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Short-selling activities in the time of COVID-19

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ABSTRACT

This study examines the daily short-selling activities in the U.S. market during the early 2020 outbreak of the COVID-19 global pandemic. Our findings indicate firms that are more sensitive to the shock (i.e., with high foreign exposure, low financial or operating flexibility, or high supply-chain exposure) were shorted more heavily. Moreover, short-selling activities during the COVID-19 pandemic, blamed for triggering stock market crashes, were primarily concentrated around overpriced stocks. This finding supports the argument that short selling plays a prominent role in improving price discoveries. Our research provides timely empirical evidence supporting the U.S. Securities and Exchange Commission's (SEC) non-intervention approach in banning short selling in the U.S. market.

1. Introduction

How did short sellers behave during the early 2020 market crisis triggered by the COVID-19 pandemic? Typically, short sellers profit from taking shorting positions when anticipating a price decline. The market turmoil resulting from the COVID-19 crisis generated significant trading opportunities for short sellers. However, aggressive short-selling activities may erode investors' confidence and trigger panic sales (Brunnermeier & Oehmke, 2014). Some European countries, such as France, Italy, and Spain implemented temporary bans on short selling in response to the escalation of market volatility following the COVID-19 outbreak. Conversely, the U.S. Securities and Exchange Commission (SEC) did not restrict short-selling activities. Our study examines daily short-selling activities during the market upheaval in early 2020 to provide timely empirical evidence for the debate surrounding the SEC's non-interventionist approach.

Short-selling activities play a controversial role in stock markets. On the one hand, short sellers are recognised as informed investors whose trades promote market liquidity and price efficiency (e.g., Boehmer & Wu, 2013; Curtis & Fargher, 2014; Dixon, 2020). On the other hand, they are often accused of exacerbating market downturns (Boehmer et al., 2013; Savor & Gamboa-Cavazos, 2014) and negatively impacting future stock returns of heavily shorted firms (e.g. Geraci et al., 2018; Purnanandam & Seyhun, 2018). The trade-off between the positive and negative aspects of short selling in financial markets has fuelled an ongoing debate about the necessity of short-selling regulations (Beber & Pagano, 2013; Gao et al., 2020).

Financial regulators faced public pressure to tighten short-selling regulations following the initial market meltdown resulting from the COVID-19 pandemic. However, the effectiveness of short-selling bans in improving the market environment remains unclear. Some evidence suggests that short-selling bans play their intended role in stabilising stock prices (Della Corte et al., 2021; Fohlin et al., 2022). However, others have indicated that short-selling bans impede price discovery and liquidity provisions (Bessler & Vendrasco,

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2022; Lee, 2022). To understand short sellers' behaviour during COVID-19 market crashes, our study seeks to answer two questions. First, did short sellers abnormally target firms that were more vulnerable to the COVID-19 shock in early 2020? Second, whether these short-selling activities were justified? Specifically, did short sellers fulfil their purported role of improving market efficiency by identifying and targeting overpriced stocks during the COVID-19 crisis?

Our study focuses on the period from the beginning of January to the end of April 2020. The sample period includes the main market meltdown in mid-March and subsequent post-crash calming period.¹ We measure short-selling activities using the daily abnormal short-volume ratio, with the an average daily short-volume ratio from 2019 as the benchmark. To gain an overview of short-selling activities from early 2020, we first plot the trend of abnormal short selling across time and industries. We observe that the overall level of short selling was significantly higher throughout the early COVID-19 pandemic period than that in the pre-COVID period. This finding aligns with prior studies that have shown that the COVID-19 pandemic caused systemic shocks in the entire market (Baker et al., 2020; Ramelli & Wagner, 2020). Additionally, we observe that the oil and petroleum, transportation, and mining industries were the three most heavily shorted sectors during this period. This corresponds to the findings of Tashanova et al. (2020), which suggested that industries such as aircraft and transportation services were more severely impacted than healthcare services and online platforms.

To answer the first research question, we used three categories of firm characteristics and Fama and MacBeth's (1973) regression to examine whether short sellers disproportionately targeted certain firm types during the 2020 market crash. Specifically, we consider firms' foreign exposure, financial and operational flexibility, and supply-chain exposure. Our analysis revealed that firms with foreign trade, such as China-related activities and non-U.S. revenue, were more heavily shorted in early 2020. Considering that demand collapse and supply chain disruptions have introduced real difficulties for firms (Hassan et al., 2020), we expect these firms to face greater exposure to COVID-19-related risks, making them more attractive targets for short sellers.

Next, we examine firms deemed more vulnerable to sudden exogenous shocks because of their low financial and operational flexibility. Inflexible firms are sensitive to periods of high uncertainty and volatility. Ramelli and Wagner (2020) and Fahlenbrach et al. (2021) showed that inflexible firms performed poorly following the COVID-19 outbreak. Using cash holdings, leverage ratios, and asset re-deployability as proxies, our results indicated that short sellers recognised these factors and targeted firms that were less financially or operationally flexible during the COVID-19 crisis.

To capture the dynamic changes and magnitude of the COVID-19 market downturns, we followed Ramelli and Wagner (2020) and split our sample period into the following four sub-periods: *Incubation*, *Outbreak*, *Fever*, and *Post-Fever*. We find a significant concentration of short selling during the incubation period of firms that disclosed their activities in China. Short-selling activities were less sensitive to the percentage of a firm's non-U.S. revenue from the same period. Our analysis further reveals that the association between abnormal short selling and firms' exposure to COVID-19 shock was most prominent during the outbreak period.

To further understand firms' exposure to the time-variant changing COVID-19 situation worldwide, we constructed four supply chain exposure proxies following Ding et al. (2021). Particularly, using the weekly growth rate of COVID-19 cases by country, we measured the extent to which each firm was exposed to the impact of COVID-19 in individual countries through its customers or suppliers. We observed that short sellers targeted firms with greater supply chain exposure during early 2020. Moreover, abnormal short selling is sensitive to customer exposure.

These results suggest that short sellers tend to target firms that were particularly vulnerable to the economic impact of the COVID-19 pandemic. Assuming that short sellers acted rationally during the market crash in early 2020, with their trades reflecting firm fundamentals and valuations, we would expect to observe abnormal short selling concentrated around overpriced stocks. To test this overpricing hypothesis, we measured whether a stock price deviates from its fundamental value using the *mispicing score* constructed using 11 return anomalies, following Stambaugh et al. (2015). We control for short- and long-term prior returns to accommodate trend traders (Diether et al., 2009b) and industry effects to account for asymmetrical short-selling spikes in heavily affected industries.

Our analysis revealed that abnormal short selling was concentrated on overpriced stocks during the early COVID-19 pandemic. This relationship remained strong across all subperiods, even during the "outbreak" and "fever" periods. Additionally, our results are robust to alternative regression approaches, and the parameter measurements are not biased towards specific industries (e.g. oil, mining, and financial industries). Furthermore, we found that short sellers continued to target overpriced stocks among heavily shorted firms (i.e. firms with high foreign or supply-chain exposure or poor flexibility). These results suggest that short sellers did not blindly attack firms more vulnerable to the COVID-19 shock. Instead, their actions were primarily driven by stock overpricing. Our results provide novel evidence supporting the positive influence of short selling on price discovery during the COVID-19 market crisis.

Our study contributes to the growing literature on the impact of the COVID-19 pandemic on stock markets and investor behaviour. Most existing studies have focused on stock price reactions to the COVID-19 shock at the market or individual stock levels (e.g., Alfaro et al., 2020; Ding et al., 2021; Gerding et al., 2020; Izzeldin et al., 2021; Ramelli & Wagner, 2020). However, stock trading reactions remain underexplored. Yuan et al. (2022) suggested that the impact of investor behaviour (e.g. attention, sentiment, and fear) on pandemic-driven financial contagions was heterogeneous across market conditions and development levels. Among the few studies on trading responses, Ortman et al. (2020) showed that the average trading intensity among retail investors sharply increased in association with infections. Our study focuses on short sellers and other unique and influential market participants. Trading activities are often negatively perceived by other market participants. Using the daily abnormal short-volume ratio, we examine short sellers' trading behaviour during the 2020 market crashes triggered by the COVID-19 pandemic.

¹ After the large dip on 23 March 2020, the S&P 500 gradually bounced back and remained relatively stable thereafter, even though the COVID-19 infection rate had not yet flattened.

To the best of our knowledge, our study is the first to investigate short-selling activities and their association with the level of stock mispricing during the COVID-19 pandemic in the U.S. stock market. While some contemporary studies also investigate short selling using the exogenous COVID-19 shock, most focus on assessing the effectiveness of the 2020 European short-selling ban (Della Corte et al., 2021; Ferreruela & Martín, 2022; Fohlin et al., 2022; Siciliano & Ventoruzzo, 2020). Greppmair et al. (2020) specifically explored short-sale activities, but they examined firms in the European Union. Contrary to our study, which primarily focuses on the role of short sellers in the price-discovery process during market crises, Greppmair et al. (2020) focused on how the fiscal capacity of local governments affects short-selling behaviour. Our results provide timely empirical evidence about the SEC's decision regarding whether to implement short-selling constraints during the 2020 pandemic period.

Our study contributes to the literature by examining the controversial functions of short sellers in stock markets. On the one hand, empirical evidence supports the positive role of short sellers in the price discovery process (e.g., Boehmer & Wu, 2013; Christophe et al., 2004; Curtis & Fargher, 2014; Diether et al., 2009a). The effectiveness of short-sale bans or constraints has also been critiqued (e.g., Autore et al., 2011; Beber & Pagano, 2013; Boehmer et al., 2013; Boulton & Braga-Alves, 2010; Bris et al., 2007; Dixon, 2020; Frino et al., 2011; Saffi & Sigurdsson, 2011). On the other hand, the voice of blame that opposes short selling and supports short-selling bans is rooted in theoretical models (e.g., Gao et al., 2020). The negative role that short sellers play in the deterioration of price declines has also been demonstrated by previous empirical studies (e.g., Kot, 2007; Lamont & Stein, 2004; Savor & Gamboa-Cavazos, 2014). Our study offers insights into how short sellers behaved when firms were vulnerable to the shock of the COVID-19 pandemic. Specifically, we explored whether short selling continued to serve the intended price discovery function when market crashes and opportunities for manipulative shorting arose.

The remainder of this study is organised as follows. We review the relevant literature, derive the hypotheses in Section 2, and explain our data and variables in Section 3. Sections 4 and 5 present the empirical results. Finally, section 6 concludes the study.

2. Literature review and hypothesis development

Short sellers are generally recognised as better informed and more sophisticated than other market players. The literature has presented mixed evidence on the impact of short selling in recent decades. Some scholars have argued that short selling generally improves market efficiency. For example, short sellers make trading decisions based on sophisticated analyses of public information (Blau et al., 2015; Boehmer & Wu, 2013; Curtis & Fargher, 2014; Dechow et al., 2001; Engelberg et al., 2012). Additionally, short sellers anticipate front-run negative corporate news, such as earnings fraud, analyst recommendation downgrades, and credit rating downgrades, by receiving tips or private information leakages from other informed parties such as insiders and brokers (Christophe et al., 2010; Henry et al., 2015; Karpoff & Lou, 2010).

Others have raised concerns that short sellers may mislead uninformed investors by spreading misinformation and rumours (Allen & Gale, 1992; Brunnermeier & Oehmke, 2014). Although the direct evidence supporting this concern is scarce, Blau and Wade (2012) found that short sellers tend to bet equivalently on equity analyst upgrades and downgrades. Lamont and Stein (2004) also found that short sellers did not fulfil a rational arbitrageur's role and were reluctant to bet against aggregate overpricing during the dot-com bubble period.

Short selling has also been accused of triggering bank failure and worsening the European sovereign debt crisis (Liu, 2015). Rising concerns regarding the role of short selling in destabilising financial markets, particularly during a market decline, have led to government bans on short selling. Gao et al. (2020) developed a theoretical model supporting short-selling bans. Their model suggests that short selling reduces ex-ante firm value, particularly when a firm is vulnerable to panic runs. Various short-selling bans have occasionally been introduced to ease market crash pressures. For example, during the 2007–2009 global financial crisis, the SEC temporarily banned the short selling of 799 financial shares in 2008 to ease the downward pressure created by market profiteers. During the same period, the UK Financial Service Authority (now the Financial Conduct Authority [FCA]) introduced a temporary emergency short-selling ban on UK financial stock.

However, some researchers have criticised short-selling bans. Boehmer et al. (2013) showed that the short-selling ban in 2008 worsened the liquidity provision and quality of the U.S. stock market. Beber and Pagano (2013) provided global evidence suggesting that short-selling bans implemented in various countries during the 2007–2009 financial crisis harmed market liquidity and slowed price discovery. Beber et al. (2021) further found that banned stocks were more likely to experience default and volatility than unbanned stocks during both the subprime and Eurozone crises. Other evidence, such as the SEC's Regulation SHO pilot program from 2005 to 2007 and China's short selling pilot scheme from 2010, have suggested that relaxing restrictions on short-selling constraints improves price efficiency and reduces divergence from fundamental value (e.g., Alexander & Peterson, 2008; Boehmer & Wu, 2013; Chang et al., 2007; Diether et al., 2009a).

The economic crisis triggered by the COVID-19 pandemic was radically different from past financial crises in terms of both the cause and scope (Didier et al., 2021). Unlike the 2008 ban on short selling in the finance sector, there was no easy solution to resolve the problems of a market-wide crisis in 2020. Hence, despite criticism regarding previous short-selling bans or constraints, short sellers

continued to be easily blamed for triggering panic sales during the COVID-19 crisis in 2020. When the markets were hit by the COVID-19 shock, restricting short selling once again became a popular topic for further debate.²

The COVID-19 outbreak has generated massive uncertainty regarding global economic prospects and sent a series of unexpected shockwaves through the financial markets (White & Haghani, 2020). Both aggregate- and firm-level price declines correspond with the predicted infection rates (Alfaro et al., 2020). Market volatility significantly increased (Baker et al., 2020). Moreover, certain industries (e.g. transportation services) and firms with internationally oriented businesses experienced significant shocks because of nationwide stay-at-home orders (Ramelli & Wagner, 2020; Tashanova et al., 2020). Firms with less financial flexibility struggled to perform well (Fahlenbrach et al., 2021). Overall, global economic recession seemed inevitable.³ This grim perspective created a significant temptation for short sellers to target vulnerable firms. Other market participants also began panicking about sales. The daily trading volume and number of shares shorted sharply increased following the outbreak and remained high throughout March and April 2020.⁴ Hence, our first research hypothesis is as follows.

H1. Short sellers abnormally targeted firms that were more vulnerable to the COVID-19 shock in early 2020.

If this pattern is observed, a new round of debate is warranted as to whether short selling should have been restricted or banned during the COVID-19 crisis. The theoretical models proposed by Miller (1997) and Chen et al. (2002) suggest that short-selling constraints impede the incorporation of negative news and delay the correction of overpriced stocks to equilibrium levels. Conversely, Diamond and Verrecchia's (1987) model suggest that market participants incorporate short-sale constraints into their pricing approaches. Hence, reducing the cost of short selling reduces stock price bias.

In response to the pandemic shock, most countries announced a series of interventionist policies to ease economic damage (Gerding et al., 2020). Temporary short-selling bans were globally implemented as an emergency tool during the 2007–2009 financial crisis. They were again imposed to stabilise markets and calm investors in 2020 by security regulators in Europe and Asia, including France, Italy, Spain, South Korea, and Malaysia.⁵

Empirical evidence on the effectiveness of the 2020 short-selling ban is mixed. On the one hand, Fohlin et al. (2022) provided evidence suggesting that although the European short short-selling ban temporarily diminished the liquidity of highly liquid stocks, it calmed stock prices and improved the liquidity of illiquid stocks. Their findings align with those of previous studies that recognise short sellers as informed predatory traders (e.g., Brunnermeier & Oehmke, 2014; Brunnermeier & Pedersen, 2005; Carlin et al., 2007). Thus, short-selling bans can selectively filter out informed predatory traders, thereby improving market quality. Along with Della Corte et al. (2021), Fohlin et al. (2022) further demonstrated that the 2020 European short-selling ban played a role in preventing dramatic price declines.

On the other hand, the 2020 short-selling bans were met with warnings from the World Federation of Exchanges and financial newspapers.⁶ Siciliano and Ventrone (2020) and Ferreruela and Martín (2022) showed that the 2020 European ban performed no differently from the previous bans in undermining price efficiency and hampering market liquidity. Bessler and Vendrasco (2022) found that smaller stock markets and stocks suffered more than their larger counterparts because of the negative impacts of short selling restrictions on market quality. Lee (2022) drew a similar conclusion on the ineffectiveness of such bans based on evidence of underpriced futures contracts on the FTSE MIB and IBEX35 indices.

Unlike some European countries, the SEC did not take any action against short-selling activities in the U.S. market during the 2020 pandemic period. This decision may have been based on the belief that short selling plays a crucial role in the price discovery process, even during market crises. Assuming that short sellers could effectively identify overpriced stocks during a market crash in 2020, we expect the following hypothesis regarding overpricing to hold.

H2. Abnormal short selling concentrated on overpriced stocks during the early COVID-19 crisis period.

² On 23 February 2020, Italy implemented a strict lockdown in the Lombardy region, affecting around 50,000 people. The U.S. stock market experienced dramatic dives from Monday, 24 February 2020, which further triggered four market circuit-breakers in March. The virus continued to spread and soon after, Italy instituted a nation-wide lockdown. The World Health Organization (WHO) declared a global pandemic. Given the highly contagious nature and rapid spread of the COVID-19 disease, the U.S. closed its borders on 11 March 2020, significantly deteriorating global mobility and collaboration.

³ On 14 April 2020, The International Monetary Fund reported that all G7 nations had already entered or were entering a recession. See <https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/>.

⁴ The movement of trading and short-selling volume between January–April 2020 is plotted in Fig. 1.

⁵ In addition to the US SEC, the UK Financial Conduct Authority (FCA) and German Federal Financial Supervisory Authority (BaFin) also avoided adopting any short-selling bans during the COVID-19 period.

⁶ The World Federation of Exchange issued warning statements on 30 March 2020 about the temporary short-selling ban. For details, visit: <https://www.world-exchanges.org/news/articles/world-federation-exchanges-warns-against-short-selling-bans>. In the following opinion piece by Bryan Corbett in the Wall Street Journal, it was suggested that short-selling restrictions would not calm the market: <https://www.wsj.com/articles/restraints-on-short-selling-wouldnt-calm-markets-11584906733>.

3. Data and variables

3.1. Short-selling data

We collected data on daily short-selling transactions from 1 January 2019 to 30 April 2020 from the Financial Industry Regulatory Authority (FINRA) database.⁷ Firms' daily stock prices and financial fundamentals are collected from Compustat Security Daily and Fundamentals Annual, respectively. For this study, we retained the data on all common stocks (CRSP share codes 10 and 11) traded on the NASDAQ and New York Stock Exchange (NYSE). Following prior studies (e.g., D'Avolio, 2002; Stambaugh et al., 2015), we excluded firms with share prices lower than \$5 USD at the end of December 2019 because it is relatively difficult to short sell these firms. To meet the inclusion criteria, all observations in our sample had data to estimate daily stock returns and short-volume ratios. We defined the *short-volume ratio* as the daily raw short volume divided by daily trading volume. To obtain daily stock returns, we adjusted daily stock prices using the daily return and price adjustment factors. For our main analyses we used daily stock data from January to April 2020, along with 2019 data, to construct the benchmark short-volume ratio and other explanatory variables.

To investigate short-selling activities during the COVID-19 outbreak, we used *abnormal short selling* (ABSS) as our primary dependent variable. We defined ABSS as the difference between the daily short-volume ratio (from 1 January 2020 to 30 April 2020) and benchmark short-volume ratio. We used pre-pandemic data and the average daily short-volume ratio over the last four months from 2019 (from 1 September 2019 to 31 December 2019) as our benchmark ratio.⁸ This abnormal short-volume ratio is measured following Christophe et al. (2004) to identify daily abnormal short selling preceding firms' earnings announcements.

Additionally, we removed observations that lacked mispricing proxies and control variables (defined in the following sections). Our final sample consisted of data on 191,914 daily observations and 2382 unique firms from 1 January 2020 to 30 April 2020.⁹

3.2. Explanatory variables

As argued previously, the COVID-19 pandemic created significant uncertainty and caused widespread global damage. Meanwhile, firms experienced the heterogeneous impact of systematic shocks. Therefore, we utilised three categories of firm characteristics to test our first research question, "Whether abnormal short selling was concentrated on firms that were more vulnerable to the pandemic?"

The first set of firm characteristics included exposure to China and foreign revenue. Ramelli and Wagner (2020) showed that firms with an international orientation, especially those with business interests and operations in China, were more affected by the COVID-19 shock. This effect was particularly significant during the incubation period. They argued that US firms with higher exports to or imports from China experienced greater disruptions. Therefore, we expected firms engaged in foreign trade (especially with China) to be more likely to have been targeted by short sellers. To test this, we employed *China (#)* and *China [0/1]* to determine whether a firm has engaged in foreign trade with China. *China (#)* indicates the total number of times China is mentioned in a firm's 10-K related to import (input) or export (output) activities. *China [0/1]* is scored as 1 for firms that openly traded with China and 0 otherwise. Additionally, we employed a more general proxy to capture firms' foreign exposure, *Foreign Revenues*, defined as the percentage of revenue from non-U.S.-based sources.

The second set of firm characteristics involved both financial and operating flexibilities. Previous findings have indicated that financially robust firms outperformed firms with weak financial positions during the pandemic period (Fahlenbrach et al., 2021; Ramelli & Wagner, 2020). Hence, we expected that short sellers were more likely to target them. Accordingly, we employed three proxies (i.e. *Cash Holding*, *Market Leverage*, and *Book Leverage*) to measure firms' financial flexibility and investigated whether short-selling activities were concentrated on financially vulnerable firms.¹⁰ *Cash Holding* was measured as the percentage of cash and short-term investments to total assets. Following Ramelli and Wagner (2020), we defined *Market Leverage* as total debt divided by the market value of assets, and *Book Leverage* as total debt divided by the book value of assets. In addition to financial inflexibility, firms with low operating flexibility are more likely to experience illiquidity risk under uncertain conditions. This is because such firms' investments are less reversible in the face of unexpected shocks (Kim & Kung, 2017). Hence, we expected that firms lacking operating flexibility would have been more vulnerable to the pandemic shock and subsequently more likely to be targeted by short sellers. Following Kim and Kung (2017), we employed *Asset Redeployability* as a proxy for operating inflexibility to explore whether short sellers target these firms.

The third set of firm characteristics involved supply-chain exposure. Ding et al. (2021) found that firms performed poorly because

⁷ To improve market transparency, FINRA publicly released daily short-sale volume data to provide prompt information on short-selling activities, typically within the same trading day. The FINRA data comprehensively covers sample stocks and trading venues, and has been used in empirical research, for example, Jain et al. (2013) and Wang et al. (2020). See <https://www.finra.org/finra-data/short-sale-volume-data/daily-short-sale-volume-files>.

⁸ The short-volume ratio is measured in percentage points. We also consider an alternative 12-month window spanning from 1 January 2019 to 31 December 2019 for the benchmark short-volume ratio. Our results are robust to use this alternative estimation window for the abnormal short-volume ratio.

⁹ The number of observations reported in the subsequent regression analyses is lower because we require lag terms for Newey standard error adjustment of the Fama–MacBeth specification.

¹⁰ We also constructed financial constraint measures, including the KZ, SA, and WW indexes. Similar to Fahlenbrach et al. (2021), we found that these financial constraint variables cannot explain the abnormal short-selling behavior during the pandemic; see results in Appendix C.

of disruptions in sales and production from customers and suppliers in countries severely affected by COVID-19. Hence, we expected firms with high COVID-19-related supply-chain exposure to be more likely to have been targeted by short sellers. Following Ding et al. (2021), we constructed four time-variant *Customer/Supplier* exposure variables to capture the dynamic impact of COVID-19 on global supply chains. *Customer Exposure* is defined as the weighted average of the weekly growth rate of COVID-19 cumulative cases among the countries in which a firm sells its products. *Supplier Exposure* is defined as the weighted average of the weekly growth rate of COVID-19 cumulative cases among the countries in which the firm's suppliers are situated. We further constructed *Customer Exposure (active)* and *Supplier Exposure (active)* using active cases instead of confirmed cases to calculate the growth rate of COVID-19. Appendix A1 provides detailed descriptions of these variables.

Next, we tested our second research question, "Whether short sellers continued to improve price efficiency by targeting overpriced stocks?" Accordingly, we constructed a stock mispricing proxy following Stambaugh et al. (2015). We estimated the *composite mispricing ranking* as a proxy of stock mispricing to examine the sensitivity of short selling to mispricing during the COVID-19 period. Composite ranking was measured as the average percentile ranking of 11 anomaly variables, computed at the most recent fiscal year-end before 2020. The 11 anomalies are net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment-to-assets, financial distress, O-score, momentum, gross profitability premium, and asset returns. We require stocks with non-missing values to estimate at least five anomalies. For anomaly estimation, each anomaly must include at least 30 stocks with no missing values. We then sorted the stocks in our sample into quintiles based on Stambaugh et al.'s (2015) composite ranking (SYR ranking).¹¹ The overpricing (under-pricing) variable was scored 1 if the SYR ranking was in the top (bottom) quintile, and 0 otherwise. See Appendix B for additional details on constructing composite mispricing rankings.

3.3. Control variables

This subsection explains our choice of control variables and their definitions. Following Dechow et al. (2001) and Curtis and Fargher (2014), we controlled for several factors related to short selling in our regression analyses, including firm *Size Rank*, *Institutional Holdings*, and *Dividend Yield*. *Size Rank* is the within-sample decile rank of firm market capitalisation at the end of December 2019. *Institutional Holdings* was calculated as the percentage of outstanding shares held by institutional investors at the end of December 2019. Firm size and institutional holdings were included to control for the supply of shares, which directly affects the number of shares available to be shorted (Nagel, 2005). Institutional holding data were obtained from the Thomson Reuters Institutional Holdings S34 database based on 13-F filings. *Dividend Yield* is defined as total common dividends per share divided by price per share. We included this variable because short sellers must pay dividends using their own capital.

Prior studies documented that short-selling activities were associated with prior stock returns and stock price levels (e.g., Diether et al., 2009b; Christophe et al., 2010; D'Avolio, 2002). Thus, when analysing the variation in short-selling activities, we control for both short- and long-term prior returns and daily stock prices. We used the following three control variables employed by Christophe et al. (2010): *Ln(Daily Price)*, *Excess Returns*, and *Momentum*. *Ln(Daily Price)* refers to the natural logarithm of daily adjusted prices. Daily prices and adjustment factors were obtained from Compustat Security Daily. *Excess Returns* describes the cumulative daily stock returns in excess of the daily market returns over the previous three days. *Momentum* is defined as the sum of the monthly returns between September–December 2019 (measured as a percentage).¹² We also control for illiquidity (*ILLIQ*), based on Amihud (2002), which imposes considerable transaction costs on short selling. Appendix Table A1 summarises all the control variables.

3.4. Summary statistics

Table 1 provides summary statistics for the study's variables. The average daily abnormal short-selling ratio is 0.5%. It substantially varies across the sample firms, ranging from above 3.57% at P75 to 3.45% at P25. This variation persists throughout all four subsample periods. The average abnormal short-selling ratio increases to 0.61% in the outbreak period from 0.07% in the incubation period. The average ratio falls to -0.11% in the fever period (possibly due to a spike in trading volume; see the trend of trading volume in Fig. 1), but bounces back to 1.05% in the post-fever period.

Table 1 also reports the summary statistics for all other variables employed in the analysis. The medians of *Size Rank* and *Momentum* are 7.00 and 10.30, respectively. *China[0,1]* and *Foreign Revenue* have means of 0.42 and 26.45%, respectively, and their distributions are consistent with those of Ramelli and Wagner (2020). Regarding measures of financial flexibility, the mean *cash holding* is 14.90%, compared to 20.32% in Ramelli and Wagner (2020) and 22.4% in Fahlenbrach et al. (2021). In our sample, the means of *market*

¹¹ Stambaugh et al. (2015) explained that, given the elements of investor sentiment regarding the market condition, the composite mispricing ranking reflects the relative mispricing within each cross-section, instead of the absolute mispricing that survives after arbitrage.

¹² For long-run returns captured by the momentum variable, we selected this four-month window because it is the same window that has been used to construct the benchmark short-volume ratio related to the main dependent variable. Using alternative windows for long-run stock returns, such as prior six-month returns or three-month returns, does not alter the interpretation of our results. For short-run returns, alternative measures, such as CAR [-3, -1] or CAR [-5, -1] do not alter our main results. Abnormal returns were calculated as daily excess returns over the risk-free rate, minus the CAPM-expected returns, following the method described in Ramelli and Wagner (2020). The CAPM-expected return was calculated as the product of a given stock's beta (calculated based on 2019 daily returns) and market premium.

Table 1

Summary statistics

This table reports the mean, median, P25, P75, and standard deviation of the dependent and explanatory variables used in this study. Panel A reports the statistics for all variables employed in the analysis based on the whole sample. Panel B reports the statistics of abnormal short selling over the four subperiods: *Incubation* (2 January to 20 January); *Outbreak* (21 January to 23 February); *Fever* (24 February to 20 March); *Post-Fever* (21 March to 30 April). The sample consists of 191,914 firm-day observations (2382 unique firms) of common stock (CRSP share codes 10 and 11) listed on the NASDAQ, NYSE, and AMEX from 1 January 2020 to 30 April 2020 with share prices no less than \$5. *Abnormal Short Selling* is measured as the difference between the daily short-volume ratio (daily shorted shares over the daily trading volume) and the benchmark short-volume ratio estimated over the period from 1 September 2019 to 31 December 2019. See [Appendix A1](#) for the detailed variable definitions.

Panel A: Whole sample						
Variables	N	Mean	P25	Median	P75	S.D.
<i>Daily variables</i>						
Abnormal Short Selling	191,914	0.50	-3.45	-0.27	3.57	6.99
Excess Returns	191,914	-0.29	-3.12	-0.35	2.42	7.15
Ln(Daily Price)	191,914	3.73	2.82	3.70	4.57	1.29
ILLIQ	191,914	2.96	0.02	0.14	0.90	10.86
<i>Firm-level variables</i>						
Size Rank	2382	6.55	5.00	7.00	9.00	2.44
Dividend Yield	2382	1.34	0.00	0.56	2.20	2.06
Institutional Holdings	2382	62.88	50.82	68.86	79.64	24.46
Momentum	2382	12.45	0.78	10.30	19.83	26.81
<i>Firm characteristics</i>						
China [0/1]	1851	0.42	0.00	0.00	1.00	0.49
China (#)	1851	5.27	0.00	0.00	4.00	13.28
Foreign Revenue	1483	26.45	0.00	21.31	45.01	26.43
Cash holding	1984	14.90	2.63	6.68	18.03	19.98
Market leverage	1984	16.45	4.72	11.70	23.59	15.57
Book leverage	1984	24.65	7.93	22.08	37.46	19.06
Asset redeployability	1984	0.45	0.37	0.41	0.53	0.15
<i>Supply-chain exposure</i>						
Customer Exposure	66,191	0.27	0.01	0.04	0.27	0.505
Supplier Exposure	66,191	0.53	0.05	0.31	0.74	0.639
Customer Exposure (active)	66,191	0.27	0.01	0.04	0.26	0.512
Supplier Exposure (active)	66,191	0.53	0.04	0.28	0.72	0.654
Panel B: Abnormal short selling during four periods						
Periods	N	Mean	P25	Median	P75	S.D.
Incubation (2 January to 20 January)	30,000	0.07	-3.62	-0.68	2.86	6.75
Outbreak (21 January to 21 February)	52,824	0.61	-3.45	-0.35	3.56	7.21
Fever (24 February to 20 March)	46,449	-0.11	-3.76	-0.70	2.84	6.70
Post-Fever (21 March to 30 April)	62,641	1.05	-3.09	0.40	4.45	7.09

leverage and *book leverage* also tend to be slightly smaller than those reported by [Ramelli and Wagner \(2020\)](#).¹³

4. Main results

This section addresses our first research question, “Whether short sellers target specific vulnerable firms more heavily?”

4.1. Short-selling activities during the COVID-19 pandemic

First, we analysed the changes in short-selling activities and trading volume across time (1 January 2020–30 April 2020) and industries. To provide further insight into the effect of the pandemic on stock markets, we followed [Ramelli and Wagner \(2020\)](#) and split the first four months of 2020 into the following four periods: *Incubation* (Thursday, 2 January–Monday, 20 January), *Outbreak* (Tuesday, 21 January–Friday, 21 February), *Fever* (Monday, 24 February–Friday, 20 March), and *Post-Fever Periods* (Monday, 23 March–Thursday, 30 April).

[Fig. 1](#) plots the daily volume of shares traded and shorted (bar graph) and daily abnormal short selling (line graph). We observed a significant surge in daily trading volume at the beginning of the fever period, starting on 24 February. Soon, this reached a maximum of approximately 10 billion shares on 20 March. On Monday 23 March, the U.S. Federal Reserve Board announced the following two new facilities in the corporate bond market to provide credit to large corporations: the “Primary Market Corporate Credit Facility” and the “Secondary Market Corporate Credit Facility.” The market slightly calmed as the daily trading volume began to decline in late March. The daily average of short selling followed a similar upward trend as the aggregate trading volume, both prior to and during the fever

¹³ The sample firms (restricted by the coverage of the short selling database) and sample periods are different; the statistics for financial flexibility proxies are not directly comparable.

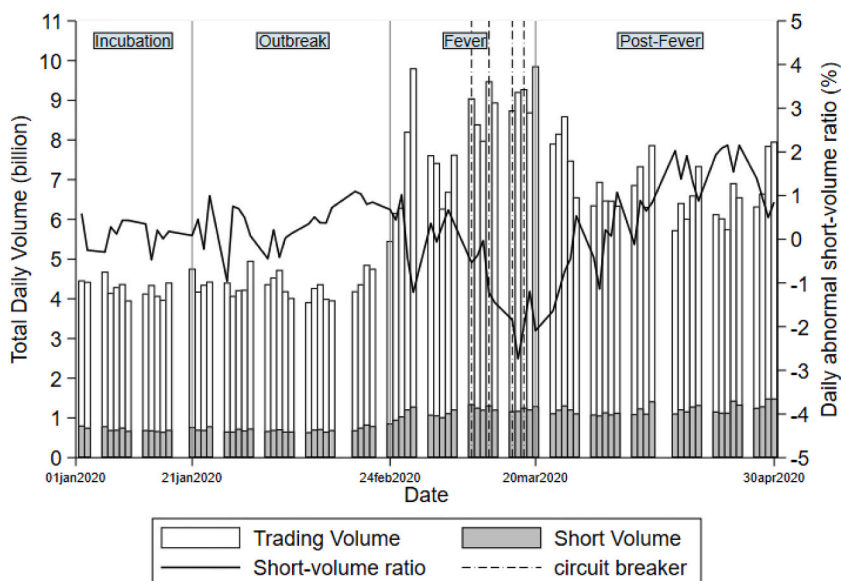


Fig. 1. Daily trading volume and abnormal short selling

This figure shows the daily trading and short-selling volume (bar graph, on the left axis) and the daily abnormal short selling (line graph, on the right axis) from 1 January 2020 to 30 April 2020. The sample consists of 195,719 firm-day observations (2432 unique firms) of common stock (CRSP share codes 10 and 11) listed on the NASDAQ, NYSE, and AMEX with share prices no less than \$5 at the end of December 2019. *Abnormal short selling* is measured as the difference between the daily short-volume ratio (daily shorted shares over the daily trading volume) and the benchmark short-volume ratio estimated over the period from 1 September 2019 to 31 December 2019. The sample period is split into four subperiods: *Incubation* (Thursday 2 January to Monday 20 January), *Outbreak* (Tuesday 21 January to Friday 21 February), *Fever* (Monday 24 February to Friday 20 March), and *Post-Fever* (Monday 23 March to Thursday 30 April). The four vertical dashed lines indicate the dates when the market circuit breaker was triggered: 9 March, 12 March, 16 March and 18 March.

period. However, this trend did not immediately reverse during the Post-fever period.

Daily abnormal short selling (solid black line), measured by the abnormal short-volume ratio, was positive and fluctuated by approximately 1% during the incubation and outbreak periods. While the level of abnormal short selling appears to have decreased during the fever period, the aggregate trading volume doubled. However, the volume of short sales did not decrease. Instead, it continued to significantly increase during the fever period. After the trading volume settled during the post-fever period, the level of abnormal short selling bounced back to the pre-fever level, with the highest point reaching approximately 2%. After late March, the daily short-sale volume did not fall as sharply as the aggregate trading volume. Thereafter, the abnormal short selling remained at a relatively higher level than the pre-fever level.

Fig. 2 depicts short-selling activities across the 17 Fama–French classified industries.¹⁴ During our sample period, the top three most heavily shorted industries by abnormal short-volume ratio were oil and petroleum products, transportation, mining, and minerals. Abnormal trading by short sellers is aligned with negative demand shocks in these industries. The pandemic caused sharp drops in demand for transportation and manufacturing, which subsequently reduced the demand in the oil and mining sectors. Conversely, the utilities, pharmaceutical, and food industries were less affected by the pandemic and subjected to less short selling, as our sample data show. For both the top three most heavily shorted and bottom three least heavily shorted industries, we checked cumulative short selling from 1 January 2020 to 30 April 2020. Panel B of Fig. 2 shows that the differences in abnormal short selling continued to grow, largely driven by increased short selling in the three most affected industries.

4.2. Short selling and pre-2020 firm characteristics

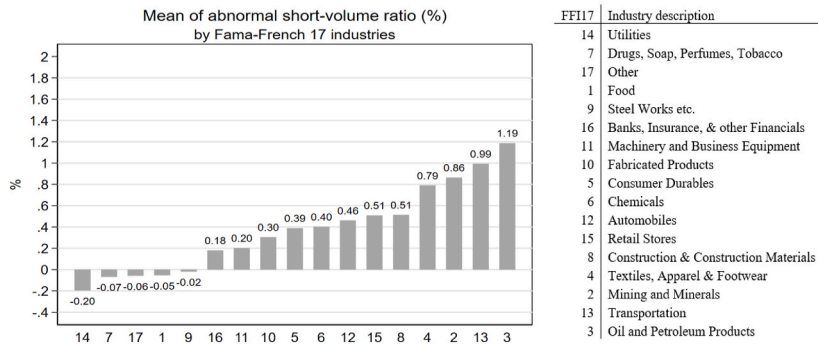
As Section 4.1 shows, short selling abnormally increased in early 2020. In this section, using two types of pre-2020 firm characteristics, we tested whether abnormal short-selling activities concentrated on certain firms that were more sensitive to COVID-19 impacts.

Following the existing literature (e.g., Boehmer et al., 2008; Boehmer & Wu, 2013; Dechow et al., 2001; Engelberg et al., 2012), we used Fama and MacBeth's (1973) two-step approach to estimate the following regression specification:

$$ABSS = \beta_0 + \beta_1 \times Firm_Chars_{pre-2020} + \beta_2 \times Controls + e \quad (1)$$

¹⁴ To evaluate robustness, we also examined the short-selling activities across 30 Fama–French classified industries. The ranking does not change our interpretation. However, we do not use GICS industries, because a large fraction of the firms in our sample have missing GICS codes.

Panel A: Daily abnormal short selling across industries



Panel B: Evolution of cumulative abnormal short selling from 1 January 2020 to 30 April 2020

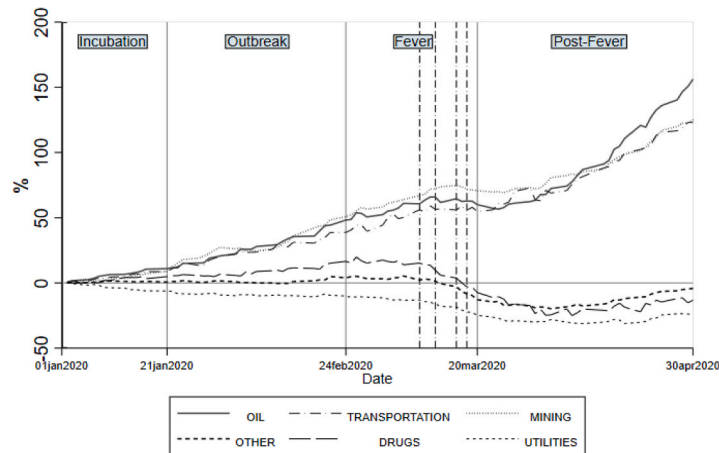


Fig. 2. Short-selling activities across industries

This figure presents short-selling activities across the Fama–French 17 industries. The sample consists of 191,914 firm-day observations (2382 unique firms) of common stock (CRSP share codes 10 and 11) listed on the NASDAQ, NYSE, and AMEX from 1 January 2020 to 30 April 2020 with share prices no less than \$5. *Abnormal Short Selling* is measured as the difference between the daily short-volume ratio (daily shorted shares over the daily trading volume) and the benchmark short-volume ratio estimated over the period from 1 September 2019 to 31 December 2019. Panel A shows the industry average daily abnormal short-volume ratio, ranked by the industry average over the sample period. *Utilities* is the least shorted industry, and *Oil and Petroleum* is the most heavily shorted industry. Panel B presents the evolution of cumulative abnormal short selling for the top three and bottom three industries, ranked by the industry average of abnormal short selling. The four vertical dashed lines indicate the dates when the market circuit breaker was triggered: 9 March, 12 March, 16 March and 18 March.

Panel A: Daily abnormal short selling across industries

Panel B: Evolution of cumulative abnormal short selling from 1 January 2020 to 30 April 2020.

The dependent variable *ABSS* is the daily abnormal short-volume ratio. *Firm_Chars* represents the following seven pre-pandemic firm characteristics estimated at the end of 2019: exposure to China and other foreign global interactions (*China [0,1]*, *China (#)*, and *Foreign Revenues*), and financial and operational flexibility (*Cash Holding*, *Market Leverage*, *Book Leverage*, and *Asset Redeployability*). *Controls* included *Size Rank*, *Dividend Yield*, *Institutional Holdings*, *Excess Returns*, *Momentum*, *Ln (Daily Price)*, and *ILLIQ*, as described in Section 3.3.

In the first stage, we ran daily cross-sectional regressions of short selling on pre-2020 firm characteristics. In the second stage, we estimated the time-series average of the coefficients from the cross-sectional regressions. To correct for potential autocorrelation in the estimated coefficients, we followed [Boehmer et al. \(2008\)](#) and calculated *t*-statistics based on the [Newey–West \(1987\)](#) standard error with five lags. As suggested by [Boehmer and Wu \(2013\)](#), the Fama–MacBeth approach captures the cross-sectional effect of firm characteristics on short-selling activities. Compared with pooled panel regression, this approach is less sensitive to cross-sectional correlations among regression errors.

[Table 2](#) presents the results of the [Fama and MacBeth \(1973\)](#) regressions examining the explanatory function of firms’ foreign exposure to abnormal daily short selling. As discussed earlier, we hypothesised that short selling would be concentrated on firms that are more sensitive to disruptions caused by the COVID-19 pandemic. Overall, the results in Columns (1) and (2) show that, among the firms analysed, those that disclosed their imports, exports, or both to China were shorted more heavily. For example, the coefficient of

Table 2

Short selling and firm foreign exposure

This table reports the results of Fama and MacBeth (1973) regressions examining the relationship between daily abnormal short selling and firms' import/export activities with China and foreign revenue. The dependent variable, *Abnormal Short Selling (ABSS)*, is measured as the difference between the daily short-volume ratio (defined as daily shorted shares normalised by daily trading volume) and the benchmark short-volume ratio calculated over the last four months of 2019. *China (#)* is the total number of times China is mentioned in a firm's 10-K related to importing (input) or exporting (output) activities. *China [0/1]* is equal to 1 if China is mentioned in a firm's 10-K related to importing (input) or exporting (output) activities and 0 otherwise. *Foreign Revenue* is the percentage of non-US revenues. See Appendix A1 for the detailed variable definitions. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

	China (#)	China [0/1]	Foreign Revenue
	(1)	(2)	(3)
Foreign Exposure	0.008*** (4.480)	0.279*** (6.903)	0.005*** (3.731)
Size Rank	-0.012 (-0.205)	-0.019 (-0.318)	-0.025 (-0.433)
Dividend Yield	0.026* (1.783)	0.024* (1.712)	0.036*** (2.829)
Institutional Holdings	0.004** (2.492)	0.004** (2.491)	0.006*** (5.551)
Excess Returns	0.031** (2.465)	0.031** (2.455)	0.027** (2.181)
Momentum	-0.012*** (-8.543)	-0.012*** (-8.611)	-0.006*** (-3.534)
Ln(Daily Price)	0.121 (1.649)	0.118 (1.602)	0.110 (1.629)
ILLIQ	-0.015 (-1.452)	-0.015 (-1.470)	-0.012 (-1.460)
Industry FE	YES	YES	YES
N	150,339	150,339	121,157

Table 3

Short selling and firm flexibility

This table reports the results of Fama and MacBeth (1973) regressions examining the relationship between daily abnormal short selling and firms' financial and operational flexibility. The dependent variable, *Abnormal Short Selling (ABSS)*, is measured as the difference between the daily short-volume ratio (defined as daily shorted shares normalised by daily trading volume) and the benchmark short-volume ratio calculated over the last four months of 2019. *Cash Holding* is defined as the cash and short-term investments divided by total assets. *Market (Book) Leverage* equals book value of total debt divided by market (book) value of total assets, whereas market value of total assets is defined as total assets minus book equity plus the market value of common equity. *Asset Redeployability* is constructed based on Kim and Kung's (2018) redeployability index. See Appendix A1 for the detailed variable definitions. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

	Cash Holding	Market Leverage	Book Leverage	Asset Redeployability
	(1)	(2)	(3)	(4)
Flexibility	-0.015*** (-5.782)	0.022*** (5.510)	0.018*** (5.289)	-1.387*** (-7.290)
Size Rank	0.015 (0.253)	0.010 (0.167)	-0.007 (-0.129)	0.018 (0.306)
Dividend Yield	-0.005 (-0.412)	-0.018 (-1.241)	-0.007 (-0.560)	0.006 (0.444)
Institutional Holdings	0.005*** (3.014)	0.003** (2.062)	0.004** (2.351)	0.005*** (2.990)
Excess Returns	0.033*** (2.846)	0.031*** (2.810)	0.031*** (2.739)	0.030** (2.528)
Momentum	-0.010*** (-6.843)	-0.011*** (-8.196)	-0.011*** (-8.286)	-0.011*** (-8.591)
Ln(Daily Price)	0.035 (0.497)	0.132 (1.638)	0.094 (1.233)	0.064 (0.870)
ILLIQ	-0.018** (-2.032)	-0.018** (-2.059)	-0.018** (-2.054)	-0.017* (-1.952)
Industry FE	YES	YES	YES	YES
N	159,910	159,910	159,910	159,910

China [0/1] indicates that firms involved in China-related import or export activities experienced an approximately 27.9% increase in abnormal short selling. Next, considering *Foreign Revenue*, defined as the percentage of firms' non-US revenues, our findings show that it is positively correlated with abnormal short selling (coefficient = 0.5%). Therefore, firms with 1% more foreign revenue (generated from outside the U.S.) experienced a 0.5% increase in abnormal short selling.

As Table 3 shows, we found a concentration of abnormal short selling among firms with low financial or operational flexibilities. Columns (1) and (2) show that firms with low cash holdings and high leverage ratios were more sensitive to abnormal short selling. For example, firms with a 1% decrease in cash holdings were associated with an approximately 1.5% increase in abnormal short selling. Column (4) shows that firms with low asset redeployability index, indicating low operational flexibility, were targeted more heavily by short sellers. Additionally, we conducted robustness tests to examine the association between short selling and financial constraints using the following different proxies: the KZ, SA, WW, and HR Indexes. However, we found a weak connection between abnormal short selling and financial constraints (Table C1 provides these results). Consistent with Fahlenbrach et al.'s (2021) findings on stock returns, our tests indicated that financial constraint measures had limited explanatory power for abnormal short selling during the pandemic period. Appendix C provides detailed explanations of the financial constraint proxies and regression results.

4.3. The dynamic of short-selling activities across periods

We further ran our regressions based on Equation (1) across the four sub-periods defined in Section 4.1 to explore the time-series variation. As Table 4 shows, except for firms that conducted business with China, abnormal short selling does not significantly affect COVID-19-sensitive or inflexible firms during the incubation period. This is consistent with Ramelli and Wagner (2020), who found that the magnitude of the pandemic's impact on financial markets followed the timeline of the global virus outbreak. In January 2020, when there were few confirmed cases of COVID-19 in the U.S., the markets showed no significant movement. For example, the S&P 500 and NASDAQ Composite continued to climb and closed at record highs on 19 February 2020; however, they started falling soon after.

The results in Panel A of Table 4 show that the concentration of short selling by COVID-19-sensitive firms commenced during the initial outbreak, which is when the number of confirmed cases of the disease was increasing. This short selling concentration spiked during the fever period, when the virus spread widely across the U.S. The significance of the short-selling concentration on firms that disclosed their activities with China or non-U.S. foreign revenues was most evident during the outbreak period. This effect gradually decreased during the fever period. This decline may be because of the efficient control of the disease in China after the 23 January 2020 imposition of the Wuhan lockdown.

Similarly, as shown in Panel B of Table 4, abnormal short selling was primarily concentrated on firms that were financially or

Table 4

Dynamics of short-selling activities

This table reports the results of Fama and MacBeth (1973) regressions examining the relationship between daily abnormal short selling and firm characteristics (foreign exposure, firm flexibility) throughout the four sub-periods: Incubation, Outbreak, Fever and Post-Fever. The dependent variable, *Abnormal Short Selling (ABSS)*, is measured as the difference between the daily short-volume ratio (defined as daily shorted shares normalised by daily trading volume) and the benchmark short-volume ratio calculated over the last four months of 2019. Panel A shows the relationship between daily abnormal short-selling ratio and each foreign exposure proxy (*China (#)*, *China [0/1]* and *foreign revenue*) through the four sub-periods. Panel B reports the association between daily abnormal short-selling ratio and each firm flexibility proxy (*cash holding*, *market leverage*, *book leverage* and *asset redeployability*) across the four periods. All regressions include control variables and the industry dummy fixed effect. See Appendix A1 for the detailed variable definitions. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

Panel A: Firm foreign exposure				
	Incubation	Outbreak	Fever	Post-Fever
	(1)	(2)	(3)	(4)
China (#)	0.012*** (4.253)	0.015*** (11.496)	0.004 (1.724)	0.003 (1.255)
China [0/1]	0.243*** (5.016)	0.396*** (12.226)	0.092*** (3.168)	0.334*** (4.448)
Foreign Revenue	0.003* (2.024)	0.012*** (12.363)	0.003 (1.396)	0.003** (2.076)
Panel B: Firm flexibility				
	Incubation	Outbreak	Fever	Post-Fever
	(1)	(2)	(3)	(4)
Cash Holding	-0.002** (-2.576)	-0.009*** (-3.811)	-0.022*** (-10.592)	-0.021*** (-5.927)
Market Leverage	0.002 (0.580)	0.011*** (5.278)	0.026*** (11.964)	0.039*** (11.208)
Book Leverage	0.001 (0.694)	0.008*** (5.869)	0.020*** (8.367)	0.033*** (15.375)
Asset Redeployability	-0.982* (-1.886)	-0.988*** (-3.244)	-1.461*** (-4.855)	-1.866*** (-5.560)

operationally inflexible at the outset. The concentration significantly increased during the fever period. For example, the estimated coefficients of the financial flexibility variables (cash holdings and market and book leverage ratios) almost doubled during the fever period (Column 3), compared to the outbreak period (Column 2). Firms with low levels of asset redeployability were also heavily targeted after the Outbreak period. Overall, short-selling activities reached abnormal levels following the outbreak of COVID-19.

4.4. Short selling and global supply-chain exposure to COVID-19 impacts

To further understand the dynamic impacts of the COVID-19 pandemic on short-selling behaviour, we used a set of weekly supply-chain exposures. We tracked the number of COVID-19 cases in the countries in which firms' customers or suppliers were located. The estimated supply-chain exposure enabled us to capture how the weekly changes in firms' exposure to the effects of the pandemic through their global supply chains impacted short-selling activities.

We employed the [Fama and MacBeth \(1973\)](#) approach to estimate the following regression:

$$ABSS = \beta_0 + \beta_1 \times \text{Supply Chain Exposures}_{\text{lag 1 week}} + \beta_2 \times \text{Controls} + \varepsilon \quad (2)$$

where *Supply Chain Exposures*_{lag 1 week} represents the following four dynamic supply-chain exposures: *Customer Exposure*, *Supplier Exposure*, *Customer Exposure (active)*, and *Supplier Exposure (active)*. We measured the supply-chain exposure variables for each firm and week and ensured that they always lag ABSS by one week in the regression.

Customer Exposure measures the extent to which a firm was exposed to COVID-19 impacts in foreign countries through its customers. This was calculated using the weighted average of the confirmed COVID-19 cases among the countries in which the firms sold their products. The weights were measured as the proportion of a firm's pre-pandemic revenue in a given country. *Supplier Exposure* measures the extent to which a firm was exposed to COVID-19 impacts in foreign countries through its suppliers. *Supplier Exposure* is calculated using the weighted average of confirmed COVID-19 cases among the countries in which a firm's suppliers were situated. The weights denote the number of pre-pandemic suppliers in a given country, expressed as a fraction of the firm's total number of suppliers. COVID-19 is defined as the weekly growth rate of the number of confirmed COVID-19 cases in an economy. *Customer Exposure (active)* and *Supplier Exposure (active)* are similarly defined and active COVID-19 cases are used instead of confirmed cases.

The regression results are presented in [Table 5](#). All four supply-chain exposure variables are positively significant. These positive coefficients suggest that firms with greater exposure to the supply-chain network (via either customers or suppliers) were heavily shorted by short sellers during the early 2020 COVID-19 outbreak. For example, a 1% increase in customer (supplier) exposure led to a 0.233% (0.166%) increase in abnormal short selling. The coefficients of *Customer Exposure* and *Supplier Exposure* indicate that

Table 5

Short selling and supply-chain exposure

This table reports the results of [Fama and MacBeth \(1973\)](#) regressions examining the relationship between daily abnormal short selling and one-week lagged supply-chain exposure. The dependent variable, *Abnormal Short Selling (ABSS)*, is measured as the difference between the daily short-volume ratio (defined as daily shorted shares normalised by daily trading volume) and the benchmark short-volume ratio calculated over the last four months of 2019. Customers/Suppliers exposures are defined by following [Ding et al. \(2021\)](#). *Customer Exposure (active)* measures the extent to which a firm is exposed to COVID-19 in countries through its customers using weighted average of confirmed (active) COVID-19 cases among countries in which the firm sells its products, where the weights are the proportion of the firm's pre-pandemic revenues in a country. *Supplier Exposure (active)* measures the extent to which a firm is exposed to COVID-19 in countries through its suppliers using weighted average of confirmed (active) COVID-19 cases among countries in which the firm's suppliers are situated, where the weights are the number of a firm's pre-pandemic suppliers from a country as a fraction of the firm's total number of suppliers. See [Appendix A1](#) for the detailed variable definitions. The *t*-statistics reported in parentheses are calculated using the [Newey–West \(1987\)](#) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

	Customer Exposure	Supplier Exposure	Customer Exposure (active)	Supplier Exposure (active)
	(1)	(2)	(3)	(4)
Supply-chain Exposure	0.233*** (2.735)	0.166*** (2.980)	0.231** (2.632)	0.168*** (2.966)
Size Rank	-0.026 (-0.330)	-0.020 (-0.283)	-0.026 (-0.330)	-0.020 (-0.283)
Dividend Yield	0.015 (1.040)	0.053*** (4.115)	0.015 (1.043)	0.053*** (4.121)
Institutional Holdings	0.001 (0.854)	0.001 (0.871)	0.001 (0.847)	0.001 (0.867)
Excess Returns	0.017 (1.583)	0.019 (1.571)	0.017 (1.584)	0.019 (1.569)
Momentum	-0.011*** (-10.550)	-0.014*** (-10.542)	-0.011*** (-10.554)	-0.014*** (-10.535)
Ln(Daily Price)	0.203*** (2.741)	0.172** (2.030)	0.203*** (2.740)	0.172** (2.030)
ILLIQ	-0.007 (-0.699)	-0.021** (-2.547)	-0.007 (-0.699)	-0.021** (-2.546)
Industry FE	YES	YES	YES	YES
N	107,643	85,885	107,643	85,885

abnormal short selling was more sensitive (by approximately 40%) to customer exposure through the supply chain. Columns (3) and (4) show that using weekly active COVID-19 cases to calculate the weekly growth rate produces similar results.

5. Further analysis

5.1. Are short-selling activities value driven?

Given that short selling was significantly concentrated on firms that were more sensitive to the impact of the COVID-19 outbreak, we asked the follow-up question, “Whether short selling should be banned to reduce the pressure of falling share prices?” To answer this question, it is necessary to recall that the important function of short selling is to facilitate price discovery and improve market efficiency by incorporating negative information into share prices. A practical approach to testing the price discovery function of short selling is to investigate whether abnormal short selling during the pandemic reflected a given company’s fundamental value. Specifically, this involves examining whether short selling is associated with share mispricing.

We employed Fama and MacBeth’s (1973) two-step regression model. Our baseline specifications are as follows:

$$ABSS = \beta_0 + \beta_1 \times \text{Overpriced} + \beta_2 \times \text{Underpriced} + \beta_3 \times \text{Controls} + \varepsilon \quad (3)$$

where *ABSS* denotes the daily abnormal short-selling ratio. *Overpriced* (*Underpriced*) is a dummy variable, *Overpriced_SYY* (*Underpriced_SYY*), taking the value of 1 if the overpricing score of firm *i* is in the top (bottom) quintile, and 0 otherwise. *Controls* consist of *Size Rank*, *Dividend Yield*, *Institutional Holdings*, *Excess Returns*, *Momentum*, *Ln(Daily Price)*, and *ILLIQ*. All regressions include industry fixed-effect dummies.

Table 6 presents the regression results of Equation (3). The estimated coefficient of *Overpriced_SYY* over the entire sample period, demonstrated in Column (1), is positive and statistically significant at the 1% level. This result indicates that stocks that were classified as overpriced based on SYY rankings were approximately 33.1% more heavily targeted by short sellers than underpriced stocks. Intuitively, the underpricing proxy (*Underpriced_SYY*) is statistically insignificant for the entire period. These results suggest that abnormal short selling continued to be driven by fundamentals during the pandemic period because it was mainly concentrated on overpriced shares and did not indicate predatory action in the markets.

Columns (2)–(5) in Table 6 show that valuation-based short selling behaviour holds across all sub-periods. The coefficients of *Overpriced_SYY* are positive and statistically significant across all the models. For example, during the incubation period, when the severity of the pandemic was not yet apparent in the U.S., overpriced shares were subject to a higher level of abnormal short selling, averaging at 0.39% for *Overpriced_SYY*. We found more positive links between share overpricing and abnormal short selling during the fever period, when markets experienced significant crashes and sharp increases in trading volumes. Overall, our findings support the view that share misvaluation was the primary influencing factor for short-selling activities initiated during the COVID-19 pandemic.

5.2. Robustness checks

We performed several robustness tests using pooled OLS regressions and alternative measures of abnormal short selling, excluding certain industries. Table 7 presents the results of the study.

First, instead of using Fama–MacBeth regressions, we conducted pooled OLS regressions with industry and date fixed effects, clustered at the firm or the firm and date levels. The results presented in Panel A of Column (1) alleviate the concern that our results may be sensitive to the choice of the regression model. The coefficients of *Overpriced_SYY* and *Underpriced_SYY* are qualitatively similar to those given in Table 6. We also considered the effect of adjusting the standard error using clustering. When the regressions are clustered by firm and date in Column (3), *Overpriced_SYY* remains positively significant at the 5% level.

Second, we used a lag length of 20 days, instead of five for the Newey–West standard error adjustment to account for a possibly higher level of autocorrelation in the daily short-volume ratio. The significance of the coefficient estimates of *Overpriced_SYY* remains unchanged, as shown in Column (1) of Panel B. We used *ABSS* (*12m benchmark*) and raw short-volume ratio as alternative measures of short selling. The former is defined as the difference between the daily short volume and firms’ average 12-month short-volume ratio, calculated using data from 1 January 2019 to 31 December 2019. The results in Columns (2) and (3) of Panel B confirm that our results are unaffected by the use of alternative short selling measures.

A final concern is that abnormal short selling might have been primarily driven by firms in certain industries. Thus, we examined the relationship between abnormal short selling and overpricing/underpricing in the sample, excluding firms in the oil and petroleum, mining and minerals, and financial industries. As shown in Panel C of Table 7, *Overpriced_SYY* is positively significant across all columns. This suggests that our established positive relationship is robust to the exclusion of specific industries.

Table 6

Short selling and stock mispricing

This table reports the results of Fama and MacBeth (1973) regressions examining the relationship between daily abnormal short selling and stock mispricing throughout the whole sample period and the four sub-periods: Incubation, Outbreak, Fever and Post-Fever. The dependent variable is *Daily Abnormal Short Selling*, measured as the difference between the daily short-volume ratio (defined as daily shorted shares normalised by daily trading volume) and the benchmark short-volume ratio calculated over the last four months of 2019. *Overpriced_SYY* (*Underpriced_SYY*) equals 1 if a firm's SYY composite mispricing ranking is in the top (bottom) quintile and 0 otherwise. See Appendix B for details about the construction of the composite mispricing ranking. All other variables are defined in Appendix A1. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

	Whole	Incubation	Outbreak	Fever	Post-Fever
	(1)	(2)	(3)	(4)	(5)
Overpriced_SYY	0.331*** (5.756)	0.387*** (6.482)	0.225* (1.821)	0.267** (2.270)	0.442*** (7.043)
Underpriced_SYY	-0.076 (-0.881)	-0.429*** (-5.804)	-0.027 (-0.258)	-0.304*** (-3.535)	0.222** (2.064)
Size Rank	0.038 (0.649)	0.066*** (4.639)	-0.051 (-0.688)	-0.156 (-1.512)	0.245*** (4.409)
Dividend Yield	0.025** (2.527)	0.064*** (3.389)	0.044*** (4.273)	-0.032*** (-3.803)	0.032*** (3.475)
Institutional Holdings	0.002* (1.906)	0.005*** (5.279)	-0.001 (-0.453)	0.004* (2.022)	0.003** (2.285)
Excess Returns	0.027** (2.357)	0.082*** (6.744)	0.038*** (8.655)	-0.026*** (-3.531)	0.031 (1.453)
Momentum	-0.011*** (-11.646)	-0.011*** (-13.604)	-0.012*** (-8.903)	-0.015*** (-11.111)	-0.008*** (-6.738)
Ln(Daily Price)	0.082 (1.114)	-0.134 (-1.426)	-0.093 (-0.852)	0.417*** (11.107)	0.088 (1.088)
ILLIQ	-0.011 (-1.547)	-0.022** (-2.515)	-0.024** (-2.508)	-0.033*** (-3.979)	0.020** (2.096)
Industry FE	YES	YES	YES	YES	YES
N	191,914	30,000	52,824	46,449	62,641

In addition to the aforementioned tests, we also employed the CAPM *alpha* and *composite alpha*, following Han et al., 2022, as alternative proxies for mispricing. Using these alternative proxies does not change our conclusion regarding the relationship between short selling and share mispricing. The results are reported in Appendix D.

5.3. Did short-selling activities remain value-driven for COVID-19-sensitive firms?

The results in Sections 5.1 and 5.2 present robust evidence that short-selling activities in early 2020 were mostly value-driven. As shown above, abnormal short-selling activities tended to concentrate on COVID-19-sensitive firms, that is, firms that were more exposed to international businesses and supply chains and were less financially or operationally flexible. Thus, short sellers may have attacked such vulnerable firms and paid less attention to mispricing when shorting them. In this subsection, we further investigate whether short-selling activities remained value-driven for firms that are more vulnerable to short-selling pressures.

To better understand whether valuation-based shorting behaviours held for COVID-19-sensitive firms, we conduct two sets of tests. First, we run a Fama–MacBeth regression analysis based on Equation (3) with additional controls for the COVID-19 exposure factors (i. e. foreign exposure, firm flexibility, and supply chain exposure) as follows:

$$ABSS = \beta_0 + \beta_1 \times Exposure + \beta_2 \times Overpriced + \beta_3 \times Underpriced + \beta_4 \times Controls + \varepsilon_t \quad (4)$$

Panel A of Table 8 shows that, after controlling for *China* (#), *China* [0/1], and *foreign revenues*, the positive relationship continues between abnormal short selling and mispricing level continues to hold (proxied by *Overpriced_SYY*). For example, overpriced stocks experienced around 28% increase in abnormal short selling after controlling for China-related exposures. A similar picture emerges in Panel B of Table 8 after controlling for firms' vulnerability in terms of financial or operating inflexibilities. The coefficients of *Overpriced_SYY* are positively significant regardless of which firm-flexibility proxy is controlled for. This suggests that, despite short selling being associated with the degree of firm flexibility, most short selling activities were driven by stocks' fundamental valuation. Finally, Panel C of Table 8 includes proxies for firms' supply chain exposure. The regression results indicate that both the mispricing

Table 7**Robustness checks**

This table reports the results of robustness tests of the relationship between daily abnormal short selling and stock mispricing. Panel A reports the results of OLS regressions with industry and date fixed effects using robust standard errors (Column 1) and adjusted for clustered standard errors (Columns 2 and 3). Panel B reports the results of Fama-MacBeth regressions using alternative parameters and variables: (1) regress with 20 lags (Column 1), (2) replace the dependent variable with *ABSS (12m benchmark)*, defined as the difference between the daily short-volume and firm average 12-month short-volume ratio calculated over the period from 1 January 2019 to 31 December 2019, and (3) replace the dependent variable with the raw daily short-volume ratio. Panel C reports the results of Fama-MacBeth regressions using subsamples that exclude certain industries: oil and petroleum products (Column 1), mining and minerals (Column 2), and financial firms (Column 3). *Overpriced_SYY (Underpriced_SYY)* equals 1 if a firm's SYY composite mispricing ranking is in the top (bottom) quintile and 0 otherwise. The sample consists of 191,914 firm-day observations (2382 unique firms) of common stock (CRSP share codes 10 and 11) listed on the NASDAQ, NYSE, and AMEX from 2 January 2020 to 30 April 2020 with share prices no less than \$5. See Appendix B for details about the construction of the composite mispricing ranking. All other variables are defined in Appendix A1. The *t*-statistics reported in Columns (3) and (4) parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

Panel A: Panel regressions (OLS)			
	OLS regressions		
	(1)	(2)	(3)
Overpriced_SYY	0.327*** (6.976)	0.327** (2.015)	0.327** (1.995)
Underpriced_SYY	-0.085** (-2.164)	-0.085 (-0.611)	-0.085 (-0.599)
Size Rank	0.043*** (3.771)	0.043 (1.146)	0.043 (0.926)
Dividend Yield	0.024*** (2.856)	0.024 (0.762)	0.024 (0.752)
Institutional Holdings	0.002*** (2.722)	0.002 (0.778)	0.002 (0.775)
Excess Returns	0.012*** (4.410)	0.012*** (3.568)	0.012 (1.334)
Momentum	-0.011*** (-18.455)	-0.011*** (-4.805)	-0.011*** (-4.763)
Ln(Daily Price)	0.041** (2.258)	0.041 (0.641)	0.041 (0.578)
ILLIQ	-0.014*** (-4.051)	-0.014** (-2.377)	-0.014* (-1.944)
Industry FE	YES	YES	YES
Date FE	YES	YES	YES
Cluster SE	NO	Firm	Firm & Date
<i>N</i>	191,914	191,914	191,914
Adjusted <i>R</i> ²	0.025	0.025	0.025
Panel B: Alternative parameters and variables			
	Fama–MacBeth (20 lags)	ABSS (12-month benchmark)	Short-volume ratio
	(1)	(2)	(3)
Overpriced_SYY	0.331*** (6.015)	0.265*** (4.534)	0.882*** (15.021)
Underpriced_SYY	-0.076 (-0.730)	0.105 (1.221)	-0.324*** (-4.024)
Size Rank	0.038 (0.456)	0.078 (1.311)	0.017 (0.293)
Dividend Yield	0.025* (1.854)	0.046*** (4.619)	0.128*** (11.609)
Institutional Holdings	0.002* (1.970)	-0.001 (-0.835)	-0.026*** (-22.215)
Excess Returns	0.027* (1.880)	0.029** (2.402)	0.065*** (4.197)
Momentum	-0.011*** (-9.257)	-0.009*** (-9.238)	-0.001 (-1.237)
Ln(Daily Price)	0.082 (0.729)	0.078 (1.058)	-0.530*** (-6.213)
ILLIQ	-0.011 (-1.234)	0.009 (1.322)	0.073*** (10.403)
Industry FE	YES	YES	YES
<i>N</i>	191914	191914	192662

(continued on next page)

Table 7 (continued)

Panel C: Excluding certain industries			
	Non-oil	Non-mining	Non-Financials
	(1)	(2)	(3)
Panel C: Excluding certain industries			
	Non-oil	Non-mining	Non-Financials
	(1)	(2)	(3)
Overpriced_SYY	0.232*** (4.126)	0.331*** (5.719)	0.389*** (7.353)
Underpriced_SYY	-0.100 (-1.191)	-0.077 (-0.871)	-0.129 (-1.562)
SzRank	0.039 (0.680)	0.034 (0.579)	0.022 (0.362)
Dividend yield (%)	0.028*** (3.002)	0.029*** (3.035)	0.053*** (4.656)
Inst holdings (%)	0.003** (2.261)	0.002* (1.901)	0.000 (0.311)
CAR [-3; -1]	0.031** (2.565)	0.029** (2.408)	0.027** (2.297)
Momentum	-0.011*** (-11.348)	-0.011*** (-11.338)	-0.012*** (-13.472)
Ln(Daily Price)	0.112 (1.480)	0.102 (1.347)	0.130* (1.888)
ILLIQ	-0.010 (-1.261)	-0.011 (-1.459)	-0.006 (-0.902)
Industry FE	YES	YES	YES
N	186537	189839	146756

factors and customer/supplier exposure are positively associated with abnormal short selling; the coefficients are mostly significant at the 1% level.

To extend the aforementioned test, instead of using the full sample, we directly examined the relationship between abnormal short selling and mispricing level for a subsample of highly COVID-sensitive firms. Moreover, we focused on the outbreak and fever periods because they include the most intense short-selling activities.

The results in Panel A of Table 9 show that valuation-based short selling occurred for firms with high foreign exposure risk. For example, Column (2) shows that the average effect of overpricing on abnormal short selling remained positively significant for firms that had disclosed their activities with China. Furthermore, the results in Panel B of Table 9 suggest a consistent positive relationship between abnormal short selling and overpricing for firms that were financially or operationally inflexible. Panel C shows a similar picture, where abnormal short-selling activities remained concentrated on overpriced stocks within a subsample of firms with high supply chain exposure. These findings further support the notion that, even during stock market crashes triggered by the COVID-19 pandemic, short sellers did not blindly target the shares of more vulnerable firms. Instead, most short selling activities were driven by stock mispricing.

Overall, the empirical evidence reported in Section 5 suggests that short sellers fulfilled the price discovery function during the COVID-19 pandemic. Short selling activities remained value-driven even for COVID-19-sensitive firms. Our findings support the argument that short sellers function as informed investors during periods of extreme market uncertainty.

6. Conclusion

Our study investigates daily short-selling activity in the U.S. market and its role in the price discovery process during the early COVID-19 pandemic. We found that certain types of firms—those with high foreign exposure, low financial or operating flexibility, and high supply chain exposure—were more likely to have been targeted by short sellers during the global health crisis. These results are consistent with contemporary COVID-19-related studies, which found that the pandemic has had heterogeneous effects on firms.

We further found that abnormal short selling was more concentrated on overpriced shares during the first four months of the COVID-19 pandemic. This result is not sensitive to the choice of the regression models, sample constraints, or mispricing measures.

Table 8

Short selling, exposure-related firm characteristics, and stock mispricing

This table reports the results of Fama and MacBeth (1973) regressions examining the sensitivity of daily abnormal short selling to stock mispricing and one of the three exposure-related firm characteristics: foreign exposure (Panel A), firm flexibility (Panel B), and supply-chain exposure (Panel C). The dependent variable is *Abnormal Short Selling*. Foreign exposure includes *China (#)*, *China [0/1]*, and *Foreign Revenue*. Firm flexibility includes *Cash Holding*, *Market Leverage*, *Book Leverage*, and *Asset Redeployability*. Supply-chain exposure includes *Customer Exposure* and *Supplier Exposure*, which are defined by following Ding et al. (2021). *Overpriced_SYY* (*Underpriced_SYY*) equals 1 if a firm's SYY composite mispricing ranking is in the top (bottom) quintile and 0 otherwise. See Appendix B for details about the construction of the composite mispricing ranking. All variables are defined in Appendix A1. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

Panel A. Firm foreign exposure				
	<u>China (#)</u>	<u>China [0/1]</u>	<u>Foreign Revenue</u>	
	(1)	(2)	(3)	
Foreign Exposure	0.008*** (4.565)	0.294*** (7.754)	0.006*** (4.086)	
Overpriced_SYY	0.270*** (4.910)	0.280*** (5.058)	0.622*** (10.538)	
Underpriced_SYY	-0.024 (-0.290)	-0.042 (-0.513)	-0.056 (-0.657)	
Industry FE	YES	YES	YES	
<i>N</i>	150,339	150,339	121,157	
Panel B. Firm flexibility				
	<u>Cash Holding</u>	<u>Market Leverage</u>	<u>Book Leverage</u>	<u>Asset Redeployability</u>
	(1)	(2)	(3)	(4)
Flexibility	-0.015*** (-5.516)	0.022*** (5.029)	0.018*** (4.755)	-1.382*** (-7.413)
Overpriced_SYY	0.324*** (4.205)	0.167*** (2.880)	0.169*** (2.870)	0.263*** (3.764)
Underpriced_SYY	-0.013 (-0.150)	0.046 (0.455)	0.056 (0.533)	-0.112 (-1.409)
Industry FE	YES	YES	YES	YES
<i>N</i>	159,910	159,910	159,910	159,910
Panel C. Supply-chain exposure				
	<u>Customer Exposure</u>	<u>Supplier Exposure</u>	<u>Customer Exposure (active)</u>	<u>Supplier Exposure (active)</u>
	(1)	(2)	(3)	(4)
Supply-chain Exposure	0.211** (2.592)	0.162*** (2.829)	0.208** (2.463)	0.162*** (2.805)
Overpriced_SYY	0.248*** (3.606)	0.309*** (4.533)	0.249*** (3.615)	0.309*** (4.535)
Underpriced_SYY	-0.071 (-1.066)	0.121 (1.348)	-0.071 (-1.067)	0.120 (1.342)
Size Rank	-0.020 (-0.253)	-0.016 (-0.231)	-0.020 (-0.253)	-0.016 (-0.231)
Industry FE	YES	YES	YES	YES
<i>N</i>	107,643	85,885	107,643	85,885

Although COVID-19-sensitive firms seem to have been more vulnerable to short-selling pressure, short selling among these firms remained value-driven.

Overall, our findings suggest that banning short selling during the pandemic may not have been necessary. Short sellers are sophisticated traders who engage in value-based activities. Targeting overpriced stocks and short selling helps correct market mispricing. Therefore, restricting short selling activities in the wake of COVID-19 might have been short-sighted because such constraints limited

Table 9

Short selling among firms with high exposure during the Outbreak and Fever

This table reports the results of Fama and MacBeth (1973) regressions examining the relationship between daily abnormal short selling and stock mispricing during the Outbreak and Fever periods for subsamples of firms with high foreign exposure, low flexibility, or high supply-chain exposure. The dependent variable is *Daily abnormal short selling*. The median values of foreign exposure proxies (*China (#)*, *China [0/1]*, *Foreign Revenue*), firm flexibility (*Cash Holding*, *Market Leverage*, *Book Leverage*, *Asset Redeployability*), and supply-chain exposure (*Customer Exposure*, *Supplier Exposure*, *Customer Exposure (active)*, *Supplier Exposure (active)*) are used to classify high COVID-19 exposure, respectively. *Overpriced_SYY* (*Underpriced_SYY*) equals 1 if a firm's SYY composite mispricing ranking is in the top (bottom) quintile and 0 otherwise. See Appendix B for details about the construction of the composite mispricing ranking. All variables are defined in Appendix A1. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

Panel A. Firm foreign exposure				
	<u>High China (#)</u>	<u>High China [0/1]</u>	<u>High Foreign Revenue</u>	
	(1)	(2)	(3)	
Overpriced_SYY	0.399*** (4.016)	0.328*** (2.942)	0.514*** (5.969)	
Underpriced_SYY	-0.343** (-2.568)	-0.120 (-0.755)	0.017 (0.122)	
Industry FE	YES	YES	YES	
N	39,115	33,205	31,890	
Panel B. Firm flexibility				
	<u>Low Cash Holding</u>	<u>High Market Leverage</u>	<u>High Book Leverage</u>	<u>Low Asset Redeployability</u>
	(1)	(2)	(3)	(4)
Overpriced_SYY	0.286** (2.170)	0.432*** (4.776)	0.541*** (6.666)	1.074*** (6.931)
Underpriced_SYY	-0.260* (-1.794)	-0.181 (-1.153)	-0.085 (-0.543)	-0.103 (-0.830)
Industry FE	YES	YES	YES	YES
N	48,665	49,033	49,256	36,503
Panel C. Supply-chain exposure				
	<u>High Customer Exposure</u>	<u>High Supplier Exposure</u>	<u>High Customer Exposure (active)</u>	<u>High Supplier Exposure (active)</u>
	(1)	(2)	(3)	
Overpriced_SYY	0.301** (2.261)	0.313** (2.428)	0.305** (2.370)	
Underpriced_SYY	-0.061 (-0.753)	0.033 (0.234)	-0.066 (-0.759)	
Industry FE	YES	YES	YES	
N	40,777	33,615	40,799	

market liquidity and slowed the incorporation of negative information, potentially creating barriers to price discovery.

Declaration of competing interest

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

Data availability

Data derived from public domain resources and subscribed database. Detailed information about the data resources is included in the paper.

Appendix A. Variable definitions and descriptive statistics

Table A1
Variable definitions

Variables	Definitions
<i>Main variables</i>	
Abnormal Short Selling	The excess of the daily short-volume ratio over a firm's average daily short-volume ratio from 1 September 2019–31 December 2019, measured as a percentage. (Source: Reg SHO & Compustat Security Daily)
<i>Explanatory variables</i>	
Size Rank	The rank of all firms in our sample based on the natural logarithm of firms' market capitalisation ($csho \times prcc.c$) at the end of December 2019. (Source: CRSP)
Dividend Yield	Dividend per share divided by price per share ($dvspx.c/prcc.c$), measured in percentage. (Source: Compustat Annual)
Institutional Holdings	Total institutional holdings of a firm at the preceding quarter divided by total share outstanding, measured in percentage. (Source: Thomson Reuters Institutional Holdings)
Excess Returns	Cumulative daily returns in excess of the market returns over the preceding three days, measured in percentage. (Source: Compustat Security Daily)
Momentum	Sum of monthly returns from September 2019–December 2019, measured as a percentage. (Source: Compustat Security Daily)
Ln (Daily Price)	Natural logarithm of the daily stock price (Source: Compustat Security Daily).
ILLIQ	Daily illiquidity is equal to absolute daily returns divided by dollar trading volume, winsorised at the 1% and 99% levels. (Source: CRSP Daily)
<i>Firm characteristics</i>	
China (#)	The total number of times China is mentioned in a firm's 10-K in relation to import (input) or export (output) activities. (Source: Hoberg and Moon text-based offshoring network data)
China [0/1]	A dummy variable that is scored at 1 for firms that had disclosed activities with China, via import, export, or both (Source: Hoberg and Moon text-based offshoring network data).
Foreign Revenue	A firm's percentage of revenue from non-US sources. (Source: Compustat Segments database)
Cash Holding	Cash and short-term investments divided by total assets (che/at), measured as a percentage. (Source: Compustat Annual)
Market Leverage	Book value of total debt ($dltt + dlc$) divided by market value of total assets, measured as a percentage. The market value of total assets is defined as total assets minus book equity plus the market value of common equity ($at - ceq + csho * prcc.c$). (Source: Compustat Annual)
Book Leverage	Book value of total debt ($dltt + dlc$) divided by book value of total assets (at), measured as a percentage. (Source: Compustat Annual)
Asset Redeployability	Based on Kim and Kung's (2018) Redeployability Index, we take the average of the index over 2013, 2014 and 2015, and use the calculated average as a proxy for the Redeployability Index in 2019; the index is time-series invariant. (Source: https://blogs.cornell.edu/hyunseobkim/asset-redeployability/)
<i>Supply-chain exposure</i>	
Customer Exposure	For each firm i and week w , the weighted average of COVID-19 cases among the countries in which the firm sells its products, where the weights are the proportion of the firm's pre-pandemic revenues in a country. COVID-19 is defined as the weekly growth rate of the number of confirmed COVID-19 cases in an economy. For economy c in week t , $COVID-19 = \log(1 + \text{Cumulative Cases in week } w) - \log(1 + \text{Cumulative Cases in week } w-1)$, where Cumulative Cases refers to the cumulative number of confirmed cases in an economy. (Source: Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE), FactSet Revere)
Supplier Exposure	For each firm i in week w , the weighted average of COVID-19 cases among the countries in which the firm's suppliers are situated, where the weights are the number of a firm's pre-pandemic suppliers in a country as a fraction of the firm's total number of suppliers. COVID-19 is defined above and varies weekly. (Source: JHU CSSE, FactSet Revere)
Customer Exposure (Active)	Constructed in similar fashion to Customer Exposure, but uses 'Active COVID-19', defined as the growth rate of the number of active COVID-19 cases in an economy. For economy c in week w , $Active\ COVID-19 = \log(1 + \text{Active Cases in week } w) - \log(1 + \text{Active Cases in week } w-1)$, where Active Cases = Cumulative Cases (the cumulative number of confirmed cases) – Recoveries (the number of recoveries) – Deaths (the number of deaths). (Source: JHU CSSE, FactSet Revere)
Supplier Exposure (Active)	Constructed in similar fashion to Supplier Exposure, but uses Active COVID-19, which is defined above and varies weekly. (Source: JHU CSSE, FactSet Revere)

Appendix B. Mispricing measures from Stambaugh et al. (2015)

The 11 returns anomalies used to construct Stambaugh et al.'s (2015) composite mispricing score have been identified in prior studies. These anomalies include net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment-to-assets, distress, O-score, momentum, gross profitability premium, and return on assets. We then assigned a rank to each stock, to reflect the sorting on a given anomaly variable, with the highest rank assigned to the value of the anomaly variable that is associated with the lowest average abnormal returns as determined in previous studies. The square brackets below show the sign of association between each return anomaly and the composite mispricing ranking. The SYY-mispricing ranking is the average of the percentile rankings on the 11 return anomaly variables computed at the most recent fiscal year-end before 2020 (Compustat), or at the end of December 2019. We followed the detailed description from Stambaugh et al. (2015) and relevant papers on return anomalies, to construct each return anomaly and SYY ranking. All variables were measured at the most recent fiscal year-end before 2020 (Compustat items) or December 2019 (CRSP items). Brief descriptions of each of the 11 return anomalies are shown in the below.

1. *Net Stock Issues*: the annual log change in split-adjusted shares outstanding. Split-adjusted shares equal shares outstanding (*csht*) times the adjustment factor (*adjex_c*). [+]
2. *Composite Equity Issues*: the difference between the growth of firms' total equity market value (12-month growth) and stock rate of return (12-month cumulative stock returns). Data have been obtained from CRSP monthly files. [+]
3. *Accruals*: the annual change in non-cash working capital ($\Delta act - \Delta che - \Delta dlc + \Delta lct + \Delta txp$) minus depreciation and amortization expenses (*dp*), divided by the average of the prior 2-year total assets (*at*). [+]
4. *Net Operating Assets*: operating assets (*at - che*) minus operating liabilities (*at-dlc-dlts-ceq-mib-pstk*), divided by lagged total assets. Items *mib* and *pstk* are set to 0 if missing. [+]
5. *Asset Growth*: the growth rate of total assets in fiscal year 2019 (*at*). [+]
6. *Investment-to-Assets*: the change in gross property, plant, and equipment (*ppegt*), plus changes in inventory (*invnt*), divided by lagged total assets (*at*). [+]
7. *Distress*: the probability of failure is estimated via a dynamic logit model that uses firm accounting measures. These include average net income, total liability, cash, and short-term investments, all scaled by total asset, and firm equity market variables that include stock price, book-to-market, stock volatility (sigma), size relative to the S&P 500, and cumulative excess returns relative to the S&P 500. [+]
8. *O-Score*: the financial distress score is estimated from Ohlson's (1980) model as employed in [Stambaugh et al. \(2015\)](#). [+]

$$O_{score} = -0.407 \times \ln(ra) + 6.03 \times (dlc + dlts) - 1.43 \times \frac{(act - lct)}{at} + 0.076 \times \frac{lct}{act} \\ - 1.72 \times oneeg - 2.37 \times \frac{ni}{at} - 1.83 \times \frac{pi}{dlc + dlts} + 0.285 \times intwo - 0.521 chin - 1.32$$

where *oneeg* is scored 1 if total liabilities (Compustat item *lt*) exceed total assets and 0 otherwise. In addition, *intwo* is set to 1 if net income for the last two fiscal years is negative and 0 otherwise. The definition of *chin* is $\frac{ni_t - ni_{t-1}}{|ni_t| + |ni_{t-1}|}$, and *ni* is the Compustat item *Net Income*.

9. *Momentum*: the momentum measured at the end of December 2019 uses the cumulative returns of the prior 11 months, from January–November 2019. [–]
10. *Gross Profitability Premium*: the difference between total revenue (*revt*) and the cost of goods sold (*cogs*), scaled by total assets (*at*). [–]
11. *Returns on Assets*: constructed using Compustat quarterly data. This variable is defined as income before extraordinary items (Compustat quarterly item *ibq*) divided by lagged total assets (*atq*). [–]

Appendix C. The effect of financial constraints on abnormal short selling

As discussed in the main results, we found that financial-constraint measures have little power to explain the abnormal short-selling activities during the onset of the COVID-19 pandemic. In this section, we explain the proxies for financial constraints and show the estimates of the effect of financial constraints on abnormal short selling. We employed the following four proxies for financial constraints: the [Kaplan and Zingales \(1997\)](#) index (KZ Index), the [Hadlock and Pierce \(2010\)](#) size–age index (SA Index), the [Whited and Wu \(2006\)](#) index (WW Index), and the [Huang and Ritter \(2021\)](#) cash ex-ante measure (HR Index). Firms with higher financial-constraint values than others (based on each of the above proxies) are deemed to be more financially constrained.

KZ Index: We constructed the KZ Index as a proxy for firms' financial constraints following [Lamont et al. \(2001\)](#). We used the latest fiscal-year data from Compustat Annual data and equity market value data from CRSP. Our analysis required that stocks are classified as common stocks (CRSP share code 10 and 11), and that the June and December market values of equity for 2018 and 2019 are available. We also required the following items to be non-zero: total assets (*at*), total debt (*dlts + dlc*), total stockholders' equity (*seq*), and total common equity (*ceq*). Following [Kaplan and Zingales \(1997\)](#), the KZ Index is defined as:

$$KZ_{index} = -1.001909 \times \frac{ib + dp}{L.ppent} + 0.2826389 \times \frac{(at + mve_{December, CRSP} - ceq - txdb)}{at} + 3.139193 \times \frac{dlts + dlc}{dlts + dlc + seq} - 39.3678 \times \frac{dvc + dvp}{L.ppent} \\ - 1.314759 \times \frac{che}{L.ppent}$$

SA Index: [Hadlock and Pierce \(2010\)](#) construct this proxy for firms' financial constraints as follows:

$$SA_{index} = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age$$

where *size* equals the log of inflation-adjusted book assets (2004 value), and *age* represents the number of years a firm has been listed with a non-missing stock price on Compustat. We imposed the same criteria used in [Hadlock and Pierce](#): *Size* is winsorised (i.e., capped) at (the log of) \$4.5 billion, and *Age* is capped at 37 years.

WW Index: [Whited and Wu \(2006\)](#) propose an alternative measure of financial constraints:

$$WW_index = -0.091 \times \frac{ib + dp}{at} - 0.062 \times dvdp[0, 1] + 0.021 \times \frac{dltr}{at} - 0.044 \times \ln(at) + 0.102 \times ISG - 0.035 \times SGL$$

where *SGL* is a firm's sale growth, *ISG* is a firm's three-digit SIC industry sales growth, and *dvdp[0, 1]* is a dividend variable that equals 1 if dividends (*dvc + dp*) are positive and 0 otherwise. We used Compustat Quarterly data, annualised for fiscal year 2019, to construct this variable. Each measure (except *dvdp[0, 1]*) was winsorised at the 5% level to construct the index.

HR Index: Following Huang and Ritter (2021), we constructed the ex-ante cash variable as:

$$HR_index = 2 \times che_{2019} - che_{2018} - (dltris_{2019} - dltr_{2019} + dlcch_{2019}) - (sstk_{2019} - prstkc_{2019})$$

Following Fahlenbrach et al. (2021) for the calculation of the HR cash ex-ante index, we next set missing Compustat variables *sstk*, *prstkc*, *dltris*, and *dltr* to 0, and replaced *dlcch*₂₀₁₉ by *dlc*₂₀₁₉ - *dlc*₂₀₁₈.

We then defined indicator variables for financial constraint based on each of the four financial-constraint (FC) indices. An indicator variable equals 1 if the firm's FC Index is in the top tercile of our sample distribution, and 0 otherwise. As discussed in the main text, the estimates across different measures of financial constraints are inconsistently significant in explaining the abnormal short-selling activities during the early COVID-19 pandemic. These results align with Fahlenbrach et al. (2021), showing that financial flexibility, instead of financial constraint, can explain the abnormal returns during this period.

Table C1

Abnormal short selling and financial constraints

This table reports the results of Fama and MacBeth (1973) regressions examining the relationship between daily abnormal short selling and firm financial constraints. The dependent variable is *Daily Abnormal Short Selling*, measured as the difference between the daily short-volume ratio (defined as daily shorted shares normalised by daily trading volume) and the benchmark short-volume ratio calculated over the last four months of 2019. *Overpriced_SYY* (*Underpriced_SYY*) equals 1 if a firm's SYY composite mispricing ranking is in the top (bottom) quintile and 0 otherwise. See Appendix B for details about the construction of the composite mispricing ranking. All other variables are defined in Appendix A1. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

	KZ Index	SA Index	WW Index	HR Index
	(1)	(2)	(3)	(4)
Financial constraints	0.550*** (5.880)	-0.158** (-2.533)	-0.065 (-0.841)	0.051 (0.756)
Overpriced_SYY	0.354*** (4.831)	0.379*** (5.094)	0.370*** (4.966)	0.374*** (4.976)
Underpriced_SYY	-0.127 (-1.459)	-0.198** (-2.320)	-0.192** (-2.275)	-0.204** (-2.554)
SzRank	0.038 (0.615)	0.038 (0.618)	0.032 (0.510)	0.032 (0.582)
Dividend yield (%)	0.032** (2.253)	0.002 (0.160)	0.003 (0.182)	0.006 (0.378)
Inst holdings (%)	0.002 (1.412)	0.003 (1.648)	0.003* (1.722)	0.003* (1.735)
CAR [-3; -1]	0.026** (2.111)	0.026** (2.115)	0.025** (2.060)	0.025** (2.039)
Momentum	-0.010*** (-7.575)	-0.010*** (-7.365)	-0.010*** (-7.428)	-0.010*** (-7.392)
Ln(Daily Price)	0.109 (1.391)	0.046 (0.587)	0.067 (0.925)	0.071 (0.963)
ILLIQ	-0.019** (-2.306)	-0.019** (-2.332)	-0.018** (-2.299)	-0.019** (-2.339)
Industry FE	YES	YES	YES	YES
N	141,542	141,542	141,542	141,542

Appendix D. Alternative measures of mispricing

We employed alternative measures of mispricing as robustness checks. First, instead of measuring mispricing based on the above 11 anomaly variables, we defined overpricing or under-pricing using the simple CAPM alpha, estimated via the standard CAPM model. CAPM alpha is a commonly used variable in portfolio-allocation decisions (Barber et al., 2016; Berk & van Binsbergen, 2016). Harvey and Liu (2019) argue that the CAPM is by far the most important factor model in explaining cross-sectional stock returns.

Second, instead of using the simple CAPM alpha, we used the *composite alpha* following Han et al. (2022) to define the mispricing. The *composite alpha* was measured as the equal-weighted average alpha of five different asset pricing models: the CAPM model; the Fama–French three-factor model; the Fama–French three factors plus a momentum-factor model; the Fama–French five-factor model;

and Hou et al.'s (2015) q-factor model.¹⁵

We estimated the alpha of individual stock for each asset pricing model at the end of December 2019 with its daily stock returns in 2019.^{§§§§} The CAPM alpha/composite alpha was transformed into a score ranging from 1 to 100. Stocks with a low (high) alpha were defined as overpriced (under-priced), and hence assigned a high (low) score. We then sorted stocks into within-sample quintiles based on their respective alpha overpricing scores. The overpricing (under-pricing) variable equals 1 if the overpricing score of alpha is in the top (bottom) quintile and 0 otherwise.

Table D1

Alternative measures of stock mispricing

This table reports the results of Fama and MacBeth (1973) regressions examining the relationship between daily abnormal short selling and alternative measures of stock mispricing for the sub-sample of firms with high-exposure risk during the Outbreak and Fever periods. The dependent variable is *Daily Abnormal Short Selling*, measured as the difference between the daily short-volume ratio (defined as daily shorted shares normalised by daily trading volume) and the benchmark short-volume ratio calculated over the last four months of 2019. *Overpriced_alpha* (*Underpriced_alpha*) equals 1 if firms' 2019 alpha ranking is in the top (bottom) quintile and 0 otherwise. *Overpriced_alpha5* (*Underpriced_alpha5*) equals one if firms' 2019 composite alpha ranking is in the top (bottom) quintile and zero otherwise. See Appendix A1 for the detailed variable definitions. The *t*-statistics reported in parentheses are calculated using the Newey–West (1987) standard errors with 5 lags. ***, **, * indicates significance at the 1%, 5% and 10% levels, respectively.

Panel A: CAPM alpha					
	Whole	Incubation	Outbreak	Fever	Post-Fever
	(1)	(2)	(3)	(4)	(5)
Overpriced_alpha	0.485*** (9.380)	0.754*** (4.831)	0.518*** (11.214)	0.470*** (4.730)	0.339*** (5.402)
Underpriced_alpha	-0.111 (-1.542)	-0.040 (-0.333)	-0.385*** (-4.210)	-0.149 (-1.458)	0.115 (1.347)
Control variables	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
N	191,914	30,000	52,824	46,449	62,641
Panel B: Composite alpha (5-factor model)					
	Whole	Incubation	Outbreak	Fever	Post-Fever
	(1)	(2)	(3)	(4)	(5)
Overpriced_alpha5	0.326*** (5.116)	0.532** (2.231)	0.431*** (6.349)	0.225* (1.918)	0.211** (2.495)
Underpriced_alpha5	-0.122** (-2.013)	0.030 (0.199)	-0.280*** (-3.910)	-0.232** (-2.400)	0.020 (0.230)
Control variables	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
N	191,914	30,000	52,824	46,449	62,641

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¹⁵ We collect Fama–French factors from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, and the q factors of Hou et al. (2015) from <http://global-q.org/factors.html>.

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