Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
On the importance of fiscal space: Evidence from short sellers during the COVID-19 pandemic

Stefan Greppmair\textsuperscript{a}, Stephan Jank\textsuperscript{a}, Esad Smajbegovic\textsuperscript{b,}\textsuperscript{*}

\textsuperscript{a}Deutsche Bundesbank, Germany

\textsuperscript{b}Erasmus Universiteit Rotterdam, the Netherlands

\textbf{A R T I C L E  I N F O}

Article history:
Received 18 May 2021
Accepted 26 August 2022
Available online 11 September 2022

\textbf{JEL classification:}
G14
G23
H30

\textbf{Keywords:}
COVID-19 pandemic
Short selling
Fiscal space
Institutional investors

\textbf{A B S T R A C T}

Using the exogenous shock of the COVID-19 pandemic, we study how informed market participants incorporate fiscal space into their trading decisions. At the onset of the pandemic, short-selling activity shifted towards companies with low financial flexibility but only in countries with limited fiscal space. Among such companies, short sellers specifically targeted those that generate their revenues mainly in the domestic market. These short sellers entered their positions before the market crash, thereby generating significant abnormal returns. We find no evidence of either herding behavior prior to the market crash or a long-run performance reversal of short sellers. These findings support the notion that short sellers help to promote price efficiency in times of crisis, where governments with budgetary constraints are unable to provide sufficient stimuli to their economies.

\textsuperscript{*} Corresponding author.

\textsuperscript{a}E-mail address: smajbegovic@ese.eur.nl (E. Smajbegovic).

\textsuperscript{b}Ramey (2011, 2019) and Céspedes and Gali, 2013 provide a useful summary of the literature on fiscal policy.

1. Introduction

The relevance of fiscal policy to economic activity has been the subject of long-standing debate among both academics and policymakers (e.g., Aschauer, 1985; Barro, 1990; Blanchard, 1985; Blanchard and Perotti, 2002; Fatás and Mihov, 2003; Gali et al., 2007; Giavazzi and Pagano, 1990; Perotti, 1999).\textsuperscript{1} The global financial crisis, the European sovereign debt crisis, and the low interest rates that have persisted over the past decade have revived discussion on the right timing (e.g., Auerbach and Gorodnichenko, 2012; Jordà and Taylor, 2016) and effectiveness (e.g., Feldstein, 2009; Taylor, 2009; Reinhart and Rogoff, 2010; Herndon et al., 2014) of implementing changes in fiscal policy. More specifically, recent work has recognized that any room for maneuver that governments may enjoy plays a key role in the success of fiscal policies (e.g., Bi, 2012; Leeper and Walker, 2011; Aizenman and Jinjarak, 2010). This fiscal space or, in other words, the “room for undertaking discretionary fiscal policy relative to existing plans without endangering market access and debt sustainability” (IMF, 2018) is crucial in economic downturns (Romer and Romer, 2019).

The aim of our paper is to understand how this room for fiscal maneuver shapes the behavior of financial market participants, and to what extent it affects the cross section of individual firms. Our empirical analysis is based on daily micro-level data for individual stock positions, and takes advantage of the rich heterogeneity among country and firm characteristics. In particular, we study the outbreak of the COVID-19 pandemic and the extensive fiscal countermeasures against economic fallout adopted by different countries, in order to examine how variations in the limits of fiscal space impact the investment behavior of short sellers across stocks. Short sellers are a natural candidate for investigation during the 2020 market crash. Several shorting bans in Europe during this time but also the trading frenzy in several stocks in the U.S. in 2021 (most prominently “GameStop”), have renewed the debate in the popular press regarding the role of short sellers in financial markets.

The COVID-19 pandemic represents an exogenous shock of unprecedented proportions to the world economy. In its June 2020 economic outlook, the OECD estimates that the GDP of mem-
ber states would decline by up to 9.3% during 2020. In order to cushion the economic consequences of the pandemic, many governments have responded with forceful countermeasures on a scale never witnessed before. By September 2020, fiscal actions totaled $11.7 trillion, equivalent to 12% of global GDP (IMF, 2020). Although spending was unequivocally high in most countries, (Augustin et al., 2022) show that the financial markets’ assessment of a country’s fiscal responses depends on the latter’s fiscal space. Countries with limited fiscal space experienced large increases in CDS spreads during the COVID-19 crisis, as excessive spending endangers debt sustainability and a country’s ability to respond to future crises. Thus, narrow fiscal space can limit a country’s resilience to external shocks.

In an effort to understand how fiscal space matters for individual companies, we examine whether and how informed economic agents incorporate this information into asset prices. Our approach to studying investor behavior stems from the vast empirical literature showing that demand curves for individual stocks are downward-sloping and that changes in demand are reflected in asset prices (Shleifer, 1986; Chang et al., 2015). In a demand system asset pricing framework, Kojien and Yogo (2018) find that changes in investors’ latent demand are instrumental in explaining the majority of price variation of individual stocks. We focus on the trading behavior of short sellers, as a specific group of financial market participants, for the following reasons. First, at times of large equity drawdowns, as seen during the COVID-19 pandemic, their negative equity exposure makes this group of investors a natural candidate for investigation. Second, there is overwhelming evidence that short sellers are informed traders. When there is a high level of short-selling activity, future returns are predictably low and prices are more efficient (see, for example, Senchack and Starks, 1993; Asquith et al., 2005; Boehmer et al., 2008; Blau et al., 2011; Blau, 2012; Rapach et al., 2016). Finally, hedge funds, which hold the vast majority of short positions in our sample, appear to be the most elastic institutional investors, and are especially important in determining asset prices (Kojien et al., 2020).

For our analysis we use disclosed short positions from the EU Short Selling Regulation (SSR), which are particularly suitable for the purposes of our analysis. The SSR is implemented equally across all European Union (EU) countries, as well as in Norway and the United Kingdom, giving us comparable data across a wide range of different countries. The scope of the regulation is far-reaching, covering investors’ large short positions in all stocks for which the main trading venue is located in one of the above-listed countries, irrespective of the origin of investors. In contrast to quarterly or monthly records on investor holdings, the data are reported daily in a fine grid of reporting bins. Such granularity is particularly important for studying investor behavior during the pandemic-induced market crash. It allows for an analysis of the precise timing of investors’ positions during a period that witnessed the fastest fall in global stock markets in financial history. The disclosed information also includes the name of the short seller. This data allows us to track individual short positions over time, control for investor unobservables and explore cross-sectional variation at the investor level.

In terms of testing the effect of fiscal space on individual stocks, we use sovereign credit rating as a proxy for the market’s perception of fiscal space. Sovereign credit ratings represent a direct measure of market access and are generally considered to be an important dimension of fiscal space (Kose et al., 2017). As argued by (Augustin et al., 2022), a low credit rating hampers a country’s ability to issue new debt at low cost. Consequently, this limits its fiscal space and, ultimately, its resilience to external shocks.

While differences in fiscal space represent an important indicator of the extent to which a country was able to alleviate the enormous negative shock of COVID-19, individual firms have also varied in their ability to cope with this unprecedented event. Faced with a sudden drop in revenues, otherwise solvent companies had to draw on their short-term liquidity reserves in order to survive. Companies with “deep pockets” have found themselves in a better position to absorb the revenue shock, while those with lower short-term liquidity have run into trouble (Fahlenbrach et al., 2021). We scrutinize this heterogeneity in financial maneuverability to argue that limited fiscal space is particularly detrimental for companies with a low degree of flexibility.

Our main findings reflect this idea and suggest that during the COVID-19 pandemic, short sellers altered their trading behavior in countries with limited fiscal space. More specifically, we find short-selling activity to be focused on illiquid companies headquartered in countries with a low credit rating. To the contrary, illiquid firms in countries with a high credit rating did not experience increased short-selling activity. This finding holds when we control for time-varying stock characteristics associated with short selling, as well as for unobservable time-varying heterogeneity at the country, industry and investor levels. Our evidence is also robust to using different measures of company liquidity buffers, fiscal space, and short-selling proxies.

Consistent with the notion that short sellers are informed investors, we find that they already established their short positions in illiquid companies headquartered in countries with a poor credit rating ahead of the market collapse on February 24, 2020. Hence, they anticipated the importance of fiscal space in supporting vulnerable companies during the COVID-19 crisis, especially in countries facing binding government budget constraints. Also, we observe that they maintained large net short positions in the stocks of illiquid firms in these countries, despite the fact that regulators enforced shorting bans in many of them (i.e. Italy, Spain, Belgium, France, Greece and Austria).

We also capitalize on the disclosed identity of the short sellers on an individual position level and link two investor characteristics to speculations on fiscal space and firm liquidity. First, we study the role of short position substitution of short positions within investors and, second, we link investor types to short selling on the basis of firm illiquidity and country creditworthiness. Our results show that the increased short-selling activity concerning illiquid firms in low-rated countries during the market crash was driven by the same investors who decreased their exposure to less vulnerable, liquid positions. We also find that the increased exposure towards illiquid firms was largely driven by hedge funds.

Additionally, we examine whether the trading behavior of short sellers during the COVID-19 crisis depended on the behavior of other short sellers. More specifically, we test whether a recent disclosure by one short seller makes a new disclosure by another more likely. We show that this type of follow-on behavior was only present once the market had already collapsed. That is, we observe herding in reaction to the market crash. Importantly, we do not observe such follow-on behavior in the weeks prior to the crash when short sellers established their positions. This supports...

---

2 Source: http://www.oecd.org/economic-outlook/june-2020/
3 For further details on this regulation, see Jones et al. (2016); Jank and Smajlbe-govic (2015); Galema and Gerritsen (2019); Jank et al. (2021).

4 De Vito and Gomez (2020) conduct a simulation study demonstrating that firms with limited operating flexibility would run out of cash within the span of two years, and that 10% of firms in their sample would become illiquid within six months. In line with this idea, Ding et al. (2021) and Fahlenbrach et al. (2021) show that companies with small cash holdings experienced a larger drop in stock prices during the COVID-19 crisis.

5 These bans prohibit the opening of new positions and the increase of existing ones.
the conjecture that short sellers’ actions in advance of the market crash reflected informed trading rather than uninformed herding.

An alternative explanation for our main finding could be that short sellers focused on the liquidity buffers of companies located in countries most affected by the COVID-19 pandemic, instead of their fiscal space. Given that some countries with a poor credit rating had been severely affected by the disease, resulting in stricter lockdown measures, this explanation is a plausible alternative to our interpretation. We show, however, that it is not consistent with our evidence. A country’s credit rating remains equally important when we control for the interaction between company liquidity and: (1) the severity of the outbreak (in terms of both new cases and number of deaths); (2) the extent of government measures to limit the spread of the virus; (3) the capacity of a country’s healthcare system.

In addition, we study the trading behavior of short sellers in the context of different fiscal policy approaches. A large proportion of fiscal packages around the world were aimed specifically at stimulating consumer demand for goods and services once local lockdowns were lifted. Any increase in consumption will ultimately translate into increases in production, revenue and earnings, and will indirectly support corporations. In addition to offering consumption stimuli, other fiscal measures were designed to provide immediate support for companies through direct liquidity provision. We distinguish between these two types of fiscal support measures and find that short sellers mainly speculated on the inability of fiscally constrained governments to stimulate local consumption successfully. Short sellers specifically targeted illiquid companies that are headquartered in countries with low credit rating and which generated their revenue by conducting their main activities there. There is no evidence to suggest that short sellers have speculated more on illiquid companies that were less likely to receive direct liquidity provision from their national government.

Finally, we examine whether the incorporation of information on fiscal space by short sellers is reflected in capital markets. If short sellers are indeed smart traders with superior information-processing skills, we expect that their shift towards illiquid firms in countries with a low credit rating is followed by significant returns, in excess of standard asset-pricing factors during the market downturn. Our evidence from portfolio sorts indicates that the portfolio of shorted illiquid companies headquartered in countries with a low credit rating yielded an abnormal return of up to -15% during the market crash, with only a slight reversal back to -10% towards the end of our sample period. In contrast, there is no evidence of significant underperformance associated with liquid firms headquartered in countries with equally low ratings. Similarly, firms based in countries with high credit rating did not show signs of underperformance, irrespective of their level of liquidity. The absence of a reversal and the fact that we do not observe any follow-on behavior prior to market collapse indicate that short sellers did not merely create temporary price pressure with their trading but, instead, their actions helped to incorporate the importance of fiscal space into the prices of vulnerable companies during the initial stages of the pandemic.

1.1. Related literature

Our paper builds on various strands of literature. First, the paper relates to the New Keynesian literature examining the role of fiscal space and sovereign credit risk as central determinants of government spending and aggregate demand (e.g., Bi, 2012; Bianchi et al., 2019; Leeper and Walker, 2011; Aizenman and Jinjarak, 2010). Recent work focuses on the sustainability of government debt after the introduction of unprecedented fiscal stimulus packages in response to the COVID-19 lockdown policies around the globe (e.g., Augustin et al., 2022; Benmelech and Tzur-Ilan, 2020; Casado et al., 2020; Hürten, 2020). Other studies highlight the importance of sovereign debt in explaining equity risk (Gerdig et al., 2020) in the context of the pandemic. We contribute to this literature by examining in detail when and how short sellers, as important informed economic agents, incorporate information on fiscal space into their trading decisions. Our direct micro-level evidence of investor behavior in individual stocks is crucial for gaining a better understanding of fiscal foresight and the flow of aggregate macroeconomic information (Leeper et al., 2013). Instead of concentrating on the effect of fiscal space on aggregate macro-level measures, our paper analyzes how limited fiscal space is reflected in the trading decisions of informed investors and, thus, in the prices of affected firms.

This paper also contributes to the growing literature on the impact of COVID-19 on global financial markets. Confirming the pandemic’s detrimental effect on economic activity, existing studies document strong negative reactions of equity markets to COVID-19, both in terms of stock returns (Ramelli and Wagner, 2020; Alfaro et al., 2020) and macroeconomic or firm-specific growth expectations (Gormsen and Koljen, 2020; Landier and Thesmar, 2020). Some scholars have argued for the heightened importance of cash and short-term liquidity during the pandemic compared to previous crises. Consistent with the notion that investors prefer companies with stable funding and sources of finance, stock market losses have been less dramatic for firms with lower leverage (Ramelli and Wagner, 2020), larger cash holdings (Ding et al., 2021), greater financial flexibility (Fahlenbrach et al., 2021) and better access to credit lines (Acharya and Steffen, 2020). Our work differs from these studies in two respects. First, we do not focus on the market- or firm-side reactions to the pandemic, as measured by realized returns. Instead, we look at the trading behavior of informed economic agents, namely short sellers. By analyzing trading data instead of prices, we are able to document that informed investors traded on the economic consequences of the pandemic even before the COVID-19 shock itself materialized at the market level. Second, the fact that informed investors traded on a combination of the short-term ability of firms to stay liquid and a government’s ability to direct the necessary funds to firms experiencing cash shortfalls not only emphasizes the central role of short-term funding in the context of COVID-19, but also highlights the interplay between the well-being of companies and the fiscal space of governments.

Finally, this paper also relates to the short-selling literature more broadly. Both the ability of short sellers to generate superior performance and the reasons why they are able to do so have been the subject of a considerable number of studies. For example, it has been shown that their informational advantage can stem either from private information (Karpoff and Lou, 2010; Berkman et al., 2017; Boehmer et al., 2020) or from their superior ability to process publicly available information (Engelberg et al., 2012; Chakrabarty and Shilklo, 2013). The literature provides evidence for short sellers’ skills in the context of regular repeated events, such as earning calls, analyst recommendations and merger news. Conversely, in this paper, we study whether short sellers continue to exhibit superior information-processing abilities in an entirely unprecedented situation with no blueprint at hand. Our evidence suggests that, after the outbreak of the pandemic, short sellers correctly anticipated the underperformance of illiquid firms in countries with low credit ratings. This highlights yet another dimension of their skill set: short sellers are also adept at processing complex information about an unprecedented “black swan” event, such

---

6 See, for example, Asquith et al. (2005), Boehme et al. (2006), Cohen et al. (2007), Blau et al. (2008), Dieter et al. (2009), Blau et al. (2011), Blau and Tew (2014), Rapach et al. (2016), and Chague et al. (2019).
as the COVID-19 pandemic, linking the economic consequences of this market-wide shock to company-level characteristics.

The remainder of the paper is organized as follows. Section 2 describes the data sources, defines the variables used in our analysis, and provides descriptive statistics. Section 3 uses a triple-difference approach to argue that the trading behavior of short sellers is based on the liquidity of firms and the creditworthiness of the country in which the latter are headquartered. In Section 4, we study the underlying motives of short sellers’ trading behavior. In Section 5, we examine the trading performance of short sellers. Section 6 presents our conclusions.

2. Data and descriptive statistics

2.1. Data sources and variable construction

Our main data source is based on the disclosure requirement for net short sale positions in the European Union (EU), as laid out in Article 9 of Regulation (EU) No 236/2012. For all stocks for which the principal trading venue is in the EU, investors must disclose any significant net short position, where significant means larger than 0.5% of the market capitalization of the company shorted, on the next trading day. The notification must be updated every time the short position crosses a 0.1% threshold above 0.5% and once the position falls below the 0.5% disclosure threshold.7 The disclosure requirement is obligatory for all investors, irrespective of their origin. Disclosures are standardized across all European countries and contain the name of the investor, the date of the short position, identifying information on the shorted stock, and the magnitude of the position reported as a percentage of the shorted firm’s market capitalization. The regulation applies to short as well as derivative positions, which must be accounted for on a delta-adjusted basis. An investor’s net short position is calculated by netting all long, short, and delta-adjusted derivative positions of the same underlying stock. Exemptions apply to market-making activities for which no disclosure is required. The regulation and relevant data are described in detail in Jones et al. (2016), Jank and Smajilbegovic (2015), and Jank et al. (2021).

The disclosed long short positions have a number of advantages compared to security-level shorting measures, such as the short interest ratio or the utilization of lendable securities. First and foremost, the data allows us to track individual short sellers over time, allowing us to control for investor unobservables and to explore the cross section of short sellers. Furthermore, the disclosed long short positions represent the largest bets of short sellers in the market. In contrast to security-level shorting measures provided by commercial databases, the disclosed short positions exclude hedging purposes and market-making activities.

For our main analyses, we use an indicator variable that takes the value of one if we observe a reported large short position (zero otherwise) on the investor-stock-time level. The size of the reported short positions is left-censored and not ideal for the purpose of our study due to the nature of the disclosure rule. Any interpretation of the value itself might be misleading. For instance, while an increased exposure to certain stocks would be reflected in an increased size of previously established positions, newly established positions that have just crossed the publication threshold (missing value is replaced by a small value just above the threshold) bias the average over all reported positions downwards. Thus, throughout our study, our main dependent variable is the indicator variable that takes a value of one for all investor-stock-days with a reported short position (zero otherwise). In addition to the indicator variable on investor-stock level, we also employ well-known aggregate stock-level short-selling measures as dependent variables in our robustness tests. Analyses using the number of reported short positions per stock, as well as utilization and short interest extracted from a commercial database, corroborate the main findings of our position-level analysis.

We collect data on short position notifications from the web pages of national competent authorities as prescribed by the EU’s Short Selling Regulation.8 Our sample covers 15 countries: thirteen EU countries, the United Kingdom, and Norway, which have also adopted the regulation. The remaining EU member states did not report any notifications in the sample period.9 For an overview of the countries covered, see Table 1 or the map in Fig. OA2 in the Online Appendix. The notification data cover the entry, exit and changes of net short positions above the 0.5% publication threshold. We use this information to construct a daily panel of investors’ open short positions. Our sample period ranges from July 1, 2019 to June 26, 2020.

We merge the position data of short sellers with company characteristics and stock returns from Refinitiv Eikon/Datastream, to which we apply several commonly used data filters to ensure their quality (Ince and Porter, 2006). The inclusion criteria for firms in our analysis were as follows: (1) the headquarters and (2) place of exchange of participating firms must be located in one of the 15 states, listed above. Furthermore, in our analysis, we only consider common equity while excluding penny stocks (stocks with a stock price below $1 at the end of June 2019, i.e. just prior to our sample period). We obtain daily return data of the five Fama and French (2015) factors and the momentum factor for the European market from Kenneth R. French’s data library.10 Examples of studies that use these factors in an international setting include Baltussen et al. (2018), Kou et al. (2018) and Alessi et al. (2021).

Country-level data come from various sources and are described in detail in Table OA1 of the Online Appendix.

In our analysis, we use sovereign credit ratings as a proxy for the market’s perception of fiscal space. Sovereign credit ratings represent a direct measure of market access and are generally considered an important dimension of fiscal space (Kose et al., 2017). A low credit rating curbs a country’s ability to issue new debt at low cost. This limits its fiscal space and resilience to external shocks (Augustin et al., 2022). For our purposes, we define the dummy variable D(Low country rating)) as one if the firm is headquartered in a country with a credit rating below AA- and zero otherwise. In order to categorize countries, we use Standard & Poor’s (S&P) long-term country rating as of the end of December 2019, i.e. prior to the COVID-19 crisis. We use the headquarters country rather than the country of exchange as the relevant country for a firm because we expect that fiscal stimulus packages and liquidity support would emanate from that direction.

We expect insufficient fiscal support to matter most for companies that were heavily affected by the sudden drop in revenues caused by the COVID-19 pandemic. Here, we draw on findings by Fahlenbrach et al. (2021) and Laeven et al. (2020), who argue that liquidity squeezes were the key issue for companies in the initial phase of the pandemic. Companies with “deep pockets” and lower level of short-term obligations were in a better position to absorb the revenue shock, while companies with less short-term liquidity ran into trouble. In order to measure the liquidity buffer of companies, we use the quick ratio, also known as the acid-test ratio. It

7 Jank and Smajilbegovic (2015) provide an example for a course of disclosures of net short positions.

8 The list of competent authorities designated for the purposes of Regulation (EU) No 236/2012 on short selling and certain aspects of credit default swaps is provided in the following document: https://www.esma.europa.eu/sites/default/files/short_selling.pdf

9 The national competent authority of Portugal, CMVM, does not provide an archive of historical positions and is, therefore, excluded from our analysis.

10 https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
is defined as \textit{Current assets less Inventories over Current liabilities}. Current liabilities are a company's debts or obligations that are due within one year. Hence, the quick ratio measures a company's ability to meet its short-term obligations using its most liquid assets, without the need to sell inventory or raise external capital. It is a key ratio in determining the financial health of a company, and is readily available to market participants in standardized reports. As a rule of thumb, a quick ratio above one is considered healthy. There are, however, differences in financing structures across industries that need to be addressed.\footnote{We also use the current ratio, which is defined as \textit{Current assets over Current liabilities}, as an alternative proxy. This ratio, however, is less conservative and, hence, less suitable for the purposes of our study because it includes inventories in the numerator. As converting inventories to cash might have been difficult during the COVID-19 outbreak, the quick ratio is likely to capture the concept of short-term liquidity more effectively than the current ratio during the same time period. Additional tests (compare Table 3 to Table OA.8) show that our results are, as expected, slightly weaker but overall robust to this change in liquidity proxy.}

We obtain information on companies' quick ratio and additional balance sheet characteristics from Eikon. We use information up to the 2018 fiscal year to ensure that it is available to market participants. For a less noisy measurement of a company's underlying liquidity, we use the median value of the quick ratio over the previous three years (fiscal years 2016–2018). We employ the same approach for all other balance sheet variables. Furthermore, we make use of the entire universe of companies from our sample countries to assess the liquidity of the shorted companies. More specifically, we download the list of stocks admitted to trading in our sample countries from ESMA's Financial Instruments Reference Data System (FIRDS) and obtain their balance sheet characteristics. We also require that the companies' headquarters must be located in these countries. Industry classification is a significant determinant of a company's liquidity level (e.g. Harford et al., 2008). In order to control for this component, we compute an industry-adjusted quick ratio by subtracting the industry median from the raw quick ratio.\footnote{We use the industry classification system provided by Refinitiv. The Refinitiv Business Classification (TRBC) is a market-oriented system that tracks the primary business of an organization and reflects global industry practices by grouping together correlated companies and organizations that offer products and services into similar end markets. TRBC is a five-level hierarchical structure consisting of (from top to bottom): 13 Economic Sectors, 32 Business Sectors, 61 Industry Groups, 155 Industries, and 895 Activities. Industries is the level of interest in our study. For information about the TRBC, see \url{https://www.refinitiv.com/en/financial-data/indices/trbc-business-classification}.} Our final variable, Company illiquidity is a percentile rank of firm illiquidity, ranging from zero to one, with zero representing the most liquid firm and one the most illiquid.

2.2. Descriptive statistics

Table 1 reports the time-series average of the total number of reported short positions and their cross-sectional average across different jurisdictions and market phases, for both illiquid (Panel A) and liquid firms (Panel B). The pre-COVID-19 phase begins on July 1, 2019, the start of our sample period, and ends on February 23, 2020; the market crash phase spans from February 24, to March 23, 2020; and the recovery phase dates from March 24, 2020 to the end of the sample. We distinguish between two recovery periods: the first ranges from March 24, to May 17, 2020 and the second from May 18, to June 26, 2020. The period cut-off is based on major market events and announcements: February 24, 2020 represents the first large drop in the European market return (-3.8%) and also in global equity markets, as the coronavirus outbreak had substantially worsened in Europe over the preceding weekend. Over the course of the crash, from February 24, to March 23, 2020, the market declined by more than 35%. On March 24, 2020 the market began to recover with a daily return of 8.4%. The definition of crash and recovery closely follows Ramelli and Wagner (2020).\footnote{Ramelli and Wagner (2020) define the beginning of the crash period as we do. Their recovery period starts with the Federal Reserve Board’s announcement of major interventions in the corporate bond market on March 23, 2020 at 8:00 a.m. EDT. As this falls in the afternoon trading hours for the European markets, our recovery period starts on the next day.} The second recovery period starts with the announcement of a French-German initiative for an EU Recovery Fund on May 18, 2020.\footnote{Official press release: \url{https://www.bundesregierung.de/resource/blob/975226/7373772/4f1a4b5a1ca9f1d4f146ee6b2639e72b/2020-05-18-deutsch-franzoesische-erklarung-eng-data.pdf}}

The development of the European stock market return over the different time periods is shown in Fig. OA.1 in the Online Appendix.

In the pre-COVID-19 phase, the UK was the country with the largest number of reported short positions. It was followed by Germany, France, Sweden and Italy. Prior to the market crash, the daily average total number of all reported short positions across all countries and stocks combined was 1,064. During the crash phase, the aggregate number of positions increased only slightly to 1,101, but there are notable differences when comparing illiquid firms with liquid firms. There was also substantial heterogeneity across countries with respect to the increase in short positions at the onset of the pandemic. While the number of positions in illiquid firms only slightly increased or even decreased in countries such as Denmark, Germany, Sweden and the United Kingdom, there was a more pronounced (relative) increase for such firms in Ireland, Italy, France and Spain.\footnote{It is important to note that the average size of the reported short positions within each country is shown for information purposes only and should not be interpreted in light of our main hypothesis. Any interpretation of the value itself might be misleading because of the nature of the disclosure rule. While increased exposure to certain stocks would be reflected in increased sizing of previously established positions, newly established positions that have just crossed the publication threshold (missing value being replaced by a small value just above the threshold) bias the average over all reported positions downwards. Therefore, due to the nature of the disclosure rule, the simple average value of reported positions is not a suitable measure for the purposes of our analysis.} In the first and second recovery periods, the total number of short positions declined by 12% and 8.7% to 968.8 and 884.8, respectively. The decrease in the number of reported short positions was most pronounced in illiquid firms, particularly in those countries in which we observed the largest increases during the crash period. Overall, these descriptive statistics already suggest an interesting pattern of heterogeneity in short-selling activity that depends on both the creditworthiness of states and the vulnerability of firms.\footnote{It is important to note that the percentage of low-rated countries is unbalanced. The bulk of disclosed short positions comes from Italy and Spain whereas only few short positions are disclosed for Poland and Greece on average, in particular for the subsample of high-liquidity firms. Thus, any effect we document for low-rated countries is likely driven by Italy and Spain. In fact, we conduct additional robustness checks and find that the results remain unchanged if we exclude observations from Poland and Greece. Importantly, however, we also find that the results are not country-specific as they are neither driven by Spain nor by Italy alone.}

Six of the 15 countries – Austria, Belgium, France, Italy, Greece and Spain – imposed short-selling bans during the period of high market turbulence. For most jurisdictions, major bans were introduced until March 17/18, 2020 and lasted until the end of May 18, 2020.\footnote{A number of countries had already enforced temporary, less-comprehensive bans prior to this, with Italy introducing the first ban on March 13, 2020.} For a detailed overview of all shorting bans and their scope, see Table OA.2 in the Online Appendix. The first recovery period largely overlaps with the comprehensive shorting bans, which were in effect in respective jurisdictions until May 18, 2020. The regulations prohibited investors from entering new net short positions or from increasing existing ones.

Table 2 provides summary statistics on various stock and firm characteristics for the sample of firms with at least one large short position disclosure during the sample period. The median values...
for the stocks’ market capitalization, the Amihud illiquidity ratio, and the relative bid-ask spread are comparable to the values reported by Jank et al. (2021), who use both public and confidential large short position disclosures. Their conclusion that large short positions are concentrated in large and very liquid stocks carries over to our sample.

Moreover, the median value for the quick ratio is 0.97, which translates into a company illiquidity measure (percentile rank, ranging between 0–1) of 0.57, which is slightly above 0.50. Since we compute the percentile rank of a company’s quick ratio using the entire universe of companies within our sample countries, this figure suggests that the shorted firms are slightly more illiquid relative to all listed firms.

3. Betting on limited fiscal space

3.1. Triple-difference estimation approach

The COVID-19 crisis represents a clear exogenous shock to companies’ revenues. The various measures taken to contain the virus led to a massive drop in income for a large number of firms. At the same time, companies with limited operating flexibility were not able to sufficiently cut their costs in order to offset the drop in revenues. Thus, their ability to manage the sudden cash flow shortfall crucially depended on their short-term liquidity buffer (Fahlenbrach et al., 2021). Companies with limited liquid assets were more vulnerable and, thus, more reliant on fiscal support than companies with abundant liquid assets. Governments across the globe rolled out a considerable number of stimulus programs, including emergency measures to restore companies’ short-term liquidity, as well as programs to stimulate demand. Countries themselves, however, may have also faced constraints during the crisis. While those with small budget deficits had more leeway to provide economic relief, countries with large deficits may not have been able to adopt the necessary policies to support their most vulnerable firms. Indeed, there is considerable heterogeneity in the responses adopted by different countries (Anderson et al., 2020). Firms with liquidity constraints in countries with fiscal constraints are, thus, at greater risk of COVID-related business disruption than either similarly constrained firms in fiscally healthy countries or firms with no liquidity problems. This makes them an ideal target for short sellers.

This naturally leads to a triple-difference estimation strategy, in which we split the sample of firms along the dimension of fiscal...
Table 2
Summary statistics: main variables. This table reports summary statistics for all variables used in the main analysis. These include the number of observations (N), mean, standard deviation (SD), and the 25th, 50th, and 75th percentiles. Panel A provides summary statistics for the daily investor-stock panel, Panel B for the daily country panel, and Panel C for the time series of daily asset pricing factors. The sample period is from July 1, 2019, to June 26, 2020.

### Panel A: Company and position characteristics

| Variable | N    | Mean  | SD   | 25th | 50th | 75th |
|----------|------|-------|------|------|------|------|
| Market value | 951,105 | 4,447.96 | 8,512.84 | 849.88 | 2,237.42 | 4,821.95 |
| Trading Volume | 940,845 | 2,263.28 | 7,594.81 | 115.22 | 506.78 | 1,806.93 |
| ln(Average) | 921,431 | -5.98 | 1.65 | -7.10 | -6.14 | -4.99 |
| ln(BidAsk) | 944,248 | -6.23 | 0.97 | -6.95 | -6.41 | -5.62 |
| ln(ISVolatility) | 950,591 | -3.77 | 0.52 | -4.14 | -3.81 | -3.44 |
| Market beta | 950,642 | 1.21 | 0.45 | 0.90 | 1.18 | 1.51 |
| Utilization | 891,597 | 23.73 | 23.56 | 5.82 | 15.40 | 33.37 |
| Indicative fee | 865,867 | 2.44 | 6.19 | 0.40 | 0.52 | 1.14 |
| Lender concentration | 891,602 | 0.24 | 0.14 | 0.16 | 0.20 | 0.27 |
| DIPS | 889,034 | 27.99 | 5.38 | 25.10 | 26.84 | 29.64 |
| DIMV | 889,034 | 34.61 | 6.16 | 30.45 | 32.58 | 36.43 |
| sd(Indicative fee) | 889,356 | 1.05 | 2.48 | 0.09 | 0.23 | 0.79 |
| Quick ratio | 856,753 | 1.37 | 2.20 | 0.71 | 0.97 | 1.36 |
| Quick ratio (percentile Rank) | 856,753 | 0.55 | 0.22 | 0.40 | 0.57 | 0.72 |
| Current Ratio | 856,753 | 1.72 | 2.27 | 0.95 | 1.28 | 1.77 |
| Undrawn revolving credit | 899,198 | 0.20 | 0.38 | 0.01 | 0.09 | 0.16 |
| Total undrawn credit | 899,198 | 0.23 | 0.44 | 0.03 | 0.11 | 0.18 |
| ROA | 922,886 | 4.22 | 8.78 | 1.30 | 4.07 | 7.11 |
| ROE | 858,517 | 10.47 | 27.08 | 4.33 | 11.29 | 19.36 |
| Price-to-book | 930,332 | 3.45 | 4.15 | 1.25 | 2.30 | 3.83 |
| Z-score | 833,175 | 6.31 | 4.37 | 4.61 | 5.76 | 7.46 |
| Interest coverage ratio | 654,551 | 25.73 | 287.82 | 3.56 | 7.98 | 20.88 |
| D(Zombie) | 654,551 | 0.10 | | | | |
| Net Debt-to-EBITDA | 743,119 | 3.35 | 8.09 | 0.80 | 1.81 | 3.44 |
| ST Debt-to-T Debt | 845,451 | 0.22 | 0.24 | 0.06 | 0.15 | 0.29 |
| ST Debt-to-T Assets | 881,487 | 6.00 | 9.16 | 1.35 | 3.66 | 7.43 |
| Resilience DN | 950,853 | 0.43 | 0.22 | 0.31 | 0.38 | 0.72 |
| Resilience KP | 881,696 | 35.22 | 18.47 | 20.00 | 29.00 | 51.00 |
| Resilience HR | 938,496 | 6.93 | 1.33 | 6.16 | 7.00 | 7.67 |
| Local share 1 | 730,440 | 0.27 | 0.30 | 0.01 | 0.15 | 0.45 |
| Local share 2 | 730,440 | 0.28 | 0.30 | 0.04 | 0.16 | 0.45 |
| Local share 3 | 629,683 | 0.33 | 0.30 | 0.09 | 0.23 | 0.52 |
| No. of Employees | 902,912 | 24,028.22 | 56,096.49 | 1,937.00 | 7,424.00 | 20,909.00 |
| Total Assets (in mil. USD) | 921,626 | 11,810.82 | 27,553.03 | 1,220.10 | 3,299.05 | 8,288.68 |
| Revenue (in mil. USD) | 865,825 | 4,646.38 | 7,484.60 | 593.00 | 1,873.79 | 4,540.46 |
| D(Short position) | 951,105 | 0.29 | | | | |
| D(Shorting ban) | 951,105 | 0.04 | | | | |
| Short position | 274,924 | 0.97 | 0.61 | 0.60 | 0.78 | 1.11 |
| D(Short entry) | 274,924 | 0.01 | | | | |

### Panel B: Country characteristics

| Variable | N    | Mean  | SD   | 25th | 50th | 75th |
|----------|------|-------|------|------|------|------|
| D(Low country rating) | 3764 | 0.23 | | | | |
| Rating notch | 3764 | 2.52 | 3.28 | 0.00 | 1.00 | 3.00 |
| CDSSy | 3516 | 38.32 | 58.15 | 9.35 | 13.84 | 34.95 |
| Cases | 3708 | 9.23 | 26.82 | 0.00 | 0.00 | 4.49 |
| Deaths | 3708 | 0.83 | 2.77 | 0.00 | 0.00 | 0.09 |
| Government response | 3759 | 20.94 | 31.13 | 0.00 | 0.00 | 46.30 |
| Health Expenditure | 3764 | 4,562.68 | 1,122.65 | 4,126.35 | 5,013.99 | 5,263.83 |
| Hospital beds | 3764 | 433.16 | 180.60 | 297.00 | 328.00 | 598.00 |
| ICU beds | 3764 | 11.78 | 7.41 | 6.50 | 8.00 | 15.90 |
| Liquid to total assets | 3569 | 0.16 | 0.03 | 0.13 | 0.16 | 0.20 |
| Tier 1 capital ratio | 3569 | 0.17 | 0.02 | 0.16 | 0.17 | 0.19 |
| Loan-to-deposit ratio | 3569 | 1.13 | 0.42 | 0.90 | 0.93 | 1.24 |

### Panel C: Asset-pricing factors

| Variable | N    | Mean  | SD   | 25th | 50th | 75th |
|----------|------|-------|------|------|------|------|
| MKTRF | 252 | -0.02 | 1.67 | -0.43 | 0.09 | 0.63 |
| SMB | 252 | 0.00 | 0.57 | -0.30 | -0.01 | 0.29 |
| HML | 252 | -0.09 | 0.73 | -0.45 | -0.09 | 0.25 |
| RMW | 252 | 0.02 | 0.27 | -0.13 | 0.03 | 0.18 |
| CMA | 252 | -0.06 | 0.34 | -0.27 | -0.06 | 0.13 |
| WML | 252 | 0.06 | 1.06 | -0.36 | 0.14 | 0.52 |
space and company liquidity buffers. First, we divide the sample of firms according to whether they are headquartered in countries with high (≥AA-) or low credit ratings (<AA-). Second, we distinguish between companies with high and low liquidity buffers using our company illiquidity measure.

Fig. 1, Panel A, shows the percentage change of disclosed short positions (relative to December 20, 2019) for companies with different degrees of liquidity in countries with a low credit rating.18 The number of short positions in liquid and illiquid firms follows a common trend prior to the onset of the COVID-19 crisis. Around the market crash on February 24, 2020, shorting of illiquid firms increased substantially, peaking in the week of March 9–13, 2020. The figure also shows that the gap between liquid and illiquid firms was already widening before the market crash on February 24, 2020. This suggests that short sellers had anticipated, at least to some extent, the importance of liquidity reserves in withstanding the immediate economic consequences of the COVID-19 outbreak. The number of disclosed short positions declined after March 13, 2020 but stayed at an elevated level relative to the shorting of liquid firms, which declined over the same time period. The overall decline in disclosed short positions coincides with a strong market recovery after the market crash, as indicated by the solid gray line which depicts the return index for the European stock market. As short sellers only profit from a price decline, it is to be expected that they at least cover a fraction of their large short positions (which in turn leads to fewer disclosed positions) in order to limit the losses associated with a broad market recovery. The fact that short sellers withdrew at such a time emphasizes the idea that they are informed investors, and is consistent with the findings of Boehmer et al. (2018), who show that it is more likely for short sellers to cover their trades when market returns are positive.

Panel B of Fig. 1 shows the same sample split for firms headquartered in countries with a high credit rating. Interestingly, we observe no intensification of shorting of illiquid firms in countries with high creditworthiness. The number of short positions in liquid and illiquid firms follows a common trend both before and during the COVID-19 crisis. After February 24, 2020, the number of shorts in both groups increased slightly but both declined in the following weeks of market recovery.

The striking difference between Panels A and B suggests that short sellers were not trading on company illiquidity alone. Instead, it was the combination of illiquid firms and poorly rated countries that was driving most short-selling activity during the COVID-19 crisis. Indeed, short sellers seemed to bet on certain countries providing only limited support to vulnerable firms because of their limited fiscal space.

3.2. Regression framework

In this section, we formalize the graphic analysis in a regression framework, using Company illiquidity as a continuous treatment variable for a company’s exposure to the COVID-19 revenue shock. We make use of our high-dimensional panel data set by controlling for various fixed effects at the investor, stock and time levels. We choose a linear probability model (LPM) instead of a non-linear model (probit or logit) due to the incidental parameter bias (Neyman and Scott, 1948) arising in the latter.19 For our baseline model, we run the following regression:

\[
D(\text{Short position}_{i,t}) = \sum_{j} \beta_j D(\text{Period}_j) \times D(\text{Low country rating}_i) \times \text{Company illiquidity}_i + \sum_{j} \beta_j D(\text{Period}_j) \times \text{Company illiquidity}_i + \sum_{j} \beta_j^2 D(\text{Period}_j) \times D(\text{Low country rating}_i) + \textbf{X}_{i,t-1} \gamma + \alpha_i + \alpha_j + \epsilon_{i,j,t}. \]

(1)

where \(D(\text{Short position}_{i,t})\) is a dummy variable that equals 1 if investor \(j\) reported a net short position above the 0.5% publication threshold in stock \(i\) on day \(t\), and equals 0 otherwise. \(D(\text{Period}_j)\) are dummy variables for the time periods of interest, where \(\text{Period}_j = \{\text{Crash: Recovery 1: Recovery 2}\}\). The Crash period is from February 24, to March 23, 2020, the Recovery 1 period is from March 24, to May 17, 2020, and the Recovery 2 period is from May 18, to June 26, 2020. \(D(\text{Low country rating}_i)\) is a dummy variable that equals 1 if the headquarters country of stock \(i\) has a credit rating below AA - and is zero otherwise.20 Company illiquidity, is the percentile rank (ranging between 0 and 1) of firm illiquidity, based on the industry-adjusted quick ratio.

Our benchmark model also includes stock \((\omega_i)\), investor \((\alpha_j)\), and time fixed effects \((\alpha_t)\). It must be noted that the variables \(D(\text{Period}_j)\), \(D(\text{Low country rating}_i)\), Company illiquidity, and some of the double interactions are absorbed by these fixed effects. We control for various lagged stock-level characteristics, which may affect the likelihood of establishing a short position. All control variables are collected in vector \(\textbf{X}_{i,t-1}\), which includes a short-selling ban dummy, past stock returns at different horizons, the Amihud (2002) ratio, bid–ask spread, idiosyncratic volatility, market beta and various securities lending characteristics. More specifically, we use the following securities lending controls: Utilization, Indicative fee, Lender concentration, DIPS (the price squeeze indicator provided by Markit), DIMV (the volatility indicator provided by Markit) and sd(Indicative fee). The definitions of the variables are provided in Table OA.1 in the Online Appendix. These controls should account for the facts that lending fees vary considerably in the cross section and over time (Porras Prado et al., 2016; Boehmer et al., 2021), and that risks arising from the securities lending market inhibit short selling (Engelberg et al., 2018; Muravyev et al., 2022).

All of these time-varying stock characteristics may affect investors’ tendency to short a given stock. It should be noted that stock fixed effects \(\alpha_i\) absorb stock characteristics that are largely time-invariant in our relatively short sample period of 12 months (July 2019 to June 2020). Such characteristics would include balance sheet variables that represent signals to popular quantitative trading strategies. These trading strategies – for example, the size and value strategies – are typically re-balanced once a year (Fama and French, 1993). In order to account for other prominent trading strategies at higher frequency, such as short-term reversal (Lehmann, 1998; Jegadeesh, 1990) or momentum (Jegadeesh and Titman, 1993), we control for lagged returns at different time horizons, as mentioned previously.

18 Fig. OA.3 of the Online appendix shows the raw numbers of reported short positions.
19 As a robustness check, we run a logit and probit without any fixed effects to avoid incidental parameter bias. Marginal effects obtained from both non-linear models are very similar compared with those of the LPM (see Table OA.3 in the Online Appendix).

20 In a robustness check, we study in more detail the grouping in low- and high-rated countries. We run the regression with finer rating dummy variables for ratings AAA, AA, A and BBB. The results show that, during the market crash, countries with AA rating do not experience significantly more shorting activity in illiquid firms than countries with AAA rating. To the contrary, countries with A or BBB rating experience significantly higher shorting activity in illiquid firms, which is of comparable economic magnitude. The results are shown in Fig. OA.5 in the Online Appendix.
Fig. 1. Relative change of disclosed short positions in liquid and illiquid companies during the COVID-19 crisis. This figure shows the relative change of disclosed short positions (in percent) for companies with different degrees of liquidity that are either domiciled in countries with a low credit rating (Panel A) or a high credit rating (Panel B). The percentage change is calculated relative to the average number of disclosed positions in the week December 15 – December 22, 2019. We split the sample of firms using the median of the industry-adjusted quick ratio as the break point. The median value is calculated using the entire universe of companies of sample countries as outlined in Section 2. For each group the figure plots the weekly average number of disclosed short positions at the end of each business week (i.e. Friday). The area shaded in red indicates the market crash period (February 24 – March 23, 2020), the area shaded in light green indicates the first market recovery period (March 24 – May 17, 2020), and the area shaded in dark green indicates the second market recovery period (May 18 – June 26, 2020). The sample period is June 01, 2019 - June 26, 2020. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Table 3, Column (1), shows the regression results of the baseline model. The coefficient of the triple interaction $D\text{(Crash)} \times D\text{(Low country rating)} \times \text{Company illiquidity}$ is positive and statistically significant at all conventional significance levels. This result shows that, during the market crash, short sellers increased their positions in illiquid firms in countries with low credit ratings. The coefficient of the triple interaction $D\text{(Recovery)} \times D\text{(Low country rating)} \times \text{Company illiquidity}$ is also positive and statistically significant, indicating that this strategy was also followed in the first market recovery phase. For the second recovery period, the triple interaction is still positive but its statistical significance is weaker. To the contrary, the coefficients of all double interactions, $D\text{(Period)} \times \text{Company illiquidity}$, are statistically different from zero for all market phases. These results highlight a striking difference in short sellers’ trading behavior: investors specifically shorted illiquid firms headquartered in countries with a low credit rating, while such behavior was not observed for firms in countries with a high credit rating. Hence, the degree to which a country can provide fiscal easements to its companies influences the investment behavior of short sellers. The size of this effect is economically significant. An increase in firm illiquidity by the interquartile range (which corresponds to 0.5 in the percentile rank) increases an investor’s propensity to establish a short position by $0.5 \times 0.56 = 0.28$. Relative to the average likelihood of a short position disclosure of 0.29 (see Table 2), this is an increase of 97%.

In terms of the control variables, our results are by and large as expected. Short positions are less likely to be taken in stocks for which a shorting ban is in place. Short sellers seem to take into account short term reversals in daily returns (Lehmann, 1990; Jegadeesh, 1990). After an increase in stock price over the previous 20 trading days, short sellers are less likely to establish a position in that stock and vice versa. Investors show a contrarian trading strategy at the yearly momentum horizon ($t - 250$ to $t - 21$ trading days), despite the fact that momentum is, on average, a profitable strategy. We also find that increased illiquidity, as measured by the price impact, reduces the likelihood of establishing a short position. This finding is in line with the notion that short sellers are concerned with covering their positions (Boehmer et al., 2018). Finally, the propensity of short sellers to establish a large short position is positively related to idiosyncratic volatility, which is insignificant for the first specification, but significant for the more saturated models (2)–(5).

Next, we include various high-dimensional fixed effects in our regression model. The most saturated regression includes country×time, industry×time, investor×time, and investor×stock fixed effects. Country-time fixed effects are an important control, as they absorb any time-varying country-specific shocks. For example, they account for how much a country has been affected by the COVID-19 pandemic or for any country-specific measures taken in response to the pandemic. Industry-time fixed effects control for any time-varying industry heterogeneity across companies. Investor-time fixed effects control for any time-varying investor heterogeneity, such as hedge funds’ leverage constraints or differences in risk aversion that may arise during the crisis. Finally, fixed effects for each investor-stock pair control for any stock-specific expertise an investor might have.

In Columns (2)–(5) in Table 3, we include the different fixed effects on a step-by-step basis. The coefficient of the triple interaction $D\text{(Crash)} \times D\text{(Low country rating)} \times \text{Company illiquidity}$ remains stable at 0.57 when country-time fixed effects are included in the specification shown in Column (2). The coefficient of the shorting ban dummy becomes insignificant, as much of its variation is absorbed by country-time fixed effects. The coefficient is not entirely absorbed, because we use the headquarters’ country as the relevant country for a firm. The shorting ban dummy, however, is defined by the country of exchange. Moreover, for some countries, not all listed stocks were subject to a shorting ban, so that some variation, albeit relatively little, is left. When industry-time and investor-time fixed effects are included in Columns (3) and (4) respectively, the coefficient of interest remains statistically and economically significant. The results remain virtually the same in the fully saturated model shown in Column (5), including country-time, industry-time, investor-time and investor-stock fixed effects with an adjusted $R^2$ of over 49%.

We conduct various robustness checks on how fiscal space is measured in the regression specifications. For reasons of brevity, we report these in the Online Appendix and only briefly describe the main results here. First, we use the rating notch as a finer market-based measurement for fiscal space in Table OA.4, confirming our main result. Second, we use the 5-year CDS spread as an alternative market-based measure for fiscal space (Kose et al., 2017) in Table OA.5. Similar to our main result based on ratings, we find that short sellers have targeted illiquid companies in countries with high CDS spreads. Third, we use fiscal cyclicality as an additional proxy for fiscal space in Table OA.6. This choice is motivated by the empirical observation that counter-cyclical fiscal policies at times of crises are considerably lower in countries with high sovereign risk (Romer and Romer, 2019; Bianchi et al., 2019). We find results consistent with our main finding. At the onset of the pandemic, short sellers targeted illiquid companies in countries that had exhibited procyclical government spending in the past. Lastly, we also aim at capturing as many fiscal space indicators as possible into one index. The motivation is that we cannot discern the exact indicators that short sellers have considered in their trading decisions; however, an index that extracts the common variations in a set of many different proxies may provide us with an aggregate measure on the information set that investors were exposed to before the pandemic. In order to achieve this, we construct a fiscal limit index using various fiscal space categories suggested in Kose et al. (2017), based on a principal component analysis. The results are provided in Table OA.7 in the Online Appendix. Again, we find results consistent with our expectations: at the onset of the pandemic, short sellers targeted illiquid companies in countries with limited fiscal space. Overall, various proxies for fiscal space yield very similar results regarding short sellers’ trading during the COVID-19 crisis.

3.3. The timing of short sellers

The estimation of the combined effect of limited fiscal space and firm illiquidity over the three different phases of the pandemic is useful for the overall understanding of short sellers’ trading behavior. This does not reveal, however, at exactly which point in time short sellers entered their positions in illiquid firms in countries with a low credit rating. Have short sellers initiated their shift towards these vulnerable companies before the market anticipated the consequences of the pandemic? In order to answer this question, we run the most saturated regression model using time indicators at weekly frequency. $D\text{(Period)}$ is now a dummy that equals 1 if the business week equals $p$, and is zero otherwise, with $p$ covering business weeks from December 16, 2019 to June 26, 2020. The reference period in this empirical exercise ranges from July 1, 2019, to December 15, 2019.23

23 We also use a similar specification to assess the validity of the common trends assumption in our setting (Autor, 2003) and adapt Equation (1) so that $D\text{(Period)}$ is now a dummy that equals 1 if the calendar month equals $p$, and zero otherwise, with $p$ covering the months from July 2019 to June 2020. Fig. OA.4 in the Appendix plots the coefficient of interest, i.e. the coefficient of the triple interaction $D\text{(Month)} \times D\text{(Lowcountryrating)} \times \text{Companyilliquidity}$, over time. The reference period in this regression is December 2019, which takes the value of 0 by construction. In the period from July 2019 to January 2020, we observe no significant increase in publicly disclosed net short positions above the 0.3% threshold for illiquid


Table 3

|                | (1)       | (2)       | (3)       | (4)       | (5)       |
|----------------|-----------|-----------|-----------|-----------|-----------|
| D(Short position) |           |           |           |           |           |
| D(Crash) × D(Low country rating) × Company illiquidity | 0.5706*** | 0.5756*** | 0.5561*** | 0.5094*** | 0.5108*** |
| D(Recovery 1) × D(Low country rating) × Company illiquidity | 0.4126*** | 0.4008*** | 0.3996*** | 0.3723*** | 0.3753*** |
| D(Recovery 2) × D(Low country rating) × Company illiquidity | 0.2286*   | 0.2414*   | 0.2232    | 0.2119    | 0.2112    |
| D(Crash) × Company illiquidity | -0.0113   | -0.0107   | 0.0082    | -0.0182   | -0.0173   |
| D(Recovery 1) × Company illiquidity | (0.12)    | (0.09)    | (0.30)    | (-0.19)   | (-0.17)   |
| D(Recovery 2) × Company illiquidity | 0.0175    | 0.0133    | 0.0219    | -0.0245   | -0.0250   |
| D(Crash) × D(Low country rating) | -0.0039   | -0.0057   | -0.0087   | -0.0075   |           |
| D(Recovery 1) × D(Low country rating) | 0.0085    | -0.0039   | -0.0135   | -0.0107   |           |
| D(Recovery 2) × D(Low country rating) | -0.0039   | -0.0057   | -0.0087   | -0.0075   |           |
| D(Shorting Ban) | -0.0058** | -0.0735   | -0.0612   | -0.0461   | -0.0441   |
| ret,5–12,1     | (2.42)    | (-1.49)   | (-1.11)   | (-0.69)   | (-0.66)   |
| ret,20-12-6    | (-0.51)   | (-0.93)   | (-1.35)   | (-1.67)   | (-1.68)   |
| ret,250-1-23   | (-1.75)   | (-1.84)   | (-2.24)   | (-2.07)   | (-2.08)   |
| ln(Arthur),5–51,1 | 0.0073*   | -0.0080** | -0.0073*  | -0.0097*  | -0.0097*  |
| ln(BidAsk),5–51,1 | 0.0095*** | -0.0099*** | -0.0099*** | -0.0099*** | -0.0099*** |
| ln(ISVola),5–10 | 0.0080    | 0.0126    | 0.0124    | 0.0119    | 0.0117    |
| ρ /σ /5–1      | (0.68)    | (1.06)    | (0.94)    | (0.92)    | (0.90)    |
| Utilization    | -0.0253   | -0.0205   | -0.0094   | -0.0128   | -0.0121   |
| Indicative fee | (12.87)   | (12.97)   | (12.28)   | (12.05)   | (12.09)   |
| Lender concentration | -0.2097** | -0.2114** | -0.1521*  | -0.1268   | -0.1291   |
| DIPS           | 0.0089*** | 0.0093*** | 0.0095*** | 0.0093*** | 0.0094*** |
| DMIV           | (5.94)    | (6.41)    | (6.15)    | (6.16)    | (6.18)    |
| sd(Indicative fee) | -0.3964   | -0.4069   | -0.3667   | -0.5665   | -0.5664   |

|                | (6)       | (7)       | (8)       | (9)       | (10)      |
|----------------|-----------|-----------|-----------|-----------|-----------|
| adj. R²        | 0.2664    | 0.2650    | 0.2620    | 0.2569    | 0.5060    |
| adj. within R² | 0.0332    | 0.0318    | 0.0248    | 0.0233    | 0.0350    |
| Nobs           | 649,885   | 649,750   | 647,436   | 626,140   | 626,137   |
| Stock FE       | Yes       | Yes       | Yes       | Yes       | -         |
| Investor FE    | Yes       | Yes       | Yes       | -         | -         |
| Time FE        | Yes       | Yes       | Yes       | -         | -         |
| Country × time FE | No       | Yes       | Yes       | Yes       | Yes       |
| Industry × time FE | No       | No       | Yes       | Yes       | Yes       |
| Investor × time FE | No       | No       | No       | Yes       | Yes       |
| Investor × stock FE | No       | No       | No       | No       | Yes       |
Fig. 2 plots the coefficient of the triple interaction $D(\text{Week}) \times D(\text{Low country rating}) \times \text{Company illiquidity}$ for the period from December 16, 2019, to June 26, 2020, along with major events in the COVID-19 pandemic. On December 31, 2019, China reported to the World Health Organization (WHO) that cases of pneumonia of an unknown cause had been detected in Wuhan City. For the second half of December and until the end of January, point estimates for the triple interaction coefficient are close to zero and statistically insignificant. After the WHO declared the COVID-19 outbreak a Public Health Emergency of International Concern (PHEIC) on January 30, 2020, shorting of illiquid firms in low-rated countries steadily increased throughout February. The coefficient is already statistically different from zero in the business week starting February 17, 2020 – i.e. one week before the beginning of the market crash on February 24, 2020. This result suggests that short sellers had started to bet on the combination of a government’s limited fiscal space and firms’ liquidity buffers well ahead of the market crash.

The tendency to short such firms continued to increase throughout the market crash period, peaking in the week immediately prior to the introduction of short-selling bans in some European countries. On March 17/18, 2020, six countries (Austria, Belgium, France, Greece, Italy and Spain) introduced comprehensive short-selling bans for stocks traded on their exchanges.22 The restrictions prohibited the establishment or expansion of short positions. Already established short positions could be maintained. Since the large majority of stocks in low-rated countries were subject to the shorting ban, we would expect no further increase in these countries. Over the period of the shorting ban and during the first phase of the market recovery, the tendency to short illiquid firms in low-rated countries gradually declined. The triple interaction, nevertheless, remains economically large and statistically significant until the end of the first recovery period. This suggests that at least some of the short sellers maintained their positions. The short-selling bans lasted until May 18, 2020. After this date, we do not observe an increase in shorting in illiquid firms in low-rated countries. The end of short-selling bans, however, coincided with the French-German initiative for an EU Recovery Fund, which was announced on May 18, 2020. This date marks the beginning of our second market recovery period, during which the triple interaction coefficient becomes largely insignificant.

3.4. The cross section of short sellers

In this section, we present how we capitalize on the disclosed identity of the short sellers on an individual position level, linking firms in countries with low credit ratings. The significantly elevated shorting activity in illiquid firms in low-rated countries is only present in the months during the COVID-19 crisis (February through June 2020), peaking in March.  

22 Some of these countries had introduced temporary, less-comprehensive bans prior to this, with Italy being the first to do so on March 13, 2020. For a detailed overview of all shorting bans, see Table OA.2 in the Online Appendix.
two investor characteristics to speculations on fiscal space and firm liquidity. First, we study the role of substitution of short positions within investors and, second, we link investor types to short selling on the basis of firm illiquidity and country creditworthiness.

Fig. 1a shows a divergence in aggregate short-selling activity between liquid and illiquid firms in countries with a low credit rating. So far, we have focused on the increase in positions in illiquid firms. There exists, however, a simultaneous decrease of positions in liquid firms. One potential explanation for this pattern in low-rated countries depicted in Fig. 1a, is that those short sellers who have increased their exposure to illiquid firms did so by simultaneously decreasing their exposure to liquid firms. Such position substitution is common when investors impose limits on allowable deviations from performance targets and investment philosophies. Namely, next to regulatory and statutory constraints, asset managers’ investment behavior is often subject to self- and client-imposed restrictions, such as limits on investing in international stocks, diversification rules, limits on leverage, limits on short selling and limits on the use of derivatives (Bank for International Settlements, 2003). These restrictions result in fund managers choosing between different investment options and, if necessary, replacing existing, less profitable investments with presumably better ones. In order to test this explanation, we first group investors into those who closed a short position in a liquid company headquartered in a low-rated country in the period of four weeks prior or during the market crash, and those who did not. If such replacement within investors drives the pattern in Fig. 1a, we expect that the increase of short positions in illiquid firms would be driven by the same investors who closed their short positions in liquid firms. Columns (1) and (2) of Table 4 report the results of the most saturated regression specification for the two sub-samples separately. In these two columns, we observe that in low-rated countries the effect of increased exposure to illiquid firms is mainly present in the sample of investors who close their existing positions in liquid firms. Such an effect is not present for the other investors.

This finding is consistent with the notion that investors replaced their short positions in less vulnerable companies with positions in more vulnerable companies.

Next, we turn our attention to the cross section of investor types. There is ample evidence that hedge funds display several characteristics that differentiate them from other investor types and that may influence the informativeness of their trades. These include flexible investment strategies, strong managerial incentives, substantial managerial investment and sophisticated investors (Fung and Hsieh, 1997; Ackermann et al., 1999; Fung and Hsieh, 1999; Liang, 1999; Fung et al., 2008). Jank and Smajlbe-govic (2015) show that the short positions of hedge funds significantly outperform the positions reported by other investors. Based on existing evidence about hedge funds in general, their characteristics and performance incentives, we expect that the shift towards illiquid firms prior to the market crash was stronger for them, relative to other investors. In order to test this heterogeneity in investor characteristics, we query the names of investment firms in Refinitiv Eikon and use the investor type description to categorize investors. We split the sample of short positions in those held by (1) Hedge funds, (2) Hedge funds/Investment advisers and (3) Other investors. Refinitiv Eikon distinguishes between hedge funds that need to register as investment advisers and those that are exempt from the registration provisions (see Section 203(b)(3) of the Investment Advisers Act). Exempt hedge funds include private fund advisers with regulatory assets under management below $150 million, advisers to purely venture capital funds, and foreign private advisers. In our analysis, we assume that hedge funds, as defined by Refinitiv Eikon, are the most sophisticated group of investors in our sample. This is because they are less reg-

23 For more details on fund types that are exempt from the registration provisions, see https://www.rivelleslawgroup.com/launching-a-hedge-fund-is-investment-adviser-registration-required/.
ulated, have less investment constraints, are more likely to be secretive and, more importantly for this study, because they are more likely to be informed short sellers (Jank et al., 2021). The results in Columns (3) to (5) in Table 4 are consistent with our expectations. During the market crash, hedge funds were most likely to trade on the combination of compromised fiscal space and firm illiquidity. Hedge funds registered as investment advisers show a slightly decreased effect compared to the first group, while other investors exhibited economically and statistically less significant exposure to these stocks. Overall, the evidence supports the notion that investors who were generally thought to be better informed and more profitable were those who increased their exposure to vulnerable firms during the pandemic.

3.5 Follow-on behavior

In this section, we analyze whether the trading behavior of short sellers depends on the behavior of other short sellers. In particular, we are interested in whether the decision to disclose a new short position during the COVID-19 pandemic is influenced by the presence of other short sellers with publicly disclosed positions in the same stock. Our analysis is based on Jones et al. (2016), who document significant follow-on behavior in large short position disclosures. More specifically, they show that the propensity to initiate a large short position more than doubles when there are new disclosures in the same stock over the previous week. Our focus lies on whether this type of position clustering is also visible during the COVID-19 pandemic, especially in those stocks that are primarily targeted by short sellers. In order to shed light on this question, we follow Jones et al. (2016) and define a dummy variable $D(\text{Disclosure}_{t-3:t-1})$, which is equal to 1 when there is at least one new disclosure in a particular stock in the previous three trading days. We then augment our baseline regression by interacting this dummy with the variables $D(\text{Pre-Crash}_t)$, $D(\text{Crash}_t)$, $D(\text{Low country rating}_t)$, and $\text{Company illiquidity}_t$, and their interactions. $D(\text{Pre-Crash}_t)$ is a dummy variable denoting the period prior to the stock market crash (January 30, to February 22, 2020), while the rest of the variables are defined as before. The additional dummy variable allows us to consider “uninformed” follow-on behavior prior to the market crash as an alternative explanation for the “informed” anticipation effect we document in Fig. 2.

Since we focus on the clustering of newly disclosed positions in a stock, we use $D(\text{Short Entry}_{ij,t})$ as the dependent variable, which is a dummy that equals 1 if there is a new disclosure by investor $j$ in stock $i$ on a given day, and zero otherwise. In all specifications, we include the same vector of time-varying control variables, $X_{i,t-1}$, as before. Our baseline specification includes fixed effects at the investor, stock and time levels. For brevity, we only report the coefficients associated with the $D(\text{Disclosure}_{t-3:t-1})$ dummy.

Table 5 presents the results. First, we observe a positive and significant coefficient for $D(\text{Disclosure}_{t-3:t-1})$ in Column (1), where we follow Jones et al. (2016) and only include country-fixed effects. The magnitude of the coefficient is similar to that found in the original study. The estimate in Column (1) suggests that a disclosure in the previous three trading days increases the likelihood of a new disclosure by 0.11 percentage points. Compared to the baseline probability of 0.44%, this is a relative increase of 30%.24

Second, we observe that the remaining interactions of $D(\text{Disclosure})$ with $D(\text{Low country rating})$ and $\text{Company illiquidity}$ are insignificant across all specifications. This suggests that the type of position clustering under analysis is generally not dependent on the liquidity of the firm or the location of its headquarters in either high- or low-credit rating countries.

Third, turning to the main period of interest, the only group of stocks for which we find more follow-on behavior during the COVID-19 pandemic is illiquid firms headquartered in countries with low credit rating, as can be seen from the positive and significant coefficients for the interaction $D(\text{Crash}) \times D(\text{Low country rating}) \times D(\text{Disclosure})$ across all columns. Importantly, a higher propensity to engage in follow-on short selling of illiquid firms headquartered in countries with low credit rating is only observable during the stock market crash, but not prior to it. This implies that the anticipation effect we see in Fig. 2 cannot be explained by a higher degree of position clustering in these firms. Moreover, the magnitude of the $D(\text{Crash}) \times D(\text{Low country rating}) \times D(\text{Disclosure})$ coefficient relative to the other coefficients suggests that the increase in herding for illiquid firms in low-rated countries during the stock market collapse is also economically sizable. Based on an increase in firm illiquidity by the interquartile range ($=0.5$), a recent disclosure of a short position in a company headquartered in a low-rated country increases the likelihood of another disclosure in the same company by about 3 percentage points during the COVID-19 crisis ($0.5 \times 0.0594 = 0.0297$). Compared to a baseline probability of 0.44% to enter a new short position, a disclosure is more than five times more likely. We note that although this result suggests a certain degree of similarity in the behavior of short sellers, we cannot distinguish whether herding is a result of investors using the disclosure as a coordination device or whether they simply receive similar signals leading to similar conclusions based on which they trade. Taking into account the absence of increased position clustering during the pre-crash period, however, the overall picture is more consistent with short sellers acting on similar information once the stock market collapsed.

3.6 Main robustness checks

In this section, we discuss several robustness checks to corroborate our empirical results. For reasons of brevity, we only summarize the robustness checks conducted and present results in the Online Appendix.

First, we discuss and test an alternative interpretation of our main finding: what if short sellers focused on the severity of the COVID-19 outbreak in a particular country and not on the latter’s fiscal space? As shown in Table OA.9, our results are robust to controlling for various measures for the severity of the pandemic as well as proxies for health system capacity. Second, we investigate whether short sellers focused on countries with a weaker banking system rather than fiscal space. Table OA.10 shows that this is not the case. Third, we explore whether short sellers traded on other company characteristics that might reflect a company’s vulnerabilities. Table OA.11 shows that our results are robust to various proxies measuring firm vulnerability. We show that neither of these alternative scenarios can explain our main result. Lastly, we examine whether the position-level results hold when we use common stock-level short-selling activity measures. In Table OA.12 of the Online Appendix we show that the analysis including stock-level shorting activity data from Markit yields results that are consistent with the findings based on short-selling notification data.

For purposes of the analysis, we drop all observations once the stock is subject to a short-selling ban, as it prohibited the opening of new positions and $D(\text{Disclosure})$ would automatically be zero in these cases. For the same reason, we also do not consider separately the recovery periods after the stock market crash. Once we account for the ban, which mainly affected stocks in countries with poor credit ratings, we cannot properly identify the different coefficients in the recovery phase.

The difference in terms of economic significance compared to Jones et al. (2016), who find that the likelihood is three times as high when there is another disclosure in the previous week, is due to the difference in the baseline probability of observing a new disclosure. In our sample, this baseline probability is 0.44%, whereas in the sample of the original paper it is only 0.08%.

24 For purposes of the analysis, we drop all observations once the stock is subject to a short-selling ban, as it prohibited the opening of new positions and $D(\text{Disclosure})$ would automatically be zero in these cases. For the same reason, we also do not consider separately the recovery periods after the stock market crash. Once we account for the ban, which mainly affected stocks in countries with poor credit ratings, we cannot properly identify the different coefficients in the recovery phase.

25 The difference in terms of economic significance compared to Jones et al. (2016), who find that the likelihood is three times as high when there is another disclosure in the previous week, is due to the difference in the baseline probability of observing a new disclosure. In our sample, this baseline probability is 0.44%, whereas in the sample of the original paper it is only 0.08%.
Table 5 shows the results for the fixed-effects panel regressions with the dependent variable D(Short entry), which is a dummy variable that equals one if a disclosure of investor j in stock i is observed on day t and no disclosure is observed on day t-1. The main explanatory variables are: D(Disclosure), which is a dummy variable that equals 1 if there was a new short position disclosure for stock i in the previous three trading days. D(Pre-Crash), which is a dummy variable that equals 1 for the period after the PHEIC and prior to the stock market crash (January 30 – February 23, 2020), and D(Crash), D(Low country rating) and Company illiquidity, which are all defined in Table 3. The sample period is July 2019 to June 2020. We report t-statistics based on standard errors, clustered at the stock and time level, in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

|          | (1)       | (2)       | (3)       |
|----------|-----------|-----------|-----------|
| D(Pre-Crash) × D(Low country rating) × Company illiquidity × D(Disclosure)_{t-3-1} | 0.0114** | 0.0116** | 0.0127** |
|          | (0.78)    | (0.80)    | (0.72)    |
| D(Crash) × D(Low country rating) × Company illiquidity × D(Disclosure)_{t-3-1} | 0.0578*** | 0.0594*** | 0.0521*** |
|          | (3.81)    | (3.58)    | (2.17)    |
| D(Pre-Crash) × Company illiquidity × D(Disclosure)_{t-3-1} | 0.0022    | 0.0022    | 0.0035    |
|          | (0.53)    | (0.55)    | (0.68)    |
| D(Crash) × Company illiquidity × D(Disclosure)_{t-3-1} | -0.0088*  | -0.0084   | -0.0060   |
|          | (-1.69)   | (-1.58)   | (-0.81)   |
| D(Pre-Crash) × D(Low country rating) × D(Disclosure)_{t-3-1} | -0.0091*** | -0.0099*** | -0.0093*** |
|          | (-3.37)   | (-3.74)   | (-2.89)   |
| D(Crash) × D(Low country rating) × D(Disclosure)_{t-3-1} | -0.0043   | -0.0031   | -0.0064   |
|          | (-1.06)   | (-0.70)   | (-1.14)   |
| D(Pre-Crash) × D(Disclosure)_{t-3-1} | 0.0017    | 0.0018*   | 0.0013    |
|          | (1.64)    | (1.72)    | (1.06)    |
| D(Crash) × D(Disclosure)_{t-3-1} | 0.0009    | 0.0007    | -0.0003   |
|          | (0.74)    | (0.57)    | (-0.22)   |
| D(Low country rating) × Company illiquidity × D(Disclosure)_{t-3-1} | -0.0138   | -0.0138   | -0.0096   |
|          | (-0.96)   | (-1.25)   | (-0.68)   |
| Company illiquidity × D(Disclosure)_{t-3-1} | 0.0002    | 0.0002    | -0.0007   |
|          | (-0.10)   | (-0.08)   | (-0.32)   |
| D(Low country rating) × D(Disclosure)_{t-3-1} | 0.0011    | 0.0003    | -0.0019   |
|          | (0.55)    | (-0.16)   | (-0.85)   |
| D(Disclosure)_{t-3-1} | 0.0011*** | 0.0005    | 0.0004    |
|          | (2.75)    | (1.26)    | (0.89)    |

| Stock-level control variables | Yes | Yes | Yes |
| Country FE                  | Yes | No  | No  |
| Stock, investor, time FE    | No  | Yes | No  |
| Country × time, industry × time, investor × time, Investor × stock FE | No  | No  | Yes |

4. Trading on limited demand stimulus or insufficient direct liquidity support?

So far, our results show that during the COVID-19 crisis, short sellers have traded on the limited ability of some fiscal authorities to shield their corporations from negative revenue shock. Governments across the European Union have initiated a variety of fiscal responses to the economic disruption caused by the lockdown measures in response to the pandemic. We distinguish between two types of fiscal support that were implemented during this crisis. A large share of these stimulus packages aimed at encouraging consumer demand for goods and services once local lockdowns were lifted (Casado et al., 2020; Chetty et al., 2020; Cobon et al., 2020). A possible increase in consumption ultimately translates into more production, revenue and profit and indirectly supports corporations. In addition to consumption stimuli, a number of alternative fiscal measures that aimed at providing immediate support to troubled companies by offering direct liquidity have been adopted. We differentiate between these two types of fiscal support, and test whether short sellers have speculated on the inability of countries with limited fiscal space to: (1) stimulate local demand for goods and services successfully; and/or (2) support vulnerable corporations through direct liquidity provision and guarantees.

If short sellers traded on the insufficient stimulus packages offered by governments of countries with low credit rating, we would expect that our main effect from Table 3 would be stronger for companies that are mainly active in the country hosting their headquarters. In other words, short sellers should be less likely to target illiquid multinational corporations in low-rated countries, because these companies profit from stimulus packages offered by other governments. Alternatively, if the driving force behind the trading behavior of short sellers was the limited direct liquidity support offered by governments to companies in countries with low credit rating, then we would expect them to target firms that are less important politically and economically. The main reason behind this is that such companies are less likely to be bailed out in case of bankruptcy. We define these companies as having fewer employees, fewer total assets and lower revenues relative to all companies in a given country.

In order to distinguish between the two mutually non-exclusive hypotheses, we run our most-saturated regression model for different sub-samples. In Panel A of Table 6, we split the sample in companies that generate their main revenue in the domestic market and those that generate their revenue in multiple countries. We obtain geographic segment data on company revenues from Refinitiv Eikon. Unfortunately, the reporting of geographic data is not uniform across companies. For this reason, we construct three different variations of the revenue share that is generated in the domestic market to ensure the robustness of our results. For the first, we only calculate the revenue share of the headquarters country if the country is mentioned as a single, separate segment in the firm’s reporting. If segment data is available but data on the headquarters country is not reported, we assume that it is less likely to be an important sales market and define the share as 0. No local share is defined for firms with no data on geographic segments at all. For the second specification, we calculate the local revenue share also for firms when the headquarters country is part of a broader geographic segment with multiple additional markets. In this case, since we do not know the exact share that pertains to the headquarters country, we split it across all mentioned markets equally. Lastly, we relax the assumption that headquarters coun-
Table 6
Trading on limited local demand stimulus or insufficient direct liquidity support? Table 6 shows the result for the fully saturated version of the fixed effects panel regression described in Eq. (1) using different subsamples of the universe. The dependent variable is D(Short position), which is a dummy variable equal to 1 if investor i holds a short position in stock j on day t and is zero otherwise. The main explanatory variables are D(Crash), D(Recovery 1), D(Recovery 2), D(Low country rating), Company illiquidity, all defined as in Table 3. The sample splits are defined by the median of the following variables: three different definitions of the share of the revenue generated in the headquarters country (Panel A), as well as the number of employees, total assets and revenue adjusted by the country median (Panel B). In Column (1) and (2) of Panel A, we only calculate the revenue share of the headquarters country if the country is mentioned as a single, separate segment in the firms’ reporting. If segment data is available and no data on the headquarters country is reported, we assume that the headquarters country is less likely to be an important sales market and define the share as 0. In Column (3) and (4), we alter the first definition by also calculating the local revenue share if the headquarters country is part of a firm’s geographic segment with multiple mentioned markets. In this case, we do not know the exact share that pertains to the headquarters country and split the share across all mentioned markets equally. In Column (5) and (6), we relax the assumption that headquarters countries that are not reported in the segment data are likely to be less important and define those as missing rather than 0. We use the median revenue share of the domestic market for the previous three fiscal years and define companies to have a high local share if that share is above the cross-sectional median of the distribution. Those below the median are included in the low local share sample. The sample splits in Panel B are conducted using the median of the previous three fiscal years of the number of employees.

Panel A: Trading against local demand stimulus

|                | Local share<sub>1</sub> | Local share<sub>2</sub> | Local share<sub>3</sub> |
|----------------|------------------------|------------------------|------------------------|
|                | High | Low | High | Low | High | Low |
| D(Crash) × D(Low country rating) × Company illiquidity | 1.0094*** | 0.0676 | 1.0546*** | -0.0701 | 1.1589*** | 0.2354 |
|                | (3.05) | (0.03) | (2.87) | (0.32) | (2.88) | (1.10) |
| D(Recovery 1) × D(Low country rating) × Company illiquidity | 0.9436** | 0.0285 | 0.8949** | -0.1092 | 1.0730** | 0.0915 |
|                | (2.55) | (0.12) | (2.19) | (0.46) | (2.57) | (0.40) |
| D(Recovery 2) × D(Low country rating) × Company illiquidity | 0.8059** | -0.1247 | 0.7377* | -0.2620 | 0.8544** | -0.0027 |
|                | (2.20) | (0.04) | (1.82) | (0.01) | (2.04) | (-0.61) |
| D(Crash) × Company illiquidity | -0.0380 | -0.1577** | -0.0426 | -0.1758** | -0.1337 | -0.1218 |
|                | (-0.37) | (-2.09) | (-0.45) | (-2.31) | (-1.38) | (-1.26) |
| D(Recovery 1) × Company illiquidity | 0.0037 | -0.1157 | 0.0178 | -0.1211 | -0.0672 | 0.0387 |
|                | (0.04) | (-1.53) | (0.17) | (-1.61) | (-0.63) | (0.41) |
| D(Recovery 2) × Company illiquidity | 0.0294 | -0.0381 | 0.0038 | -0.0285 | -0.0712 | 0.1487 |
|                | (-0.28) | (-0.46) | (0.04) | (-0.35) | (-0.66) | (1.39) |
| Adj. R<sup>2</sup> | 0.4952 | 0.4912 | 0.4967 | 0.4831 | 0.5016 | 0.4816 |
| Adj. within R<sup>2</sup> | 0.0079 | 0.0043 | 0.0071 | 0.0038 | 0.0070 | 0.0025 |
| Nobs | 279,599 | 272,143 | 277,731 | 273,007 | 236,396 | 234,812 |

Panel B: Trading against direct liquidity support

|                | No. of Employees | Total Assets | Revenue |
|----------------|------------------|--------------|---------|
|                | Low | High | Low | High | Low | High |
| D(Crash) × D(Low country rating) × Company illiquidity | 0.5934*** | 0.6619** | 0.5196** | 0.6328*** | 0.4790** | 0.6709** |
|                | (2.70) | (2.26) | (2.28) | (2.66) | (2.16) | (2.47) |
| D(Recovery 1) × D(Low country rating) × Company illiquidity | 0.4227** | 0.5579* | 0.4348* | 0.6209** | 0.3117 | 0.6689** |
|                | (1.97) | (1.84) | (1.86) | (2.36) | (1.46) | (2.41) |
| D(Recovery 2) × D(Low country rating) × Company illiquidity | 0.1831 | 0.0678** | 0.3246 | 0.6337** | 0.0586 | 0.8467** |
|                | (0.82) | (2.16) | (1.31) | (2.44) | (0.25) | (3.27) |
| D(Crash) × Company illiquidity | -0.1515*** | 0.1199 | -0.0702 | 0.0293 | -0.0693 | 0.0336 |
|                | (-2.62) | (1.48) | (-1.28) | (0.35) | (-1.26) | (0.39) |
| D(Recovery 1) × Company illiquidity | -0.0992 | 0.1247 | -0.0734 | 0.0176 | -0.0286 | 0.0584 |
|                | (-1.49) | (1.34) | (-1.15) | (0.19) | (-0.44) | (0.61) |
| D(Recovery 2) × Company illiquidity | -0.1037 | -0.0047 | -0.1237 | 0.0565 | -0.0312 | -0.0077 |
|                | (-1.49) | (-0.05) | (-1.64) | (0.62) | (-0.42) | (-0.07) |
| Adj. R<sup>2</sup> | 0.4806 | 0.5154 | 0.4849 | 0.5068 | 0.4088 | 0.5127 |
| Adj. within R<sup>2</sup> | 0.0071 | 0.0035 | 0.0049 | 0.0036 | 0.0055 | 0.0038 |
| Nobs | 313,479 | 315,112 | 350,203 | 310,946 | 320,667 | 336,794 |

Stock-level control variables: Yes Yes Yes Yes Yes Yes
Country × time, industry × time, investor × time, investor × stock FES: Yes Yes Yes Yes Yes Yes

tries that are not reported in the segment data are likely to be less important, and define those as missing rather than 0. For all three proxies, we use the median revenue share of the domestic market for the previous three fiscal years and define companies as having a high local share if that share is above the cross-sectional median of the distribution. Those below the median are included in the low local share sample.

Across all three sample splits in Panel A, we consistently find that in countries with lower fiscal space, short sellers have targeted only those illiquid companies that generate their revenue mainly in the domestic market. The coefficient of the triple interaction D(Crash) × D(Low country rating) × Company illiquidity in the sample of companies that depend more on the demand of the domestic market (Columns (1), (3) and (5)) doubles relative to our baseline specification. By contrast, in Columns (2), (4) and (6), we find that this effect is reduced to essentially zero for illiquid, multinational corporations. These findings support the argument that short sellers have speculated on the limited fiscal space of some governments to provide sufficient stimulation to the local economy and increase demand for goods and services. To the contrary,
troubled companies that did not solely rely on the local stimulus package of fiscally constrained countries have not been targeted by short sellers.

In Panel B of Table 6, we test whether short sellers have speculated on the inability of governments in low-rated countries to support all companies in trouble with direct liquidity impulsion. Put differently, we investigate whether short sellers targeted companies deemed less important for the local economy and, thus, less likely to receive direct funding from the government. For this purpose, we split our sample into firms with a lower number of employees, fewer total assets and lower revenue relative to the median company in the country and above median companies in the same country. All three variables are calculated using the median of the previous three fiscal years and normalized with the country-specific median. For all three sample splits in Panel B, we did not find a difference in the triple interaction \(D(\text{Crash}) \times D(\text{Low country rating}) \times \text{Company illiquidity}\) coefficient between the two sub-samples. Short sellers have, thus, traded illiquid companies headquartered in fiscally constrained countries irrespective of the economic importance or relevance of a company for the country.\(^{26}\)

5. Performance analysis

In this section, we study whether short seller’s trading on the importance of fiscal space during the COVID-19 pandemic is also reflected in their performance. We begin our analysis with the traditional calendar-time portfolio approach. We first split the universe of stocks from European countries with a disclosure requirement for net short sale positions above 0.5% of market capitalization in 2 \(\times\) 2 portfolios, using an independent double sort based on the median of Company illiquidity and \(D(\text{Low country rating})\).\(^{27}\)

For each group, we include a stock in the corresponding portfolio, depending on whether there was a large open short position the day before. We exclude the stock from the portfolio when the large short position fell below the 0.5% disclosure threshold the day before.\(^{28}\) We form value-weighted portfolios based on the lagged market capitalization of the stocks. In order to estimate the daily risk-adjusted returns (alphas) for the four portfolios, we run the following time-series regression:

\[
\text{ret}_{i,t} - r_{ft} = \alpha_{i} + \beta_{i1}\text{MKTRF} + \beta_{i2}\text{SMBF} + \beta_{i3}\text{HMLt} + \beta_{i4}\text{CMA}\text{t} + \beta_{i5}\text{RMW}\text{t} + \beta_{i6}\text{WMT}\text{t} + \epsilon_{i,t},
\]

(2)

where \(\text{ret}_{i,t}\) is the return of portfolio \(p = 1, 2, 3, 4; r_{ft}\) is the risk-free rate; \(\text{MKTRF, SMB, HML, CMA}\) are the five factors of the Fama and French (2015) model; and \(\text{WML}\) is the momentum factor of Jegadeesh and Titman (1993).\(^{29}\) The choice of the asset pricing model is based on previous studies on short selling, which show that short sellers correct cross-sectional mispricing and place factor bets on the basis of a diverse set of asset pricing factors (see, for example, Akbas et al., 2015; Dixon and Kelley, 2021; Wu and Zhang, 2019). Therefore, we opt for a factor model which controls for the set of factors that best explains the average performance of short sellers according to the literature (Jank and Smajlheov, 2015). We then use the daily abnormal returns, \(\alpha_{i} + \epsilon_{i,t}\), to calculate the cumulative abnormal return (CAR) for each portfolio at each point in time.

Fig. 3 depicts the time-series of CARs for each of the four portfolios using weekly updates. February 21, 2020 is the reference point for the cumulative return calculation. We find that shorted illiquid companies headquartered in countries with low credit rating experienced severe abnormal returns of around -10% during the stock market crash period. The underperformance of such stocks was carried over into the first market recovery period, rising to -15%. Importantly, this negative return is in excess of the negative market return and other risk factors. We observe a slight reversal in late April 2020, but the performance of the portfolio remained below -10% at the end of our sample period. The performance for this portfolio corresponds to a short-sale profit of approximately 0.70 billion USD.\(^{30}\) In contrast, for shorted liquid stock, there is no similar decline in CARs in countries with low credit rating. Moreover, there is no underperformance of companies headquartered in countries with high credit rating, irrespective of their illiquidity level. This finding shows that the investment strategy of shorting illiquid firms in low-rated countries was highly profitable during the market crash and remained remarkable over the subsequent period of recovery.

Next, we test the performance of short sellers during the pandemic by using the more elaborate regression-based, generalized calendar-time portfolio approach developed by Hoehlein et al. (2020). Their approach does not only reproduce the results of traditional calendar-time portfolio sorts but also has the flexibility to include multiple explanatory variables, such as company, investor, country and time characteristics within a single framework:\(^{31}\)

\[
\text{ret}_{i,j,t} - r_{ft} = \alpha + \beta_{1}\text{D(\text{Crash})} \times \text{D(\text{Low country rating})}_{i,j} \times \text{D(\text{Illiquidity})}_{i,j} + \beta_{2}\text{D(\text{Recovery})}_{i,j} \times \text{D(\text{Low country rating})} \times \text{D(\text{Illiquidity})}_{i,j} + \beta_{3}\text{D(\text{Recovery})}_{i,j} \times \text{D(\text{Low country rating})} \times \text{D(\text{Illiquidity})}_{i,j} + (X_{i,j,t} \cap P_{i}) \gamma + (X_{i,j,t} \cap F_{i}) \theta + \epsilon_{i,j,t},
\]

(3)

where \(\text{ret}_{i,j,t} - r_{ft}\) is the excess return of stock \(i\) held by investor \(j\) on day \(t\). \(\text{D(\text{Illiquidity})}_{i,j}\) is equal to 1 if Company illiquidity is above the median value of its distribution. Moreover, we define \(X_{i,j,t} = [\text{D(\text{Illiquidity})}_{i,j}, \text{D(\text{Low country rating})}_{i,j}, P_{i}] = [\text{Crash}_{t}, \text{Recovery}_{1}, \text{Recovery}_{2}]\). \(P_{i}\) is a vector of asset-pricing factors, whose definition depends on the risk-adjustment model employed.\(^{32}\) The first Kronecker product \(X_{i,j,t} \cap P_{i}\) controls for all the remaining combinations of explanatory variables with the period dummies. The second Kronecker product \(X_{i,j,t} \cap F_{i}\) adjusts the returns using different asset-pricing factors and allows for varying factor exposures for liquid and illiquid firms, as well as for coun-

\(^{26}\) Using quadruple interactions instead of sample splits yields comparable results (see Table OA.13 of the Online Appendix).

\(^{27}\) From the portfolio formations, we exclude short positions in Wirecard AG stock, an insolvent German payment processor and financial services provider. The insolvency of Wirecard was announced in late June 2020, which is near the end of our sample period, and constitutes the most wealth-destructive accounting scandal in European history (Financial Times: ‘Wirecard collapses into insolvency’, June 23, 2020). Despite its significance, it is unrelated to our research question.

\(^{28}\) This timing convention is conservative, because it assumes that investors trade at the end of each day; as such, it eschews the overestimation of short sellers’ performance due to selling pressure or a forward-looking bias.

\(^{29}\) The European factors are provided from Kenneth French’s data library. More specifically, the European version of the five factors of the Fama and French (2012) model are taken from the Fama/French European 5 Factors file. The European version of the momentum factor of Jegadeesh and Titman (1993) is from the European Momentum Factor (Mom) file. All factor and portfolio returns are based on prices in U.S. dollars.

\(^{30}\) This estimate is based on the market capitalization and the daily raw returns of all short-sale positions that are in the corresponding portfolio: \(\sum MW_{i,j,t} \times \text{Shortposition}_{i,j,t} = 703,365,602\) USD.

\(^{31}\) The generalized calendar-time portfolio approach is particularly useful for studying numerous continuous determinants of the trading performance of retail and institutional investors (e.g. Deslandes and Hvidve, 2011; Jank et al., 2021; Jenkins et al., 2016).

\(^{32}\) For the Carhart (1997) model, \(F_{i} = [\text{MKTRF, SMB, HML, WML}]\) and for the Fama and French (2015) model augmented by the momentum factor, \(F_{i} = [\text{MKTRF, SMB, HML, CMA, RMW, WML}]\).
tries with high and low credit ratings. We compute Driscoll and Kraay (1998) standard errors, which are robust to general forms of cross-sectional dependence, autocorrelation and heteroskedasticity, and exactly match the Newey and West (1987) standard errors in the standard calendar-time portfolio approach. We employ the optimal lag length as proposed by Newey and West (1994). The regression coefficients of the indicator variables are interpreted as the average abnormal returns associated with the respective characteristic/portfolio relative to the factors included in the model.

Table 7 shows the regression results using two comprehensive asset-pricing models: the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model augmented by momentum. For the sake of clarity, we do not report the θ coefficient estimates.33 For each of the two models, we employ three weighting schemes for the stocks: value weighting with the market capitalization of the stock (VW), short position weighting with the market capitalization of the short position (SPW) and equal weighting (EW) of each position. The main coefficient of interest is β1 of Eq. (3). We find that the shorted illiquid companies in low-rated countries strongly underperformed across all six specifications during the crash period; at that time, the abnormal return for these companies relative to liquid companies in low-rated countries was 11.3 percentage points lower than the same return difference in high-rated countries.34 The β1 regression coefficient is analogous to a daily return difference between two long-short strategies: the first strategy invests in illiquid companies and sells liquid companies in low-rated countries; the second strategy follows the same approach but in high-rated countries. From the regression coefficient associated with D(Crash) × D(Illiquid company), we observe that the long-short strategy in high-rated countries also yielded a negative abnormal return, albeit economically and statistically weaker relative to the strategy in countries with high credit rating.

Moreover, in countries with low credit rating, there is no significant reversal in the underperformance of illiquid companies compared to liquid ones during the recovery period. If anything, the negative β2 estimate suggests that the negative return difference even increased relative to the illiquid/liquid difference in countries with high credit rating. The estimate, however, is statistically insignificant.

Overall, the results of the return analysis show that increased short selling of illiquid companies in countries with low creditworthiness is associated with strong outperformance by short sellers. Consistent with our earlier findings on the importance of fiscal space, we show that it is the combination of two variables, namely company illiquidity and the creditworthiness of the country that

33 We run additional robustness tests using raw returns, as well as the CAPM and the Fama and French (1992) model as return risk-adjustment models. All tests yield consistent results, as evident from Table OA.14 in the Online Appendix.

34 The market crash period consists of 21 trading days resulting in $21 \times 0.54 \text{ pp.} = 11.3 \text{ pp.}$ for the short position weighted specification in Column (5).
hosts the company’s headquarters, which are essential in explaining the trading behavior and performance of short sellers, and not necessarily the two characteristics alone.

6. Conclusion

We examine the trading behavior of short sellers, generally regarded as sophisticated investors, during an unprecedented global shock: the COVID-19 pandemic. Our evidence shows that short sellers adapted quite quickly to this novel set of circumstances and incorporated relevant information into their trades well ahead of the stock market crash. In particular, they focused on less liquid companies headquartered in countries with a low credit rating. This trading pattern suggests that short sellers have bet on the inability of governments with budgetary constraints to provide sufficient economic stimuli to their businesses. This trading strategy was highly profitable: in the portfolio of shorted illiquid companies headquartered in countries with a low credit rating, we observe an abnormal return of up to -10% during the crash period. Importantly, this return is in excess of the negative performance of the market portfolio and other common risk factors. Thus, the overall portfolio performance is even higher and corresponds to a short-sale profit of approximately 0.7 billion USD. By contrast, neither liquid firms in the same country nor illiquid firms in countries with high credit rating experienced a negative abnormal return during this period.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2022.106552.

References

Acharya, V.V., Steffen, S., 2020. The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. Rev. Corp. Financ. Stud. 9 (3), 430–471. doi:10.1093/rcfs/cfaa013.

Ackermann, C., McNally, R., Ravencraft, D., 1999. The performance of hedge funds: risk, return, and incentives. J. Financ. 54 (3), 833–874. doi:10.1111/0022-1082.00229.

Akbas, F., Armstrong, W.J., Sorescu, S., Subrahmanyam, A., 2015. Smart money, dumb money, and capital market anomalies. J. Financ. Econ. 118 (2), 355–382.

Alessi, L., Osola, E., Panizza, R., 2021. What greemnt matters in the stock market? The role of greenhouse gas emissions and environmental disclosures. J. Financ. Stab. 54, 100869.

Aizenman, J., Jinjarak, Y., 2010. De facto fiscal space and fiscal stimulus: definition and assessment. Working Paper 16539. NBER. doi:10.3386/w16539.

Aminud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5 (1), 31–56. doi:10.1111/1368-4811.00024-6.

Alfaro, L., Chari, A., Greenland, A. N., Schott, P. K., 2020. Aggregate and firm-level stock returns during pandemics, in real time. Working Paper 26950. NBER. doi:10.3386/w26950.

Anderson, J. E., Bergamini, S., Brekelmans, S., Cameron, A., Darvas, Z., Dominguez Jimenez, M., Middeis, C., 2020. The fiscal response to the economic fallout from the Coronavirus. Working Paper. Bruegel.

Aschauer, D.A., 1985. Fiscal policy and aggregate demand. Am. Econ. Rev. 75 (1), 117–127.

Asquith, P., Pathak, P.A., Ritter, J.R., 2005. Short interest, institutional ownership and stock returns. J. Financ. Econ. 78, 243–276. doi:10.1016/j.jfineco.2005.01.001.
Kose, M.A., Kurlat, S., Ohnsorge, F., Sugawara, N., 2017. A Cross-Country Database of Fiscal Space. Journal of International Money and Finance 128, 102682. doi:10.1016/j.jimonfin.2022.102682.

Kou, S., Peng, X., Zhong, H., 2018. Asset pricing with spatial interaction. Manag. Sci. 64 (5), 2083–2101. doi:10.1287/mnsc.2016.2627.

Laeven, L., Schepens, G., Schnabel, I., 2020. Zombification in Europe in times of pandemic.

Landier, A., Thesmar, D., 2020. Earnings Expectations in the COVID Crisis. Rev. Asset Pricing Stud 10 (4), 598–617. doi:10.3386/w27160.

Leeper, E.M., Walker, T.B., 2011. Fiscal limits in advanced economies’. Econ. Pap.: J. Appl. Econ. Policy 30 (1), 33–47. doi:10.1111/j.1759-3441.2011.00111.x.

Leeper, E.M., Walker, T.B., Yang, S.-C.S., 2013. Fiscal foresight and information flows. Econometrica 81 (3), 1115–1145. doi:10.3982/ECTA8337.

Lehmann, B.N., 1990. Fads, martingales, and market efficiency. Q. J. Econ. 105 (1), 1–28. doi:10.2307/2937816.

Liang, B., 1999. On the performance of hedge funds. Financ. Anal. J. 55 (4), 72–85. doi:10.2469/faj.v55.n4.2287.

Muravyev, D., Pearson, N.D., Pollet, J.M., 2022. Is there a risk premium in the stock lending market? Evidence from equity options. J. Financ. 77 (3), 1787–1828. doi:10.1111/jofi.13120.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703–708. doi:10.2307/1913610.

Newey, W.K., West, K.D., 1994. Automatic lag selection in covariance matrix estimation. Rev. Econ. Stud. 61 (4), 631–653. doi:10.2320/12297912.

Neyman, J., Scott, E.L., 1948. Consistent estimates based on partially consistent observations. Econometrica 16 (1), 1–32. doi:10.2307/1904288.

Perotti, R., 1999. Fiscal policy in good times and bad. Q. J. Econ. 114 (4), 1399–1436. doi:10.1162/003355395560304.