% of retail investors' stock selection. In sum, the regular contrarian behavior of retail investors helped them pick stocks with larger selling pressure and benefit from their relatively stronger rebound.

4.2. Understanding individual investors' success in the COVID episode

Individual investors' aggregate trading during the COVID episode contrasts with existing views of their sophistication. We now focus on identifying drivers of individual investors' trading in this episode. The COVID period had two unique aspects which may have potentially influenced individual investors' aggregate trading: *i*) an unprecedented amount of monetary and fiscal policy support, *ii*) lockdowns and a new work-from-home lifestyle that provided individuals excess free-time to monitor and trade financial markets. We conjecture that the combination of these two effects created a unique positive shock to retail individual investor demand for equities. An exogeneous shock to individual investor demand for equities can be captured by the COVID-period dummy C_t in a model that controls for other known patterns in individual investor trading. This involves adding C_t into Eq.(2).

We also uncover an asymmetry in individual investors' response to positive and negative returns. Investor response to positive and negative returns may differ as they may have asymmetric effects on risk tolerance. From the econometric viewpoint, omission of a potential nonlinearity may amount to misspecification and lead to noninformative coefficient estimates. Hence, we estimate a nonlinear version of Eq.(2). For this purpose, we create a negative-return dummy variable, N_t, that takes the value of 1 when $R_t < 0$ and 0 otherwise, and estimate:

$$F_t = \omega + \omega' C_t + \omega'' B_t + \sum_{i=1}^{p} \rho_i F_{t-i} + \lambda R_t + \lambda' R_t N_t + \sum_{i=1}^{p} \theta_i R_{t-i} + \sum_{i=1}^{p} \theta_i' N_{t-i} R_{t-i} + \varepsilon_{1,t} \tag{4}$$

In Table 6, significantly positive λ' coefficients indicate that individual investors are less contrarian to positive contemporaneous returns than to negative ones. In other words, selling into price increases is more immediate compared with buying dips. With respect to past weeks' returns, however, significantly negative θ' coefficients indicate that individual investors are more contrarian to negative past returns than to positive ones. Hence, the immediate effect of negative returns on risk tolerance dissipates quickly, and motivation to buy the dip starts to dominate. Thus, we document significant asymmetries in individual investors' response to the sign of contemporaneous and past returns.

Returning to the main question, in all countries the coefficient of the COVID-period dummy C_t is significantly positive. On the other hand, the coefficient of the negative-bubble dummy B_t loses its significance in most cases. Thus, controlling for individual investors' asymmetric response to returns, a positive shock to individual investor demand for equities in the COVID environment is much more significant than a potential motive of exploiting a negative bubble in driving individual investor trading. These results are robust to EGARCH estimation which yields qualitatively identical results with sharper significance levels in several cases (available upon request). The conclusion is that a lucky coincidence of the shock to their demand for equities played a larger role than skill in accounting for the above documented success of individual investors in this episode.

We check robustness of our interpretation of a unique shock to retail investor demand for equities as follows. First, a potential driver of individual investor trading is sentiment. The historical relationship between AAII sentiment changes (*d.S* where *S* is defined as % bullish minus % bearish) and change in the number of *Robinhood* clients holding S&P500 stocks (*d.RH*) is significantly positive (even

Table 5
The cross-section of stock returns and *Robinhood* investors' positioning.

		Regressors		
Dependent	Intercept	*F0*	*R0*	R-squared
R1	0.138 (13.08)**	0.059 (3.55)**		0.024
R1	0.146 (12.34)**	0.038 (1.88)	−0.145 (−2.22)*	0.036
F0	0.438 (24.71)**		−1.402 (−7.85)**	0.195

Each regression in one row. The sample comprises S&P500 index constituent stocks. Heteroscedasticity-adjusted *t*-statistics are in parentheses. *(**) denotes statistical significance at the 5%(1%) level.

Table 6
Drivers of individual investors' trading.

	Korea	Taiwan	Thailand	Turkiye	Japan	Russia	CFTC - NR	*Robinhood*
ω	0.000007	−0.000019	0.000024	0.000017	−0.000089	0.000160	−0.001154	−1171.3
	(0.76)	(−1.85)	(3.19)**	(1.74)	(−2.05)*	(2.31)*	(−1.10)	(−0.69)
C	0.000109	0.000061	0.000040	0.000104	0.0002081	0.000142	−0.001332	20,783.0
	(4.78)**	(3.39)**	(3.10)**	(3.90)**	(2.21)*	(3.73)**	(−0.35)	(2.56)*
B	0.000224	0.000026	0.000076	0.000081	0.0001854	0.000234	−0.00286	31,651.6
	(2.86)*	(0.30)	(0.93)	(1.03)	(0.89)	(1.63)	(−0.38)	(1.65)
ρ	0.114	0.157	0.101	0.063	0.1669	0.015	−0.0552	0.191
	(8.25)**	(18.97)**	(5.19)**	(4.00)**	(2.34)*	(0.44)	(−1.81)	(4.22)**
λ	−0.0197	−0.0254	−0.0171	−0.0172	−0.0299	−0.0129	−0.0258	−87,364.8
	(−13.51)**	(−13.96)**	(−12.96)**	(−18.88)**	(−7.94)**	(−4.95)**	(−0.36)	(−0.27)
λ'	0.0105	0.0037	0.0058	0.0075	0.0157	0.0117	−0.1474	196,687.7
	(5.13)**	(1.74)	(3.26)**	(5.33)**	(3.48)**	(3.77)**	(−1.26)	(0.34)
θ	0.0009	0.0012	−0.0008	0.0003	0.0014	−0.0007	0.0283	201,832.3
	(1.66)	(2.41)*	(−1.15)	(0.75)	(0.36)	(−0.57)	−0.53	(1.59)
θ'	−0.0019	−0.0035	0.0000	−0.0015	−0.0074	0.0014	−0.0485	−451,388.1
	(−2.34)*	(−3.55)**	(0.03)	(−3.04)**	(−1.54)	(0.72)	(−0.55)	(−2.17)*

This table reports results from Eq.(4) estimated for individual investors' trading F_t (for *Robinhood* data, *d.RH*: change in the number of *Robinhood* clients holding S&P500 stocks). To keep reporting concise, sum of lag coefficients are reported in single statistics where $\rho = \sum_{i=1}^{k}\rho_i$ is an indicator of persistence (equivalent to '*F*-lag' in Table 4), $\theta = \sum_{i=1}^{k}\theta_i$ is an indicator of feedback trading with respect to positive past returns (*R*-lag in Table 4) and $\theta' = \sum_{i=1}^{k}\theta'_i$ is an indicator of differential feedback trading with respect to negative past returns. *B* is an asymmetric negative bubble dummy and *C* is a dummy that captures COVID period effects (lockdowns and work-from-home lifestyle). The data are not standardized; hence coefficients reflect relative scales of raw variables. Newey-West *t*-statistics are in parentheses. *(**) denotes statistical significance at the 5%(1%) level.

controlling for returns)[22]: $d.RH_t = c + d.RH_{t-1} + \lambda_1 R_t + \lambda_2 R_{t-1} + \gamma d.S_t + \gamma d.S_{t-1} + \varepsilon_t$.

Estimated Newey-West *t*-statistics: (2.42) (21.58) (−2.63) (−1.87) (1.77) (2.66).

Yet, Fig. 4 makes clear that *Robinhood* investors stepped up their buying although AAII individual investor sentiment remained at depressed levels. This makes *Robinhood* clients' accelerated net-buying more remarkable as it cannot be explained by- and would actually become more significant after controlling for sentiment.

Second, available statistics from around the world, presented in detail in Supplementary Material 1, clearly document an unprecedented increase in new account openings. They further show that the influx of new entrants, mostly of younger and working age, has altered the demographic composition of individual investor population.

4.3. What drove US asset managers' and foreign investors' exits?

Significant losses of US asset managers and foreign institutional investors due to selling during the COVID episode begs the question of whether this was fund managers' choice or dictated by client outflows. To investigate this, we look at flows toward global equity funds, compiled and reported by three different sources: *EPFR Global*, *Refinitiv-Lipper* and *ICI*. These three sources slightly differ in their coverage; we have cross-checked and confirmed the same pattern in each of them. Reported results are based on the weekly *Refinitiv-Lipper* data (retrieved from *Reuters Eikon*).[23]

Earlier studies find that flows toward funds is a driver of funds' trading and price impact (Edelen and Warner, 2001). Consistent with this, US asset managers' and foreign institutional investors' net trading are highly positively correlated with flows toward respective equity funds in our data (correlations on weekly data range between +0.49 and + 0.71). Furthermore, Fig. A.4 in Supplementary Material 1 clearly indicates that cumulative flows toward global equity funds go hand-in-hand with cumulative net trading by foreign institutions shown in Fig. 1.

To formally test, we run the following panel regression at the weekly frequency:

$$F_{i,t} = c_i + \sum_{k=-1}^{0} \beta_k FF_{t-k} + \boldsymbol{\gamma_i X_{i,t}} + \varepsilon_{i,t} \tag{5}$$

where $F_{i,t}$ is foreign institutional investors' net trading in country *i* in week *t*, FF_t is net client flows toward global equity funds,[24] and $\boldsymbol{X_{i,t}}$ is a vector of control variables deemed to drive foreign investors' trading and flows toward global equity funds, specifically: lagged

[22] Qualitatively identical results are obtained using *Robinhood* client counts in S&P500 ETFs SPY and VOO.

[23] Capturing a significant trend-shift from conventional funds into ETFs that has been in place in recent years, we also decompose conventional mutual funds versus ETFs in further analysis presented in Supplementary Material 2.

[24] We confirmed the robustness of our results under several alternative definitions of flows toward equity funds. Reported results pertain to flows global equity funds including ETFs domiciled in the US.

Table 7
Drivers of foreign / institutional investors' trading during the COVID episode.

Dependent	*c*	*FF*	*FF*(−1)	*R*(−1)	Covid cases	Covid deaths	TEU	*n*
Foreign investors (panel of host countries)	0.016	0.538	0.203	−0.070	0.017	−0.096	−0.228	184
	(0.25)	(6.47)*	(3.06)*	(−1.27)	(−0.07)	(−0.39)	(−3.45)*	
Asset managers (US index futures)	0.019	0.594	0.027	−0.255	0.035	0.274	−0.308	47
	(0.16)	(3.72)*	(0.25)	(−1.18)	(0.29)	(2.17)	(−3.08)*	

This first line reports the results from estimating Eq.(5) on a panel of host markets. The second line replicates the estimation for asset managers in US index futures. All variables are standardized to have zero mean and unit standard deviation at the country level, such that coefficients are comparable across variables and regressions. Panel Newey-West *t*-statistics are in parentheses.

host market return, current week's COVID cases and deaths in the host country and weekly average of daily Twitter-based economic uncertainty (TEU) index (see www.policyuncertainty.com). Estimation results over the January–November 2020 period are in Table 7.[25]

In the first line, *FF* is significant and positive both contemporaneously and with a lag, indicating that flows toward funds is a significant driver of foreign institutional investors' trading in host markets (alone, they can explain 41.7%; not in the table). In the second line, the estimation is replicated for US asset managers in S&P500 index futures: contemporaneous flows toward equity funds is a significant driver (can alone explain 39.5%) of US asset managers' futures trading.[26] Our result is consistent with Glossner et al. (2022) finding using F-13 filings data.

Lagged returns, COVID cases and deaths are insignificant, suggesting that institutional investors' trading cannot be explained by their reaction to COVID statistics. Thus, US asset managers' and foreign institutional investors' role in fomenting the negative bubble and not contributing to the rebound was largely driven by client flows toward funds at the global level.

TEU enters with significant negative signs, indicating that institutional investor net selling is associated with higher levels of the uncertainty index. As an interesting note, when TEU is removed from the right-hand side of the regressions, intercept terms become significantly negative (not in the table). This implies that part of the persistent selling by institutional investors can be related to the above-average overall economic uncertainty associated with the COVID period.

A striking note is that fund clients exited equity funds while our previous results above indicated that retail investors trading on their own ramped up their buying of equities. Thus, COVID-period evidence suggests that fund clients behave differently from individuals trading on their own. Furthermore, Fig. A.4 in Supplementary Material 1 also reveals that investors shifted from conventional mutual funds toward ETFs during the COVID period (an acceleration of the existing trend). Taken together, we interpret this as a COVID-induced trend toward self-servicing.

This shift toward self-servicing led to a temporary increase in home bias, as clients' exiting international funds were replaced by new entrants' direct purchases of home-country stocks and ETFs, possibly as individuals with limited expertise to trade foreign equities focused on home-country equities. Fig. OA4 in Supplementary Material 2 shows that this home bias was rectified later after October 2020.

An extended period of analysis in Fig. OA.4 reveals that fund clients returned back (mostly in the form of ETFs) between late November 2020 and May 2021 well after the rebound was completed and US indices headed to new highs. Hence, equity fund clients' aggregate trading during the COVID episode displayed particularly poor timing, consistent with Akbaş et al. (2015) 'dumb money' characterization.

5. Conclusion

During the COVID period, individual investors emerged with significant net buying in world stock markets, which can be explained by a combination of their regular contrarian behavior and a unique positive shock to working-age retail investor demand for equities. This shock was likely driven by excessive monetary and fiscal stimulus and free time to access stock markets thanks to lockdowns and work-from-home practices. This lucky sequence made them winners of this episode, as a peculiar outcome. Foreign institutional investors and US asset managers sold into the negative bubble, at least partly driven by client outflows. Unlike the tech bubble, the rebound was not associated with their pivoting. Dealers in the US equity futures and some domestic institutions in emerging markets harvested significant profits from their sophisticated timing exploiting a negative bubble.

The COVID circumstances accelerated the trend from delegated investment management toward self-serviced investing. As a result, the participant structure of world stock markets has changed. While a component of individual investor influx was due to ultra-expansionary policies and transient, another component due to a new work-from-home lifestyle is likely enduring. This adds increased relevance to individual investor behavior as a factor affecting the dynamics of stock markets, on which we document the following fresh findings: *i*) characterization of individual investors as noise traders in the existing literature needs caution, *ii*) the

[25] Results employing random effects estimator (accepted by Hausman test) with clustered robust standard errors and those using a two-stage GMM method (to address potential heterogeneity between institutional investors' trading and flows toward equity funds) are similar (available upon request).

[26] The correlation between weekly S&P500 returns and aggregate flows toward US equity funds is +0.53 when ETFs are included and + 0.50 ETFs excluded.

timing of individual investors' response to positive and negative returns is asymmetric, *iii*) margin traders and cash traders behave differently, where the latter display more contrarian trading and signs of the disposition effect.

This paper's primary contribution is to provide case-based evidence to answer the question 'who are agents of negative bubbles?'. Using Korean data, but based only on the sign of feedback trading with no attempt to identify bubbles, Choi et al. (2015) suggest that institutional investors, rather than individuals, are agents of bubbles. Using worldwide data on a well-identified negative bubble, we provide direct evidence that bubble-formations develop with institutional investors responding to significant new information (where response may be reinforced due to client flows), whereas self-trading individuals tend to counteract thanks to their contrarian behavioral traits.

CRediT authorship contribution statement

Numan Ülkü: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing. **Fahad Ali:** Data curation, Validation, Investigation, Resources, Investigation, Writing - review & editing. **Saidgozi Saydumarov:** Data curation, Formal analysis, Resources, Investigation. **Deniz İkizlerli:** Data curation, Resources, Investigation.

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Appendix A. Appendix

Table A.1
Data description and summary statistics.

			Pre-COVID period:				COVID period:			
Country	Nature of the data	Variable	Mean	St.Dev.	Skew.	Kurt.	Mean	St.Dev.	Skew.	Kurt.
Korea	Daily		4 Jan 2010–21 Feb 2020				24 Feb - 20 Nov 2020			
	All stocks	*Indiv*	−0.0000162	0.0002128	−0.41	8.11	0.0001417	0.0003814	0.05	3.64
	Precise, compiled	*Inst*	0.0000004	0.0001863	0.45	7.10	−0.0000491	0.0002607	0.23	3.79
	from electronic	*For*	0.0000163	0.0002179	0.07	8.55	−0.0001012	0.0002804	−0.60	4.81
	records by the Exchange	*R*	0.000111	0.0093	−0.46	7.03	0.000808	0.0195	−0.24	7.46
Taiwan	Daily		4 Jan 2010–21 Feb 2020				24 Feb - 20 Nov 2020			
	All stocks	*Indiv*	−0.0000070	0.0003184	0.36	5.61	0.0001001	0.0004479	0.95	4.56
	Precise, compiled	*Inst*	−0.0000046	0.0000251	−0.05	5.54	0.0000087	0.0000266	0.38	3.44
	from electronic	*For*	0.0000154	0.0002876	−0.41	6.14	−0.0000867	0.0003927	−1.07	4.82
	records by the Exchange	*R*	0.000293	0.0092	−0.71	7.51	0.001039	0.0141	−0.40	6.88
Thailand	Daily		4 Jan 2010–21 Feb 2020				24 Feb - 20 Nov 2020			
	All stocks	*Indiv*	−0.0000008	0.0002413	−0.96	21.40	0.0000670	0.0002626	−0.71	10.38
	Precise, compiled	*Inst*	0.0000123	0.0001429	0.19	8.46	0.0000239	0.0002046	0.14	6.80
	from electronic	*For*	−0.0000127	0.0001998	1.20	28.73	−0.0000985	0.0001901	1.74	18.40
	records by the Exchange	*R*	0.000286	0.0095	−0.29	7.58	−0.000387	0.0207	−1.58	12.39
Turkiye	Daily		4 Jan 2010–21 Feb 2020				24 Feb - 30 Oct 2020			
	All stocks	*Indiv*	−0.0000034	0.0002673	−0.14	4.40	0.0001358	0.0002478	−0.23	5.47
	Precise, compiled	*Inst*	0.0000039	0.0000931	−0.10	6.26	0.0000239	0.0001058	0.31	4.84
	from daily	*For*	0.0000006	0.0002879	0.08	4.53	−0.0001663	0.0002335	−0.37	3.77
	settlements by the Central Registry	*R*	0.000352	0.0136	−0.58	7.10	0.000228	0.0184	−1.42	8.19
Pakistan	Daily		24 Jan - 21 Feb 2020				24 Feb - 31 Dec 2020			
	All stocks	*Indiv*	0.0000164	0.0001073	−0.61	3.45	0.0000304	0.0002887	−0.57	4.95
	Precise, compiled	*Inst*	0.0001410	0.0001620	0.38	2.91	0.0001844	0.0003250	0.25	3.95
	from daily	*For*	−0.0001530	0.0001610	−1.20	4.07	−0.0002188	0.0002345	−0.96	6.53
	settlements by the Clearing House	*R*	−0.002729	0.0113	−0.31	3.59	0.000390	0.0159	−1.25	8.13
Japan	Weekly		3 Jan 2011–21 Feb 2020				24 Feb - 28 Nov 2020			
	All stocks	*Indiv*	−0.0002381	0.0008587	−0.58	5.39	−0.0000663	0.0006867	−0.33	3.50
	Compiled from	*Inst*	0.0001165	0.0007782	−0.31	7.76	0.0004258	0.0007938	1.80	8.74
	electronic surveys	*For*	0.0001334	0.0010973	0.83	8.26	−0.0003042	0.0009172	−0.64	3.45

(*continued on next page*)

Table A.1 (*continued*)

Country	Nature of the data	Variable	Pre-COVID period: Mean	St.Dev.	Skew.	Kurt.	COVID period: Mean	St.Dev.	Skew.	Kurt.
		R	0.001328	0.0257	−0.59	5.16	0.001442	0.0465	−0.77	5.99
	Weekly, only *Indiv*		2 Jan 2018–21 Feb 2020				24 Feb - 28 Nov 2020			
Russia	All stocks, Precise,	*Indiv*	0.0000230	0.0001361	0.06	2.87	0.0001478	0.0004486	−2.13	9.85
	Compiled by MOEX	*R*	0.003453	0.0179	−0.28	3.00	0.001273	0.0410	−1.74	8.04
	Daily		3 May 2018–21 Feb 2020				24 Feb - 13 Aug 2020			
US *Robinhood*	number of retail	*dRH*	5361.4	10,024	7.67	94.59	84,920.6	69,066	0.83	3.43
	clients holding S&P500 stocks	*R*	0.000538	0.0089	−0.38	6.92	0.000088	0.0298	−0.64	6.92
	Weekly		4 Jan 2010–18 Feb 2020				19 Feb - 20 Nov 2020			
	Index futures	NR	0.0000	0.0151	−1.26	14.43	−0.0002	0.0202	−3.43	17.87
US CFTC	Compiled from	AM	−0.0000	0.0176	−0.40	4.59	−0.0027	0.0206	−0.89	3.84
	surveys by CFTC	DL	−0.0000	0.0158	0.85	6.99	0.0023	0.0232	1.25	7.61
	Proportion of open	HF	0.0001	0.0178	−0.77	8.09	0.0009	0.0141	0.16	2.09
	interest	*R*	0.002072	0.0191	−0.88	7.01	0.001334	0.0388	−1.11	4.99

Indiv, Inst and *For* stand for net trading flows as a proportion of free-float market capitalization (i.e., F_t^m) of individual, domestic institutional and foreign investors, respectively. For the US *Robinhood* data, the variable is the daily change in the number of investors holding S&P500 stocks (*dRH*). For the US CFTC data, the variable is the net change in futures position as a proportion of open interest (NR = Nonreportables, comprising mainly individual investors, AM = Asset Managers, DL = Dealers, HF=Hedge Funds. CFTC weeks start on Wednesday and end on Tuesday). *R* is the return (first difference of the log) of the respective market index.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pacfin.2023.102044.

References

Abreu, D., Brunnermeier, M., 2002. Synchronization risk and delayed arbitrage. J. Financ. Econ. 66, 341–360.
Abreu, D., Brunnermeier, M., 2003. Bubbles and crashes. Econometrica 71, 173–204.
Akbaş, F., Armstrong, W., Sorescu, S., Subrahmanyam, A., 2015. Smart money, dumb money, and capital market anomalies. J. Financ. Econ. 118, 355–382.
Arkes, H., Hirshleifer, D., Jiang, D., Lim, S., 2010. A cross-cultural study of reference point adaptation: evidence from China, Korea, and the US. Organ. Behav. Hum. Decis. Process. 112, 99–111.
Barber, B., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21, 785–818.
Barber, B., Lee, Y.T., Liu, Y.J., Odean, T., 2009. Just how much do individual investors lose by trading. Rev. Financ. Stud. 22, 609–632.
Barrot, J., Kaniel, R., Sraer, D., 2016. Are retail traders compensated for providing liquidity? J. Financ. Econ. 120, 146–168.
Berkman, H., Malloch, H., 2023. Stock valuation during the COVID-19 pandemic: an explanation using option-based discount rates. J. Bank. Financ. 147, 106386.
Bing, T., Ma, H., 2021. COVID-19 pandemic effect on trading and returns: evidence from the Chinese stock market. Econom. Analy. Policy 71, 384–396.
Bourdeau-Brien, M., Kryzanowski, L., 2020. Natural disasters and risk aversion. J. Econ. Behav. Organ. 177, 818–835.
Broner, F., Gelos, G., Reinhart, C., 2006. When in peril, retrench: testing the portfolio channel of contagion. J. Int. Econ. 69, 203–230.
Carpentier, C., Suret, J., 2021. On the rationality of institutional investors: the case of major industrial accidents. J. Behav. Financ. 22, 289–305.
Chang, C., Hsieh, P., Wang, Y., 2015. Sophistication, sentiment, and misreaction. J. Financ. Quant. Anal. 50 (4), 903–928.
Choi, J.J., Kedar-Levy, H., Yoo, S.S., 2015. Are individual or institutional investors the agents of bubbles? J. Int. Money Financ. 59, 1–22.
Choi, P.B.S., Choi, J.H., Chuing, C.Y., 2020. Do individual traders undermine firm valuation? Financ. Res. Lett. 36, 101567.
Djalilov, A., Ülkü, N., 2021. Individual investors' trading behavior in Moscow exchange and the COVID crisis. J. Behav. Exp. Financ. 31, 100549.
Edelen, R., Warner, J., 2001. Aggregate price effects of institutional trading: a study of mutual fund flow and market returns. J. Financ. Econ. 59, 195–220.
Foley, S., Kwan, A., Philip, R., Ødegaard, B.A., 2021. Contagious margin calls: how COVID-19 threatened global stock market volatility. J. Financ. Mark. 59, 100689.
Foley, S., Frijins, B., Garel, A., Roh, T.Y., 2022. Who buys bitcoin? The cultural determinants of bitcoin activity. Int. Rev. Financ. Anal. 84, 102385.
Glossner, S., Matos, P., Ramelli, S., Wagner, A., 2022. Do Institutional Investors Stabilize Equity Markets in Crisis Periods? Evidence from COVID-19. ECGI Working Paper.
Goetzman, W., Kim, D., 2018. Negative bubbles: what happens after a crash. Eur. Financ. Manag. 24, 171–191.
Gong, B., Pan, D., Shi, D., 2017. New investors and bubbles: an analysis of the Baosteel call warrant bubble. Manag. Sci. 63, 2397.
Greenwood, R., Shleifer, A., You, Y., 2019. Bubbles for Fama. J. Financ. Econ. 131, 20–43.
Griffin, J., Harris, J., Shu, T., Topaloğlu, S., 2011. Who drove and burst the tech bubble? J. Financ. 66, 1251–1290.
Griffin, J., Harris, J., Topaloğlu, S., 2003. The dynamics of institutional and individual trading. J. Financ. 48, 2285–2320.
Gürkaynak, R., 2008. Econometric tests of asset price bubbles: taking stock. J. Econ. Surv. 22, 166–186.
Hasso, T., Pelster, M., Breitmayer, B., 2020. Terror attacks and individual investor behavior: evidence from the 2015–2017 European terror attacks. J. Behav. Exp. Financ. 28, 100397.
Hoopes, J., Langetieg, P., Nagel, S., Reck, D., Slemrod, J., Stuart, B., 2016. Who Sold During the Crash of 2008-9? Evidence from Tax-Return Data on Daily Sales of Stock. NBER Working Paper 22209.
Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. J. Financ. 63, 273–310.
Li, X., Subrahmanyam, A., Yang, X., 2021. Winners, losers, and regulators in a derivatives market bubble. Rev. Financ. Stud. 34, 313–350.
Linnainmaa, J., 2010. Do limit orders alter inferences about investor performance and behavior? J. Financ. 65, 1473–1506.
Naik, P.K., Shaikh, I., Huynh, T.L.D., 2022. Institutional investment activities and stock market volatility amid COVID-19 in India. Econ. Res. 35, 1542–1560.
Onishchenko, O., Ülkü, N., 2022. Investor types' trading around the short-term reversal pattern. Int. J. Financ. Econ. 27, 2627–2647.
Pagano, M., Sedunov, J., Velthuis, R., 2021. How did retail investors respond to the Covid-19 pandemic? The effect of Robinhood brokerage customers on Market Quality. Financ. Res. Lett. 43, 101946.
Schmeling, M., 2007. Institutional and individual sentiment: smart money and noise trader risk. Int. J. Forecast. 23, 127–145.

Shiller, R.J., 2000. Irrational Exuberance. Princeton University Press, Princeton, NJ.
Shu, P., Yeh, Y., Chiu, S., Chen, H., 2005. Are Taiwanese individual investors reluctant to realize their losses? Pac. Basin Financ. J. 13, 201–223.
Wang, A., Young, M., 2020. Terrorist attacks and investor risk preference: evidence from mutual fund flows. J. Financ. Econ. 137, 491–514.
Weitzel, U., Huber, C., Huber, J., Kirchler, M., Lindner, F., Rose, J., 2020. Bubbles and financial professionals. Rev. Financ. Stud. 33, 2659–2696.
Welch, I., 2020. Retail Raw: Wisdom of the Robinhood Crowd and the COVID Crisis. NBER Working. Paper 27866.
Zhang, J., Mao, R., Wang, J., Xing, M., 2021. The way back home: trading behaviours of foreign institutional investors in China amid the COVID-19 pandemic. Pac. Basin Financ. J. 68, 101618.