Stock Market Stimulus*

Robin Greenwood
Harvard Business School and NBER

Toomas Laarits
NYU Stern School of Business

Jeffrey Wurgler
NYU Stern School of Business and NBER

January 20, 2023

Abstract

We study the stock market effects of the arrival of the three rounds of "stimulus checks" to U.S. taxpayers and the single round of direct payments to Hong Kong citizens. The first two rounds of U.S. checks appear to have increased retail buying and share prices of retail-dominated portfolios. The Hong Kong payments increased overall turnover and share prices on the Hong Kong Stock Exchange. We cannot rule out that these price effects were permanent. The findings raise novel questions about the role of fiscal stimulus in the stock market.

* We are grateful to Raj Chetty, John Friedman, and Dawn Nettles for sharing data. We thank Valerie Baldinger of the New York Federal Reserve, Nithin Kavi of Harvard College, and especially Cody Wan of NYU for excellent research assistance. We thank Arvind Krishnamurthy, Owen Lamont, Fabio Braggion, two anonymous referees, the editor, and seminar participants at Harvard Business School, the NBER, Helsinki Finance Summit, the NYU Stern School of Business for helpful comments.

1 Introduction

In the midst of an escalating pandemic, the US government enacted fiscal stimulus of an unprecedented magnitude between March 2020 and March 2021. The multifaceted stimulus acts provided for sizable Economic Impact Payments, better known as “stimulus checks”, beginning with a first round in mid-April 2020, a second round in early January 2021, and a third round in March 2021. In total, the Treasury disbursed approximately $814 billion in payments directly to taxpayers.

As Figure 1 shows, these payments occurred in the context of significant growth in retail trading accounts and stock prices, particularly the prices of stocks that retail investors tend to favor. Surveys suggest that on the order of 10%-15% of the payments may have shortly found their way into the stock market.[1] There are contemporaneous bursts of discussion about stimulus checks in popular online discussion venues. The figure therefore begs a question: Did the stimulus checks—ostensibly an instrument of fiscal policy intended for economic relief of American households in unprecedented distress—affect the stock market when they were delivered? The sums involved, the temporal concentration of checks to households idled by the pandemic, and the large and growing literature documenting price responses to investor demand shocks amply motivate an investigation.

There are two non-mutually exclusive channels through which stimulus funds could impact the stock market. The first comes immediately to mind: The market should react swiftly to the announcement of provisions in the stimulus acts that bear on corporate fundamentals, including the direct payments to households insofar as these payments alter the present value

[1] Per US Census Bureau surveys and Thatte, Jalagani, and Chadha (2021), discussed later.

of expected cash flows to shareholders. There is little debate that well over $5 trillion in total stimulus spending would bolster firm fundamentals. We confirm this in the context of the CARES Act, which (among many relevant provisions) authorized the first round of stimulus checks.

The second channel, which is the focus of this paper, is also simple but less obvious. It arises through the potential price impact of those stimulus funds that actually enter the stock market. In this channel, unstudied in the literature about stimulus checks, retail investors use some portion of stimulus funds to invest in stocks, but in light of downward-sloping demand curves (e.g., Shleifer (1986), Harris and Gurel (1986), and others) these funds drive up prices of the stocks they target.

Importantly, the first channel would be reflected around the announcement of the stimulus acts, and the second channel would be reflected weeks later upon the arrival of the checks to retail investors. Our main analysis therefore begins with a careful determination of the effective date of the arrival of the checks, specifically the roughly 100 million directly-deposited payments that make up the *leading edge* of each round and constitute most of the eventual payout. We can pin down when the first tranches of checks arrived from credit- and debit-card-level spending data and online chatroom discussions.

We then determine that the distribution of the stimulus checks was associated with increases in retail trading. We use the algorithm of Boehmer, Jones, Zhang, and Zhang (2021) to estimate stock-day-level measures of retail-initiated buys and sells. Aggregating the stock-level measures to the market level, we find that the stimulus check disbursement days saw increases in retail trading, particularly retail-initiated buy trades. Digging deeper, we find that stocks with higher prior retail trading volume see greater increases in retail trading activity around check disbursement dates. That is, the stocks that retail investors already had their eyes on were the most targeted by stimulus check inflows.

Finally, we find that these trading effects increased prices. High-retail-share portfolios experience abnormal returns of about 5-7% within a few days of the first and second rounds of stimulus checks, but no portfolio return effects on the third round. While long-run cumulative abnormal returns on long-short portfolios must be treated with caution, the effects grow to abnormal returns of 10-18% over the three weeks after the first round of stimulus payments, 13-24% over the three weeks after the second round, and again nothing in the third round (with point estimates insignificantly negative). This is consistent with either delayed investment of checks or, as always, an incomplete control for other forces affecting portfolio returns. Interestingly, value-weighted market returns are close to zero over these periods. We repeat the analysis for other sorting variables that also seek to capture stocks favored by retail investors. As one might expect, the effects are strongest among those stocks with a high number of Robinhood-using owners, high retail trading according to FINRA's measure, lower capitalization, low nominal price, and high volatility.

The United States is not the only country with a Covid-19 response that included direct payments. Hong Kong, famous for its extensive retail investment community, presents another experiment.[2] The Cash Payout Scheme (CPS) of July 2020 provided for direct payments of US$1,290 to all adult permanent residents. We find that these payments also coincide with a boost in prices and volume on the Hong Kong Stock Exchange. This is interesting in its own right, and adds a comforting aspect of robustness to the U.S. results.

[2] See, for example, https://fundselectorasia.com/hong-kong-tops-world-for-retail-share-traders/.

Our findings are related to other studies of how stimulus checks were spent. Baker, Farrokhnia, Meyer, Pagel, and Yanellis (2022), Coibion, Gorodnichenko, and Weber (2020), and Parker, Schild, Erhard, and Johnson (2022) study consumption patterns in detail. Parker et al. find that people spent less of their EIPs in the months following check arrival than in similar previous policy episodes, with a potential implication that they invested more funds in the stock market. Divakaruni and Zimmerman (2022) finds a small but detectable increase in Bitcoin buy trades for exactly $1200—the amount of the CARES Act checks for those that file taxes individually—for up to three weeks after the first checks arrived. There is no reason to expect that the duration of trading effects in the stock market is any different, so we tabulate returns up to this same horizon, as noted above.

Our findings also shed new light on the consequences of the resurgence of retail trading. Barber, Huang, Odean and Schwarz (2021), Eaton, Green, Roseman and Wu (2021), and Welch (2021) describe the behavior and role of retail traders on the Robinhood platform. Pedersen (2021) models how misperceptions can spread via social media and lead to mispricing. In the pandemic context, Cox, Greenwald, and Ludvigson (2020) conclude that the post-March 2020 rebound "has been driven more by sentiment than substance." Levine (2020) coined the term "bored markets hypothesis" to describe individuals beginning to invest because the trading platforms make it fun and for many there was nothing better to occupy the time. Ozik, Sadka, and Shen (2021) exploit staggered stay-at-home advisories to show that retail trading and liquidity increased when retail investors suddenly had more free time.

The paper proceeds as follows. Section 2 gives background on the stimulus acts and the structure of the stimulus payments. Section 3 explores how the checks affected trading, and

Section 4 explores the effect on prices. Section 5 studies these questions in the context of the Hong Kong stimulus payment. Section 6 concludes.

2 The U.S. Stimulus Acts and Economic Impact Payments

Our analysis begins with a recounting of the background economic and health context. We then turn to an overview of the legislation authorizing stimulus checks, the basic structure of the three waves of payments, the market reaction to the CARES Act passage, and the determination of the "event dates" when each round of stimulus checks first became investable.

2.1 Context

The health and economic context in which the major stimulus acts were passed was obviously extraordinary. The top panel of Figure 2 plots new Covid-19 cases against the unemployment rate as a crude measure of economic activity. Unemployment insurance claims soared to a weekly rate of over six million as businesses closed in late March 2020. The infection rate rose and fell in waves over this period, each time upsetting politics and plans.

The bottom panel compares two more measures of aggregate economic activity—aggregate spending relative to January 2020, and time away from home—based on data from the Opportunity Insights Economic Tracker.[3] Time away from home plummets as a result of lockdowns, voluntary behavior, and the contraction of employment. For these and other reasons, total spending fell by over 30% relative to January 2020. There is a slow return to normalcy in all indicators by the end of the sample, although jobless claims remain high.

2.2 Overview of the Stimulus Acts

[3] https://opportunityinsights.org/tracker-resources/. We thank Raj Chetty and Jon Friedman for advice on using these data. For a thorough accounting of the economic impacts of the onset of Covid-19, see Chetty, Friedman, Hendren, Stepner, and The Opportunity Insights Team (2020).

Congress passed three multifaceted acts to provide economic stimulus. One feature of each was direct taxpayer relief to around 170 million households in the form of Economic Impact Payments that are our main focus, but it is worth keeping in mind that these were only a portion of sprawling pieces of legislation.

The first round of stimulus came as part of the Coronavirus Aid, Relief and Economic Security Act (CARES), which was passed by Congress and signed by President Trump on March 25, 2020. The CARES Act authorized over $2 trillion in spending, including loan and grant programs for small businesses, support for medical providers, support for states, payments for businesses and industries affected by the pandemic, enhanced unemployment benefits, and direct cash disbursements to individual citizens. Notably, fewer than ten of the 335 pages of the CARES Act text are devoted to the stimulus checks, although at a $292 billion budgetary cost they represent a nontrivial fraction of its total cost.[4]

We think about the fundamental impacts of the stimulus acts through the lens of efficient markets, in which the market should react to all provisions in the Acts that bear on stock fundamentals: provisions for public health; direct payments to households (i.e., expected stimulative effect of the checks that bear on firm fundamentals, such as through a consumption-wealth effect); small business lending; support for unemployed workers; provisions to support specific industries; the signal, strongest in the case of the CARES Act, that the federal government can act with scope and speed, increasing the probability of additional stimulus; and so on. All these fundamental impacts should be summarily expressed in the announcement effect to the extent that they were not anticipated.

[4] Cost figures from https://crsreports.congress.gov/product/pdf/IN/IN11605.

And, indeed, the CARES Act was received as a large positive shock to fundamentals. After a crash of -30.7% in the Fama French value-weighted market return (Mktrf plus rf) from Monday, February 3 through Monday, March 23, 2020, passage of the Act was received as good news. Contemporaneous media accounts date the market impact to Tuesday, March 24 through Thursday, March 26 as a series of political hurdles were resolved, and the three-day Fama French value-weighted market return over this period was +17.3%.[5]

The cross-industry reaction pattern is particularly convincing evidence of a revision to fundamentals. For each Fama-French 49 industry portfolio, Figure 3 plots the announcement effect of CARES against the crash return. If the cross-industry pattern of declines can be attributed to deteriorating fundamentals, the restorative pattern upon the passage of CARES could be ascribed to rebounding fundamentals.[6] Investors clearly interpreted CARES as coming to the rescue of sectors that they felt would be most affected by the pandemic.

The second round of payments came as part of the Consolidated Appropriations Act of 2021, a $2.3 trillion spending bill that combined $900 billion in Covid relief funds with a $1.4 trillion omnibus spending bill. It was passed by Congress on December 21, 2020, and after a bit of political uncertainty was signed into law by President Trump on December 27, 2020. The budgetary cost of this round of stimulus checks was $164 billion.

[5] See, for example, "Dow Rallies 6.4% After Stimulus Vote; The blue-chip index is now up 20% from its low, qualifying as a new bull market" (Caitlin McCabe, Anna Hirtenstein and Chong Koh Ping, *Wall Street Journal Online* March 26, 2020).

[6] The two outliers in Figure 3, aircraft and coal, can be understood as follows. Airlines and aircraft and related contractors faced enormous losses as borders closed indefinitely. The CARES Act included extensive provisions related to such firms. These included benefits to firms "critical to maintaining national security," which include Boeing, General Dynamics, and Raytheon, all members of this Fama-French industry; an extensive list of support for airline workers and contractors; and billions in grants, loans, and loan guarantees. Coal is another exception that proves the rule. "Despite concerted lobby efforts from the U.S. coal industry, including the National Mining Association, it will not be receiving direct assistance under the voted through CARES Act." (https://www.gem.wiki/CARES_Act_and_Fossil_Fuels).

Finally, the third round of payments was the result of the $1.9 trillion American Rescue Plan Act, passed on March 10, 2021, and signed by President Biden the next day. The budgetary cost of these checks was $410 billion.

We were not able to find clear market jumps around news of the second two stimulus acts. We suspect this is because major uncertainties were resolved by CARES and/or because these acts were in discussion for weeks and the probability of passage tracked upward slowly and erratically. The absence of an identifiable spike in returns in a narrow window around passage, however, hardly rules out these two acts offered additional, fundamentals-based support to stocks.

It is perhaps obvious that any effects of the actual arrival of the stimulus checks to retail investors are of an entirely different character. That is, the huge announcement effect of CARES does not constitute a meaningful benchmark by which such effects might be judged. The stimulus checks were both preannounced and represented only a fraction of immense, complex stimulus acts. Within the logic of the efficient markets hypothesis, preannounced payments should generate no price reaction upon investment since rational expectations should have incorporated them weeks before.

Any stock market effect we do observe on the actual arrival date of the checks is likely to present a lower bound on the total "demand curve" effect for at least two reasons. First, many investors' deployment of these checks may take some time. Contemporaneous accounts indicate that different brokerages cleared the direct deposits at different speeds, for example. And for many, getting around to investing the checks may have taken weeks. The fungibility of money makes it difficult to attribute longer-run stock market investment to the checks themselves. Consider a retail investor who receives a $1,200 check in March 2020 and two months later opens a Robinhood account to invest $1,000 into the stock market. It is not possible for us to include this realistic, and perhaps common, circumstance. Second, any "anticipation effect" embodies two components: an anticipation-of-better-fundamentals effect plus an anticipation-of-demand-price-boost; the latter would be properly counted as part of the total demand curve effect, but would occur prior to the check arrival event date.

2.3 The Structure of Stimulus Checks

Table 1, which is based on U.S. Treasury press releases, GAO reports, and Baker et al. (2022), provides an overview of the structure of the authorizing acts and the stimulus payments in particular. Most households qualified for direct payments. Under CARES, for example, all adults with a social security number who filed taxes and with incomes less than $99,000 (individual) or $198,000 (married) were eligible for something, with the size of the payment phasing out with higher incomes.

The details of eligibility vary slightly from one stimulus act to the next, but the basic structure of the payment of the checks is consistent. In an initial wave, the funds were directly deposited to households with account information on file with the IRS. Those without such information on file typically received paper checks with a delay due in part to IRS printing capacity constraints. For simplicity, we use the popular terminology and refer to both forms of payment as stimulus checks unless clarification is useful.

The last panel of the table details the Treasury-reported timing of disbursements, based on periodic press releases that do not pin down exact dates. Approximately $160 billion, or 59% of the total eventually disbursed in the CARES Act, arrived via 89 million direct deposits with an official check date of April 17. The remaining $110 billion was disbursed in several waves over the next two months because the Treasury could print only a few million paper checks per week. In total, at least 168 million tax filers received payments of some amount.

As of this writing, the total disbursed in the three rounds was at least $276 billion, $147 billion, and $391 billion, respectively, for a grand total of $814 billion. Based on the reported total number of payments we can deduce the average dollar amount of the stimulus checks. The first Economic Impact Payment (under the CARES Act), i.e., the first EIP or stimulus check, averaged $1,643. The second EIP (under the Consolidated Appropriations Act) averaged $955. The third EIP (under the American Rescue Plan Act) averaged $2,341.

2.4 Identifying First Actual Payment Dates

The "First Actual Payment Date" in Table 1 is an important one for our analysis. The timing of the full distribution of the checks, and when they became investable as opposed to arriving in a mailbox, is unknown. Consequently, we focus on the more specific, measurable notion of the *first day in which those receiving the first wave of direct deposits could invest the funds*. Fortunately, in each of the three rounds of stimulus checks, around 100 million payments—constituting most of the eventual total—were made in the initial tranche of direct deposits. The first *trading* day on which these funds were available is our date [t=0], so this is the date on which we might first see a direct demand effect.

The Treasury offers a loose "official" payment date, which we report for comparison, but other data sources help us identify the first actual payment date in a more precise sense. In particular, social media discussions and detailed data on retail spending are compelling. Figure 4 shows retail spending over the course of the sample period. To make use of the fact that the stimulus checks were particularly important for low-income households, we plot the difference in non-grocery retail spending between low-income and high-income zip codes based on

Opportunity Insights credit and debit card data. The units of this series are in cumulative percentage change compared to baseline January 2020 spending. An increase in this measure indicates that consumers in low-income ZIP codes are increasing their spending on non-grocery retail more than consumers in high income ZIP codes. Since consumers in low-income ZIP codes are more likely to be liquidity constrained, this is a good indicator that stimulus checks have started to reach consumers. Consistent with this intuition, Parker et al. (2013) find that the 2008 economic stimulus payments boosted spending among lower-income households, and Baker et al. (2022) and Coibion et al. (2020) find a similar differential for the CARES Act payments.

The three dashed vertical lines in Figure 4 represent the passage dates of the Acts authorizing the spending. The solid vertical lines show our estimates of when the funds became available to consumers (first of the pair of solid lines, as more precisely determined below), which is what we define as date 0, and the official check dates as reported by the Treasury (second of the pair of the solid lines). The figure shows that consumers, especially those in low-income zip codes, began spending their stimulus checks as soon as they became available and typically days before the "official" Treasury dates.

The closeups in Figure 5 help us pin down the first actual payment dates. Each panel corresponds to a round of stimulus. At a minimum, retail investors knew about the arrival of the checks, as evidenced by their message board activity. The solid grey line in Figure 5 shows the total number of posts on the "r/stimuluscheck" subreddit message board, which peaks just as the first payments are being made for each round.[7] The solid blue line shows the number of

[7] We download reddit comments using the pushshift.io Reddit API. Summary statistics on subreddit usage are from subredditstats.com.

reddit comments on posts within that subreddit that include the phrase "bank account." The blue dotted line again shows the low-minus-high-income data on non-grocery retail spending from Opportunity Insights. Days in which the U.S. stock market was closed are shaded out. Based on these data, as well as on other retail spending categories tracked by Opportunity Insights and Texas state lottery ticket sales (omitted for brevity), we identify 4/13/20, 12/30/20, and 3/12/21 as best estimates for the first actual payment date of the three rounds of stimulus checks. These are the dates reported in Table 1. The first date of 4/13/20 receives "out-of-sample" support from Divakurani and Zimmerman (2022), as it is the first day in which their data show a persistent, statistically significant increase in the number of $1,200 Bitcoin buy trades.

3 Effect of U.S. Stimulus Checks on Stock Trading

3.1 Surveys

What fraction of the $814 billion of stimulus checks described in Table 1 might have swiftly made its way into the stock market? There are no direct measures, but some surveys shed a bit of light.

Beginning in late April 2020, the US Census Bureau, in conjunction with five other government agencies, administered weekly surveys asking individuals about their employment status, spending, housing, access to health care, and educational disruptions. In addition, in weeks 12, 22, and 27, the survey asked respondents about their receipt or expected receipt of a check (corresponding to EIP1, EIP2, and EIP3) and their expected use of the proceeds. Table 2 summarizes the findings. 9.3% of households surveyed mostly invested or saved their first stimulus check. For the second check, this rose slightly to 15.1%. For the third stimulus check, 18.7% reported mostly saving or investing the proceeds. These estimates are a lower bound on the population-wide percentages, because a substantial portion of respondents (e.g., 42.4% in the third survey) did not provide a breakdown of their spending.

A second survey was conducted in July 2020 by Coibion et al. (2020). They survey the Nielsen Homescan panel of representative U.S. individuals about (in part) their use of CARES Act stimulus payments. Of those who report receiving a check, 33% say they used it "mostly to increase savings."

Although these surveys suggest that a meaningful fraction of the stimulus dollars were saved or invested, they did not ask whether that money went into the stock market. A survey by Deutsche Bank DIG Primary Research by Thatte et al. (2021), which conducted a survey of 430 users of online broker platforms over February 5-9, 2021, speaks to this point. Bearing in mind their selected sample—although perhaps not too unrepresentative since there are over 100 million online brokerage accounts in the U.S.—72% of respondents reported receiving a stimulus payment and over half of those said they invested some of the payment in the stock market. From these numbers, the authors extrapolated that up to $170 billion of the third stimulus checks (EIP3) could be invested into stocks, but they do not attempt to match the prediction with evidence on the eventual flow.

A fourth survey by SaverLife is studied by Baker et al. (2022). This firm also asked its users about the receipt and use of stimulus checks, which it could match to spending data. The fascinating result of this study is that users who believed that a stock market rise was "likely" showed an MPC of less than 0.1 after the first stimulus payment, while those who considered such a rise "unlikely" displayed an MPC above 0.5.

A triangulation of the surveys, with their attendant errors, low response rates, and biases, suggests a reasonable estimate might be 10-15% of the total stimulus check payout of $814 billion, for a point estimate around $100 billion. This is notably less than the Deutsche Bank survey but reflects more of a balance with other information.

3.2 Retail Trading Upon Check Arrival

Which stocks to focus on? $100 billion is well under 1% of the U.S. stock market capitalization; the stimulus checks could hardly overwhelm the whole stock market. At the same time, they are unusual shocks in being entirely new money, as opposed to funds being reallocated across stocks, and they could lead to potentially millions of liquidity-demanding market orders. The funds are also in the hands of retail investors who disproportionately invest in a subset of stocks. A natural hypothesis is therefore that trading (and returns) effects are most likely to appear among stocks with the greatest retail interest. Suggestively, Figure 1 showed that such stocks had standout performance in the post-crash market.

Our main measures of retail order buys and sells are based on the algorithm of Boehmer, Jones, Zhang, and Zhang (2021). Their method exploits the feature that retail order flow, but not institutional order flow, receives price improvement measured in fractions of a penny per share. We apply their algorithm to the trades marked with exchange code "D" (meaning trades reported to the Financial Industry Regulatory Authority Trade Reporting Facility) on the TAQ database. Following Boehmer et al., transactions are classified as retail buys if the fraction of a penny of trade price is between .6 and 1, and as retail sells if the fractional penny of a trade is between 0 and .4. We apply their algorithm to all CRSP stocks with share codes 10 and 11, and exchange codes 1 to 3, generating daily measures of net retail buys (buys minus sells), retail volume (buys plus sells), or retail dollar volume (buys×price+sells×price).[8] The retail *fraction* of dollar volume for any security is retail dollar volume divided by total dollar volume. We also define two measures of net retail trading: net retail buys over total dollar volume, and net retail buys over retail volume. Additionally, we construct three alternative measures of retail trading by repeating these calculations using the number of distinct trades, rather than dollar amounts.

We aggregate these security-level measures to portfolio- or market-level measures using market cap weights from the end of the prior month. Our RSVOL quintile portfolios are based on monthly sorts on this retail fraction of dollar volume. In tables reporting retail volume we also screen out trades with dollar values exceeding $100,000. The securities with some of the highest net retail demand around EIP1 as a share of market capitalization included some large caps, such as American Airlines and other airlines, MGM Resorts, and many small caps such as Soligenix.

Here we document a significant increase in retail trading on the days around EIP check disbursement. We first study the impact of the stimulus payments on the number and dollar volume of retail-initiated trades across the market. Figure 6 plots the time series of retail fraction of aggregate trading volume. The series is constructed by aggregating stock-level retail fractions using market cap weights from the end of the previous month. The dots are daily values, and the solid line is a five trading-day moving average (and so an immediate rise will appear to take multiple days).

The figure does suggest spikes in retail trading around EIP checks disbursement dates. This can be better established using time-series regressions of the form:

[8] The Boehmer, Jones, Zhang, and Zhang (2021) algorithm must be treated with a bit of caution because it will identify, for example, trading days with retail buys or sells exceeding the total market capitalization. Where we use the data directly, we winsorize it at the 99% and 1% levels to account for such outliers. Barber, Huang, Jorion, Odean, and Schwarz (2022) describe refinements to the algorithm.

$$\textit{Retail Trading}_t = a + b{*}3 \textit{ EIP Event Days} + u_{t,}$$

where *Retail Trading* is one of six time-series measures of market-level retail trading based on weighting stocks' trading activity by their capitalization. *3 EIP Event Days* is an indicator variable that takes a value of 1 in the three-day window [0,+2] upon and following one of the three first actual payment dates. That is, it takes the value 1 for a total of nine days of the sample. Accordingly, the *b* coefficient reflects the increase in trading activity during these windows. The regressions are estimated using daily data from January 2020 through the end of June 2021. We include, but the results do not depend on, weekly fixed effects to account for the variability in trading measures that is evident in Figure 6. We use Newey-West standard errors with five lags to account for the serial dependence in retail trading.[9]

The first columns of Table 3 Panel A measure trading based on the total number of retail-initiated trades. Column 1 shows that the retail fraction of value-weighted trading activity is elevated by 0.60% over a baseline level of 6.40%, a statistically significant relative increase of eight percent. Columns 2 and 3 look at the direction of those trades. Column 2 shows that value-weighted net retail buying ((buys-sells)/total number of trades) is elevated by 0.18% during EIP event days over a baseline of 0.07%, while Column 3 shows that a similar measure, but scaled by the total number of retail-only trades, rises 1.66% over a baseline average of -.19%. The next three columns repeat these regressions but use dollar volume rather than the number of trades. The results are similar. Upon receipt of the first stimulus checks, we observe more retail trading and more buys in particular. Panel B of Table 3 repeats this analysis but breaks out the three rounds of EIP on the right-hand-side. We find that retail trading was elevated on the

[9] We obtain similar results from specifications in first differences.

arrival of all three rounds of stimulus checks, with all six measures seeing the largest boost on EIP1 event days.

A sharper test is whether there are spikes in retail-initiated trading in retail-favored stocks. We conduct this using the five portfolios sorted on prior-month retail fraction of trading volume (RSVOL), extremes of which were plotted in Figure 1, and repeat Column 4 of Table 3 for each portfolio in Table 4. That is, the left-hand-side variable is the retail fraction of volume, aggregated using market cap weights from the end of the prior month. In line with the aggregate results, we find significant increases in retail-initiated trading across the five portfolios. The boost in the retail share of dollar volume is apparent in each portfolio, and it increases monotonically from Q1 to Q5. The extreme retail portfolio, which has a high baseline retail fraction by construction, sees an average increase of .69% over each of the nine EIP event days. The coefficient increase across the portfolios is statistically significant. The bottom panel of Table 4 breaks down these results further to show the day-by-day elevation of volume beginning when the checks are first received. Focusing on the fifth and sixth columns, the retail volume impact is largest on the first EIP event day, although it continues to be statistically significant for all portfolios on the second day, and for some on the third.

Table 3 and Table 4 document an increase in retail trading volume around the disbursement of stimulus checks, but a natural question is whether the composition of retail volume is similar to that on previous days and weeks. In general, retail trading is highly persistent: a stock that is in the highest quintile of retail trading has a 69% probability of remaining in the highest quintile of retail trading 12 months later, and an 25% probability of being in the next-highest quintile (see Internet Appendix Table A2).[10] We also find that retail

[10] See Laarits and Sammon (2022) for more on the persistence and determinants of retail trading intensity.

fraction is highly persistent across the three EIP episodes. For example, the probability that a stock in the top quintile of retail fraction of volume the week before EIP1 remains in that quintile during the week of EIP1 is 78%.[11]

In results available on request, we report specifications like these using a fifteen-day window, rather than a three-day window, to look for elevated retail trading over longer periods. Divakaruni and Zimmerman (2022) find that Bitcoin buy trades for the modal dollar amount of the first CARES Act checks ($1,200) stayed high for at least three weeks after the arrival of the first checks and, as Welch's (2021) analysis highlights, it takes a few days to complete a transfer of funds into an online trading account. Our results suggest that the elevated retail trading effect is clearer in windows shorter than fifteen days.

4 Effect of U.S. Stimulus Checks on Stock Prices

4.1 Retail-Biased Portfolios

In addition to our RSVOL portfolios based on estimates of retail-initiated buys and sells from the algorithm of Boehmer et al. (2021), we form portfolios in other ways to isolate stocks that are most likely to be affected by retail investment of stimulus checks.

A second source of data on retail ownership comes from Robinhood, the online investment platform known for pioneering commission-free trades. By mid-2021, Robinhood had over 30 million users and over 18 million active monthly users. The database Robintrack tracked the daily number of owners of individual US-listed stocks and ETFs between 2019 and August 2020. Robinhood stopped providing these data in August 2020, making it most useful for

[11] The corresponding numbers for EIP2 and EIP3 are 77% and 83%, respectively. Net retail demand is less persistent than the retail share of volume, but still exhibits some persistence at weekly horizons.

the first round of checks. Another limitation is that the data report only the total number of owners of the security, not daily changes in positions or intensity of trading, which leads to a significant size bias. Our RH portfolios are thus formed simply on the raw number of Robinhood shareholders. Notably, Robinhood also had a program in which new accounts were endowed with a single share of Robinhood's choice; 98% of new accounts came with a stock with a share price between $2.50 and $10. This may be part of the explanation why Robinhood accounts disproportionately own lower-price stocks. Overall, the most-Robinhood-owned stocks in the period around the first wave of stimulus checks were Ford, General Electric, Disney, GoPro, and American Airlines.[12]

We also form portfolios based on data from the Financial Industry Regulatory Authority (FINRA). FINRA reports security-week level trading volume of shares traded over-the-counter and not in an Alternative Trading System (ATS).[13] Market participants view such trades, mostly executed by wholesalers such as Citadel or Virtu, as a proxy for retail volume. We normalize this OTC non-ATS trading volume with corresponding weekly share volume from CRSP. The resulting weekly retail trading volume aligns fairly well with the measure based on Boehmer et al. (2021), with a Spearman correlation of .76 in our sample.

Our remaining three portfolios are formed on standard characteristics that literature has documented as relatively more dominated by U.S. retail investors, such as low nominal share price, low market capitalization, and high total return volatility (e.g., Baker and Wurgler (2006), Baker, Greenwood, and Wurgler (2009), Kumar and Lee (2006), and Kumar (2009)). The portfolios CAP and PRC are based on end-of-prior-month values from CRSP, and volatility

[12] See Da, Feng, and Lin (2021) for use of the above two proxies for retail trading in the context of fractional shares.
[13] https://otctransparency.finra.org/otctransparency/OtcData

portfolios SD are based on the standard deviation of daily returns as of the end of the second previous month.[14]

We sort all CRSP stocks with share codes 10 and 11 and exchange codes 1 to 3 into quintile portfolios based the six characteristics (RSVOL, RH, FINRA, CAP, PRC, SD) and examine the performance of equal-weighted high-minus-low portfolios around the check arrivals, except in the case of CAP and PRC, where we examine low-minus-high portfolios. Each of the portfolios is rebalanced monthly, based on the prior month value of the sorting variable. This procedure results in six long-short portfolios designed to highlight the effect of retail investors.

4.2 Returns Upon Check Arrival

Table 5 shows event studies around EIP1, EIP2, and EIP3 check arrival. For each of the three events, we first estimate pre-event CAPM betas and alphas of the six portfolios using daily returns from February 2019 to 30 days prior to the event window. With the betas and alphas in hand, we calculate abnormal returns.

Panel A of Table 5 reports these abnormal returns for the six long-short portfolios over four different return windows. Each of the return windows starts with the first trading day on which checks are investable [t=0], namely, April 13, 2020 (EIP1), December 30, 2020 (EIP2), and March 12, 2021 (EIP3). The first trading day abnormal returns are in the left column. The other columns report summed abnormal portfolio returns over the three-trading-day window [0,+2], the five-trading-day window [0,+4], and, as suggested by the results of Divakaruni and Zimmerman (2022), the fifteen-trading-day window [0,+14]. The standard errors of are

[14] Defining the April 2020 SD portfolios based on February 2020 volatility sidesteps the crash of March 2020, in which price drops varied dramatically across industries (see Figure 3).

calculated from the volatility of daily abnormal returns in the pre-event window, assuming zero serial correlation. The value-weighted Fama French market excess return is included for comparison purposes. Panel B repeats the same analysis but uses the long leg of the six portfolio (i.e., high retail ownership, high volatility, low price, or low market cap).

We start with EIP1. The aggregate market is down on April 13, 2020, and approximately flat over the three-day period from April 13 through April 15. However, the long-short portfolio formed on retail fraction of trading volume (RSVOL) sees a large abnormal return on 5.62% on April 13, and a cumulative abnormal return of 10.73% over the three-day window starting with EIP1 check disbursement. High RSVOL stocks outperform low RSVOL stocks by a wide margin of 14.74% over the fifteen-trading-day window. Similarly, high retail ownership stocks (measured by the Robinhood ownership breadth) rose 3.51% more than low retail ownership stocks on April 13 and continue to grow over the fifteen-trading-day period. The market portfolio, in contrast, is only up by 2.35% over the fifteen-day window. Largely similar results obtain for the long-short portfolios sorted on the FINRA measure of retail share and on market cap, nominal share price, and return volatility.

Panel B shows that these results are driven by the long side of the portfolio compared to the market. For example, low price stocks experience abnormal returns of 17.78% in the fifteen-day window, compared to 18.37% for the long-short portfolio. Unlike "anomalies" that are often driven by the short leg, stronger results on the long side are just what we would expect from a pure new-money inflow.

Table 5 also shows the results for EIP2, which was a lower per-check average payment than EIP1, seems to have generated a weaker short-term response but a similar longer-term response. All six long-short portfolios have positive abnormal returns in the three-day announcement window, but only the market cap and nominal price sorted portfolios see statistically significant responses. Note again that the aggregate market portfolio loses value in the three-day event window starting with EIP2 check disbursement.

The returns following EIP2 merit more comment. Over the widest window ending 1/21/2021, cumulative returns resemble those of EIP1. This window just starts to include the beginning of the GameStop (GME) short squeeze: GME had risen from $19.38 to $43.03 between 12/30/2020 and the end of our longest window, but it had a long way to run before it hit its intraday peak of $483 on 1/28/2021. While the GameStop frenzy plays only a modest role in our measurements, one wonders whether the episode would have been as dramatic without the fresh arrival of over 130 million stimulus checks.[15]

Across all three events, the long-short portfolios outperformed the market in the event windows around initial EIP disbursement. That said, there is no evidence of a returns boost around EIP3 check arrivals in isolation. This is interesting based on the Census survey results and the spending figures which previous figures demonstrate there was still an immediate boost to consumption spending. One might speculate that the market learned based on the experiences of the first two checks; institutional liquidity to offset market buy orders had been adequately restored; based on the economics and psychology of the pandemic at this point, the retail inflows into stocks associated with stimulus checks were less concentrated, making our portfolio approach less able to capture the principal components of check-induced flows; or, the degree of attention on the stock market was simply lower by the time the third round arrived. A careful look at previous figures is consistent with this last explanation. In Figure 5, Reddit postings in the relevant chat threads were far higher around the first round of checks

[15] See Jones, Reed, and Waller (2021) for evidence on the role of retail trading in the GameStop episode.

than the second round, and attention to the third round was lower still. And, in Figure 2, at the time of the third check's arrival, time away from home was increasing around the third check—more time at work means less free time to play the market.

As an alternative to the event study approach in Table 5, we estimate the impact of stimulus check arrival on retail-biased portfolios by regressing the daily long-short portfolio returns on dummy variables corresponding to the three rounds of EIP. These results are reported in Internet Appendix Table A5. In Panel A we include daily market excess returns as a control, in Panel B we control for multi-factor returns using the Fama French four factor model. For comparability with the event study evidence, we multiply all returns with three. As the top three rows of Panel A and Panel B show, this alternate approach results in similar estimates, with the RSVOL long-short portfolio earning a 10.30% alpha in the three trading day window starting with the arrival of EIP1 checks. The difference in the estimates from what is reported in Table 5 Panel A stems from the event study approach using only the pre-event data to estimate alphas and betas, while the regression approach uses the entire sample.

One might ask whether some of the patterns in returns upon check arrival are driven by investors recognizing changing consumption patterns in the stock market, such as the shift away from services and towards goods (Tauber and Van Zandweghe 2021). This hypothesis asks investors to be unaware of this effect until the moment the checks arrived, at which time they observe it and suddenly price it in (and the effect must itself correlate with the retail share of trading volume). In any event, we test this hypothesis in Appendix Table A3. Here we report estimates from day-stock-level regressions of returns on EIP event dummies, interacted with dummy variables indicating the RSVOL quintile of the stock. Reflecting the event study results in Table 5 Panel A, the three-day return on EIP1 event days of stocks in the highest retail fraction quintile is 11.01% (note that all returns are multiplied with three to maintain comparability with the event study numbers). In the second, fourth, and sixth columns we include Fama-French 49 industry times day fixed effects. In other words, we remove all variation common to a given industry on a given day. We find that the inclusion of these industry-day fixed effects does not have a large effect on the interaction terms. For instance, with these fixed effects included, the coefficient on EIP1 dummy interacted with the highest RSVOL quintile dummy has a value of 9.69%, statistically significant at the 1% level. The results in Internet Appendix Table A3 therefore suggest that the abnormal returns on EIP event days do not represent an industry effect.

Finally, another potential question is whether the returns we find around EIP1 and EIP2 are reversed at longer horizons. This is an important but unfortunately complicated question to address because of the small number of events, the noise in returns, and the potentially ongoing nature of stimulus check investment (checks were received and invested presumably for weeks following the leading edge). In Internet Appendix Table A6 we repeat the event study analysis from Table 5 Panel A, but extend the event horizon to include [0, +28] and [0, +60]. There is no obvious evidence of reversal, but there is limited statistical power to say much about what happens far beyond day t=0. For example, the two-week abnormal return for the high retail portfolio (RSVOL) is 14.06%, and grows to 19.19% at four weeks, and 37% at twelve weeks.

4.3 Interpreting Magnitudes

High retail-interest portfolios have risk-adjusted outperformance on the order of 5% over the few days following the first EIP1 and EIP2 payments and no unusual performance upon EIP3. It is interesting to compare the implied elasticities with prior literature that estimates price impact based on other exogenous events such as stocks entering indexes.[16] Gabaix and Koijen (2021) compile estimates from other papers, suggesting a typical price "multiplier" of about 1, essentially an inverse price elasticity in which a 1% inflow as a percentage of market capitalization implies a price increase of 1% for individual stocks. Other studies report significantly higher numbers. Chang, Hong, and Liskovich (2015) conclude from their study of Russell Index reconstitutions that the multiplier is approximately 1/0.39 = 2.56. The papers compiled in Wurgler and Zhuravskaya (2002) indicate a still broader range. These elasticities are hard to pin down, as they vary across stocks and over time with liquidity and attention considerations and also vary with the response horizon.[17]

Despite these difficulties, it is interesting to put our results in this context. In an ideal experiment, we would measure the stimulus dollars into each stock and then compare the price impact over the window in which those dollars were spent (potentially extending the window to see whether the price impact was permanent). Such an analysis is confounded here because retail traders select which stocks to buy. For example, they may purchase stocks that rose at the beginning of the day, giving the positive correlation between daily return and net demand an ambiguous interpretation. Nonetheless, we again use the algorithm of Boehmer et al. to measure retail-initiated trades in each stock-day and then link this demand with price changes around the days of the stimulus payments. We run regressions of the form:

$$R_{i,EIP} = a + b \cdot NetRetail_{i,EIP} + u_{i,EIP},$$

[16] For example, see Shleifer (1986), Harris and Gurel (1986), Lynch and Mendenhall (1997), Kaul, Mehrotra, and Morck (2000), Wurgler and Zhuravskaya (2002), and Greenwood (2005).

[17] For example, Gofran, Gregoriou, and Haar (2022) document a decline in market liquidity, as evidenced by higher bid-ask spreads, during the early days of the pandemic.

where $R_{i,EIP}$ denotes the [0,+2] three-day cumulative return of stock *i* over EIP1, EIP2, or EIP3, and $NetRetail_{i,EIP}$ measures net retail demand (buys minus sells) as a fraction of market capitalization and is winsorized at the 1% and 99% levels. The sample includes all 6,600 securities on CRSP and TAQ for which data are available.

For EIP1, we estimate a coefficient of 4.40 (t-stat 4.61); for EIP2, a coefficient of 2.49 (t-stat of 3.49); for EIP3, a coefficient of 2.19 (t-stat of 3.43). Interestingly, this experiment suggests a meaningful and statistically significant return impact from EIP3 that does not come through in the long-short portfolio returns. Overall, these results imply a multiplier between 2 and 4, which is on the high side of recent estimates. One adjustment to consider is based on Barber, Huang, Jorion, Odean, and Schwarz (2022)'s evidence that the BJZZ algorithm correctly identifies only about 40% of retail trades. A crude adjustment would then suggest multipliers in the range of 0.4x2=0.8 to 0.4x4=1.6. With more general random measurement error, whatever estimates we obtain would tend to understate the true "impact" coefficient. Our main observation here is that the implied price impacts in our setting resembles those found by other authors.

5. A Second Experiment: The Hong Kong Stimulus Payments

The United States is not the only country with an early Covid-19 response that included direct payments to large fraction of its population as opposed to support targeted to subsets most affected (e.g., self-employed or low-income individuals). Hong Kong, Israel, Japan, Serbia, South Korea, and Singapore also provided broad-based "coronavirus handouts." Among these, Hong Kong's Cash Payout Scheme (CPS) of July 2020 provides the best complement to the U.S.

analysis.[18] While the CPS was also just one aspect of an extensive and ongoing relief plan, it presents a simpler experiment than in the U.S. because the bulk of the payments arrived to citizens at the same moment. We conduct a streamlined version of our U.S. analysis.

5.1. Structure and Timing

As detailed in Table 6, the Hong Kong budget proposal released February 26, 2020, provided for direct payments to permanent residents of HK$10,000 (US$1,290). The Legislative Council provided formal funding approval on April 28, 2020, again in the context of a variety of other relief measures. What makes the experiment more straightforward than the U.S. payments is the timing: over 3.5 million payments were electronically transferred on July 6, 2020, another 0.8 million were transferred the next day, and a further 1 million over the next ten days.[19] This stands in contrast to the U.S. payments where one needs spending data to determine when the faucet of stimulus payments was first turned on.

As in the U.S., the fraction of these payments that made their way into stocks is unknown. That said, estimates suggest that Hong Kong leads the world in the fraction of adults who actively trade shares.[20] Accordingly, there was speculation that the flow into the market would be meaningful. "What are Hongkongers going to do with their HK$10,000 payout? Bet on the stock market, from the looks of it," read a headline on July 5, 2020, in the *South China Morning Post* (Yiu and Choi 2020).

[18] In Japan, the timing of direct payments was spread out across the population due to administrative complications (https://voxeu.org/article/covid-19-stimulus-payments-evidence-japan). In South Korea, direct payments were in the form of vouchers that could be redeemed only at local small businesses (https://ftp.iza.org/dp13567.pdf). In Singapore, the payments were only S$600 (US$430). Israel and Serbia made even smaller payments.

[19] Per government press releases at https://www.cashpayout.gov.hk/eng/press.html.

[20] https://fundselectorasia.com/hong-kong-tops-world-for-retail-share-traders/.

5.2. Effect on Trading and Returns

We are interested in trading volume and returns on the Hong Kong Stock Exchange around the check arrival date of July 6, 2020. The analysis is complicated by the fact that on the very same day that stimulus monies were received by Hong Kongers, mainland shares were affected by speculation about Chinese government market intervention.[21] To keep an unrelated event from contaminating our analysis, we first remove all H-shares, which may tend to comove with any projected manipulation of mainland A-shares. Of the remaining Hong Kong shares, some are eligible for "southbound" trading via the Stock Connect system, meaning mainland investors have an ability to trade them and so influence volume (and returns), while others are unavailable to mainland investors. While any shares on the HKSE could be influenced by Hong Kongers with fresh stimulus money, those in this last set—non-H, southbound-ineligible stocks—are relatively insulated from the event on the mainland.

Our return and volume data for Hong Kong shares are from the Compustat Global Security database and include all common shares excluding stocks categorized as investment vehicles.[22] As mentioned above, we exclude H-shares entirely, and form value-weighted portfolios based on non-H shares that are, and are not, exposed to trading by mainland investors. Just like in the U.S. analysis, we use market cap weights from the end of the prior month to form value-weighted portfolios. We are not aware of a stock-level measure of retail share along the lines of the Boehmer et al. measure.[23] That said, comparing the southbound-eligible and -ineligible portfolios that we examine already build in a strong capitalization and

[21] https://www.cnbc.com/2020/07/06/china-stocks-lead-rally-after-beijing-tells-people-to-buy---we-have-the-fed-to-juice-bull-markets-china-has-its-state-media.html.

[22] These are firms with SIC codes starting with 672 and GICS codes 601010 and 402040.

[23] Nor can we apply the familiar logic from some of our other U.S. cross-sectional portfolios. For example, nominal price is less useful because it is routine for large-cap companies to trade at nominal prices below US$1.

liquidity contrast: the median capitalization of the southbound-eligible shares is HK$25 billion while the median capitalization of the southbound-ineligible shares is HK$500 million.

The first panel of Table 7 suggests that there was a boost in volume on July 6, 2020, relative to the prior two trading days. In the "SB Shares" portfolio that might have benefited indirectly from the tailwind of speculation about intervention on the mainland as well as any HK stimulus demand, the value-weighted turnover rises with a point estimate the order of 10-30% over the previous trading days. Importantly, however, the same is true for the "Non-SB" portfolio that is not available to mainland investors. Overall, share turnover in Non-H shares increases by about .10% points in the three-day window starting with July 6, 2020—relative to an unconditional average of .17%—and this increase is statistically significant at the 1% level.[24]

The second panel of Table 7 shows the effect on prices. We calculate value-weighted returns of each of the three portfolios by employing market cap weights from the end of the prior month. We use the sample from February 2019 to 30 days prior to the event date to estimate average returns and standard errors are calculated under the assumption of serially independent returns. On July 6, 2020, we find statistically significant price increases of approximately 2% across the non-H shares on the HKSE. Interestingly, while the SB-ineligible shares continue to see positive returns over the next week, with rising cumulative returns, the more liquid and considerably larger SB-eligible shares do not. This is consistent with slow relative-value arbitrage into the smaller and less liquid SB-ineligible portfolio.

In summary, that the subset of Hong Kong shares that represent the cleanest test of the effect of the stimulus checks—the non-H, non-SB portfolio—there is a volume boost associated

[24] The analysis mirrors the approach taken with U.S. data in Table 3. We use market cap weights at the end of the prior month to aggregate stock-level turnover to a portfolio level value and regress the portfolio level measures on event day dummies, as well as monthly fixed effects. We use Newey-West standard errors with five lags to account for serial correlation in turnover.

with significant stock returns. It is difficult to make a statement about magnitudes in this context because we do not have a good measure of retail order flow, but in general the Hong Kong experiment reaffirms the results of our U.S. analysis.

6 Conclusion

We investigate whether the arrival of the pandemic-era stimulus checks had detectable effects on the stock market. Our findings suggest that they generally increased trading and prices of stocks favored by retail investors—those with high retail trading, small capitalization, and low nominal share price, for example. A similar stimulus payment scheme in Hong Kong also appears to have increased prices and volume on the Hong Kong Stock Exchange.

Our results extend a large literature documenting the effect of demand shocks on individual stock prices to a novel, policy-level domain. They also highlight a new and perhaps undesirable channel for fiscal stimulus. While fiscal policy can impact stocks intendedly through changes in fundamentals, and this was clear in the case of the CARES Act, our results suggest that direct payments to individuals may also provide fuel for speculation. The potential for broad-based direct payments to increase speculative activity should be an element of future policy discussions.

References

1040.com, 2021, "Stimulus Payment Amounts and Qualification," at https://www.1040.com/tax-guide/coronavirus-pandemic-news-and-resources/stimulus-payment-amounts-and-qualification/.

Baker, Malcolm and Jeffrey Wurgler, 2006, "Investor Sentiment and the Cross-Section of Stock Returns," *The Journal of Finance* 61 (4), 1645-1680.

Baker, Malcolm, Robin Greenwood, and Jeffrey Wurgler, 2009, "Catering through Nominal Share Prices," *The Journal of Finance* 64 (6), 2559-2590.

Baker, Scott R., R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis, 2022, "Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments," *Review of Finance*, forthcoming.

Barber, Brad M., Xing Huang, Terrance Odean, and Chris Schwarz, 2021, "Attention-Induced Trading and Returns: Evidence from Robinhood Users," *The Journal of Finance*, forthcoming.

Barber, Brad M., Xing Huang, Philippe Jorion, Terrance Odean, and Chris Schwarz, 2022, "A (Sub)penny For Your Thoughts: Tracking Retail Investor Activity in TAQ," University of California, Davis working paper.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xiran Zhang, 2021, "Tracking Retail Investor Activity," *The Journal of Finance* 76 (5), 2249-2305.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2015, "Regression Discontinuity and the Price Effects of Stock Market Indexing," *The Review of Financial Studies* 28 (1), 212-246.

Chetty, Raj, John Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team, 2020, "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data," National Bureau of Economic Research working paper.

Chinco, Alex, and Marco Sammon, 2021, "Excess Reconstitution-Day Volume," Baruch College working paper.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, 2020, "How Did US Consumers Use Their Stimulus Payments?" National Bureau of Economic Research working paper.

Cox, Josue, Daniel L. Greenwald, and Sydney C. Ludvigson, 2020, "What Explains the COVID-19 Stock Market?" National Bureau of Economic Research working paper.

Crandall-Hollick, Margot L., 2021, "COVID-19 and Direct Payments: Comparison of First and Second Round of 'Stimulus Checks' to the Third Round in the American Rescue Plan

Act of 2021 (ARPA; P.L. 117-2)," Congressional Research Service, IN11605 (March 25, 2021 update).

Da, Zhi, Vivian W. Fang, and Wenwei Lin, 2021, "Fractional Trading," University of Notre Dame working paper.

Divakaruni, Anantha, and Peter Zimmerman, 2022, "Uncovering Retail Trading in Bitcoin: The Impact of Covid-19 Stimulus Checks," *Management Science*, forthcoming.

Eaton, Gregory W., T. Clifton Green, Brian Roseman, and Yanbin Wu, 2021, "Retail Trader Sophistication and Stock Market Quality: Evidence from Brokerage Outages," Emory University Working Paper.

Gabaix, Xavier and Ralph S. J. Koijen, 2021, "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis," Harvard University Working Paper.

Gofran, Ruhana Zareen, Andros Gregoriou, and Lawrence Haar, "Impact of Coronavirus on Liquidity in Financial Markets", *Journal of International Financial Markets*, Institutions and Money. 2022 May; 78: 101561.

Greenwood, Robin, 2005, "Short- and Long-Term Demand Curves for Stocks: Theory and Evidence on the Dynamics of Arbitrage," *Journal of Financial Economics* 75 (3), 607-649.

Greenwood, Robin, Samuel G. Hanson, and Gordon Y. Liao, 2018, "Asset Price Dynamics in Partially Segmented Markets," *The Review of Financial Studies* 31 (9), 3307-3343.

Greenwood, Robin, and Andrei Shleifer, 2014, "Expectations of Returns and Expected Returns," *The Review of Financial Studies* 27 (3), 714-746.

Harris, Lawrence and Eitan Gurel, 1986, "Price and Volume Effects Associated with Changes in the S&P 500 List: New Evidence for the Existence of Price Pressures," *The Journal of Finance* 41 (4), 815-829.

Jones, Charles M., Adam V. Reed, and William Waller, 2021, "When Brokerages Restrict Retail Investors, Does the Game Stop?" Columbia University Working Paper.

Kaul, Aditya, Vikas Mehrotra, and Randall Morck, 2000, "Demand Curves for Stocks Do Slope Down: New Evidence from an Index Weights Adjustment," *The Journal of Finance* 55 (2), 893-912.

Kumar, Alok, and Charles M.C. Lee, 2006, "Retail Investor Sentiment and Return Comovements," *The Journal of Finance* 61 (5), 2451-2486.

Kumar, Alok, 2009, "Who Gambles in the Stock Market?" *The Journal of Finance* 64 (4), 1889-1933.

Laarits, Toomas, and Marco Sammon, 2022, "The Retail Habitat," NYU Stern Working Paper.

Levine, Matt, 2020, "If You're Bored You Can Trade Stocks," *Bloomberg Opinion*, at: https://www.bloomberg.com/opinion/articles/2020-04-30/if-you-re-bored-you-can-trade-stocks.

Lynch, Anthony W., and Richard R. Mendenhall, 1997, "New Evidence on Stock Price Effects Associated with Changes in the S&P 500 Index," *Journal of Business* 70 (3), 351-83.

Parker, Jonathan A., Jake Schild, Laura Erhard, and David Johnson, 2022, "Household Spending Responses to the Economic Impact Payments of 2020: Evidence from the Consumer Expenditure Survey," National Bureau of Economic Research Working Paper.

Parker, Jonathan A., Nicholas S. Souleles, David S. Johnson, and Robert McClelland, 2013, "Consumer Spending and the Economic Stimulus Payments of 2008," *American Economic Review* 103 (6), 2530-53.

Pedersen, Lasse, 2021, "Game On: Social Networks and Markets," Copenhagen Business School working paper.

Shleifer, Andrei, 1986, "Do Demand Curves for Stocks Slope Down?" *The Journal of Finance* 41 (3), 579-590.

Tauber, Kristen, and Willem Van Zandweghe. 2021. "Why Has Durable Goods Spending Been So Strong during the COVID-19 Pandemic?" Federal Reserve Bank of Cleveland, Economic Commentary 2021-16.

Thatte, Parag, Srineel Jalagani, and Binky Chadha, 2021, "Investor Position and Flows," Deutsche Bank Research, 21 February.

Welch, Ivo, 2021, "The Wisdom of the Robinhood Crowd," *The Journal of Finance*, forthcoming.

Wurgler, Jeffrey, and Ekaterina Zhuravskaya, 2002, "Does Arbitrage Flatten Demand Curves for Stocks?" *Journal of Business* 75 (4), 583-608.

Yiu, Enoch, and Martin Choi, July 5, 2020. "What are Hongkongers going to do with their HK$10,000 payout? Bet on the stock market, from the looks of it." *South China Morning Post.*

Table 1. Economic Impact Payments (stimulus checks). Pertinent details of the Acts authorizing the three stimulus checks. Details from the Congressional Research Service (Crandall-Hollick (2021)) and 1040.com (2021). First actual payment date is the first market-open date at which the arrival of impact payments was being actively discussed online and were being spent based on data from Opportunity Insights. Further details in text.

		EIP1: Coronavirus Aid, Relief and Economic Security Act (CARES Act)			EIP2: Consolidated Appropriations Act of 2021			EIP3: American Rescue Plan Act		
Passed Congress		3/27/20			12/21/20			3/10/21		
Signed		3/27/20			12/27/20			3/11/21		
Eligibility		U.S. citizens and resident aliens with a work-eligible SSN and not a dependent.			Those eligible for EIP1 plus taxpayers with work-eligible SSNs.			Same as EIP2		
Direct Payment	Single filers	$1,200			$600			$1,400		
	Joint filers	$2,400			$1,200			$2,800		
	With children under 17	Additional $500 per child			Additional $600 per child			Additional $1400 per dependent		
Eligibility Phaseout Thresholds	Single filers making $75,000+ Joint filers making $150,000+ Household heads with dependents making $112,500+	Any income over the threshold reduces the stimulus payment by 5% of the amount above the threshold. Phaseout thresholds increase $10,000 for each qualifying child.			Same as EIP1, except slightly more aggressive phaseout rates and phaseout thresholds increase by $12,000 per qualifying child.			Same as EIP2, except slightly more aggressive phaseout rates and phaseout thresholds do not change with children.		
First Actual Payment	Reddit, Consumption, Treasury; first market-open date	4/13/20			12/30/20			3/12/21		
First Official Payment	Treasury's announced first payment date	4/15/20			1/4/21			3/17/21		
Cumulative Payments Sent by Type and Approximate Date	Initial Direct Deposits	through 4/17/2020	N = 89 million	$160 billion	through 1/1/21	N = 133 million	$128 billion*	through 3/17/21	N = 90 million	$242 billion
	Direct Deposits + Checks	5/8/20	128 million	$217 billion	2/15/21	147 million	$141 billion	3/24/2021	127 million	$325 billion
	Direct Deposits + Checks	5/22/20	152 million	$258 billion	2/28/21	154 million	$147 billion	3/31/2021	131 million	$335 billion

	Direct Deposits + Checks	6/5/20	160 million	$270 billion		4/7/2021	156 million	$372 billion
	Direct Deposits + Checks	2/28/21	168 million	$276 billion		4/14/2021	159 million	$376 billion
Cumulative Payments Sent by Type and Approximate Date (continued)	Direct Deposits + Checks					4/21/2021	161 million	$379 billion
	Direct Deposits + Checks					4/28/2021	163 million	$384 billion
	Direct Deposits + Checks					5/5/2021	164 million	$386 billion
	Direct Deposits + Checks				* Based on extrapolation from next row	5/12/2021	165 million	$388 billion
	Direct Deposits + Checks					5/26/2021	167 million	$391 billion

Table 2. Household Pulse Surveys. A new, online survey administered by the U.S. Census Bureau as a part of the federal government response to the Coronavirus pandemic. Data collection started on April 23, 2020, less than two weeks after the first EIP checks were sent out.

	EIP1	**EIP2**	**EIP3**
Did not receive or did not expect	14.5%	35.3%	35.2%
Used some portion on:			
Food	59.7%	28.1%	28.7%
Household supplies or personal care products	44.4%	16.2%	18.3%
Rent	25.6%	12.5%	12.7%
Mortgage	21.7%	9.5%	10.8%
Utilities	45.3%	21.2%	22.3%
Vehicle payments	21.7%	10.3%	13.4%
Debt payments	19.6%	17.4%	22.4%
Mostly invested or saved it:	**9.3%**	**15.1%**	**18.7%**

Table 3. Regressions to explain retail trading volume. We estimate daily stock-level retail-initiated buys and sells from 1/2020 to 6/2021 using the Boehmer, Jones, Zhang, and Zhang (2021) methodology. "EIP Event Days" are dummies for nine days: April 13, 2020 and the subsequent two trading days; December 30, 2020 and the subsequent two trading days; March 12, 2021 and the subsequent two trading days. Panel A combines all event days in one dummy variable, Panel B separates out first, second, and third event days. Retail Fraction is the fraction of total orders classified as retail-initiated. Net Buys denotes net retail buying (buys minus sells), Total denotes all orders, and Retail denotes all retail orders (retail buys plus retail sells). All measures are constructed on the stock-day level, then aggregated to the market level using market cap weights from the end of the prior month. Dollar volume is measured analogously. Retail-initiated trades larger than $100,000 classified as not retail. Newey-West SE with five lags. All specifications include weekly fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A.

	Number of Trades			Dollar Volume		
	Retail Fraction	Net Buys/ Total	Net Buys/ Retail	Retail Fraction	Net Buys/ Total	Net Buys/ Retail
3 EIP Event Days	0.60***	0.18***	1.66**	0.43***	0.07***	1.07**
	(3.50)	(2.97)	(2.48)	(3.50)	(2.63)	(2.19)
Constant	6.40***	0.07	-0.19	5.23***	-0.04	-1.28*
	(26.09)	(0.78)	(-0.20)	(29.31)	(-1.09)	(-1.79)
Weekly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	377	377	377	377	377	377
R^2	0.82	0.65	0.65	0.76	0.60	0.69

Panel B.

	Number of Trades			Dollar Volume		
	Retail Fraction	Net Buys/ Total	Net Buys/ Retail	Retail Fraction	Net Buys/ Total	Net Buys/ Retail
1st EIP Event Days	0.75***	0.24***	2.40**	0.50***	0.09**	1.57**
	(3.06)	(2.78)	(2.41)	(2.77)	(2.35)	(2.15)
2nd EIP Event Days	0.52**	0.09	0.81	0.40**	0.05	0.80
	(2.03)	(1.04)	(0.81)	(2.15)	(1.14)	(1.08)
3rd EIP Event Days	0.51**	0.18**	1.67*	0.37**	0.07*	0.82
	(2.12)	(2.17)	(1.71)	(2.07)	(1.71)	(1.14)
Constant	6.40***	0.07	-0.19	5.23***	-0.04	-1.28*
	(26.13)	(0.78)	(-0.20)	(29.34)	(-1.09)	(-1.79)
Weekly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	377	377	377	377	377	377
R^2	0.82	0.65	0.65	0.76	0.60	0.69

Table 4. Share of retail-initiated trades on EIP event days. Q1 to Q5 denote five portfolios sorted on retail fraction of trading volume (RSVOL) in the previous month. Q5 represents the portfolio with the highest share of retail-initiated trades. Within each portfolio we calculate the value-weighted mean of stock-level retail-initiated trade in terms of dollar volumes, using market cap weights from the end of the prior month. Retail-initiated trades larger than $100,000 classified as not retail. In Panel A, "3 EIP Event Days" is a dummy variable capturing the nine days described in Table 4. Panel B separates out first, second and third event days. Newey-West SE with five lags. All specifications include weekly fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
3 EIP Event Days	0.21***	0.36***	0.47***	0.45***	0.69***	0.49**
	(3.17)	(3.98)	(3.48)	(2.81)	(3.16)	(2.43)
Constant	2.20***	3.10***	4.95***	6.57***	7.98***	5.78***
	(23.16)	(23.49)	(25.07)	(27.72)	(25.02)	(19.92)
Weekly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	377	377	377	377	377	377
R^2	0.70	0.70	0.73	0.74	0.86	0.88

Panel B.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
1st EIP Event Days	0.30***	0.50***	0.60***	0.45*	0.75**	0.45
	(3.13)	(3.81)	(3.01)	(1.86)	(2.36)	(1.59)
2nd EIP Event Days	0.17*	0.30**	0.33	0.47*	0.93***	0.76**
	(1.74)	(2.18)	(1.62)	(1.90)	(2.81)	(2.55)
3rd EIP Event Days	0.15	0.27**	0.47**	0.45*	0.44	0.30
	(1.53)	(2.08)	(2.37)	(1.88)	(1.41)	(1.07)
Constant	2.20***	3.10***	4.95***	6.57***	7.98***	5.78***
	(23.24)	(23.59)	(25.13)	(27.72)	(25.03)	(19.93)
Weekly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	377	377	377	377	377	377
R^2	0.70	0.71	0.73	0.74	0.86	0.88

Table 5. Cumulative abnormal returns of long-short portfolios around stimulus check arrival. Equal-weighted portfolio returns and value-weighted market excess returns. CAPM betas and alphas estimated using daily returns from February 2019 to 30 days before the event window. Abnormal returns in the event window are cumulated starting with the leftmost date, e.g., the 4/15/2020 return is the cumulative long-short portfolio abnormal return from 4/13/2020 through 4/15/2020. The reported market excess return is also cumulated. Standard errors calculated under the assumption of serially independent abnormal returns. The first trading day [t=0] is in the leftmost column. The other columns report the three-trading-day window [0,+2], the five-trading-day window [0,+4], and the fifteen-trading-day window [0,+14]. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A. Long-short portfolios

	[0, 0]	[0, +2]	[0, +4]	[0, +14]
EIP1	**4/13/2020**	**4/15/2020**	**4/17/2020**	**5/1/2020**
RSVOL q5-q1	5.62%***	10.73%***	9.43%***	14.74%***
RH q5-q1	3.51%***	7.64%***	7.28%***	10.10%***
FINRA q5-q1	5.83%***	11.82%***	10.68%***	14.42%***
CAP q1-q5	4.47%***	8.66%***	7.70%***	17.16%***
PRC q1-q5	5.26%***	7.36%***	5.55%***	18.37%***
SD q5-q1	4.93%***	8.48%***	7.47%***	14.84%***
Market Excess Ret.	-0.92%	-0.12%	3.23%	2.35%
EIP2	**12/30/2020**	**1/4/2021**	**1/6/2021**	**1/21/2021**
RSVOL q5-q1	1.07%	1.71%	-0.23%	18.48%***
RH q5-q1	1.01%	1.77%	0.81%	10.73%***
FINRA q5-q1	1.45%	2.91%	1.75%	21.95%***
CAP q1-q5	1.32%	2.97%*	4.16%*	19.98%***
PRC q1-q5	1.49%	4.06%**	5.68%**	22.64%***
SD q5-q1	1.76%	1.22%	4.50%	13.95%***
Market Excess Ret.	0.27%	-0.76%	0.89%	4.32%
EIP3	**3/12/2021**	**3/16/2021**	**3/18/2021**	**4/1/2021**
RSVOL q5-q1	-0.12%	0.54%	0.05%	-4.27%
RH q5-q1	-0.29%	0.16%	-1.60%	-2.23%
FINRA q5-q1	0.02%	0.81%	0.22%	-3.73%
CAP q1-q5	0.12%	0.15%	0.35%	-4.80%
PRC q1-q5	0.37%	0.10%	0.20%	-5.82%
SD q5-q1	0.26%	-0.77%	-1.80%	-7.10%
Market Excess Ret.	0.10%	0.37%	-1.19%	1.00%

Panel B. Long only portfolios

EIP1	[0, 0] **4/13/2020**	[0, +2] **4/15/2020**	[0, +4] **4/17/2020**	[0, +14] **5/1/2020**
RSVOL q5	3.82%***	5.89%***	5.09%***	14.06%***
RH q5	1.45%***	1.01%	0.70%	9.23%***
FINRA q5	3.76%***	5.93%***	5.39%***	13.55%***
CAP q1	3.45%***	6.42%***	6.01%***	16.73%***
PRC q1	4.17%***	5.12%***	4.26%**	17.78%***
SD q5	2.95%***	3.30%**	2.54%	13.64%***
Market Excess Ret.	-0.92%	-0.12%	3.23%	2.35%

EIP2	**12/30/2020**	**1/4/2021**	**1/6/2021**	**1/21/2021**
RSVOL q5	1.58%	2.20%	4.13%*	20.47%***
RH q5	1.49%	2.51%	5.05%**	13.46%***
FINRA q5	1.90%*	3.42%*	6.02%**	24.40%***
CAP q1	1.73%	3.21%*	5.81%**	21.07%***
PRC q1	1.93%	4.04%*	7.25%**	23.90%***
SD q5	1.94%	1.68%	5.87%**	15.68%***
Market Excess Ret.	0.27%	-0.76%	0.89%	4.32%

EIP3	**3/12/2021**	**3/16/2021**	**3/18/2021**	**4/1/2021**
RSVOL q5	0.60%	0.05%	0.28%	-6.06%
RH q5	0.29%	-1.07%	-1.77%	-5.29%
FINRA q5	0.67%	0.15%	0.16%	-5.84%
CAP q1	0.41%	0.27%	0.58%	-5.00%
PRC q1	0.50%	-0.13%	-0.06%	-6.64%
SD q5	0.54%	-0.80%	-1.16%	-7.49%
Market Excess Ret.	0.10%	0.37%	-1.19%	1.00%

Table 6. Cash Payout Scheme in Hong Kong. Details from https://www.scmp.com/news/hong-kong/politics/article/3131401/hong-kong-budget-sails-through-legco-record-time-pro and payment statistics from government press releases at https://www.cashpayout.gov.hk/eng/press.html.

	Cash Payout Scheme (CPS)		
Budget Proposal Released	2/26/20		
Approved	4/28/20		
Eligibility	Hong Kong permanent residents 18 or over		
Direct Payment	HK$10,000 ($1,290 USD)		
First Payment Date	7/6/20		
Cumulative Payments (almost all Direct Deposit)	7/6/20	N=3.5 million	$4.5 billion USD
	7/7/20	4.3 million	$5.5 billion
	7/13/20	4.5 million	$5.8 billion
	7/17/20	5.3 million	$6.8 billion
	7/27/20	5.5 million	$7.1 billion
	8/11/20	5.9 million	$7.6 billion
	11/19/21	6.6 million	$8.5 billion

Table 7. Trading and returns in Hong Kong. Value-weighted portfolios of non-H shares, non-H non-southbound eligible shares, and non-H southbound eligible shares. Panel A shows total volume in millions HKD, as well as value-weighted daily share turnover. Portfolios constructed using market cap weights from the end of the prior month. The first wave of Hong Kong payments arrived July 6, 2020, so the trading days represented in the columns of Panel A are t = -2, -1, 0, +1, +2, respectively. HK$1 = $0.13 on July 6, 2020. Panel B shows excess returns of the same three value-weighted portfolios. Average returns estimated relative to the pre-event window from February 2019 to 30 days before the event day. Standard errors calculated under the assumption of serially independent returns. The trading days represented in the columns are t = 0, the three-trading-day window [0,+2], the five-trading-day window [0,+4], and the fifteen-trading-day window [0,+14]. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A.

	7/2/2020	**7/3/2020**	**7/6/2020**	**7/7/2020**	**7/8/2020**
Volume in millions of HKD					
HKSE Non-H Shares	109,826	99,711	136,267	136,204	117,702
HKSE Non-H, Non-SB Shares	16,275	15,663	21,066	22,203	16,970
HKSE Non-H, SB Shares	93,551	84,048	115,201	114,000	100,732
Daily Share Turnover in Percent					
HKSE Non-H Shares	0.32	0.28	0.37	0.38	0.32
HKSE Non-H, Non-SB Shares	0.17	0.16	0.21	0.21	0.16
HKSE Non-H, SB Shares	0.39	0.33	0.44	0.44	0.39

Panel B.

	$[0, 0]$	$[0, +2]$	$[0, +4]$	$[0, +14]$
Returns	**7/6/2020**	**7/8/2020**	**7/10/2020**	**7/24/2020**
HKSE Non-H Shares	2.32%*	3.60%	4.44%	0.77%
HKSE Non-H, Non-SB Shares	2.04%*	5.32%***	9.95%***	6.19%
HKSE Non-H, SB Shares	2.44%*	2.90%	2.18%	-1.39%

Figure 1. Growth in retail investor accounts. Cumulative returns of retail fraction and cap sorted portfolios. The top panel shows the number of unique Robinhood user-stock pairs, the number of unique stocks held by Robinhood users, and the number of funded accounts (x4 for scale). The bottom panel shows cumulative log returns, in excess of cumulative log returns on the risk-free asset, of the Fama French market portfolio, the top and bottom cap quintile portfolios, the top and bottom retail share quintile portfolios according to the measure by Boehmer, Jones, Zhang, and Zhang (2021), and the assets under Robinhood custody. All log returns are shifted to intersect 0 on March 23, 2020, the aggregate stock market trough in the Covid era.

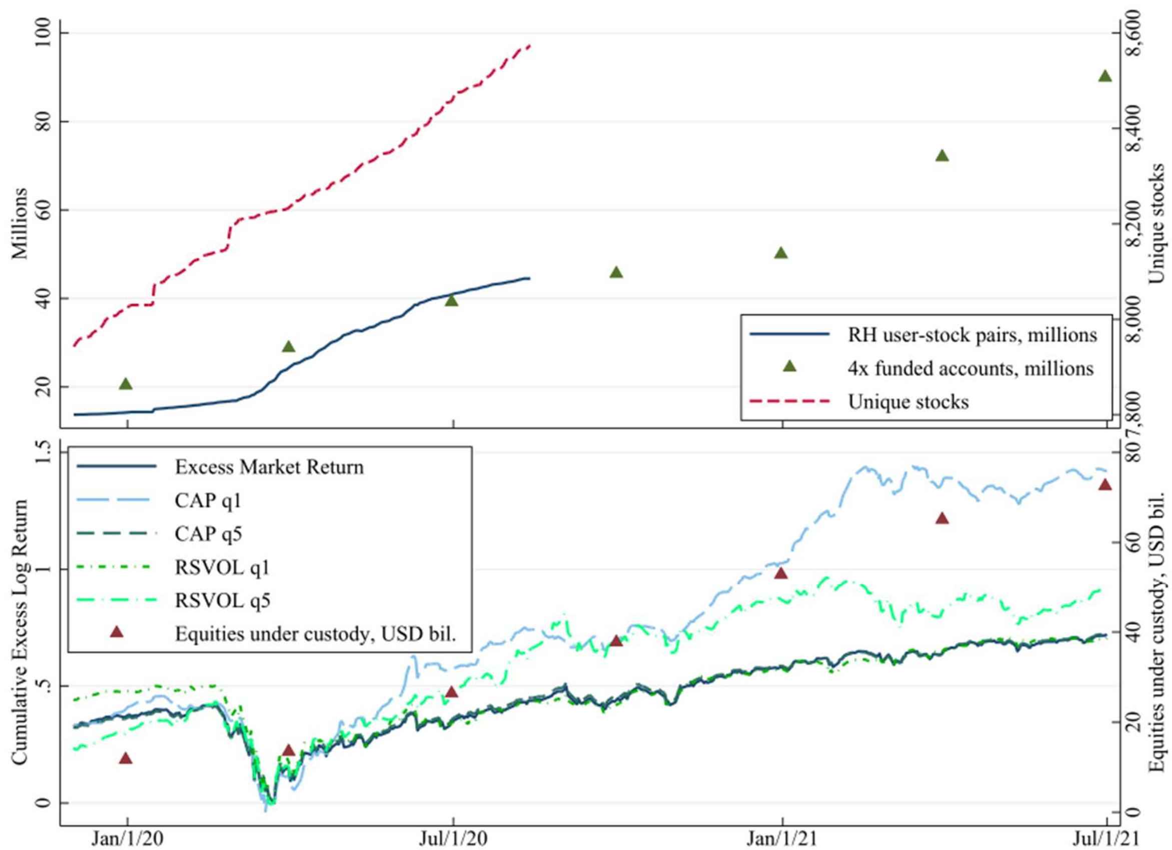


Figure 2. Economic and health context. Top panel shows the number of positive Coronavirus tests. Middle panel shows the number of initial unemployment insurance claims and positive Coronavirus tests. Bottom panel shows indices of aggregate retail spending and time spent away from home. Spending data from consumer credit and debit card data, indexed relative to January 2020. Time away from home estimated using cellphone location data, indexed relative to January 2020. All data from the Opportunity Insights Economic Tracker website.

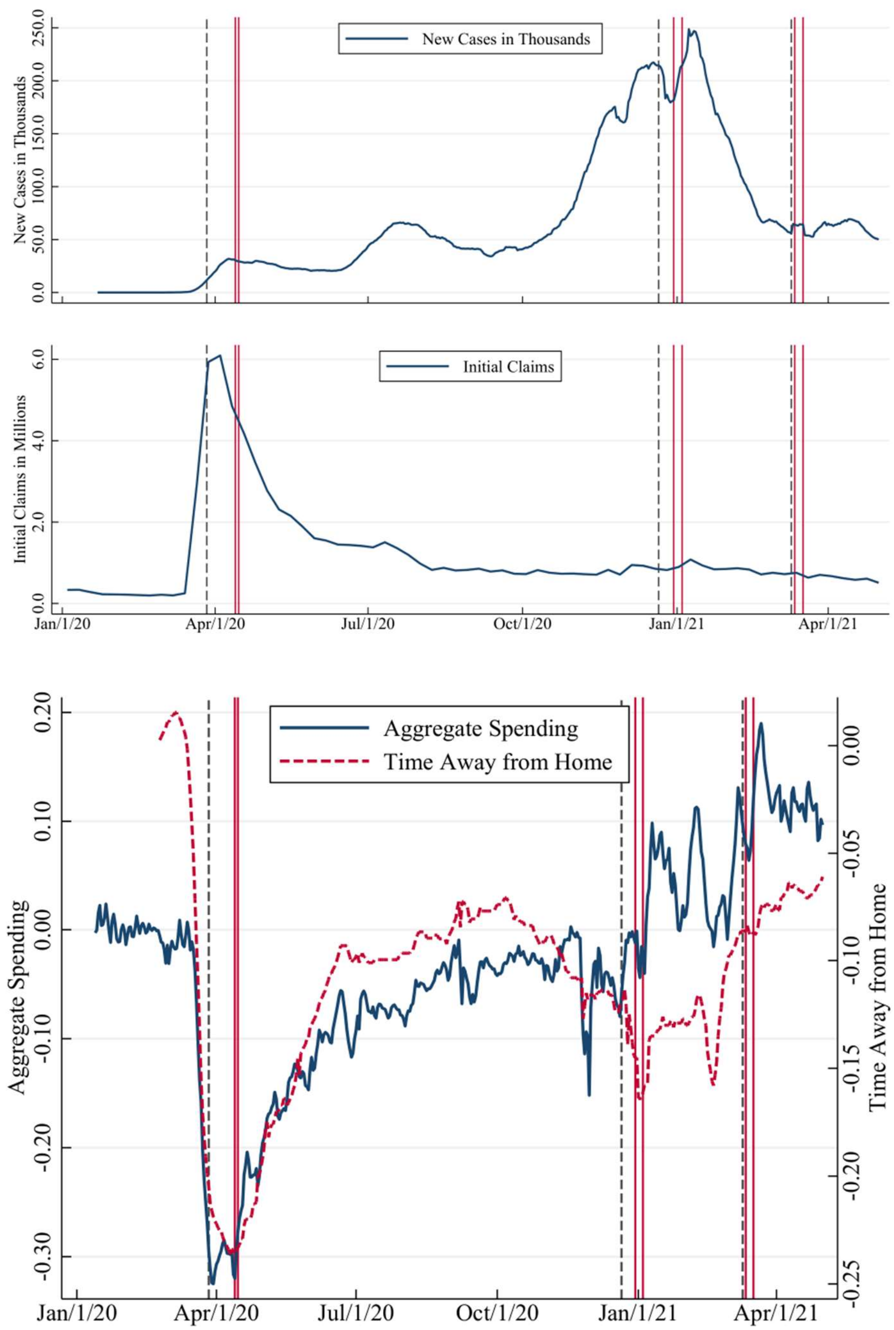


Figure 3. Industry returns around CARES Act passage relative to industry returns around previous crash. Fama-French 49 industry portfolio performance around the passage of the CARES Act (March 24-26, 2020).

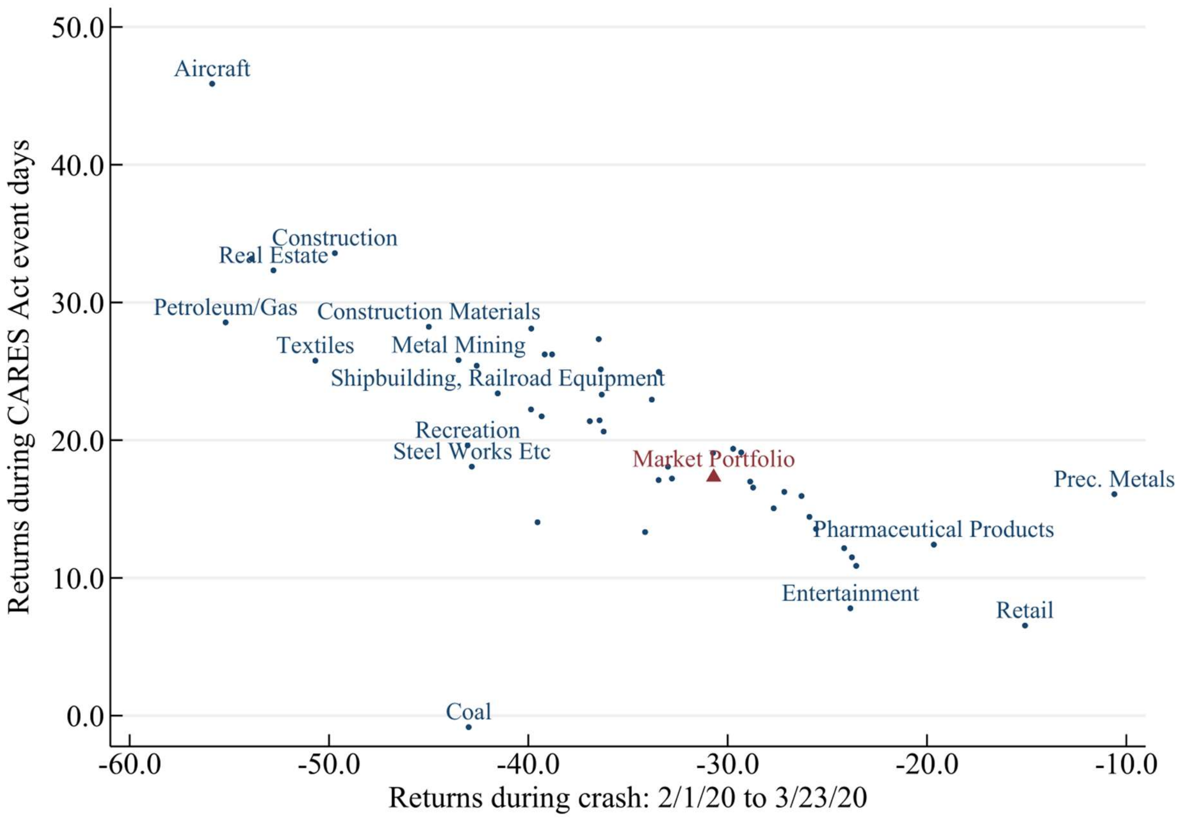


Figure 4. Retail spending around stimulus check arrival. Difference in non-grocery retail spending, low income zip codes minus high income zip codes. The dashed vertical line represents the date of the passage of the authorizing Act. The first solid vertical line denotes the first trading date that checks appear to have been available to a significant number of investors: 4/13/20, 12/30/20, and 3/12/21. The second solid vertical line is the official first payment date.

Figure 5. Social media activity and retail spending in short windows around stimulus check arrival. The first line is the adjudged first trading date that checks appear to have been available to a significant number of investors: 4/13/20, 12/30/20, and 3/12/21. The second line is the official first payment date. Spending from Opportunity Insights' credit and debit data measures the difference between non-grocery retail spending in low- and high-income ZIP codes. The solid lines show the number of posts in the stimulus check subreddit and the number of comments on posts that include the words "bank account". Days that the stock market was closed are shaded.

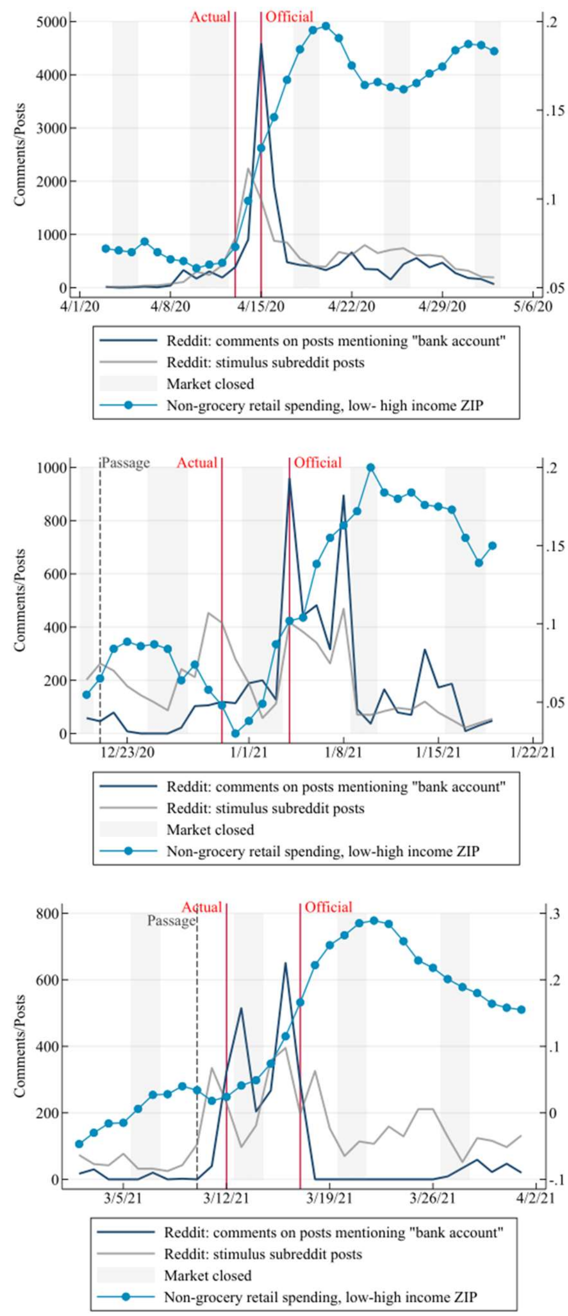
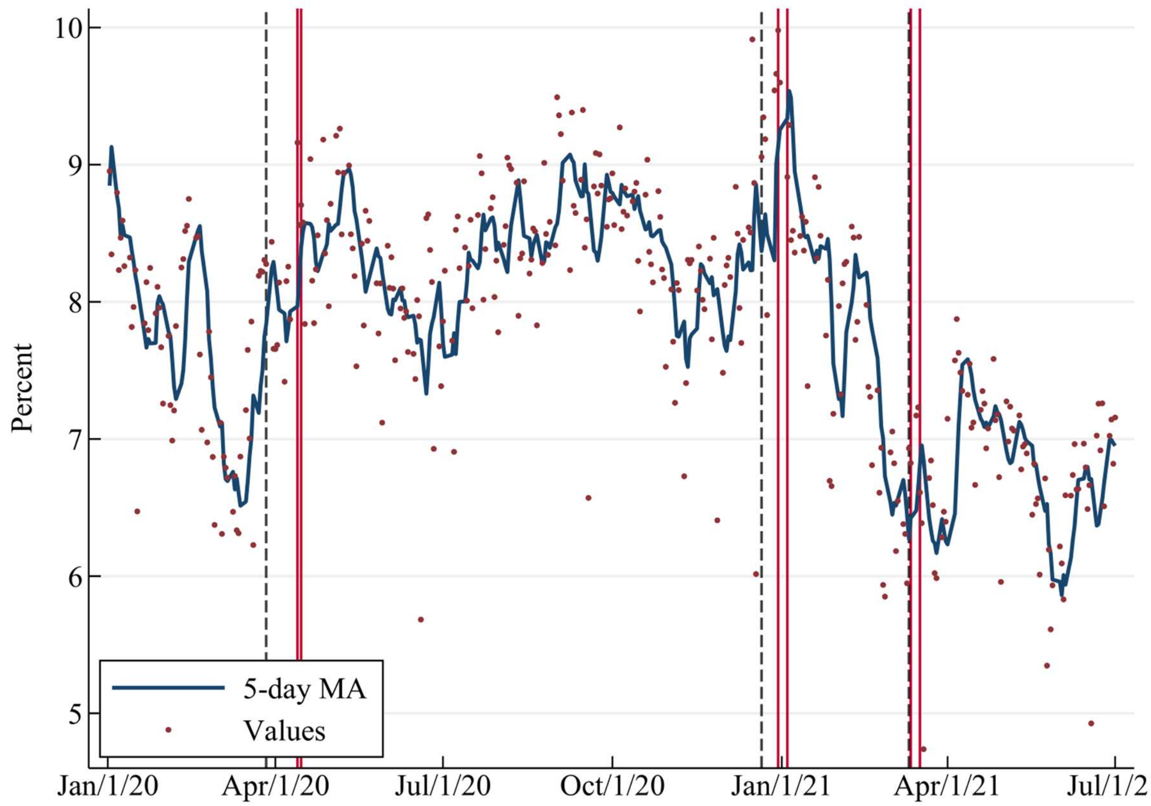


Figure 6. Retail fraction of trading volume. Retail-initiated trades measured based on the algorithm of Boehmer, Jones, Zhang, and Zhang (2021). Graph shows value-weighted averages of stock-level retail-initiated trading volume, as well as the 5-day moving average. The value-weighted average calculated using market cap shares from the end of the prior month. The dashed vertical line is when the associated act was signed, the first solid line is the first actual payment date, and the second solid line is the first official payment date.



Internet Appendix Tables

Table A1. Regressions to explain retail trading volume, restricting to trades no larger than $1,200. We estimate daily retail-initiated buys and sells from 1/2020 to 6/2021 from TAQ using the Boehmer, Jones, Zhang, and Zhang (2021) methodology. "EIP Event Days" are dummies for nine days: April 13, 2020 and the subsequent two trading days; December 30, 2020 and the subsequent two trading days; March 12, 2021 and the subsequent two trading days. Retail Fraction is the fraction of total orders classified as retail-initiated. Net Buys denotes net retail buying (buys minus sells), Total denotes all orders, and Retail denotes all retail orders (retail buys plus retail sells). All measures are constructed on the stock-day level, then aggregated to the market level using market cap weights from the end of the prior month. Dollar volume is measured analogously. Panel B repeats the same analysis with dummies separately for days in each EIP window. All specifications include weekly fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A.

	Number of Trades			Dollar Volume		
	Retail Fraction	Net Buys/ Total	Net Buys/ Retail	Retail Fraction	Net Buys/ Total	Net Buys/ Retail
3 EIP Event Days	0.30***	0.10***	1.97**	0.02***	0.01***	2.08**
	(3.26)	(2.80)	(2.30)	(4.03)	(4.12)	(2.48)
Constant	1.68***	0.07	2.15*	0.09***	0.00	0.18
	(12.81)	(1.42)	(1.73)	(13.58)	(0.38)	(0.15)
Weekly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	377	377	377	377	377	377
R^2	0.80	0.73	0.66	0.78	0.64	0.63

Panel B.

	Number of Trades			Dollar Volume		
	Retail Fraction	Net Buys/ Total	Net Buys/ Retail	Retail Fraction	Net Buys/ Total	Net Buys/ Retail
1st EIP Event Days	0.40***	0.13***	2.88**	0.02***	0.01***	2.83**
	(3.06)	(2.59)	(2.30)	(3.37)	(3.26)	(2.29)
2nd EIP Event Days	0.18	0.05	0.64	0.01	0.00	0.86
	(1.33)	(0.88)	(0.51)	(1.64)	(1.54)	(0.69)
3rd EIP Event Days	0.30**	0.11**	2.22*	0.02***	0.01***	2.39**
	(2.34)	(2.31)	(1.81)	(3.03)	(3.41)	(1.97)
Constant	1.68***	0.07	2.15*	0.09***	0.00	0.18
	(12.83)	(1.43)	(1.74)	(13.61)	(0.39)	(0.15)
Weekly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	377	377	377	377	377	377
R^2	0.80	0.73	0.66	0.78	0.64	0.63

Table A2. Persistence of RSVOL (retail fraction of trading volume) Portfolio Assignments. This table shows the probability that a stock in the indicated RSVOL portfolio at time t=-12 ends up in the indicated RSVOL portfolio 12 months later.

RSVOL 12-month Transition Probability

	Retail Portfolio at $t = 0$				
$t = -12$	1	2	3	4	5
1	56.49	26.62	10.32	4.22	2.35
2	28.34	41.46	22.07	6.58	1.54
3	10.05	28.25	37.94	19.59	4.16
4	2.86	7.49	26.40	44.87	18.38
5	0.68	1.09	4.32	25.07	68.84

Table A3. Returns on Stimulus Check Receipt. Day-stock level returns, regressed on EIP event dummies, interacted with RSVOL quintile dummies (the middle RSVOL quintile is excluded). Standard errors clustered by firm and trading day. The second, fourth, and sixth column include Fama French 49 industry times day fixed effects. All returns multiplied by three for ease of comparability with event study results. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	EIP1		EIP2		EIP3	
EIP 3 days x Q1	0.27	0.21	-0.12	-0.04	0.21	0.16
	(0.73)	(0.61)	(-0.21)	(-0.10)	(0.33)	(0.31)
EIP 3 days x Q2	-0.01	0.14	0.00	0.01	-0.01	-0.14
	(-0.07)	(0.77)	(0.00)	(0.03)	(-0.02)	(-0.42)
EIP 3 days x Q4	3.13***	2.84***	1.01*	0.95**	0.42	0.40
	(2.77)	(2.69)	(1.77)	(2.08)	(0.80)	(0.76)
EIP 3 days x Q5	11.01***	9.69***	1.84	1.62	0.97	0.98
	(3.63)	(3.19)	(0.96)	(1.00)	(0.47)	(0.48)
Constant	0.30	0.27***	0.28	0.27***	0.28	0.27***
	(1.53)	(8.98)	(1.43)	(8.84)	(1.43)	(8.83)
Industry x Day FE		Yes		Yes		Yes
Q1=Q5 p-val.	0.001	0.002	0.430	0.405	0.773	0.744
N	2,598,961	2,598,961	2,598,961	2,598,961	2,598,961	2,598,961
R^2	0.00	0.15	0.00	0.15	0.00	0.15

Table A4. Regressions to explain retail trading volume. We estimate daily retail-initiated buys and sells from 1/2020 to 6/2021 from TAQ using the Boehmer, Jones, Zhang, and Zhang (2021) methodology. "3 EIPx Event Days" are dummies for sets of three days: April 13, 2020 and the subsequent two trading days; December 30, 2020 and the subsequent two trading days; March 12, 2021 and the subsequent two trading days. Retail Fraction is the fraction of total orders classified as retail-initiated. Net Buys denotes net retail buying (buys minus sells), Total denotes all orders, and Retail denotes all retail orders (retail buys plus retail sells). All measures are constructed on the stock-day level, then aggregated to the market level using market cap weights from the end of the prior month. Dollar volume is measured analogously. Retail-initiated trades larger than $100,000 classified as not retail. Newey-West SE with five lags. All specifications include weekly fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Number of Trades			Dollar Volume		
	Retail Fraction	Net Buys/ Total	Net Buys/ Retail	Retail Fraction	Net Buys/ Total	Net Buys/ Retail
3 EIP1 Event Days	0.69**	0.12	0.98	0.48*	0.11**	1.46
	(2.01)	(1.02)	(0.73)	(1.94)	(2.05)	(1.48)
3 EIP2 Event Days	0.15	0.27***	2.98***	0.15	0.05	0.80
	(0.53)	(2.75)	(2.67)	(0.75)	(1.11)	(0.98)
3 EIP3 Event Days	0.94***	0.12	0.89	0.64***	0.06	1.07
	(3.57)	(1.30)	(0.84)	(3.38)	(1.53)	(1.39)
Constant	6.40***	0.07	-0.19	5.23***	-0.04	-1.28*
	(26.38)	(0.78)	(-0.20)	(29.52)	(-1.09)	(-1.79)
Weekly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	377	377	377	377	377	377
R^2	0.83	0.65	0.65	0.76	0.60	0.69

Table A5. Alternative event study regressions. Daily returns on six long-short strategies used in the event study. Sample from February 2019 to July 2021. Daily returns multiplied by three to maintain comparability with the event study evidence in Table 5. EIP dummies correspond to the first three trading days on which the stimulus checks were investable: April 13, 2020 and the subsequent two trading days; December 30, 2020 and the subsequent two trading days; March 12, 2021 and the subsequent two trading days ***, **, and * denote significance at the 1%, 5%, and 10% levels. Mkt-Rf, SMB, HML, and UMD are the Fama French four factors.

Panel A.

	Equal-Weighted Portfolios					
	RSVOL q5-q1	RH q5-q1	FINRA q5-q1	CAP q1-q5	PRC q1-q5	SD q5-q1
3 EIP1 Event Days	10.30***	7.40***	11.37***	8.16***	6.78***	8.13***
	(4.56)	(4.25)	(4.74)	(4.30)	(2.94)	(3.20)
3 EIP2 Event Days	1.58	1.79	2.81	2.81	3.85*	1.20
	(0.70)	(1.03)	(1.17)	(1.48)	(1.67)	(0.47)
3 EIP3 Event Days	0.61	0.28	0.92	0.20	0.15	-0.66
	(0.27)	(0.16)	(0.38)	(0.11)	(0.06)	(-0.26)
Mkt-Rf	-0.17***	0.19***	-0.36***	-0.34***	-0.11***	0.24***
	(-5.06)	(7.26)	(-9.89)	(-11.72)	(-3.08)	(6.28)
Constant	0.44***	0.30**	0.55***	0.49***	0.52***	0.28
	(2.74)	(2.46)	(3.25)	(3.68)	(3.19)	(1.57)
Observations	608	608	608	608	608	608
R^2	0.073	0.106	0.169	0.209	0.034	0.076

Panel B.

	Equal-Weighted Portfolios					
	RSVOL q5-q1	RH q5-q1	FINRA q5-q1	CAP q1-q5	PRC q1-q5	SD q5-q1
3 EIP1 Event Days	8.21***	4.54***	8.75***	9.03***	8.79***	9.54***
	(4.05)	(3.04)	(3.97)	(5.09)	(4.25)	(4.54)
3 EIP2 Event Days	1.92	2.25	3.23	2.67	3.52*	0.96
	(0.96)	(1.53)	(1.49)	(1.53)	(1.73)	(0.46)
3 EIP3 Event Days	1.04	0.13	1.19	0.71	0.77	0.11
	(0.52)	(0.09)	(0.55)	(0.41)	(0.38)	(0.05)
Mkt-Rf	-0.15***	0.24***	-0.32***	-0.37***	-0.17***	0.19***
	(-4.81)	(10.34)	(-9.51)	(-13.53)	(-5.21)	(5.79)
SMB	0.52***	0.33***	0.36***	0.56***	0.76***	1.09***
	(8.49)	(7.26)	(5.33)	(10.38)	(12.10)	(17.01)
HML	-0.36***	-0.52***	-0.36***	-0.09*	-0.07	-0.28***
	(-5.90)	(-11.57)	(-5.42)	(-1.67)	(-1.08)	(-4.37)
UMD	0.08	-0.10***	0.11**	-0.06	-0.15***	-0.21***
	(1.61)	(-2.90)	(2.08)	(-1.39)	(-3.21)	(-4.36)
Constant	0.37***	0.21**	0.49***	0.45***	0.47***	0.18
	(2.60)	(2.05)	(3.19)	(3.65)	(3.24)	(1.25)
Observations	608	608	608	608	608	608
R^2	0.278	0.363	0.322	0.331	0.250	0.388

Table A6. Long horizon event study. We repeat the analysis in Table 5 Panel A and include two longer event windows, ending 28 and 60 days after the days EIP checks first became investable. Equal-weighted portfolio returns. CAPM betas and alphas estimated using daily returns from February 2019 to 30 days before the event window. Abnormal returns in the event window are cumulated starting with the leftmost date, e.g., the 4/15/2020 return is the cumulative long-short portfolio abnormal return from 4/13/2020 through 4/15/2020. Standard errors calculated under the assumption of serially independent abnormal returns. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

EIP1	[0,+2]	[0,+14]	[0,+28]	[0,+60]
RSVOL q5	5.89%***	14.06%***	19.19%***	36.93%***
RH q5	1.01%	9.23%***	16.45%***	26.34%***
FINRA q5	5.93%***	13.55%***	21.18%***	44.46%***
CAP q1	6.42%***	16.73%***	23.22%***	45.43%***
PRC q1	5.12%***	17.78%***	26.09%***	48.35%***
SD q5	3.30%**	13.64%***	19.62%***	33.95%***
EIP2				
RSVOL q5	2.20%	20.47%***	49.76%***	36.09%***
RH q5	2.51%	13.46%***	28.04%***	18.70%***
FINRA q5	3.42%*	24.40%***	52.08%***	37.45%***
CAP q1	3.21%*	21.07%***	43.17%***	35.10%***
PRC q1	4.04%*	23.90%***	51.61%***	39.01%***
SD q5	1.68%	15.68%***	35.09%***	18.36%*
EIP3				
RSVOL q5	0.05%	-6.06%	-19.72%***	-11.57%
RH q5	-1.07%	-5.29%	-13.97%***	-9.46%
FINRA q5	0.15%	-5.84%	-19.62%***	-12.82%
CAP q1	0.27%	-5.00%	-16.52%***	-12.07%
PRC q1	-0.13%	-6.64%	-20.78%***	-13.41%
SD q5	-0.80%	-7.49%	-23.10%***	-17.22%*