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On the importance of fiscal space: Evidence from short sellers during the COVID-19 pandemic

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Non-technical summary

Research Question

The outbreak of the COVID-19 pandemic had an unprecedented impact on the global economy, forcing governments to take rapid fiscal action. However, generous government support programmes depend on the government having a good credit rating. How do financial market participants incorporate fiscal constraints into their investment decisions? In our discussion paper we study this question by analysing developments in short positions during the first few months of the COVID-19 pandemic in Europe.

Contribution

We examine how short sellers, as important informed economic agents, incorporate information about fiscal space into their trading decisions. For this purpose, we use micro-level data, which cover short sellers' positions in stocks above a certain disclosure threshold. Our direct evidence of investor behaviour in individual stocks is crucial for gaining a better understanding of how the flow of macroeconomic information during an unprecedented event, such as the COVID-19 pandemic, is processed.

Results

Our study suggests that short sellers anticipated the importance of fiscal space. During the stock market collapse in February 2020, we see a clear rise in short positions in companies with low liquidity headquartered in countries with a poor credit rating. In countries with a good credit rating, we do not observe this change in short sellers' strategy. This trading strategy suggests that short sellers incorporate the limited ability of fiscally constrained governments to support firms with liquidity problems into their decisions. We find that they shifted their strategy ahead of the market collapse, anticipating the importance of fiscal space. Their strategy resulted in high abnormal returns during the market downturn period of the pandemic.

Nichttechnische Zusammenfassung

Fragestellung

Der Ausbruch der COVID-19-Pandemie hatte beispiellose Auswirkungen auf die Weltwirtschaft. Dabei mussten die Staaten rasch finanzpolitisch handeln. Doch großzügige staatliche Hilfsprogramme setzen eine hohe Bonität des Staates voraus. Wie berücksichtigen Finanzmarktakteure den unzureichenden finanzpolitischen Spielraum in ihren Investitionsentscheidungen? Dieses Diskussionspapier untersucht diese Frage, indem sie die Entwicklung der Leerverkaufspositionen in den ersten Monaten der COVID-19-Pandemie in Europa analysiert.

Beitrag

Wir untersuchen auf welche Weise Leerverkäufer, die als wichtige informierte Marktteilnehmer gelten, Informationen über den finanzpolitischen Spielraum in ihre Entscheidungen einfließen lassen. Dafür nutzen wir Mikro-Daten, die die jeweilige Position der Leerverkäufer in einzelnen Aktien, ab einem gewissen Meldeschwellenwert, abbilden. Die direkte Untersuchung trägt zu einem besseren Verständnis bei, auf welche Weise makroökonomische Information in einem nie dagewesenen Ereignis, wie der COVID-19-Pandemie, verarbeitet werden.

Ergebnisse

Während des Einbruchs des Aktienmarkts im Februar 2020 sehen wir einen deutlichen Anstieg von Leerverkaufspositionen in Firmen mit geringen liquiden Mitteln, die in Ländern mit schlechtem Rating beheimatet sind. In Ländern mit guter Bonität können wir diesen Strategiewechsel der Leerverkäufer nicht beobachten. Diese Tatsache deutet darauf hin, dass Leerverkäufer die begrenzten Fähigkeiten bonitätsschwacher Staaten, Unternehmen mit Liquiditätsproblemen zu unterstützen, in ihre Entscheidungen einfließen lassen. Der Strategiewechsel findet bereits vor dem Einbruch des Aktienmarktes statt. Leerverkäufer antizipieren also die Wichtigkeit finanzpolitischen Spielraumes während der COVID-19-Pandemie. Ihre Strategie generiert hohe abnormale Renditen während des Markteinbruchs.

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Abstract

Using the exogenous shock of the COVID-19 pandemic, we study how informed market participants evaluate fiscal space. Short-selling activity shifted upon the onset of the pandemic towards companies with low financial flexibility only in countries with limited fiscal space. Among these companies, short sellers targeted especially those that generate their revenue mainly in the domestic market. These short sellers entered their positions before the market crash, generating thereby a significant abnormal return. These findings support the notion that short sellers bet on the inability of governments with budgetary constraints to provide sufficient stimulus to their economy in times of crises.

Keywords: COVID-19 pandemic, short selling, fiscal space, institutional investors

JEL classification: G14, G23, H30.

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1 Introduction

The relevance of fiscal policy for economic activity is subject of longstanding debate among academics and policy makers (e.g., Aschauer, 1985; Blanchard, 1985; Barro, 1990; Giavazzi and Pagano, 1990; Perotti, 1999; Blanchard and Perotti, 2002; Fatás and Mihov, 2003; Galí, López-Salido, and Vallés, 2007).[1] The global financial crisis, the European sovereign debt crisis, and persistently low interest rates over the past decade have revived discussion about the timing (e.g., Auerbach and Gorodnichenko, 2012; Jordà and Taylor, 2016) and effectiveness (e.g., Feldstein, 2009; Taylor, 2009; Reinhart and Rogoff, 2010; Herndon, Ash, and Pollin, 2014) of fiscal policy. More specifically, recent work has recognized that governments' room for maneuver plays a key role for the effectiveness of fiscal policies (e.g., Aizenman and Jinjarak, 2010; Leeper and Walker, 2011; Bi, 2012). This fiscal space – that is, the "room for undertaking discretionary fiscal policy relative to existing plans without endangering market access and debt sustainability" (IMF, 2018) – is particularly 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 affects the cross section of individual firms to varying degrees. Our empirical analysis is based on daily micro-level data of individual stock positions, and takes advantage of a rich heterogeneity in country and firm characteristics. In particular, we study the outbreak of the COVID-19 pandemic and countries' massive fiscal countermeasures against economic fallout to examine how differences in the limits of fiscal space impact the investment behavior of short sellers across stocks.

The COVID-19 pandemic represents an exogenous shock of unprecedented proportion to the world economy. In its June 2020 economic outlook, the OECD estimated that GPD in its member countries would decline by up to 9.3% during 2020.[2] 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, equiv-

[1] Ramey (2011, 2019) and Céspedes and Galí (2013) lucidly summarize the literature on fiscal policy.
[2] Source: http://www.oecd.org/economic-outlook/june-2020/

alent to 12 percent of global GDP (IMF, 2020). However, there is substantial heterogeneity across countries in their fiscal responses (Benmelech and Tzur-Ilan, 2020). While countries with a large fiscal space have more leeway to launch stimulus packages, countries closer to their fiscal limit may not be able to do so.

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 large 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, Hong, and Liskovich, 2015). In a demand system asset pricing framework, Koijen and Yogo (2018) find that the changes in investors' latent demand are the most important in terms of 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, in periods 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, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Blau, Fuller, and Van Ness, 2011; Blau, 2012; Rapach, Ringgenberg, and Zhou, 2016). Lastly, hedge funds, which hold the vast majority of short positions in our sample, appear to be the most elastic institutional investors and especially important in determining asset prices (Koijen, Richmond, and Yogo, 2020).

For our analysis we use disclosed short positions from the EU Short Selling Regulation (SSR)[3], which are particularly suitable for our purpose. This regulation 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 regulation's scope is far reaching, covering investors' large short positions in all stocks for which the main trading

[3]For further details on the regulation, see Jones, Reed, and Waller (2016); Jank and Smajlbegovic (2015); Galema and Gerritsen (2019); Jank, Roling, and Smajlbegovic (2021)

venue is in one of the above-listed countries, irrespective of investors' origin. Moreover, in contrast to other data on investor holdings, which are generally quarterly or monthly at best, the data are reported at daily frequency in a fine grid of reporting bins. Such granularity is particularly important for studying investor behavior around the pandemic-induced market crash. It allows analysis of the precise timing of investors' positions during a period that saw the fastest fall in global stock markets in financial history.

To test the role of fiscal space for 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, Kurlat, Ohnsorge, and Sugawara, 2017). Our choice is based on the empirical observation that counter-cyclical fiscal policies at times of crisis are considerably lower in countries with high levels of sovereign risk (Bianchi, Ottonello, and Presno, 2019). In line with this, Benmelech and Tzur-Ilan (2020) find that credit ratings are the best predictor of fiscal spending during the COVID-19 pandemic.

While differences in fiscal space represent an important factor in explaining the extent to which a country can alleviate the enormous negative shock of COVID-19, individual firms have also differed in their ability to cope with this unexpected event. Faced with a sudden drop in revenues, otherwise solvent companies needed to draw on their short-term liquidity reserves in order to survive. Companies with deep pockets have been in a better position to absorb the revenue shock, while those with less short-term liquidity have run into trouble (Fahlenbrach, Rageth, and Stulz, 2020).[4] We exploit this heterogeneity in financial flexibility and 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. In contrast, illiquid firms in countries with a high credit rating

[4] De Vito and Gomez (2020) have conducted a simulation study that shows that firms with limited operating flexibility would run out of cash within two years and that 10% of firms in their sample would become illiquid within six months. In line with this idea, Ding, Levine, Lin, and Xie (2020) and Fahlenbrach et al. (2020) show that companies with small cash holdings experienced more negative stock returns during the COVID-19 crisis.

are not subject to increased activity from short sellers. 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 level. Our evidence is also robust to different ways of measuring company liquidity buffers and different measures of fiscal space.

Consistent with the notion that short sellers are informed investors, we find that they 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 anticipate the importance of fiscal space for supporting vulnerable companies during the COVID-19 crisis, especially in countries which face a binding government budget constraint. Also, we observe that they maintained significant short positions in stocks of illiquid firms in these countries, despite the fact that regulators enacted shorting bans in Italy, Spain, Belgium, France, Greece, and Austria.[5]

An alternative explanation for our finding could be that short sellers were focusing on companies' liquidity buffers in countries most affected by the COVID-19 pandemic instead of a country's fiscal space. Given that some countries with a poor credit rating have been severely affected by the disease resulting in stricter lockdown measures, this explanation is a plausible alternative to our interpretation. Moreover, a significant number of US non-financial companies drew down bank credit lines to raise their cash levels in the first weeks of the outbreak (Acharya and Steffen, 2020; Li, Strahan, and Zhang, 2020). A country's fiscal space may thus also correlate with the strength of its banking sector and the extent to which its banks are able to meet the demand for short-term liquidity. However, we show that neither of the two alternative explanations is consistent with our evidence. The importance of a country's credit rating remains unchanged 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 severity of the measures taken by the government to limit the spread of the virus, (3) the capacity of a country's health system as well as (4) multiple measures of the liquidity and

[5]These bans prohibit the opening of new positions and the increase of existing ones.

health of a country's banking sector.

We also explore whether short sellers have also targeted other firm characteristics that may reflect a company's vulnerability with regard to the COVID-19 pandemic. In particular, it might be that they have increasingly sold short stocks from ex-ante riskier, unprofitable, or unproductive firms during the downturn. Therefore, we augment our analysis with various proxies for company profitability, creditworthiness, or resilience to social distancing measures, but we find that these additional firm characteristics cannot explain the short sellers' focus on a firm's liquidity buffer.

In addition, we study short sellers' trading behavior in the context of different fiscal policy approaches. In particular, a large proportion of the fiscal packages around the world are aimed at stimulating consumers' demand for goods and services once local lockdowns are lifted. An increase in consumption will ultimately translate into more production, revenue, and earnings and will indirectly support corporations. In addition to consumption stimulus, other fiscal measures were designed to provide immediate support for companies with direct liquidity provision. We distinguish between the two types of fiscal support measures and find that short sellers have mainly speculated on the inability of fiscally constrained governments to stimulate local consumption to a sufficient degree. They have targeted only those illiquid companies that are headquartered in low-rated countries and that generate their revenue mainly in those countries. There is no evidence that short sellers have speculated more on illiquid companies that are less likely to receive direct liquidity provision from their national government.

Finally, we study whether the anticipation by short sellers to incorporate information about fiscal space is reflected in capital markets. We expect that the investors' shift towards illiquid firms in countries with a low credit rating is rewarded 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 yields an abnormal return of up to -15% during the market crash period, with only a slight reversal back to -10% towards the end of our sample period. In contrast, there is no significant underperformance associated with liquid firms headquartered in countries with such low ratings. There is also no underperformance by firms headquartered in countries with high creditworthiness, irrespective of their level of liquidity. All in all, short sellers' correct anticipation of the importance of fiscal space in pricing vulnerable companies resulted in high abnormal returns during the market downturn period 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., Aizenman and Jinjarak, 2010; Leeper and Walker, 2011; Bi, 2012; Bianchi et al., 2019). 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., Benmelech and Tzur-Ilan, 2020; Casado, Glennon, Lane, McQuown, Rich, and Weinberg, 2020; Hürtgen, 2020). We add to this literature by taking a detailed look at 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, Walker, and Yang, 2013).

This paper also contributes to the rapidly evolving 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 by equity markets to COVID-19, both in terms of stock returns (Ramelli and Wagner, 2020; Alfaro, Chari, Greenland, and Schott, 2020) and macroeconomic or firm-specific growth expectations (Gormsen and Koijen, 2020; Landier and Thesmar, 2020). Some studies have examined the crucial role of cash and short-term liquidity during the pandemic compared to previous crises. Consistent with the notion that investors appreciate 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., 2020), greater financial flexibility (Fahlenbrach et al., 2020), or better access to credit lines (Acharya and Steffen, 2020). Other studies have highlighted the importance of sovereign debt in explaining equity risk (Gerding, Martin, and Nagler, 2020) or the importance of fiscal capacity in explaining sovereign default risk (Augustin, Sokolovski, Subrahmanyam, and Tomio, 2021) in the context of the pandemic. Our work differs from these studies in two important ways. First, we do not focus on the market- or firm-side reactions to the pandemic but instead we analyze the trading behavior of informed economic agents, namely short sellers. Second, the fact that informed investors trade on a combination of firms' short-term ability to stay liquid and their government's ability to provide the necessary funds to firms experiencing cash shortfalls not only emphasizes the central role of short-term funding in the context of COVID-19, it also highlights the interplay between the well-being of companies and the fiscal space of governments.

Lastly, 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.[6] For example, it has been shown that their informational advantage can stem either from private information (Karpoff and Lou, 2010; Berkman, McKenzie, and Verwijmeren, 2017; Boehmer, Jones, Wu, and Zhang, 2020) or from their superior ability to process publicly available information (Engelberg, Reed, and Ringgenberg, 2012; Chakrabarty and Shkilko, 2013). Our finding that, after the outbreak of the pandemic, short sellers correctly anticipated the underperformance of illiquid firms in countries with low credit ratings highlights yet another dimension of their skill set. Short sellers are also skilled in processing complex information about an unprecedented "black swan" event such as the COVID-19 pandemic and link 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 examine how the trading behavior of short sellers is based on

[6]See, for example, Asquith et al. (2005), Boehme, Danielsen, and Sorescu (2006), Cohen, Diether, and Malloy (2007), Blau, Van Ness, and Wade (2008), Diether, Lee, and Werner (2009), Blau et al. (2011), Blau and Tew (2014), Rapach et al. (2016), and Chague, De-Losso, and Giovannetti (2019).

the liquidity of firms and the creditworthiness of the country in which they are headquartered. Section 4 provides robustness checks, controlling for alternative explanations. In Section 5, we study the underlying motives of short sellers' trading behavior. In Section 6, we examine the trading performance of short sellers. Section 7 provides 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 significant net short sale positions in the European Union (EU), which requires any net short position larger than 0.5% of the market capitalization of the company shorted to be disclosed on the next trading day. Disclosures 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 not only to short positions but also to derivative positions, which must be accounted for on a delta-adjusted basis. Net short positions are calculated by netting all long, short, and delta-adjusted derivative positions of the underlying stock. Exemptions apply to market-making activities for which no disclosure is required. The regulation and data are described in detail in Jones et al. (2016), Jank and Smajlbegovic (2015), and Jank et al. (2021).

We collect data on significant short position notifications from the web pages of the countries' national competent authorities. Our sample covers 15 countries: thirteen EU countries, and the United Kingdom and Norway, which also adopted the regulation. The remaining EU countries did not report any notifications in the sample period.[7] For an overview of the countries covered see Table 1 or the map of Figure OA.2 in the Online Appendix. From the notification data, which covers the entry, exit and changes of significant short positions, we construct a daily panel of investors' open short positions. Our sample period is from July 1, 2019, to June 26, 2020.

[7]The national competent authority of Portugal, CMVM, unfortunately does not provide an archive of historical positions and is therefore not considered in our analysis.

We merge short sellers' position data with company characteristics and stock returns from Refinitiv Eikon/Datastream, to which we apply several commonly used data filters to ensure the quality of the data (Ince and Porter, 2006). For firms to be included in our analysis we require the headquarters country and country of exchange to be in one of the 15 countries with short position disclosures. Furthermore, for our analysis we only consider common equity and exclude penny stocks (stocks with a stock price below $1 at the end of June 2019, i.e. just before our sample period). We obtain the daily five Fama and French (2015) factor returns and the momentum factor returns for Europe (Fama and French, 2012) from Kenneth R. French's data library.[8] Country-level data come from various sources and are in detail described in Table OA.1 of the Data Appendix.

In our analysis we use the 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 to be an important dimension of fiscal space (Kose et al., 2017). This particular choice is further 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). This relationship between sovereign ratings and counter-cyclical fiscal spending is also observed in case of the COVID-19 pandemic. Benmelech and Tzur-Ilan (2020) find that sovereign credit ratings are the best predictor of fiscal spending during the COVID-19 pandemic. For our purposes, we then define the dummy variable $D(\textit{Low country rating})$ to be one if the firm is headquartered in a country with a credit rating below AA- and zero otherwise. To categorize countries, we use Standard & Poor's (S&P) long-term country rating as of the end of December 2019, i.e., before the COVID-19 crisis. We use the headquarters country rather than the country of exchange as the relevant country for a company, because we expect that fiscal stimulus packages and liquidity support will be targeted in this way.[9]

We expect insufficient fiscal support to matter most for companies that are most affected by

[8] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[9] In our robustness tests, we also use a country's 5-years sovereign CDS spread as an alternative measure of a government's market access and fiscal space (Kose et al., 2017). These tests yield results comparable to our main findings.

the sudden drop in revenues caused by the COVID-19 pandemic. Here we draw on findings by Fahlenbrach et al. (2020) and Laeven, Schepens, and Schnabel (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. To measure companies' liquidity buffer we use the quick ratio also known as the acid-test ratio. It is defined as *Current assets* less *Inventories* over *Current liabilities*. Current liabilities are company's debts or obligations that are due within one year. The quick ratio hence measures a company's ability to meet its short-term obligations with its most liquid assets, without the need of selling inventory or raising external capital. It is a key ratio to determine financial health of a company, which is readily available to market participants in standardized reports. As a rule of thumb a quick ratio above one is considered healthy, however, there are also differences in financing structures across industries that need to be addressed.[10]

We obtain information on companies' quick ratio and additional balance sheet characteristics from Eikon. We use information up the 2018 fiscal year to ensure that this information 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, i.e., the fiscal years 2016–2018. We use the same approach for all other balance sheet variables. Furthermore, we use the entire universe of companies of our sample countries to assess the liquidity of the shorted companies. Specifically, we download from ESMA's Financial Instruments Reference Data System (FIRDS) the list of stocks admitted to trading in our sample countries and obtain their balance sheet characteristics. We also require the companies' headquarters to be in these countries. Industry classification is a significant determinant of a company's liquidity level (e.g., Harford, Mansi, and Maxwell, 2008). To control for this industry component, we compute an industry-adjusted quick ratio by subtracting the industry median from the raw

[10]We also use the current ratio, which is defined as *Current assets* over *Current liabilities*, as an alternative proxy. This ratio, however, is less conservative and suitable for the purpose of our study, because it includes inventories in the numerator. As converting inventories to cash may be difficult during the COVID-19 outbreak, the quick ratio is likely to better capture the concept of short-term liquidity than the current ratio during that time period. In our additional tests, we show that our results are, as expected, slightly weaker but robust to this change in liquidity proxy.

quick ratio. Our final variable, *Company illiquidity* is a percentile rank of firm illiquidity, ranging from zero to one, where zero represents the most liquid firm and one represents the most illiquid firm.

2.2 Descriptive statistics

Table 1 reports the time-series average of the total number of open short positions and their cross-sectional value across different jurisdictions and for different market phases. The pre-COVID-19 phase is from July 1, 2019, the beginning of our sample period, to February 23, 2020; the market crash phase is from February 24 to March 23, 2020; and the recovery phase is from March 24 to the end of sample. We distinguish between two recovery periods: the first recovery period is from March 24 to May 17, 2020; and the second recovery period is from May 18 to June 26, 2020. The period cutoffs are based on major stock market events and announcements: February 24 represents the first large drop in the the European market return (-3.8%) and also global equity markets as the coronavirus outbreak worsened substantially in Europe over the preceding weekend. Over the course of the crash, from February 24 to March 23, the market declined by more than 35%. On March 24 the market started to recover with a daily return of 8.4%. The definition of crash and recovery closely follows Ramelli and Wagner (2020).[11] The second recovery period starts with the announcement of a French-German initiative for a EU Recovery Fund on May 18, 2020.[12] The development of the European stock market return over the different time periods is shown in Figure OA.1 of the Online Appendix.

Looking at the pre-COVID-19 phase, the UK is the country with the largest number of reported short positions. It is followed by Germany, France, Sweden, and Italy. Before the market crash the daily average total number of all reported short positions of all countries combined is 1174.9, with an average reported position of 1.00%. During the crash phase there is little change in these aggregate figures. The total number of reported short positions is

[11] Ramelli and Wagner (2020) define the beginning of the crash period as we do. Their recovery period begins with the Federal Reserve Board's announcement of major interventions in the corporate bond market on March 23, at 8:00 a.m. EDT. Because this is in the afternoon trading hours of the European markets, our recovery period starts on the next day.

[12] Official press release: https://www.bundesregierung.de/resource/blob/975226/1753772/414a4b5a1ca91d4f7146eeb2b39ee72b/2020-05-18-deutsch-franzoesischer-erklaerung-eng-data.pdf

1199.7, with an average value of 0.98%. In the first and second recovery period the total number of short positions declines by 12% and 7.9% to 1052.5 and 969.1, respectively. The value of the significant short positions, on the contrary, remains stable at 0.98%.

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

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 a sample of public and confidential large short position disclosures. Hence, 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 revenues for a large number of firms. At the same time, companies with limited operating flexibility are not able to cut their costs in the same way and their ability to manage the sudden cash flow shortfall crucially depends on their short-term liquidity buffer (Fahlenbrach et al., 2020). Companies with only few liquid assets are more vulnerable and thus more reliant on fiscal support than companies with abundant liquid assets. Governments across the globe brought in a considerable number of stimulus programs, including emergency measures to restore companies' short-term liquidity as well as programs to stimulate demand. However, countries may themselves face constraints during the crisis. While those with small budget deficits have more leeway to bring in countermeasures, countries with large deficits may not be able to adopt sufficient policies to support their vulnerable firms. Indeed, there is considerable heterogeneity in the responses taken by countries (Anderson, Bergamini, Brekelmans, Cameron, Darvas, Domínguez Jíménez, and Midões, 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 leads naturally to a triple difference estimation strategy, in which we split the sample of firms along the dimension of fiscal space and company liquidity buffers. First, we divide the sample of firms according to whether they are headquartered in countries with high credit ratings (≥AA-) or low credit ratings (<AA-). Second, we distinguish between companies with high and low liquidity buffers using our company illiquidity measure.

Figure 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. The number of short positions in liquid and illiquid firms follows a common trend before 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. It declined after that week but stayed at an elevated level relative to shorting of liquid firms, which declined over the same time period. The figure also shows that the gap between liquid and illiquid firms was already widening before the market crash occured on February 24. This suggests that short sellers had anticipated at least to some extent the importance of liquidity reserves when it comes to withstanding the immediate economic consequences of the COVID-19 outbreak.

Panel B of Figure 1 shows the same sample split for firms headquartered in countries with a high credit rating. Interestingly, there is no intensified 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, shorts in both groups increase slightly but both then decline in the following weeks.

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

3.2 Regression framework

We now formalize the graphical 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 level. For our baseline model we run the following regression:

$$
\begin{aligned}
&D(\textit{Short position}_{i,j,t}) = \\
&\sum_p \beta_1^p D(\textit{Period}_p) \times D(\textit{Low country rating}_i) \times \textit{Company illiquidity}_i + \\
&\sum_p \beta_2^p D(\textit{Period}_p) \times \textit{Company illiquidity}_i + \\
&\sum_p \beta_3^p D(\textit{Period}_p) \times D(\textit{Low country rating}_i) + \\
&\mathbf{X}'_{i,t-1}\gamma + \alpha_i + \alpha_j + \alpha_t + \epsilon_{i,j,t},
\end{aligned} \tag{1}
$$

where $D(\textit{Short position}_{i,j,t})$ is a dummy variable that equals 1 if investor j has a reported significant short position in stock i at day t, and equals 0 otherwise. $D(\textit{Period}_p)$ are dummy variables for the time periods of interest, where $\textit{Period}_p = \{\textit{Crash}; \textit{Recovery } 1; \textit{Recovery } 2\}$. The *Crash* period is from February 24 to March 23, the *Recovery* 1 period is from March 24 to May 17, and the *Recovery* 2 period is from May 18 to June 26, 2020. $D(\textit{Low country rating}_i)$ is a dummy variable that equals 1 if the headquarters country of stock i has a credit rating below AA−.[13] $\textit{Company illiquidity}_i$ 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 (α_i), investor (α_j), and time fixed effects (α_t). Note that the variables $D(\textit{Period}_p)$, $D(\textit{Low country rating}_i)$, $\textit{Company illiquidity}_i$ and their remaining double interactions are absorbed by these fixed effects. We control for various lagged stock-level characteristic that are collected in vector $\mathbf{X}_{i,t-1}$, which include a short-selling ban dummy, past stock returns at different horizons, the Amihud (2002) ratio, bid-ask spread, idiosyncratic volatility and market beta. All of these time-varying stock characteristics may affect investors' tendency to short a given stock. Note that the stock fixed effects α_j absorb stock characteristics that are largely time-invariant in our relatively short sample period of 12

[13] In a robustness check we study the grouping in low- and high-rated countries in detail. We run the regression with finer rating dummy variables for ratings AAA, AA, A and ≤BBB. The results show that in the market crash period countries with AA rating experience not significantly more shorting activity in illiquid firms than countries with a AAA rating. Countries with a A or ≤BBB rating, on the contrary, experience significantly higher shorting activity in illiquid firms, which is of comparable economic magnitude. The results are shown in the Table OA.6 of the Online Appendix.

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 strategy – are typically rebalanced once a year (Fama and French, 1993). To account for the other prominent trading strategies at higher frequency such as short-term reversal (Lehmann, 1990; Jegadeesh, 1990) or momentum (Jegadeesh and Titman, 1993) we control for lagged returns at different horizons as mentioned before.

Table 3, Column (1), shows the regression results of the baseline model. The coefficient of the triple interaction $D(Crash) \times D(Low\ country\ rating) \times Company\ illiquidity$ 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 country ratings. The coefficient of the triple interaction $D(Recovery\ 1) \times D(Low\ country\ rating) \times Company\ illiquidity$ is also positive and statistically significant, indicating this strategy has also been followed in the first market recovery phase. For the second recovery period, the triple interaction is still positive but statistical significance is weaker. The coefficients of all double interactions $D(Period_p) \times Company\ illiquidity$ on the contrary, are statistically not different from zero for all market phases. These results highlight a striking difference in short sellers' trading behavior: Investors short particularly illiquid firms headquartered in countries with a low credit rating, while we do not find such behavior for firms in countries with a high credit rating. Hence, the degree to which a country can provide fiscal means 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 investors' 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 the propensity to establish a short position.

When we examine the control variables, the results are by and large as might be 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. Somewhat surprisingly, investors show a similar 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 notion that short sellers are concerned about covering their positions (Boehmer, Duong, and Huszár, 2018). Finally, short sellers propensity to establish a large short position is positively related to idiosyncratic volatility, which is insignificant only for the first specification, but significant for the more saturated models (2) - (5).

We next include various high-dimensional fixed effects in our regression model. The most saturated regression is given by the following specification:

$$
\begin{aligned}
&D(Short\ position_{i,j,t}) = \\
&\sum_p \beta_1^p D(Period_p) \times D(Low\ country\ rating_i) \times Company\ illiquidity_i + \\
&\sum_p \beta_2^p D(Period_p) \times Company\ illiquidity_i + \\
&\mathbf{X}'_{i,t-1}\gamma + \alpha_{c,t} + \alpha_{ind,t} + \alpha_{j,t} + \alpha_{i,j} + \epsilon_{i,j,t},
\end{aligned} \tag{2}
$$

where $\alpha_{c,t}$ is a vector of country$\times$time dummies. Country-time fixed effects are an important control as they absorb any time-varying country specific shocks; this includes, for example, how much a country has been affected by the COVID-19 pandemic or any country-specific measures taken in response to the pandemic. $\alpha_{ind,t}$ are industry-time fixed effects that control for any time-varying industry heterogeneity across companies. $\alpha_{j,t}$ are investor-time fixed effects which 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, $\alpha_{i,j}$ are fixed effects for each investor-stock pair, which controls for any stock-specific expertise an investor might have.

In Colums (2) – (5) of Table 3 we include the different fixed effects on a step-by-step basis. The coefficient of the triple interaction $D(Crash)\times D(Low\ country\ rating)\times Company\ illiquidity$ 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. However, the shorting ban dummy is defined on country of exchange. Moreover, for some countries not all listed stocks are subject to a shorting ban, leaving some, albeit relatively little, remaining variation. 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. 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%.

3.3 Parallel trends assumption and short sellers' timing

The parallel trends assumption in our setting requires that during the pre-COVID-19 phase the trend in short positions for both illiquid and liquid firms is similar. To assess the validity of the common trends assumption we first inspect, in Figure 1, the growth of short positions in liquid and illiquid firms during this phase. Eyeballing the data suggests that the numbers of short positions in illiquid and liquid firms follow each other quite closely before the treatment period. For a more formal test of the parallel trends assumption we follow Autor (2003) and run our regression model for each calendar month. Specifically, we adapt Equation (2) the following way: $D(Period_p)$ is now a dummy that equals 1 if the calendar month equals p and is zero otherwise, with p covering the months from July 2019 to June 2020.

Figure 4 plots the coefficient of interest, the coefficient of the triple interaction $D(Month) \times D(Low\ country\ rating_i) \times Company\ illiquidity$, 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 large short positions for illiquid 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 of the COVID-19 crisis (February through June 2020), with a peak in March. The triple interaction coefficient is insignificant, though, for the entire pre-COVID-19 period of 2019, supporting the validity of the parallel trends assumption.

The monthly estimation of the triple interaction is useful for evaluating the common trends assumption, however, it does not show at exactly which point in time short sellers entered their positions in illiquid firms in countries with a low credit rating. To study this question we run the regression at a weekly frequency. For more statistical power we use a longer reference period, namely from July 1, 2019, to December 15, 2019. Formally, we adapt Equation (2) the following way: $D(Period_p)$ is now a dummy that equals 1 if the business week equals p and it is zero otherwise, with p covering business weeks from December 16, 2019 to June 26, 2020.

Figure 5 plots the coefficient of the triple interaction $D(Week) \times D(Low\ country\ rating_i) \times Company\ illiquidity$ for the period from December 16, 2019, to June 26, 2020, along with major events in the COVID-19 pandemic. On 31 December 2019 China reported to the World Health Organization (WHO) that cases of pneumonia of 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 30 January 2020, shorting of illiquid firms in low-rated countries increased continuously throughout February. The coefficient is already statistically different from zero in the business week starting February 17 – i.e., one the week before the start of the market crash on February 24. This result suggests that short sellers already 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 these 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 six countries (Austria, Belgium, France, Greece, Italy, and Spain) introduced comprehensive short-selling bans for stocks traded on their exchanges.[14]

[14] Some of these countries had introduced temporary, less-comprehensive bans before this, with Italy being the first to do so on March 13. For a detailed overview of all shorting bans, see Table OA.2 of the Online Appendix.

The restrictions forbade the establishment or expansion of short positions. Short positions already established, could, however, 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 the first phase of the market recovery the tendency to short illiquid firms in low-rated countries declined gradually. However, the triple interaction nevertheless remains still economically large and statistically significant until the end of the first recovery period, suggesting that at least some of the short sellers maintained their positions. The short-selling bans lasted until May 18. After this date we do not observe an increase in shorting in illiquid firms in low rated countries. However, the end of short-selling bans falls together with the French-German initiative for a EU Recovery Fund, which was announced on May 18. This date marks the beginning of our second market recovery period, during which the triple interaction coefficient becomes largely insignificant.

4 Robustness checks

4.1 Controlling for severity of the pandemic, lockdown measures, and health system capacity

The COVID-19 pandemic affected countries very differently and also at different points in time. At the same time, countries adopted various responses against COVID-19. In this section, we study the degree to which short sellers traded on these differences in conjunction with firms' liquidity provision. This exercise serves as a robustness check, since many countries with a high credit risk, such as Italy and Spain, were also most affected by COVID-19. If the severity of the pandemic in particular countries is by chance correlated with countries' credit ratings, this may also result in a spurious relationship with regard to short selling.

To measure the extent to which a country is affected by the pandemic, we use the number daily reported cases of COVID-19 and the daily reported deaths associated with it. Both proxies have drawbacks: For the number of COVID-19 cases the estimated number of undetected cases may vary considerably across countries due to different testing schemes. The reported number of deaths may be more reliable in terms of undetected cases, but lags behind the current state of infections. Although the two measures are imperfect proxies for the actual infections in a country, these were the actual data available to market participants at the time. We also measure the efforts of governments to contain the disease, which had a far-reaching impact on the economy. Here we use the novel Oxford COVID-19 Government Response Tracker (OxCGRT) compiled by Hale, Angrist, Kira, Petherick, and Phillips (2020). This index combines various measures of government responses, including the closing of schools and workplaces, cancellation of public events, restrictions on the size of gatherings, the closing of public transport, 'stay at home' requirements, and restrictions on both internal movements within a country and international travel.

We augment our baseline regression model in the following way:

$$
\begin{aligned}
& D(Short\ position_{i,j,t}) = \\
& \sum_p \beta_1^p D(Period_p) \times D(Low\ country\ rating_i) \times Company\ illiquidity_i + \\
& \sum_p \beta_2^p D(Period_p) \times Company\ illiquidity_i + \\
& \sum_p \beta_3^p D(Period_p) \times D(Low\ country\ rating_i) + \\
& \beta_4 Severity_{c,t-1} \times Company\ illiquidity_i + \beta_5 Severity_{c,t-1} + \\
& \mathbf{X}'_{i,t-1}\gamma + \alpha_i + \alpha_j + \alpha_t + \epsilon_{i,j,t},
\end{aligned} \tag{3}
$$

where $Severity_{c,t-1}$ is a measure of the severity of the COVID-19 outbreak or of governments' responses to it in country c at day $t-1$. Specifically, $Severity_{c,t-1}$ is either the number of newly reported cases or deaths in a country scaled by its population or the government response index. We lag the severity measures by one day to make sure that this information would have been available to market participants. The severity measures vary over time, so we do not interact them with time period dummies. We also run a fully saturated regression, including country×time, industry×time, investor×time and investor×stock fixed effects, in which β_3^p and β_5 are absorbed by the country-time fixed effects. The coefficient of interest is β_4, which measures the degree to which short positions were established in illiquid firms in countries that were highly affected by COVID-19 in contrast to countries with a low credit rating.

Table 4, Panel A shows the regression results for different specifications of Equation (3). The coefficient *Cases* in Column (1) shows that short sellers are not more likely to establish a position in countries with a large number of new cases. The interaction term *Cases* $\times$ *Company illiquidity* is also insignificant, showing that short sellers are also not more likely to establish a short position in illiquid firms in these highly-affected countries (see Column (1) and (2)). Column (3) shows that short sellers are actually slightly less likely to establish a position in countries with a large number of new COVID-19 deaths, which is, however, marginally insignificant. Again, the interaction term of COVID-19 severity, as measured by the number of new deaths, with company illiquidity is insignificant. Moreover, the coefficient of the government response index and its interaction with company illiquidity are also insignificant (see Column (5) and (6)). Most importantly, for all specifications shown in Columns (1) to (6), the triple interaction $D(Crash) \times D(Low\ country\ rating_i) \times Company\ illiquidity$ and $D(Recovery\ 1) \times D(Low\ country\ rating_i) \times Company\ illiquidity$ remain statistically significant and virtually unchanged from our baseline specification. This finding supports the notion that short sellers target illiquid firms domiciled in countries with limited fiscal space rather than illiquid firms domiciled in countries that are heavily affected by COVID-19.

Short sellers arguably are forward-looking investors. If short sellers traded on the likelihood of a strong lockdown, we would expect them to focus their attention on variables that would predict such a lockdown in a country. For this reason we also control for ex-ante measures for the capacity of the health system. The main objective in a pandemic is to flatten the curve of infections, i.e. to spread out the number of new cases over a longer period so that it stays below health system capacity. Hence, a country with a lower capacity would be forced to earlier implement sever lockdown measures, harming its economy. To analyse whether short sellers traded on health system capacity in contrast to country ratings, we augment our baseline model the following way:

$$
\begin{aligned}
&D(Short\ position_{i,j,t}) = \\
&\sum_p \beta_1^p D(Period_p) \times D(Low\ country\ rating_i) \times Company\ illiquidity_i + \\
&\sum_p \beta_2^p D(Period_p) \times Company\ illiquidity_i + \\
&\sum_p \beta_3^p D(Period_p) \times D(Low\ country\ rating_i) + \\
&\sum_p \beta_4^p D(Period_p) \times Capacity_c \times Company\ illiquidity_i + \\
&\sum_p \beta_5^p D(Period_p) \times Capacity_c + \mathbf{X}'_{i,t-1}\gamma + \alpha_i + \alpha_j + \alpha_t + \epsilon_{i,j,t},
\end{aligned} \tag{4}
$$

where $Capacity_c$, is a proxy for the health system capacity of country c. Specifically, we use health expenditures, the number of hospital beds and intensive care units (ICU) per population as proxies for capacity. Health expenditure and hospital beds data are from from the OECD Health Statistics. ICU capacity data are not systematically collected and were obtained from Rhodes, Ferdinande, Flaatten, Guidet, Metnitz, and Moreno (2012).

Table 4, Panel B shows the regression results for different specifications of Equation (4). For all three proxies our main effect captured by the triple interaction $D(Crash) \times D(Low\ country\ rating_i) \times Company\ illiquidity$ remains significant and of similar economic magnitude compared to the baseline. The triple interaction $D(Recovery\ 1) \times D(Low\ country\ rating_i) \times Company\ illiquidity$ remains statistically significant for hospital and ICU beds, but becomes insignificant for heath expenditures. Looking at interactions with the control variables, the regression results provide no evidence that short sellers positioned themselves in countries with low health system capacity. If anything, we see the opposite in Column (1), where short sellers increased their positions in countries with high health expenditure in the crash and recovery periods. But all triple interaction terms with *Company illiquidity* are insignificant.

4.2 Controlling for liquidity and strength of the banking sector

Recent studies by Acharya and Steffen (2020) and Li et al. (2020) show that banks were "lenders of first resort" during the first weeks of the COVID-19 outbreak and that non-financial companies drew funds from bank credit lines on an unprecedented scale. In this section, we study to what degree the ability of the banking system to serve the unexpected liquidity demand affected short sellers' shift towards firms with lower liquidity buffers. The rationale behind this exercise is to test whether our main result on the importance of fiscal space is spurious and possibly driven by the strength and liquidity of the domestic banking sector instead of the size of a government's fiscal space. To do so, we add a list of country-level explanatory variables designed to capture both liquidity and strength of the banking sector to our main regression specification.

To measure the strength of a country's banking sector prior to the market crash, we use (1) the country-level liquid to total assets ratio, (2) the country-level tier 1 capital ratio, and (3) the country-level loan-to-deposit ratio of all domestic banks at the end of year 2019.[15] We run the following new augmented regression model:

$$
\begin{aligned}
&D(Short\ position_{i,j,t}) = \\
&\sum_p \beta_1^p D(Period_p) \times D(Low\ country\ rating_i) \times Company\ illiquidity_i + \\
&\sum_p \beta_2^p D(Period_p) \times Company\ illiquidity_i + \\
&\sum_p \beta_3^p D(Period_p) \times D(Low\ country\ rating_i) + \\
&\sum_p \beta_4^p D(Period_p) \times Banking\ system_c \times Company\ illiquidity_i + \\
&\sum_p \beta_5^p D(Period_p) \times Banking\ system_c + \\
&\mathbf{X}'_{i,t-1}\gamma + \alpha_i + \alpha_j + \alpha_t + \epsilon_{i,j,t},
\end{aligned} \tag{5}
$$

where $Banking\ system_c$ is one of the three proxies for the strength of the banking system in country c mentioned above.

[15]We obtain banking sector data at country level on liquid assets, total assets, tier 1 capital, deposit from the ECB data warehouse.

Table 5 shows the regression results for different specifications of Equation (5). For all three proxies of banking system strength our main effect captured by the triple interaction $D(Crash) \times D(Low\ country\ rating_i) \times Company\ illiquidity$ remains significant and of similar economic magnitude compared to the baseline. Looking at interactions with the strength of a country's banking system, the regression results provide no evidence that short sellers positioned themselves in countries with a poorer banking system of focused on companies with low liquidity buffers in these countries. That is, all double and triple interactions with *Banking system* are insignificant.

4.3 Did short sellers trade on other company characteristics?

Our results thus far are consistent with the idea that short sellers trade on the companies' inability to absorb sudden short-term liquidity shocks in countries with a low credit rating. Especially in times of severe market distress and economic distortions, however, liquidity may be correlated with other important firm characteristics such as company performance, leverage, default risk, or firms' resilience to social distancing.[16] For instance, short sellers may have exploited the exogenous shock to particularly target unproductive firms that have been kept alive by their banks just through evergreening of credit (Caballero, Hoshi, and Kashyap, 2008; Acharya, Eisert, Eufinger, and Hirsch, 2019). If the presence of such capital misallocations also correlates with the creditworthiness of the headquarter country or company illiquidity, our main findings may be spurious.

To control for such confounding effects, we augment our initial regression model with a plethora of other company characteristics and their interactions with the low creditworthiness of the headquarter country. For each employed characteristic, we run two models: the baseline model with only stock, investor and time fixed effects and our most saturated model with

[16] Short sellers in general target companies with poor accounting information quality (Dechow, Hutton, Meulbroek, and Sloan, 2001; Christophe, Ferri, and Angel, 2004; Desai, Krishnamurthy, and Venkataraman, 2006).

stock-time, investor-time, country-time, industry-time and stock-investor fixed effects:

$$
\begin{aligned}
& D(\textit{Short position}_{i,j,t}) = \\
& \sum_p \beta_1^p D(\textit{Period}_p) \times D(\textit{Low country rating}_i) \times \textit{Company illiquidity}_i + \\
& \sum_p \beta_2^p D(\textit{Period}_p) \times \textit{Company illiquidity}_i + \\
& \sum_p \beta_3^p D(\textit{Period}_p) \times D(\textit{Low country rating}_i) + \\
& \sum_p \beta_4^p D(\textit{Period}_p) \times D(\textit{Low country rating}_i) \times \textit{Company characteristic}_i + \\
& \sum_p \beta_5^p D(\textit{Period}_p) \times \textit{Company characteristic}_i + \\
& \mathbf{X}'_{i,t-1}\gamma + \alpha_i + \alpha_j + \alpha_t + \epsilon_{i,j,t},
\end{aligned} \tag{6}
$$

where $\textit{Company characteristic}_i$, is an another characteristic of company i.

First, we study how a company's access to undrawn credit lines relates to the behavior of short sellers. Acharya and Steffen (2020) show that upon the onset of the pandemic, non-financial companies raised their cash levels by drawing down preexisting credit lines, which in turn has affected their stock prices positively. Thus, short sellers may have speculated on the importance of this channel of short-term access to liquidity. In Panel A of Table 6, we find some evidence consistent with this behavior. Firms with lower levels of undrawn revolving credit and total undrawn credit (both relative to company's total assets) have been associated with higher short-selling activity. However, the effect is economically small and there is no reinforcing effect in countries with a lower credit rating. Moreover, our main findings of the combined effect of a government's fiscal space and the companies' liquidity buffers during the pandemic is not affected by the role of credit lines.

Then, we study to what degree short sellers trade on companies' pre-crisis profitability, as measured by their three-year median return on equity (ROE) and return on assets (ROA). As is evident from Columns (1) to (4) of Panel B of Table 6, neither of the two profitability proxies relates to short sellers' activity during the COVID-19 pandemic. In addition, we control for firm's price-to-book valuation ratio including its interaction with the pandemic periods and the low credit rating of a country. We motivate this specification by two observations. First, this valuation ratio is often used as a proxy for Tobin's q, a common measure of a firm's performance, and second, value stocks (low price-to-book ratio) have over-proportionally suffered during the pandemic due to their low equity duration (Dechow, Erhard, Sloan, and Soliman, 2021). In Columns (5) and (6), we indeed find an increased number of large short positions in low price-to-book ratio stocks in countries with a low credit rating during the pandemic. However, this effect is economically and statistically low. Most importantly, our two triple interactions with company illiquidity remain significantly different from zero at all conventional levels in all of the six specifications.

We further test whether companies' creditworthiness play a role in short sellers' trading behavior around the coronavirus outbreak. Unfortunately, only a small proportion of European companies have a rating from one of the agencies. We thus use three prominent proxies to measure the creditworthiness of companies. First, we employ the Altman Z-score based on four key financial ratios according to the formula proposed by Altman (1983) and Altman, Iwanicz-Drozdowska, Laitinen, and Suvas (2017). Second, similar to Acharya et al. (2019), we proxy the companies' credit rating using their EBITDA interest coverage (IC) ratio to get around this data issue. In particular, we assign synthetic credit ratings estimated from companies' three-year median IC based on S&P categories and data provided by Aswath Damodaran.[17] Lastly, we define a dummy variable, $D(Zombie)$ that equals one for each company that has a synthetic credit rating of BB or lower and a negative three-year median ROA, otherwise 0. With this sample of firms we aim to capture unproductive firms that have been kept alive by their banks just through evergreening of credit (Caballero et al., 2008; Acharya et al., 2019). We report the estimation results in Panel C of Table 6. During the pandemic and in countries with low credit rating, we find economically and statistically weak increase in the number of short positions in companies with a low Z-score, low synthetic credit rating, and in zombie firms. While controlling for these default risk proxies decreases the effect of company illiquidity on short positions during the recovery period, the results remain very strong during the more

[17]See http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datacurrent.html

important crash period of the pandemic. Thus, short sellers were not targeting companies with low creditworthiness but instead anticipated firm illiquidity to be the crucial metric during the pandemic.

Company liquidity is closely linked to company's leverage and its ability to service existing debt. To control for possible trading of short sellers on these characteristics, we include three different debt-related measures and their combination of interaction effects into the extended specifications: (1) the debt to EBITDA ratio, a core ratio in S&P Global Ratings' methodology for rating corporate industrial companies, (2) the short-term debt to total debt ratio and (3) the short-term debt to total assets ratio as proxies for a company's refinancing intensity and leverage. Results in Panel D of Table 6 suggest that these metrics do not explain our initial results relating to trading on company liquidity. Across all six specifications of the panel, we find strong evidence that short sellers targeted illiquid companies in countries with low creditworthiness during the crash period of the pandemic.

Lastly, Pagano, Wagner, and Zechner (2020) show that firms that are less resilient to social distancing significantly underperformed before and during the COVID-19 outbreak, consistent with the idea of market's gradual learning about pandemic risk. Following Pagano et al. (2020), we use three different measures of resilience to social distancing: The proxies proposed by Dingel and Neiman (2020), Koren and Pető (2020), and Hensvik, Le Barbanchon, and Rathelot (2020), which are defined on the firm's two-digit, three-digit, and four-digit NAICS industry level, respectively.[18] We report the results for each of these variables and the corresponding interaction terms in Panel E of Table 6. Interestingly, neither of the three resilience measures have affected short sellers' trading behavior during the pandemic. There is also no significant effect in countries with a low credit rating.[19] Overall, our main finding on the importance of company liquidity and its interaction with the creditworthiness of the headquarter country during the COVID-19 pandemic remain largely unaffected by controlling for a list of alternative

[18]See Pagano et al. (2020) and Table OA.1 for the exact definition of the variables.

[19]Consistent with the industry-adjustments for all of our firm-level variables, our industry-time fixed effects are estimated using the GICS industry code level, instead of the NAICS classification. This difference in industry classifications between the original resilience measures and the industry-time fixed effects, allows us to estimate the interaction effect between the crash or recovery period and the resilience measures even for the most saturated specification.

explanations.

5 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 the negative revenue shock. Governments throughout the European Union have implemented various fiscal responses to the economic disruption caused by the various lockdown measures in response to the pandemic. We distinguish between two types of fiscal support that played a role in this crisis. A large share of these stimulus packages aim towards stimulating consumers' demand for goods and services once local lockdowns are lifted (Casado et al., 2020; Chetty, Friedman, Hendren, Stepner, and Opportunity Insights, 2020; Coibion, Gorodnichenko, and Weber, 2020). A possible increase in consumption ultimately translates into more production, revenue and income and indirectly supports corporations. In addition to consumption stimulus, a number of alternative fiscal measures that aim to immediately support troubled companies with direct liquidity provision, have been adopted. We aim to distinguish between these two types of fiscal support measures and test whether short sellers have speculated on the inability of countries with limited fiscal space (1) to sufficiently stimulate the local demand for goods and services and/or (2) to sufficiently support all their vulnerable corporations through direct liquidity provision and guarantees.

If short sellers have traded on the governments' insufficient consumption stimulus measures in low-rated countries, we expect that our main effect from Table 3 is stronger for companies that generate their revenue mainly within the headquarter country. In other words, short sellers should be less likely to target illiquid multinational corporation from low-rated countries because these companies profit from stimulus packages initiated by other governments. Alternatively, if the limited direct liquidity support of companies by the government in low-rated countries has been the driving force behind short sellers' trading behavior, we expect them to target companies deemed less important by the government under political economy considerations. These less important companies are less likely to be bailed out in case of failure. We define these companies to have a lower number of employees, lower total assets, and lower revenue relative to all companies within a country.

To distinguish between the two mutually non-exclusive hypotheses, we run our initial, most-saturated regression model from Equation 2 for different sub-samples. In Panel A of Table 7, we split the sample in companies that generate their revenue mainly in the domestic market and those that generate their revenue in multiple countries. We obtain geographic segment data on the companies' revenues from Refinitiv Eikon. Unfortunately, reporting of geographic data is not uniform across companies and we construct three different variations of the revenue share that is generated in the domestic market to ensure robustness of our results. For the first specification, we only calculate the revenue share of the headquarter 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 headquarter country is reported, we assume that the headquarter country 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 alter the first definition by also calculating the local revenue share if the headquarter 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 headquarter country and split the share across all mentioned markets equally. Lastly, we relax the assumption that headquarter 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.

Overall, across all three sample splits in Panel A, we consistently find that in countries with a 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 $D(Crash) \times$

$D(\textit{Low country rating}) \times \textit{Company illiquidity}$ in the sample of companies that depend more on the demand of the domestic market (Column (1), (3), and (5)) doubles relative to our baseline specification. In contrast, in Column (2), (4), and (6), we find that this effect reduces to essentially zero for illiquid, multinational corporations. These findings support the notion that short sellers have speculated on the limited fiscal space of some governments to sufficiently stimulate the local economy and increase demand for goods and services. On the other hand, those troubled companies that do not solely depend on the *local* stimulus package of fiscally constrained countries have not been targeted by short sellers.

In Panel B of of Table 7, we test whether short sellers have speculated on the inability of low-rated country governments to support all troubled companies with direct liquidity impulses. Put differently, have short sellers targeted those companies that are 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 low number of employees, less total assets and lower revenue relative to the median company in the country and those above the median. 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 do not find a difference of the triple interaction $D(Crash) \times D(\textit{Low country rating}) \times \textit{Company illiquidity}$ coefficient between the two sub-samples. Short sellers have traded illiquid companies headquartered in fiscally constrained countries irrespective of the economic importance or relevance of a company for the country.

6 Performance in the period around the stock market crash

In this section, we study whether the anticipation by short sellers about the key role of fiscal space during the COVID-19 pandemic is reflected in their investment performance. We start the analysis with the traditional calendar-time portfolio approach. We first split the universe of stocks in 2×2 portfolios, using an independent double sort based on the median of *Company illiquidity* and *D*(*Low country rating*).[20] For each group, we include a stock in the corresponding portfolio if there is a large open short position the day before. We exclude the stock from the portfolio if the large short position falls below the 0.5% disclosure threshold the day before.[21] We form value-weighted portfolios based on the stocks' lagged market capitalization. To estimate daily risk-adjusted returns (alphas) for the four portfolios we run the following time-series regression:

$$\begin{aligned} ret_{p,t} - rf_t &= \alpha_i + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \\ &\quad \beta_4 CMA_t + \beta_5 RMW_t + \beta_6 WML_t + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $ret_{p,t}$ is the return of portfolio $p = 1, 2, 3, 4$; rf_t is the risk-free rate, $MKTRF$, SMB, HML, RMW, CMA are the five factors of the Fama and French (2015) model, and WML is the momentum factor of Jegadeesh and Titman (1993).[22] We then use the daily abnormal returns, $\alpha_i + \varepsilon_{i,t}$, to calculate the cumulative abnormal return (CAR) for each portfolio at each point in time.

Figure 6 depicts the time-series of CARs for each of the four portfolios using weekly updates, with February 21, 2020, as the reference point for the cumulative return calculation. We find that shorted illiquid companies headquartered in countries with low credit ratings experience severe abnormal returns of around -10% during the stock market crash period. This underperformance continues for these stocks even into the first market recovery period and accumulates to -15%. Importantly, this negative return is net of stocks' market exposure and other risk factors considered in our model. Only in late April do we observe a slight reversal, but the portfolio's performance still remains below -10% at the end of our sample period.

[20] We exclude short positions in Wirecard AG stock, an insolvent German payment processor and financial services provider, from the portfolio formations. The insolvency of Wirecard was announced at the end of June 2020, which is close to the end of our sample period. It represents the most wealth-destroying accounting scandal in European history (see, *Financial Times*: "Wirecard collapses into insolvency", June 25 2020.), but is unrelated to our research question.

[21] This timing convention is conservative, because it assumes that investors trade at the end of each day; it thereby avoids an overestimation of short sellers' performance due to selling pressure or a forward-looking bias.

[22] The European factors are provided through Kenneth French's data library. All factor and portfolio returns are based on prices in U.S. dollars.

In contrast, for shorted liquid stock, there is no such decline in CARs in countries with low credit ratings. Moreover, there is also no underperformance for companies headquartered in countries with high creditworthiness, irrespective of their illiquidity level. This finding shows that investors' strategy of shorting illiquid firms in low-rated countries was highly profitable over the period of the market crash and remained remarkable in the subsequent recovery.

Next, we test the performance of short sellers during the pandemic more formally. In particular, we use the regression-based, generalized calendar-time portfolio approach developed by Hoechle, Schmid, and Zimmermann (2020), which not only reproduces the results of traditional calendar-time portfolio sorts but also has the flexibility to include multiple company, investor, country, and time characteristics as explanatory variables within a single framework:[23]

$$\begin{aligned} ret_{i,j,t} - rf_t \quad = \quad & \alpha + \beta_1 D(Crash)_t \times D(Low\ country\ rating)_i \times D(Illiquid\ company)_i + \\ & \beta_2 D(Recovery)_t \times D(Low\ country\ rating)_i \times D(Illiquid\ company)_i + \\ & \beta_3 D(Low\ country\ rating)_i \times D(Illiquid\ company)_i + \\ & (\mathbf{X}_{i,j,t} \otimes \mathbf{P}_t)\gamma + (\mathbf{X}_{i,j,t} \otimes \mathbf{F}_t)\theta + \varepsilon_{i,j,t}, \end{aligned} \tag{8}$$

where $ret_{i,j,t} - rf_t$ is the excess return of stock i held by investor j on day t. $D(Illiquid\ company)_i$ is equal to 1 if $Company\ illiquidity_i$ is above the median value of its distribution. Moreover, we define $\mathbf{X}_{i,j,t} = [D(Illiquid\ company)_i \quad D(Low\ country\ rating)_i]$, $\mathbf{F}_t$ is a vector of asset-pricing factors, whose definition depends on the employed risk-adjustment model,[24] and $\mathbf{P}_t = [1 \quad Crash_t \quad Recovery\ 1_t \quad Recovery\ 2_t]$. The first Kronecker product $\mathbf{X}_{i,j,t} \otimes \mathbf{P}_t$ controls for all the remaining combinations of explanatory variables with the period dummies. The second Kronecker product $\mathbf{X}_{i,j,t} \otimes \mathbf{F}_t$ adjusts the returns using different asset-pricing factors and allows for varying factor exposures for liquid and illiquid firms as well as for countries with high and low credit ratings.[25]

[23] The generalized calendar-time portfolio approach is particularly useful for studying several, continuous determinants of retail and institutional investors' trading performance (e.g., Døskeland and Hvide, 2011; Jenkinson, Jones, and Martinez, 2016; Jank et al., 2021).

[24] For the Carhart (1997) model, $\mathbf{F}_t = [MKTRF \quad SMB \quad HML \quad WML]$ and for the Fama and French (2015) model augmented with the momentum factor, $\mathbf{F}_t = [MKTRF \quad SMB \quad HML \quad CMA \quad RMW \quad WML]$.

[25] 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

Table 8 shows regression results using two comprehensive asset-pricing models: The Carhart (1997) four-factor model and the Fama and French (2015) five-factor model augmented with momentum.[26] For each of the two models, we employ three weighting schemes for the stocks: value weighting with the stocks' market capitalization (VW), weighting with the short positions' market capitalization (SPW), and equal weighting of each position (EW). The main coefficient of interest is β_1 of Equation (8). Most importantly, across all six specifications, irrespective of the return adjustments and weighting schemes, we find strong underperformance by the shorted illiquid companies in low-rated countries during the crash period; during that period the abnormal return for these companies relative to liquid companies in low-rated countries is 11.3 percentage points (pp.) more negative compared to the same return difference in high-rated countries.[27] The β_1 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 $D(Crash)_t \times D(Illiquid\ company)_i$, we observe that the long-short strategy in high-rated countries also yields a negative abnormal return, albeit economically and statistically weaker relative to the strategy in countries with high creditworthiness.

Moreover, in low-rated countries there is no significant reversal during the recovery period in the underperformance of illiquid companies compared to liquid. If anything, the negative β_2 estimate suggests that the negative return difference even increases relative to the illiquid/liquid difference in high-rated countries. However, the estimate is statistically insignificant.

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

errors in the standard calendar-time portfolio approach. We employ the the optimal lag length as proposed by Newey and West (1994).

[26]For the sake of brevity and clarity we do not report the θ coefficient estimates.

[27]The market crash period consists of 21 trading days resulting in 21 $\times$ 0.54 pp.= 11.3 pp. for the short position weighted specification in Column (5).

of the company's headquarters country – and not necessarily the individual characteristics are essential in explaining the trading behavior and performance of short sellers.

7 Conclusion

We have examined 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 entirely new situation 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 stimulus to their economy. The short sellers' trading strategy was highly profitable: For 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 market crash period. This abnormal return is in excess of the market portfolio and other common risk factors. In contrast, neither liquid firms in the same country nor illiquid firms in countries with high creditworthiness, experienced a negative abnormal return during this period.

References

Acharya, V. V., T. Eisert, C. Eufinger, and C. Hirsch (2019): "Whatever It Takes: The Real Effects of Unconventional Monetary Policy," *The Review of Financial Studies*, 32, 3366–3411.

Acharya, V. V. and S. Steffen (2020): "The Risk of Being a Fallen Angel and the Corporate Dash for Cash in the Midst of COVID," *The Review of Corporate Finance Studies*, 9, 430–471.

Aizenman, J. and Y. Jinjarak (2010): "De facto Fiscal Space and Fiscal Stimulus: Definition and Assessment," Working Paper 16539, NBER.

Alfaro, L., A. Chari, A. N. Greenland, and P. K. Schott (2020): "Aggregate and Firm-Level Stock Returns During Pandemics, in Real Time," Working Paper 26950, NBER.

Altman, E. I. (1983): *Corporate financial distress: a complete guide to predicting, avoiding, and dealing with bankruptcy*, New York: Wiley.

Altman, E. I., M. Iwanicz-Drozdowska, E. K. Laitinen, and A. Suvas (2017): "Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model," *Journal of International Financial Management & Accounting*, 28, 131–171.

Amihud, Y. (2002): "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets*, 5, 31–56.

Anderson, J. E., S. Bergamini, S. Brekelmans, A. Cameron, Z. Darvas, M. Domínguez Jíménez, and C. Midões (2020): "The Fiscal response to the Economic Fallout from the Coronavirus," Working paper, Bruegel.

Aschauer, D. A. (1985): "Fiscal Policy and Aggregate Demand," *The American Economic Review*, 75, 117–127.

Asquith, P., P. A. Pathak, and J. R. Ritter (2005): "Short Interest, Institutional Ownership and Stock Returns," *Journal of Financial Economics*, 78, 243–276.

Auerbach, A. J. and Y. Gorodnichenko (2012): "Measuring the output responses to fiscal policy," *American Economic Journal: Economic Policy*, 4, 1–27.

Augustin, P., V. Sokolovski, M. G. Subrahmanyam, and D. Tomio (2021): "In sickness and in debt: The COVID-19 impact on sovereign credit risk," *Journal of Financial Economics*.

Autor, D. H. (2003): "Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing," *Journal of Labor Economics*, 21, 1–42.

Barro, R. J. (1990): "Government Spending in a Simple Model of Endogeneous Growth," *Journal of Political Economy*, 98, 103–125.

Benmelech, E. and N. Tzur-Ilan (2020): "The Determinants of Fiscal and Monetary Policies During the Covid-19 Crisis," Working Paper 27461, NBER.

Berkman, H., M. D. McKenzie, and P. Verwijmeren (2017): "Hole in the Wall: Informed Short Selling Ahead of Private Placements*," *Review of Finance*, 21, 1047–1091.

Bi, H. (2012): "Sovereign default risk premia, fiscal limits, and fiscal policy," *European Economic Review*, 56, 389–410.

Bianchi, J., P. Ottonello, and I. Presno (2019): "Fiscal Stimulus under Sovereign Risk," Working Paper 26307, NBER.

Blanchard, O. and R. Perotti (2002): "An Empirical Characterization of the Dynamic

Effects of Changes in Government Spending and Taxes on Output," *The Quarterly Journal of Economics*, 117, 1329–1368.

Blanchard, O. J. (1985): "Debt, Deficits, and Finite Horizons," *Journal of Political Economy*, 93, 223–247.

Blau, B. (2012): "Short Interest and Frictions in the Flow of Information," *Financial Management*, 41, 371–394.

Blau, B. M., K. P. Fuller, and R. A. Van Ness (2011): "Short selling around dividend announcements and ex-dividend days," *Journal of Corporate Finance*, 17, 628–639.

Blau, B. M. and P. L. Tew (2014): "Short sales and class-action lawsuits," *Journal of Financial Markets*, 20, 79–100.

Blau, B. M., R. A. Van Ness, and C. Wade (2008): "Capitalizing on Catastrophe: Short Selling Insurance Stocks around Hurricanes Katrina and Rita," *The Journal of Risk and Insurance*, 75, 967–996.

Boehme, R., B. R. Danielsen, and S. M. Sorescu (2006): "Short-sale constraints, dispersion of opinion and overvaluation," *Journal of Financial and Quantitative Analysis*.

Boehmer, E., T. X. Duong, and Z. R. Huszár (2018): "Short covering trades," *Journal of Financial and Quantitative Analysis*, 53, 723–748.

Boehmer, E., C. M. Jones, J. J. Wu, and X. Zhang (2020): "What Do Short Sellers Know?" *Review of Finance*.

Boehmer, E., C. M. Jones, and X. Zhang (2008): "Which Shorts are Informed?" *Journal of Finance*, 63, 491–527.

Caballero, R. J., T. Hoshi, and A. K. Kashyap (2008): "Zombie lending and depressed restructuring in Japan," *American Economic Review*, 98, 1943–77.

Carhart, M. M. (1997): "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52, 57–82.

Casado, M. G., B. Glennon, J. Lane, D. McQuown, D. Rich, and B. A. Weinberg (2020): "The Effect of Fiscal Stimulus: Evidence from COVID-19," Working Paper 27576, NBER.

Chague, F., R. De-Losso, and B. Giovannetti (2019): "The short-selling skill of institutions and individuals," *Journal of Banking & Finance*, 101, 77–91.

Chakrabarty, B. and A. Shkilko (2013): "Information transfers and learning in financial markets: Evidence from short selling around insider sales," *Journal of Banking and Finance*, 37, 1560–1572.

Chang, Y.-C., H. Hong, and I. Liskovich (2015): "Regression Discontinuity and the Price Effects of Stock Market Indexing," *Review of Financial Studies*, 28, 212–246.

Chetty, R., J. N. Friedman, N. Hendren, M. Stepner, and T. Opportunity Insights (2020): "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data," Working Paper 27431, NBER.

Christophe, S. E., M. G. Ferri, and J. J. Angel (2004): "Short-Selling Prior to Earnings Announcements," *The Journal of Finance*, 59, 1845–1876.

Cohen, L., K. B. Diether, and C. J. Malloy (2007): "Supply and Demand Shifts in the Shorting Market," *Journal of Finance*, 62, 2061–2096.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020): "The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending," Working Paper 27141, NBER.

Céspedes, L. F. and J. Galí (2013): "Fiscal Policy and Macroeconomic Performance: An Overview," in *Central Banking, Analysis, and Economic Policies Book Series*, Central Bank of Chile, vol. 17, 01–25.

De Vito, A. and J.-P. Gomez (2020): "Estimating the COVID-19 cash crunch: Global evidence and policy," *Journal of Accounting and Public Policy*, 106741.

Dechow, P. M., R. D. Erhard, R. G. Sloan, and A. M. T. Soliman (2021): "Implied Equity Duration: A Measure of Pandemic Shutdown Risk," *Journal of Accounting Research*, 59, 243–281.

Dechow, P. M., A. P. Hutton, L. Meulbroek, and R. G. Sloan (2001): "Short-sellers, fundamental analysis, and stock returns," *Journal of Financial Economics*, 61, 77–106.

Desai, H., S. Krishnamurthy, and K. Venkataraman (2006): "Do Short Sellers Target Firms with Poor Earnings Quality? Evidence from Earnings Restatements," *Review of Accounting Studies*, 11, 71–90.

Diether, K. B., K.-H. Lee, and I. M. Werner (2009): "Short-Sale Strategies and Return Predictability," *Review of Financial Studies*, 22, 575–607.

Ding, W., R. Levine, C. Lin, and W. Xie (2020): "Corporate Immunity to the COVID-19 Pandemic," Working paper, NBER.

Dingel, J. I. and B. Neiman (2020): "How Many Jobs Can be Done at Home?" Working Paper, NBER.

Driscoll, J. C. and A. C. Kraay (1998): "Consistent covariance matrix estimation with spatially dependent panel data," *Review of Economics and Statistics*, 80, 549–560.

Døskeland, T. M. and H. K. Hvide (2011): "Do Individual Investors Have Asymmetric Information Based on Work Experience?" *The Journal of Finance*, 66, 1011–1041.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg (2012): "How are shorts informed?: Short sellers, news, and information processing," *Journal of Financial Economics*, 105, 260 – 278.

Fahlenbrach, R., K. Rageth, and R. M. Stulz (2020): "How Valuable is Financial Flexibility when Revenue Stops? Evidence from the COVID-19 Crisis," Working Paper 27106, NBER.

Fama, E. F. and K. R. French (1993): "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33, 3–56.

——— (2012): "Size, value, and momentum in international stock returns," *Journal of Financial Economics*, 105, 457–472.

——— (2015): "A five-factor asset pricing model," *Journal of Financial Economics*, 116, 1–22.

Fatás, A. and I. Mihov (2003): "The Case for Restricting Fiscal Policy Discretion," *The Quarterly Journal of Economics*, 118, 1419–1447.

Feldstein, M. (2009): "Rethinking the Role of Fiscal Policy," *American Economic Review*, 99, 556–559.

Galema, R. and D. Gerritsen (2019): "The effect of the accidental disclosure of confidential short sales positions," *Finance Research Letters*, 28, 87–94.

Galí, J., J. D. López-Salido, and J. Vallés (2007): "Understanding the Effects of Government Spending on Consumption," *Journal of the European Economic Association*, 5, 227–270.

Gerding, F., T. Martin, and F. Nagler (2020): "The value of fiscal capacity in the face

of a rare disaster," *Working Paper*.
Giavazzi, F. and M. Pagano (1990): "Can Severe Fiscal Contractions Be Expansionary? Tales of Two Small European Countries," *NBER Macroeconomics Annual*, 5, 75–111.
Gormsen, N. J. and R. S. Koijen (2020): "Coronavirus: Impact on stock prices and growth expectations," *The Review of Asset Pricing Studies*, 10, 574–597.
Hale, T., N. Angrist, B. Kira, A. Petherick, and T. Phillips (2020): "Variation in government responses to COVID-19," *Blavatnik School of Government Working Paper*, 31.
Harford, J., S. A. Mansi, and W. F. Maxwell (2008): "Corporate governance and firm cash holdings in the US," *Journal of Financial Economics*, 87, 535–555.
Hensvik, L., T. Le Barbanchon, and R. Rathelot (2020): "Which Jobs are Done from Home? Evidence from the American Time Use Survey," Working paper.
Herndon, T., M. Ash, and R. Pollin (2014): "Does high public debt consistently stifle economic growth? A critique of Reinhart and Rogoff," *Cambridge Journal of Economics*, 38, 257–279, publisher: Oxford Academic.
Hoechle, D., M. Schmid, and H. Zimmermann (2020): "Does Unobservable Heterogeneity Matter for Portfolio-Based Asset Pricing Tests?" *Working Paper*.
Hürtgen, P. (2020): "Fiscal sustainability duringthe COVID-19 pandemic," Deutsche Bundesbank Discussion Paper.
IMF (2018): "Assessing Fiscal Space: An Update and Stocktaking," Report, International Monetary Fund.
——— (2020): "Fiscal Monitor: Policies for the Recovery," Report, International Monetary Fund.
Ince, O. S. and R. B. Porter (2006): "Individual Equity Return Data from Thomson Datastream: Handle with Care!" *Journal of Financial Research*, 29, 463–479.
Jank, S., C. Roling, and E. Smajlbegovic (2021): "Flying under the radar: The effects of short-sale disclosure rules on investor behavior and stock prices," *Journal of Financial Economics*, 139, 209–233.
Jank, S. and E. Smajlbegovic (2015): "Dissecting Short-Sale Performance: Evidence from Large Position Disclosures," *Working Paper*.
Jegadeesh, N. (1990): "Evidence of predictable behavior of security returns," *The Journal of Finance*, 45, 881–898.
Jegadeesh, N. and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 48, 65–91.
Jenkinson, T., H. Jones, and J. V. Martinez (2016): "Picking Winners? Investment Consultants' Recommendations of Fund Managers," *The Journal of Finance*, 71, 2333–2370.
Jones, C. M., A. V. Reed, and W. Waller (2016): "Revealing Shorts An Examination of Large Short Position Disclosures," *The Review of Financial Studies*, 29, 3278–3320.
Jordà, Ò. and A. M. Taylor (2016): "The time for austerity: estimating the average treatment effect of fiscal policy," *The Economic Journal*, 126, 219–255.
Karpoff, J. M. and X. Lou (2010): "Short Sellers and Financial Misconduct," *Journal of Finance*, 65, 1879–1913.
Koijen, R. S. J., R. J. Richmond, and M. Yogo (2020): "Which Investors Matter for Equity Valuations and Expected Returns?" Working paper, University of Chicago, Becker Friedman Institute for Economics Working Paper.
Koijen, R. S. J. and M. Yogo (2018): "A Demand System Approach to Asset Pricing,"

Journal of Political Economy, 127, 1475–1515.
Koren, M. and R. Pető (2020): "Business disruptions from social distancing," *PLOS ONE*, 15, e0239113.
Kose, M. A., S. Kurlat, F. Ohnsorge, and N. Sugawara (2017): "A Cross-Country Database of Fiscal Space," Working paper, The World Bank.
Laeven, L., G. Schepens, and I. Schnabel (2020): "Zombification in Europe in times of pandemic," .
Landier, A. and D. Thesmar (2020): "Earnings Expectations in the COVID Crisis," Working Paper 27160, NBER.
Leeper, E. M. and T. B. Walker (2011): "Fiscal Limits in Advanced Economies*," *Economic Papers: A journal of applied economics and policy*, 30, 33–47.
Leeper, E. M., T. B. Walker, and S.-C. S. Yang (2013): "Fiscal Foresight and Information Flows," *Econometrica*, 81, 1115–1145.
Lehmann, B. N. (1990): "Fads, martingales, and market efficiency," *The Quarterly Journal of Economics*, 105, 1–28.
Li, L., P. E. Strahan, and S. Zhang (2020): "Banks as Lenders of First Resort: Evidence from the COVID-19 Crisis," *The Review of Corporate Finance Studies*, 9, 472–500.
Newey, W. K. and K. D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–708.
——— (1994): "Automatic Lag Selection in Covariance Matrix Estimation," *Review of Economic Studies*, 61, 631–653.
Pagano, M., C. Wagner, and J. Zechner (2020): "Disaster Resilience and Asset Prices," Working paper, University of Naples Federico II and WU Vienna University of Economics and Business, Rochester, NY.
Perotti, R. (1999): "Fiscal Policy in Good Times and Bad," *The Quarterly Journal of Economics*, 114, 1399–1436.
Ramelli, S. and A. F. Wagner (2020): "Feverish Stock Price Reactions to COVID-19*," *The Review of Corporate Finance Studies*, 9, 622–655.
Ramey, V. A. (2011): "Can Government Purchases Stimulate the Economy?" *Journal of Economic Literature*, 49, 673–685.
——— (2019): "Ten Years after the Financial Crisis: What Have We Learned from the Renaissance in Fiscal Research?" *Journal of Economic Perspectives*, 33, 89–114.
Rapach, D. E., M. C. Ringgenberg, and G. Zhou (2016): "Short interest and aggregate stock returns," *Journal of Financial Economics*, 121, 46 – 65.
Reinhart, C. M. and K. S. Rogoff (2010): "Growth in a Time of Debt," *American Economic Review*, 100, 573–578.
Rhodes, A., P. Ferdinande, H. Flaatten, B. Guidet, P. G. Metnitz, and R. P. Moreno (2012): "The variability of critical care bed numbers in Europe," *Intensive care medicine*, 38, 1647–1653.
Romer, C. D. and D. H. Romer (2019): "Fiscal Space and the Aftermath of Financial Crises: How It Matters and Why," Working Paper 25768, NBER.
Senchack, Jr, A. J. and L. T. Starks (1993): "Short-Sale Restrictions and Market Reaction to Short-Interest Announcements," *Journal of Financial and Quantitative Analysis*, 28, 177–194.
Shleifer, A. (1986): "Do Demand Curves for Stocks Slope Down?" *The Journal of Finance*,

41, 579–590.

Taylor, J. B. (2009): "The Lack of an Empirical Rationale for a Revival of Discretionary Fiscal Policy," *American Economic Review*, 99, 550–555.

Tables and figures

Figure 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 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. 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.

Figure 2 Panel A: Countries with a low credit rating

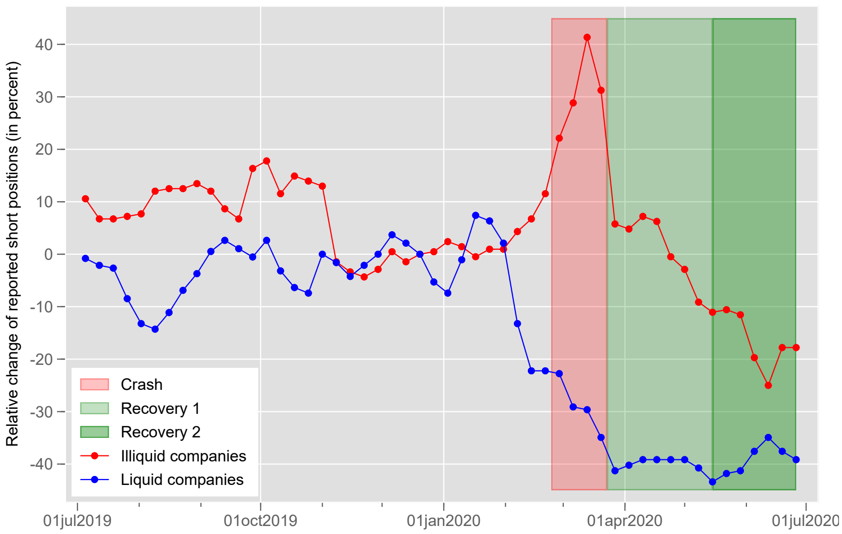

Figure 3 Panel B: Countries with a high credit rating

Figure 4
Parallel trends assumption
This figure is based on a monthly estimation of Equation (2), with period p covering months July 2019 to June 2020. The graph displays the triple interaction coefficient $D(Month) \times D(Low\ country\ rating) \times Company\ illiquidity$. the period of the COVID-19 pandemic (February to June 2020) is marked by a "C" in parentheses. We plot each coefficient with a 90% confidence interval for each month. The reference period is December 2019.

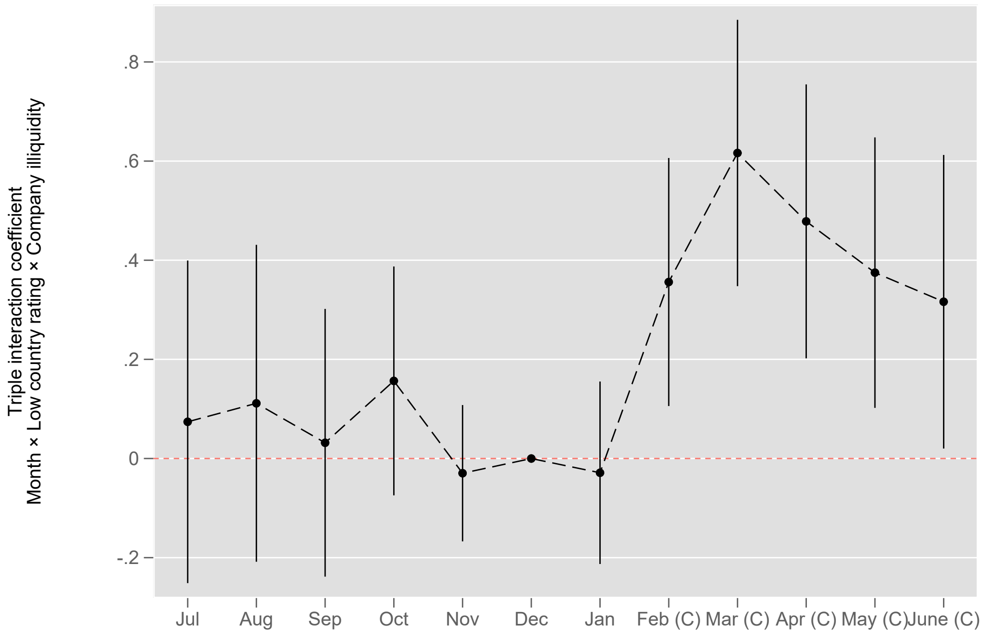

Figure 5
Timing of short sellers' trading strategy
This figure displays the coefficient of the triple interaction $D(Week) \times D(Low\ \ country\ \ rating) \times Company\ illiquidity$ for the period December 16, 2019 to June 26, 2020. We plot each coefficient with a 90% confidence interval for each week. The reference period is July 1, 2019 to December 15, 2019. Dashed vertical lines mark major events in the COVID-19 pandemic: On 31 December 2019, China reports to the WHO cases of pneumonia of unknown cause detected in Wuhan City; on 30 January 2020 the WHO declares the outbreak a Public Health Emergency of International Concern (PHEIC); 24 February 2020 marks the beginning of the stock crash; on 17/18 March 2020 comprehensive short-selling bans came into force in six countries (Austria, Belgium, France, Greece, Italy, and Spain), which all were lifted on 18 May 2020. May 18 marks also the announcement of the French-German initiative for a EU Recovery Fund. 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).

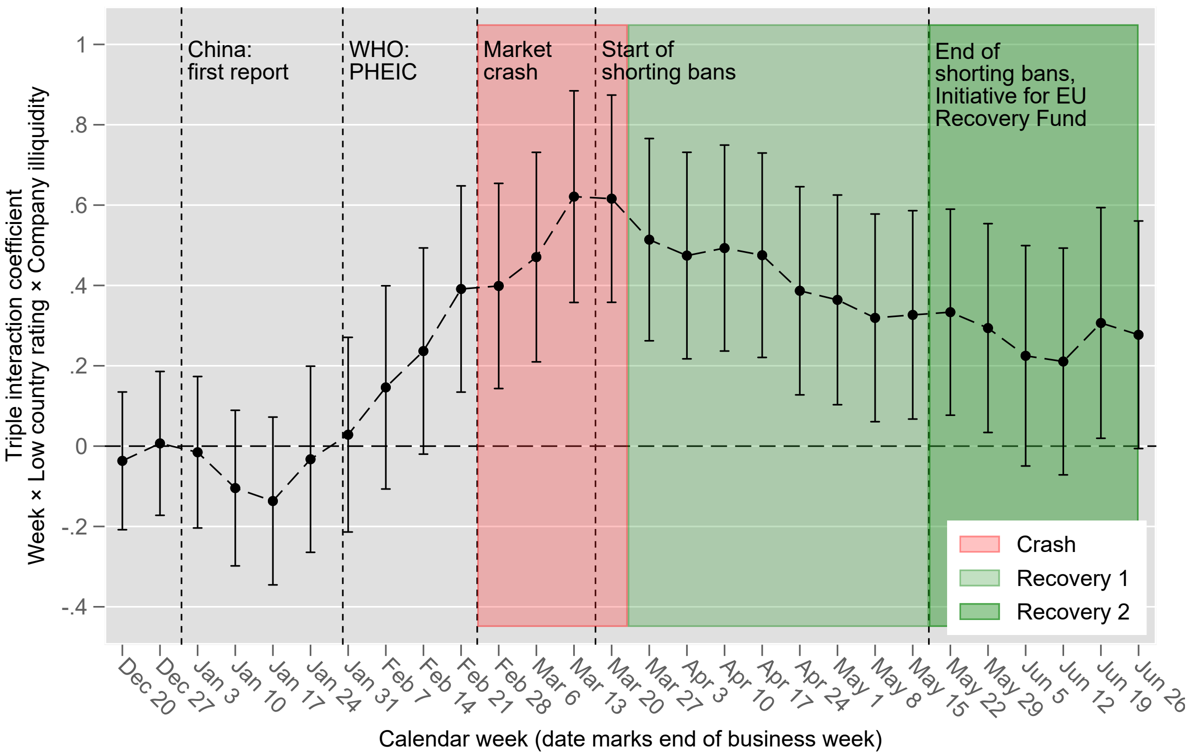

Figure 6
Performance of shorted stocks during the COVID-19 pandemic
This figure shows the cumulative abnormal returns of stocks with large short positions around the market crash associated with the COVID-19 pandemic. We first split the universe of stocks into 2×2 portfolios using an independent double sort, based on the median of *Company illiquidity* and the dummy variable *D*(*Low country rating*). For each group, we include the corresponding stocks in the portfolio if there is a large short positions and we then form value-weighted portfolios. To compute the portfolios' abnormal return we run a time-series regression using the Fama-French five-factor model augmented by the momentum factor. The figure plots the cumulative abnormal return of the four portfolios using weekly updates and February 21, 2020 as the reference point. 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 October 2019 to June 2020.

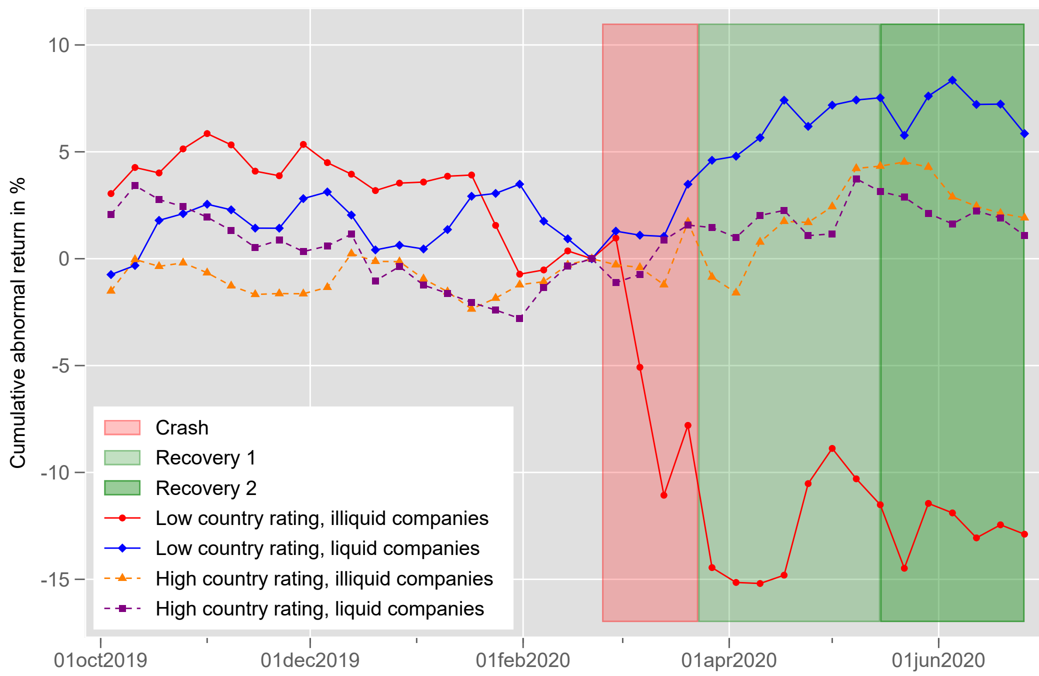

Table 1 Short positions during the COVID-19 panedmic
This table reports the time-series average of the total number of open short positions (#) and their cross-sectional value (Avg.) across different jurisdictions and for different market phases. The pre-COVID 19 phase is from July 1, 2019, to February 23, 2020; the market crash phase is from February 24, 2020, to March 23, 2020; the first market recovery period is from March 24, 2020, to May 17, 2020; and the second market recovery period is from May 18, 2020, to June 26, 2020.

	Pre-COVID 19 phase		Market crash phase		Recovery phase 1		Recovery phase 2	
Jurisdiction	#	Avg.	#	Avg.	#	Avg.	#	Avg.
Austria	18.4	0.91	20.0	0.98	15.3	1.10	15.7	1.10
Belgium	30.9	0.88	21.3	0.98	14.7	1.02	15.3	1.00
Denmark	40.4	0.97	37.7	1.04	29.0	1.22	25.0	1.29
Finland	34.5	0.86	34.9	0.92	36.7	0.99	31.6	1.03
France	115.2	0.93	133.7	0.88	96.7	0.90	94.6	0.89
Germany	157.4	1.09	167.8	1.08	166.0	1.04	162.8	1.03
Greece	9.8	1.13	10.0	1.05	10.0	1.06	10.9	0.97
Ireland	22.6	1.02	34.0	0.95	30.1	0.93	16.5	0.99
Italy	74.4	0.94	66.1	0.87	53.3	0.96	50.5	0.83
Luxembourg	23.0	1.15	25.6	1.05	21.1	0.95	23.4	0.92
Netherlands	65.0	1.22	72.3	1.10	58.8	1.13	51.0	1.17
Norway	38.3	1.07	49.9	0.98	44.0	0.91	28.6	0.91
Poland	7.0	0.80	5.1	0.77	6.3	0.80	5.6	0.81
Spain	32.5	0.85	29.0	0.84	21.1	0.84	20.0	0.81
Sweden	97.8	1.03	104.2	1.00	102.4	0.96	102.6	0.94
United Kingdom	407.7	0.99	388.0	0.97	347.0	0.96	315.0	0.98
All countries	1174.9	1.00	1199.7	0.98	1052.5	0.98	969.13	0.98

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

				Percentiles		
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	500.78	1,806.93
ln(Amihud)	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(ISVola)	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
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	3.85	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	6.80	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 HLR	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						
				Percentiles		
Variable	N	Mean	SD	25th	50th	75th
D(Low country rating)	3,764	0.23				
Rating notch	3,764	2.52	3.28	0.00	1.00	3.00
CDS5y	3,516	38.32	58.15	9.35	13.84	34.95
Cases	3,708	9.23	26.82	0.00	0.00	4.49
Deaths	3,708	0.83	2.77	0.00	0.00	0.09
Government response	3,759	20.94	31.13	0.00	0.00	46.30
Health Expenditure	3,764	4,562.68	1,122.65	4,126.35	5,013.99	5,263.83
Hospital beds	3,764	433.16	180.60	297.00	328.00	598.00
ICU beds	3,764	11.78	7.41	6.50	8.00	15.90
Liquid to total assets	3,569	0.16	0.03	0.13	0.16	0.20
Tier 1 capital ratio	3,569	0.17	0.02	0.16	0.17	0.19
Loan-to-deposit ratio	3,569	1.13	0.42	0.90	0.93	1.24

Panel C: Asset-pricing factors						
				Percentiles		
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

Table 3 Triple difference regression

Table 3 shows the result for the fixed-effects panel regression described in equation (1). The dependent variable is $D(Short\ position)$, which is a dummy variable equal to 1 if investor j holds a short position in stock i on day t and is zero otherwise. The main explanatory variables are: *D(Crash)*, which is a dummy variable that equals 1 for the stock market crash period (February 24 – March 23, 2020) and zero otherwise; *D(Recovery 1)*, which is a dummy variable that equals 1 for the first stock market recovery period (March 24 – May 17, 2020) and zero otherwise; *D(Recovery 2)*, which is a dummy variable that equals 1 for the second stock market recovery period (May 18 – June 26, 2020) and zero otherwise; *D(Low country rating)*, which is a dummy variable that equals 1 if the country of headquarters has a rating below AA- and zero otherwise; $Company\ illiquidity_i$, which is the percentile rank (ranging between 0 and 1) of firm illiquidity based on the industry-adjusted quick ratio. Stock-level controls contain a shorting ban dummy, lagged stock returns at different horizons, stock liquidity proxies, idiosyncratic volatility, and market beta. Detailed definitions of all stock-level control variables can be found in Table OA.1. 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)	(4)	(5)
	Dependent variable: $D(Short\ position)$				
D(Crash) × D(Low country rating) × Company illiquidity	0.5623***	0.5710***	0.6049***	0.5202***	0.5189***
	(3.95)	(3.73)	(3.78)	(3.12)	(3.11)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.3958***	0.3783***	0.4227***	0.3866**	0.3864**
	(2.92)	(2.67)	(2.69)	(2.23)	(2.23)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2623*	0.2563*	0.2801*	0.2511	0.2622
	(1.71)	(1.69)	(1.70)	(1.40)	(1.46)
D(Crash) × Company illiquidity	-0.0359	-0.0324	-0.0287	-0.0523	-0.0519
	(-0.86)	(-0.78)	(-0.62)	(-1.10)	(-1.10)
D(Recovery 1) × Company illiquidity	-0.0180	-0.0137	-0.0091	-0.0297	-0.0295
	(-0.35)	(-0.28)	(-0.17)	(-0.57)	(-0.56)
D(Recovery 2) × Company illiquidity	-0.0242	-0.0226	-0.0056	-0.0453	-0.0495
	(-0.41)	(-0.40)	(-0.09)	(-0.78)	(-0.86)
D(Crash) × D(Low country rating)	-0.0191	–	–	–	–
	(-0.64)				
D(Recovery 1) × D(Low country rating)	-0.0158	–	–	–	–
	(-0.47)				
D(Recovery 2) × D(Low country rating)	-0.0600*	–	–	–	–
	(-1.79)				
D(Shorting Ban)	-0.0541**	-0.0819	-0.0677	-0.0477	-0.0582
	(-2.25)	(-1.37)	(-1.06)	(-0.67)	(-0.84)
$ret_{t-5,t-1}$	-0.0285	-0.0331*	-0.0383**	-0.0444**	-0.0446**
	(-1.47)	(-1.72)	(-2.01)	(-2.59)	(-2.59)
$ret_{t-20,t-6}$	-0.0559***	-0.0592***	-0.0512**	-0.0513***	-0.0507***
	(-2.96)	(-3.12)	(-2.55)	(-2.74)	(-2.70)
$ret_{t-250,t-21}$	-0.1060***	-0.1101***	-0.0936***	-0.0827***	-0.0820***
	(-4.70)	(-4.86)	(-4.54)	(-4.25)	(-4.21)
$ln(\text{Amihud})_{t-5,t-1}$	-0.0127***	-0.0130***	-0.0139***	-0.0131***	-0.0132***
	(-3.13)	(-3.01)	(-3.10)	(-2.97)	(-2.98)
$ln(\text{BidAsk})_{t-5,t-1}$	-0.0076	-0.0057	-0.0031	-0.0064	-0.0063
	(-1.28)	(-0.90)	(-0.56)	(-1.16)	(-1.15)
$ln(\text{ISVola})_{t-1}$	0.0256	0.0321*	0.0305**	0.0307**	0.0309**
	(1.48)	(1.91)	(1.97)	(2.07)	(2.08)
$\beta^{\text{MKTRF}}_{t-1}$	0.0111	0.0158	0.0192	0.0163	0.0172
	(0.54)	(0.78)	(0.96)	(0.85)	(0.89)
adj. R^2	0.2448	0.2454	0.2471	0.2440	0.4906
adj. within R^2	0.0045	0.0041	0.0029	0.0023	0.0035
Nobs	708,177	707,931	705,043	680,669	680,669
Stock FE	Yes	Yes	Yes	Yes	–
Investor FE	Yes	Yes	Yes	–	–
Time FE	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

Table 4 Controlling for severity of the COVID-19 pandemic and health system capacity

Table 4 shows the result for the fixed effects panel regressions described in equation (3) and (4) in Panel A and B, respectively. The dependent variable is *D(Short position)*, which is a dummy variable equal to 1 if investor j holds a short position in stock i 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*$_i$, all defined as in Table 3. The control variables considered are *Cases/Deaths* (the daily number of newly reported COVID-19 cases/deaths), *Government response* (an index (0-100) measuring the overall government response to the pandemic), *Health expenditure* (the health expenditure per capital), *Hospital beds* (the number of hospital beds per 1 000 population), and *ICU beds* (the number of intensive care unit beds per 100 000 population). All regressions include the standard stock-level controls as 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.

Panel A: Controlling for severity of the COVID-19 pandemic						
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
	Severity= Cases		Severity= Deaths		Severity= Government response	
D(Crash) × D(Low country rating) × Company illiquidity	0.5501***	0.4935***	0.5601***	0.5004***	0.5421***	0.5117***
	(3.82)	(2.89)	(3.91)	(2.93)	(3.66)	(2.96)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.3869***	0.3847**	0.3738***	0.3842**	0.3855***	0.3840**
	(2.84)	(2.21)	(2.74)	(2.20)	(2.84)	(2.20)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2776*	0.2793	0.2684*	0.2756	0.2632*	0.2659
	(1.81)	(1.55)	(1.74)	(1.53)	(1.71)	(1.48)
D(Crash) × Company illiquidity	-0.0389	-0.0558	-0.0344	-0.0523	-0.0640	-0.0569
	(-0.91)	(-1.17)	(-0.82)	(-1.10)	(-1.41)	(-1.16)
D(Recovery 1) × Company illiquidity	-0.0594	-0.0626	-0.0467	-0.0541	-0.1024	-0.0463
	(-1.04)	(-1.08)	(-0.78)	(-0.92)	(-0.94)	(-0.45)
D(Recovery 2) × Company illiquidity	-0.0447	-0.0649	-0.0331	-0.0578	-0.0923	-0.0636
	(-0.76)	(-1.10)	(-0.55)	(-1.00)	(-0.88)	(-0.68)
D(Crash) × D(Low country rating)	-0.0197	–	-0.0143	–	-0.0001	–
	(-0.65)		(-0.47)		(-0.00)	
D(Recovery 1) × D(Low country rating)	-0.0170	–	-0.0122	–	-0.0174	–
	(-0.50)		(-0.36)		(-0.51)	
D(Recovery 2) × D(Low country rating)	-0.0581*	–	-0.0627*	–	-0.0614*	–
	(-1.73)		(-1.86)		(-1.83)	
Severity × Company illiquidity	0.0009	0.0007	0.0058	0.0044	0.0012	0.0002
	(1.56)	(1.44)	(1.12)	(0.96)	(0.81)	(0.16)
Severity	0.0002	–	-0.0025	–	-0.0007	–
	(1.04)		(-1.62)		(-1.33)	
adj. R^2	0.2446	0.4912	0.2446	0.4912	0.2449	0.0000
adj. within R^2	0.0047	0.0036	0.0047	0.0035	-0.8100	-0.1600
Nobs	706,282	678,881	706,282	678,881	708,151	680,647
Stock-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes	No	Yes

Panel B: Controlling for health system capacity measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
	Capacity= Health expenditure		Capacity= Hospital beds		Capacity= ICU beds	
D(Crash) × D(Low-rated country) × Company illiquidity	0.6196***	0.4320**	0.5645***	0.5159***	0.5608***	0.5186***
	(3.33)	(2.09)	(3.97)	(3.10)	(3.95)	(3.11)
D(Recovery 1) × D(Low-rated country) × Company illiquidity	0.3007	0.2210	0.3662***	0.3712**	0.3819***	0.3850**
	(1.52)	(1.00)	(2.68)	(2.14)	(2.81)	(2.22)
D(Recovery 2) × D(Low-rated country) × Company illiquidity	0.2849	0.2363	0.2482	0.2684	0.2471	0.2628
	(1.25)	(0.99)	(1.61)	(1.49)	(1.61)	(1.46)
D(Crash) × Company illiquidity	-1.1041	1.7577	-0.0687	-0.0338	-0.0389	-0.0319
	(-0.46)	(0.75)	(-0.76)	(-0.37)	(-0.57)	(-0.44)
D(Recovery 1) × Company illiquidity	1.9117	3.4197	0.0849	0.0591	0.0646	0.0360
	(0.65)	(1.26)	(0.74)	(0.55)	(0.74)	(0.43)
D(Recovery 2) × Company illiquidity	-0.3923	0.4919	-0.0068	-0.0858	0.0054	-0.0804
	(-0.11)	(0.16)	(-0.05)	(-0.70)	(0.05)	(-0.83)
D(Crash) × D(Low-rated country)	0.0296	–	-0.0144	–	-0.0186	–
	(0.78)		(-0.48)		(-0.62)	
D(Recovery 1) × D(Low-rated country)	0.0412	–	-0.0027	–	-0.0129	–
	(0.88)		(-0.08)		(-0.38)	
D(Recovery 2) × D(Low-rated country)	0.0082	–	-0.0512	–	-0.0560*	–
	(0.17)		(-1.52)		(-1.68)	
D(Crash) × Capacity × Company illiquidity	0.1257	-0.2130	0.0001	-0.0000	0.0004	-0.0017
	(0.45)	(-0.78)	(0.39)	(-0.21)	(0.07)	(-0.33)
D(Recovery 1) × Capacity × Company illiquidity	-0.2266	-0.4060	-0.0002	-0.0002	-0.0066	-0.0057
	(-0.65)	(-1.28)	(-0.89)	(-0.90)	(-0.98)	(-0.93)
D(Recovery 2) × Capacity × Company illiquidity	0.0435	-0.0637	-0.0000	0.0001	-0.0017	0.0027
	(0.11)	(-0.17)	(-0.08)	(0.33)	(-0.21)	(0.37)
D(Crash) × Capacity	0.1189**	–	0.0000	–	0.0005	–
	(2.00)		(0.93)		(0.46)	
D(Recovery 1) × Capacity	0.1325*	–	0.0001	–	0.0012	–
	(1.77)		(1.12)		(0.93)	
D(Recovery 2) × Capacity	0.1662*	–	0.0001	–	0.0030*	–
	(1.83)		(1.30)		(1.86)	
adj. R^2	0.2453	0.4912	0.2451	0.4912	0.2452	0.4912
adj. within R^2	0.0051	0.0037	0.0049	0.0036	0.0051	0.0036
Nobs	708,177	680,669	708,177	680,669	708,177	680,669
Stock-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes	No	Yes

Table 5 Controlling for strength and liquidity of the banking sector

Table 5 shows the result for the fixed effects panel regressions described in equation (5). The dependent variable is $D(Short\ position)$, which is a dummy variable equal to 1 if investor j holds a short position in stock i on day t and is zero otherwise. The main explanatory variables are *D(Crash)*, *D(Recovery 1)*, *D(Recovery 2)*, *D(Low country rating)*, $Company\ illiquidity_i$, all defined as in Table 3. Proxies for the main control variables, liquidity and strength of a country's banking system, are the ratio of *Liquid to total assets*, the *Tier 1 capital ratio* and the *Loan-to-deposit ratio*. All regressions include the standard stock-level controls as 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)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
	Bank system= Liquid to total assets		Bank system= Tier 1 capital ratio		Bank system= Loan-to-deposit ratio	
D(Crash) × D(Low country rating) × Company illiquidity	0.5576***	0.5286***	0.5371***	0.5545***	0.5668***	0.5232***
	(3.91)	(3.13)	(3.10)	(2.82)	(3.90)	(3.07)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.3828***	0.3987**	0.5265***	0.4945**	0.4110***	0.3950**
	(2.81)	(2.25)	(2.94)	(2.39)	(2.95)	(2.22)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2532	0.2611	0.3290	0.2677	0.2883*	0.2545
	(1.64)	(1.43)	(1.59)	(1.25)	(1.82)	(1.37)
D(Crash) × Company illiquidity	0.2562	-0.2403	0.0748	-0.2196	-0.1002	-0.0311
	(1.03)	(-0.90)	(0.14)	(-0.42)	(-0.77)	(-0.22)
D(Recovery 1) × Company illiquidity	0.0477	-0.3284	-0.8418	-0.6303	-0.1590	-0.0369
	(0.16)	(-1.06)	(-1.29)	(-1.04)	(-0.98)	(-0.25)
D(Recovery 2) × Company illiquidity	0.2422	-0.2042	-0.4728	-0.0920	-0.2189	-0.0077
	(0.72)	(-0.63)	(-0.63)	(-0.14)	(-1.19)	(-0.05)
D(Crash) × D(Low country rating)	-0.0160	–	-0.0246	–	-0.0164	–
	(-0.53)		(-0.68)		(-0.54)	
D(Recovery 1) × D(Low country rating)	-0.0146	–	-0.0222	–	-0.0139	–
	(-0.44)		(-0.55)		(-0.41)	
D(Recovery 2) × D(Low country rating)	-0.0632*	–	-0.0690	–	-0.0574*	–
	(-1.89)		(-1.49)		(-1.67)	
D(Crash) × Bank system × Company illiquidity	-1.7247	1.1827	-0.5657	1.0014	0.0647	-0.0102
	(-1.17)	(0.76)	(-0.19)	(0.34)	(0.63)	(-0.09)
D(Recovery 1) × Bank system × Company illiquidity	-0.3063	1.8525	4.7571	3.4589	0.1368	0.0164
	(-0.17)	(1.02)	(1.30)	(1.02)	(1.04)	(0.14)
D(Recovery 2) × Bank system × Company illiquidity	-1.5329	1.0436	2.6284	0.3547	0.1830	-0.0194
	(-0.77)	(0.53)	(0.63)	(0.10)	(1.30)	(-0.15)
D(Crash) × Bank system	-0.2011	–	-0.2756	–	0.0016	–
	(-0.60)		(-0.43)		(0.07)	
D(Recovery 1) × Bank system	-0.0991	–	-0.2336	–	0.0119	–
	(-0.25)		(-0.30)		(0.42)	
D(Recovery 2) × Bank system	-0.2208	–	-0.1662	–	0.0314	–
	(-0.47)		(-0.18)		(0.98)	
adj. R^2	0.2458	0.4936	0.2459	0.4936	0.2459	0.4936
adj. within R^2	0.0045	0.0032	0.0046	0.0032	0.0046	0.0031
Nobs	683,971	657,449	683,971	657,449	683,971	657,449
Stock-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes	No	Yes

Table 6 Controlling for other company characteristics
Table 6 shows the result for the fixed effects panel regression described in equation (6). The dependent variable is $D(Short\ position)$, which is a dummy variable equal to 1 if investor j holds a short position in stock i 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*$_i$, all defined as in Table 3. The control variables of interest are the percentile rank of the following industry-adjusted variables: *undrawn revolving credit*, *total undrawn credit*, return on equity (ROE), return on assets (ROA), the company's closing price divided by its book value per share (*Price-to-book*), Altman's *Z-score*, the synthetic credit rating implied by the EBITDA interest coverage ratio (*Synthetic credit rating*), a dummy variable equal to 1 if a company has a *Synthetic credit rating* of BB or lower and a negative return on assets, otherwise zero ($D(Zombie)$), the ratio of total debt minus cash and short-term investments to EBITDA (*Net debt-to-EBITDA*), the short-term debt to total debt ratio (*ST Debt-to-T Debt*), and the short-term debt to total assets ratio (*ST Debt-to-T Assets*). *DN resilience*, *KP resilience*, and *HLR resilience* measure how an industry is resilient to social distancing as motivated by Dingel and Neiman (2020), Koren and Pető (2020), and Hensvik et al. (2020), respectively. All regressions include the standard stock-level controls as 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.

Panel A: Controlling for undrawn credit lines				
	(1)	(2)	(3)	(4)
	Dependent variable: D(Short position)			
	Company characteristic= Undrawn revolving credit		Company characteristic= Total undrawn credit	
D(Crash) × D(Low country rating) × Company illiquidity	0.5637***	0.5352***	0.5532***	0.5257***
	(3.84)	(3.03)	(3.72)	(2.90)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.4045***	0.4195**	0.4077***	0.4071**
	(2.82)	(2.25)	(2.83)	(2.14)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.3086**	0.2846	0.3081*	0.2764
	(1.98)	(1.52)	(1.94)	(1.43)
D(Crash) × Company illiquidity	-0.0227	-0.0339	-0.0286	-0.0454
	(-0.53)	(-0.70)	(-0.66)	(-0.93)
D(Recovery 1) × Company illiquidity	-0.0179	-0.0111	-0.0239	-0.0209
	(-0.33)	(-0.21)	(-0.44)	(-0.38)
D(Recovery 2) × Company illiquidity	-0.0333	-0.0189	-0.0352	-0.0247
	(-0.55)	(-0.32)	(-0.58)	(-0.43)
D(Crash) × D(Low country rating)	-0.0641	–	-0.0713	–
	(-1.05)		(-1.09)	
D(Recovery 1) × D(Low country rating)	-0.0698	–	-0.0622	–
	(-1.13)		(-0.96)	
D(Recovery 2) × D(Low country rating)	-0.0522	–	-0.0547	–
	(-0.74)		(-0.71)	
D(Crash) × D(Low country rating) × Company characteristic	0.0584	-0.0429	0.0807	-0.0220
	(0.62)	(-0.46)	(0.79)	(-0.21)
D(Recovery 1) × D(Low country rating) × Company characteristic	0.0777	-0.1011	0.0700	-0.0518
	(0.83)	(-0.95)	(0.70)	(-0.46)
D(Recovery 2) × D(Low country rating) × Company characteristic	-0.0431	-0.1418	-0.0298	-0.0867
	(-0.40)	(-1.28)	(-0.25)	(-0.74)
D(Crash) × Company characteristic	-0.1012***	-0.0802*	-0.0833**	-0.0357
	(-2.81)	(-1.95)	(-2.13)	(-0.79)
D(Recovery 1) × Company characteristic	-0.1122***	-0.0935**	-0.0944**	-0.0623
	(-2.62)	(-2.06)	(-2.13)	(-1.29)
D(Recovery 2) × Company characteristic	-0.0638	-0.0670	-0.0602	-0.0534
	(-1.19)	(-1.36)	(-1.08)	(-1.01)
adj. R^2	0.2454	0.4923	0.2452	0.4920
adj. within R^2	0.0056	0.0046	0.0053	0.0039
Nobs	688,814	661,465	688,814	661,465
Stock-level control variables	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes

Panel B: Controlling for profitability and value						
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
	Company characteristic= ROE		Company characteristic= ROA		Company characteristic= Price-to-book	
D(Crash) × D(Low country rating) × Company illiquidity	0.5664***	0.5150***	0.5740***	0.5293***	0.5824***	0.5369***
	(3.99)	(3.11)	(4.14)	(3.18)	(4.21)	(3.38)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.3944***	0.3902**	0.4119***	0.3914**	0.4095***	0.4048**
	(2.92)	(2.26)	(3.07)	(2.27)	(3.13)	(2.42)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2590*	0.2695	0.2791*	0.2838	0.2622*	0.2744
	(1.70)	(1.51)	(1.81)	(1.59)	(1.73)	(1.57)
D(Crash) × Company illiquidity	-0.0402	-0.0513	-0.0361	-0.0448	-0.0386	-0.0557
	(-0.95)	(-1.08)	(-0.86)	(-0.95)	(-0.91)	(-1.18)
D(Recovery 1) × Company illiquidity	-0.0144	-0.0292	-0.0174	-0.0207	-0.0187	-0.0366
	(-0.27)	(-0.55)	(-0.33)	(-0.39)	(-0.35)	(-0.70)
D(Recovery 2) × Company illiquidity	-0.0188	-0.0476	-0.0192	-0.0361	-0.0233	-0.0578
	(-0.32)	(-0.82)	(-0.33)	(-0.62)	(-0.39)	(-1.01)
D(Crash) × D(Low country rating)	-0.0172	–	-0.0188	–	-0.0249	–
	(-0.58)		(-0.63)		(-0.84)	
D(Recovery 1) × D(Low country rating)	-0.0177	–	-0.0152	–	-0.0201	–
	(-0.53)		(-0.45)		(-0.59)	
D(Recovery 2) × D(Low country rating)	-0.0626*	–	-0.0575*	–	-0.0619*	–
	(-1.90)		(-1.71)		(-1.83)	
D(Crash) × D(Low country rating) × Company characteristic	0.0095	-0.0194	0.0558	0.0288	0.1163	0.0868
	(0.07)	(-0.16)	(0.39)	(0.19)	(1.05)	(0.77)
D(Recovery 1) × D(Low country rating) × Company characteristic	0.0803	0.0229	0.0680	0.0039	0.0951	0.0477
	(0.73)	(0.21)	(0.52)	(0.02)	(0.87)	(0.39)
D(Recovery 2) × D(Low country rating) × Company characteristic	0.0198	0.0237	0.0495	0.0588	0.0244	0.0024
	(0.15)	(0.19)	(0.33)	(0.36)	(0.18)	(0.02)
D(Crash) × Company characteristic	-0.0299	0.0418	0.0013	0.0526	-0.0162	0.0329
	(-0.78)	(1.06)	(0.03)	(1.21)	(-0.42)	(0.85)
D(Recovery 1) × Company characteristic	-0.0204	0.0426	0.0153	0.0671	-0.0235	0.0334
	(-0.45)	(0.94)	(0.33)	(1.39)	(-0.53)	(0.78)
D(Recovery 2) × Company characteristic	0.0395	0.0693	0.0583	0.0975*	-0.0255	0.0444
	(0.75)	(1.38)	(1.10)	(1.83)	(-0.49)	(0.95)
adj. R^2	0.2454	0.4929	0.2449	0.4914	0.2456	0.4911
adj. within R^2	0.0046	0.0038	0.0047	0.0039	0.0045	0.0037
Nobs	698,787	671,442	708,024	680,669	698,965	671,614
Stock-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes	No	Yes

Panel C: Controlling for default risk						
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
	Company characteristic= Z-Score		Company characteristic= Synthetic credit rating		Company characteristic= D(Zombie)	
D(Crash) × D(Low country rating) × Company illiquidity	0.6444***	0.5796***	0.5331***	0.4380**	0.5277***	0.4531**
	(3.51)	(2.86)	(3.71)	(2.49)	(3.63)	(2.55)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.4191***	0.3882*	0.3982***	0.3334*	0.4052***	0.3654*
	(2.60)	(1.89)	(2.81)	(1.80)	(2.85)	(1.94)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2850	0.3004	0.2414	0.2228	0.2606	0.2381
	(1.42)	(1.38)	(1.49)	(1.15)	(1.61)	(1.20)
D(Crash) × Company illiquidity	-0.0753	-0.0657	-0.0173	-0.0620	-0.0153	-0.0615
	(-1.45)	(-1.20)	(-0.34)	(-1.00)	(-0.30)	(-0.99)
D(Recovery 1) × Company illiquidity	-0.0280	-0.0299	-0.0445	-0.0938	-0.0438	-0.0926
	(-0.44)	(-0.50)	(-0.71)	(-1.41)	(-0.69)	(-1.41)
D(Recovery 2) × Company illiquidity	-0.0639	-0.0714	-0.0190	-0.0769	-0.0202	-0.0724
	(-0.91)	(-1.08)	(-0.27)	(-1.08)	(-0.29)	(-1.02)
D(Crash) × D(Low country rating)	-0.0110	–	-0.0187	–	-0.0136	–
	(-0.31)		(-0.58)		(-0.41)	
D(Recovery 1) × D(Low country rating)	-0.0089	–	-0.0137	–	-0.0048	–
	(-0.24)		(-0.38)		(-0.13)	
D(Recovery 2) × D(Low country rating)	-0.0629	–	-0.0659*	–	-0.0628	–
	(-1.64)		(-1.79)		(-1.61)	
D(Crash) × D(Low country rating) × Company characteristic	0.1096	0.1125	-0.0041	0.0036	-0.0286	0.0616
	(0.51)	(0.48)	(-0.62)	(0.53)	(-0.26)	(0.60)
D(Recovery 1) × D(Low country rating) × Company characteristic	0.0011	0.0110	-0.0005	0.0062	-0.0980	-0.0089
	(0.01)	(0.05)	(-0.07)	(0.78)	(-1.03)	(-0.08)
D(Recovery 2) × D(Low country rating) × Company characteristic	0.0147	0.0368	0.0048	0.0052	-0.0599	-0.0300
	(0.06)	(0.15)	(0.65)	(0.60)	(-0.67)	(-0.26)
D(Crash) × Company characteristic	-0.0545	-0.0365	0.0031	0.0033	0.0302	0.0413
	(-0.87)	(-0.59)	(1.27)	(1.06)	(1.06)	(0.97)
D(Recovery 1) × Company characteristic	-0.0012	0.0009	0.0009	0.0036	0.0156	0.0610
	(-0.02)	(0.02)	(0.31)	(1.03)	(0.42)	(1.22)
D(Recovery 2) × Company characteristic	-0.0528	-0.0282	-0.0020	0.0009	-0.0510	0.0040
	(-0.74)	(-0.45)	(-0.53)	(0.24)	(-1.08)	(0.08)
adj. R^2	0.2455	0.4918	0.2538	0.4931	0.2539	0.4931
adj. within R^2	0.0048	0.0036	0.0070	0.0057	0.0071	0.0056
Nobs	686,169	658,781	501,194	476,091	501,194	476,091
Stock-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes	No	Yes

Panel D: Controlling for leverage and refinancing intensity						
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
	Company characteristic= Net debt-to-EBITDA		Company characteristic= ST Debt-to-T Debt		Company characteristic= ST Debt-to-T Assets	
D(Crash) × D(Low country rating) × Company illiquidity	0.6046***	0.5895***	0.4749***	0.4438***	0.5537***	0.5234***
	(4.01)	(3.07)	(3.27)	(2.64)	(3.78)	(3.11)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.3885**	0.3477*	0.3151**	0.3198*	0.3922***	0.3901**
	(2.47)	(1.74)	(2.29)	(1.85)	(2.76)	(2.20)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2341	0.2157	0.1860	0.1910	0.2258	0.2385
	(1.37)	(1.11)	(1.17)	(1.03)	(1.43)	(1.30)
D(Crash) × Company illiquidity	-0.0287	-0.0334	-0.0301	-0.0602	-0.0360	-0.0645
	(-0.58)	(-0.56)	(-0.67)	(-1.19)	(-0.83)	(-1.31)
D(Recovery 1) × Company illiquidity	-0.0111	0.0357	-0.0194	-0.0469	-0.0237	-0.0471
	(-0.17)	(0.54)	(-0.35)	(-0.85)	(-0.43)	(-0.86)
D(Recovery 2) × Company illiquidity	0.0083	0.0964	-0.0138	-0.0467	-0.0027	-0.0420
	(0.12)	(1.43)	(-0.22)	(-0.77)	(-0.05)	(-0.70)
D(Crash) × D(Low country rating)	-0.0217	–	-0.0048	–	-0.0169	–
	(-0.68)		(-0.15)		(-0.57)	
D(Recovery 1) × D(Low country rating)	0.0021	–	0.0004	–	-0.0110	–
	(0.06)		(0.01)		(-0.32)	
D(Recovery 2) × D(Low country rating)	-0.0565	–	-0.0401	–	-0.0515	–
	(-1.55)		(-1.11)		(-1.53)	
D(Crash) × D(Low country rating) × Company characteristic	0.0069	-0.0102	0.0757	0.0124	-0.0370	-0.0145
	(0.06)	(-0.08)	(0.58)	(0.10)	(-0.36)	(-0.14)
D(Recovery 1) × D(Low country rating) × Company characteristic	0.0681	0.0258	0.0119	0.0627	-0.0240	0.0016
	(0.62)	(0.17)	(0.10)	(0.47)	(-0.24)	(0.01)
D(Recovery 2) × D(Low country rating) × Company characteristic	-0.0428	-0.1167	0.0035	0.0035	0.0167	0.0296
	(-0.34)	(-0.75)	(0.02)	(0.02)	(0.16)	(0.25)
D(Crash) × Company characteristic	0.0192	0.0151	0.0312	0.0115	0.0352	0.0158
	(0.50)	(0.38)	(0.73)	(0.29)	(1.01)	(0.45)
D(Recovery 1) × Company characteristic	0.0010	-0.0009	0.0325	0.0078	0.0163	0.0072
	(0.02)	(-0.02)	(0.66)	(0.17)	(0.38)	(0.18)
D(Recovery 2) × Company characteristic	0.0152	-0.0181	0.0138	0.0246	-0.0153	-0.0211
	(0.28)	(-0.38)	(0.25)	(0.45)	(-0.33)	(-0.50)
adj. R^2	0.2570	0.4947	0.2493	0.4926	0.2465	0.4928
adj. within R^2	0.0063	0.0052	0.0047	0.0034	0.0047	0.0034
Nobs	564,556	537,817	649,510	624,868	675,948	650,803
Stock-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes	No	Yes

Panel E: Controlling for industry-specific resilience to social distancing						
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
	Company characteristic= DN Resilience		Company characteristic= KP Resilience		Company characteristic= HLR Resilience	
D(Crash) × D(Low country rating) × Company illiquidity	0.5582***	0.5459***	0.5908***	0.5516***	0.5739***	0.5541***
	(3.92)	(3.24)	(4.04)	(3.42)	(3.82)	(3.16)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.3960***	0.4189**	0.4318***	0.4406**	0.4213***	0.4227**
	(2.86)	(2.35)	(3.13)	(2.57)	(2.93)	(2.33)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2564*	0.2876	0.3072*	0.3233*	0.2810*	0.3132*
	(1.66)	(1.57)	(1.91)	(1.83)	(1.74)	(1.65)
D(Crash) × Company illiquidity	-0.0325	-0.0536	-0.0415	-0.0522	-0.0373	-0.0591
	(-0.76)	(-1.13)	(-0.98)	(-1.09)	(-0.88)	(-1.25)
D(Recovery 1) × Company illiquidity	-0.0113	-0.0310	-0.0128	-0.0270	-0.0228	-0.0413
	(-0.22)	(-0.59)	(-0.24)	(-0.52)	(-0.44)	(-0.79)
D(Recovery 2) × Company illiquidity	-0.0196	-0.0535	-0.0008	-0.0401	-0.0294	-0.0600
	(-0.33)	(-0.93)	(-0.01)	(-0.71)	(-0.49)	(-1.04)
D(Crash) × D(Low country rating)	-0.0168	–	-0.0149	–	-0.0193	–
	(-0.58)		(-0.51)		(-0.60)	
D(Recovery 1) × D(Low country rating)	-0.0152	–	-0.0066	–	-0.0195	–
	(-0.45)		(-0.20)		(-0.54)	
D(Recovery 2) × D(Low country rating)	-0.0578*	–	-0.0527	–	-0.0616*	–
	(-1.76)		(-1.64)		(-1.76)	
D(Crash) × D(Low country rating) × Company characteristic	0.1541	0.0700	-0.0004	0.0002	0.0001	-0.0044
	(1.33)	(0.59)	(-0.22)	(0.10)	(0.01)	(-0.19)
D(Recovery 1) × D(Low country rating) × Company characteristic	0.0596	-0.0058	0.0006	0.0001	0.0077	-0.0061
	(0.51)	(-0.04)	(0.33)	(0.06)	(0.33)	(-0.24)
D(Recovery 2) × D(Low country rating) × Company characteristic	0.1475	0.0709	0.0004	-0.0007	-0.0015	0.0043
	(1.13)	(0.49)	(0.20)	(-0.33)	(-0.06)	(0.17)
D(Crash) × Company characteristic	0.0342	-0.0114	0.0007	0.0009	-0.0083	-0.0108
	(0.82)	(-0.17)	(1.62)	(1.45)	(-1.18)	(-1.04)
D(Recovery 1) × Company characteristic	0.0666	-0.0170	0.0004	0.0003	-0.0087	-0.0092
	(1.16)	(-0.22)	(0.75)	(0.40)	(-1.04)	(-0.81)
D(Recovery 2) × Company characteristic	0.0455	-0.0629	-0.0001	0.0002	-0.0041	-0.0053
	(0.69)	(-0.73)	(-0.13)	(0.28)	(-0.44)	(-0.39)
adj. R^2	0.2451	0.4914	0.2455	0.4924	0.2445	0.4914
adj. within R^2	0.0049	0.0037	0.0046	0.0036	0.0048	0.0038
Nobs	707,929	680,421	687,995	661,265	696,969	669,399
Stock-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock, investor, time FEs	Yes	No	Yes	No	Yes	No
Country×time, industry×time, investor×time, investor×stock FEs	No	Yes	No	Yes	No	Yes

Table 7 Trading on limited local demand stimulus or insufficient direct liquidity support?

Table 7 shows the result for the fixed effects panel regression described in equation (2) using different subsamples of the universe. The dependent variable is $D(\textit{Short position})$, which is a dummy variable equal to 1 if investor j holds a short position in stock i 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*$_i$, 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 headquarter 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 headquarter country is reported, we assume that the headquarter 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 headquarter 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 headquarter country and split the share across all mentioned markets equally. In Column (5) and (6), we relax the assumption that headquarter 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, total assets and revenue adjusted by the country median. All regressions include the standard stock-level controls as 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)	(4)	(5)	(6)
Panel A: Trading against local demand stimulus						
	Local share$_1$		Local share$_2$		Local share$_3$	
	High	Low	High	Low	High	Low
D(Crash) × D(Low-rated country) × Company illiquidity	1.0094***	0.0067	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-rated country) × 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-rated country) × Company illiquidity	0.8059**	-0.1247	0.7377*	-0.2620	0.8544**	-0.0027
	(2.20)	(-0.44)	(1.82)	(-0.95)	(2.04)	(-0.01)
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	-0.0383	0.0038	-0.0285	-0.0732	0.1487
	(-0.28)	(-0.46)	(0.04)	(-0.35)	(-0.66)	(1.39)
adj. R^2	0.4952	0.4912	0.4967	0.4831	0.5016	0.4816
adj. within R^2	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
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
Panel B: Trading against direct liquidity support						
	No. of Employees		Total Assets		Revenue	
	Low	High	Low	High	Low	High
D(Crash) × D(Low-rated country) × Company illiquidity	0.5934***	0.6619**	0.5196**	0.6328***	0.4790**	0.6700**
	(2.70)	(2.26)	(2.28)	(2.66)	(2.16)	(2.47)
D(Recovery 1) × D(Low-rated country) × Company illiquidity	0.4227**	0.5579*	0.4348*	0.6209**	0.3137	0.6689**
	(1.97)	(1.84)	(1.86)	(2.36)	(1.46)	(2.41)
D(Recovery 2) × D(Low-rated country) × Company illiquidity	0.1831	0.6784**	0.3246	0.6337**	0.0586	0.8487***
	(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^2	0.4806	0.5154	0.4849	0.5068	0.4808	0.5127
adj. within R^2	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

Table 8 Performance of large short positions

Table 8 shows the result for the pooled weighted least-squares regression described in equation (8). The dependent variable is $ret_{i,j,t} - rf_t$, which is the excess return of stock i held by investor j at day t. The main explanatory variables are *D(Crash)*, *D(Recovery 1)*, *D(Recovery 2)*, and *D(Low country rating)*, all defined as in Table 3, and $D(Illiquid; Company)_i$, which is a dummy variable that equals 1 if *Company illiquidity*$_i$ is above the median value of the cross-sectional distribution. For the purposes of brevity, we only report the regression coefficients associated with all interaction effects. The sample period is July 2019 to June 2020. We report in parentheses t-statistics based on Driscoll and Kraay (1998) standard errors, which are robust to general forms of cross-sectional dependence, autocorrelation, and heteroskedasticity. We use the optimal lag-length, as proposed by Newey and West (1994). *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Carhart (1997)			Fama and French (2015) + WML		
	VW	SPW	EW	VW	SPW	EW
D(Crash) × D(Low country rating) × D(Illiquid company)	-0.56***	-0.56***	-0.47**	-0.57***	-0.57***	-0.47**
	(-2.92)	(-2.99)	(-2.49)	(-3.00)	(-3.08)	(-2.51)
D(Recovery 1) ×D(Low country rating) × D(Illiquid company)	-0.13	-0.21	-0.28*	-0.13	-0.21	-0.28*
	(-0.62)	(-0.93)	(-1.74)	(-0.63)	(-0.94)	(-1.76)
D(Recovery 2) ×D(Low country rating) × D(Illiquid company)	0.33	0.38	0.11	0.32	0.38	0.11
	(1.22)	(1.30)	(1.31)	(1.22)	(1.29)	(1.32)
D(Low country rating) × D(Illiquid company)	-0.16**	-0.15*	-0.04	-0.16**	-0.15*	-0.04
	(-2.14)	(-1.93)	(-0.96)	(-2.12)	(-1.92)	(-0.93)
D(Crash) × D(Illiquid company)	-0.07	-0.03	-0.09	-0.06	-0.03	-0.09
	(-0.91)	(-0.45)	(-1.14)	(-0.77)	(-0.33)	(-1.11)
D(Crash) × D(Low country rating)	0.14	0.18	0.31**	0.16	0.19	0.34**
	(0.92)	(1.13)	(2.04)	(1.08)	(1.21)	(2.18)
D(Recovery 1) × D(Illiquid company)	0.02	0.07	0.17**	0.02	0.07	0.17**
	(0.21)	(0.89)	(2.52)	(0.25)	(0.97)	(2.53)
D(Recovery 1) × D(Low country rating)	0.03	0.07	0.00	0.04	0.08	0.02
	(0.30)	(0.67)	(0.03)	(0.40)	(0.67)	(0.19)
D(Recovery 2) × D(Illiquid company)	-0.06	-0.06*	-0.07	-0.06	-0.07*	-0.08*
	(-1.44)	(-1.67)	(-1.54)	(-1.44)	(-1.71)	(-1.84)
D(Recovery 2) × D(Low country rating)	-0.10	-0.15	-0.12	-0.10	-0.16	-0.12
	(-0.77)	(-1.03)	(-0.96)	(-0.88)	(-1.19)	(-0.98)
α	-0.08**	-0.07*	-0.02	-0.07*	-0.06	-0.01
	(-2.09)	(-1.85)	(-0.32)	(-1.70)	(-1.47)	(-0.17)
R^2	0.3619	0.3543	0.2884	0.3621	0.3544	0.2885
Nobs	246,508	246,508	246,508	246,508	246,508	246,508

Online appendix

Figure OA.1
Stock market crash of the COVID-19 pandemic
This figure shows the return index for the European stock market over the sample period July 2019 to June 2020. The return is the U.S. dollar return of the value-weight market portfolio of the region Europe provided in Kenneth R. French's data library. For further details see Fama and French (2012).

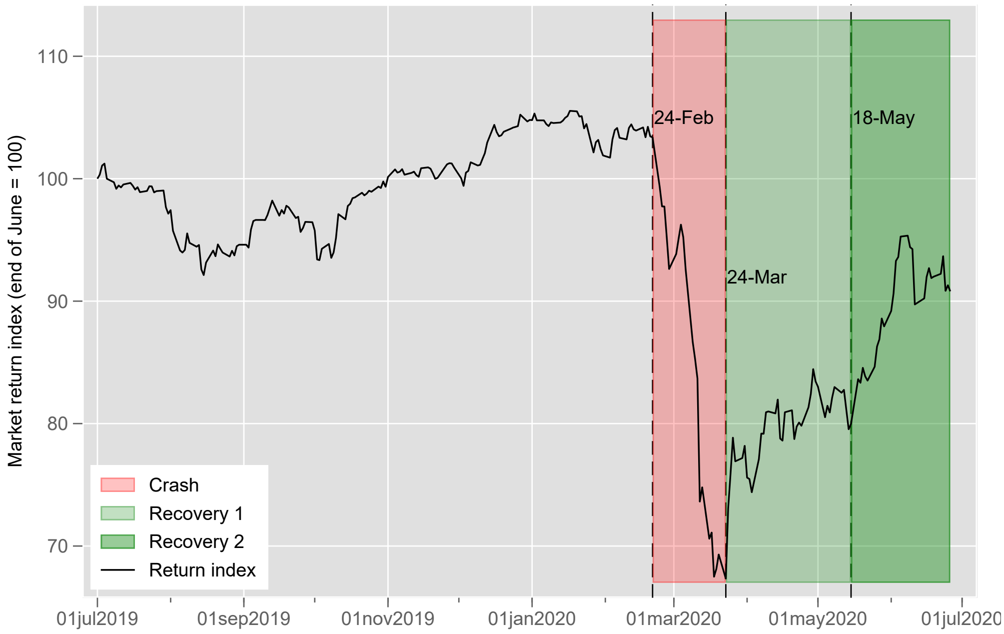

Figure OA.2

S&P's long-term issue credit ratings of sample countries

This figure displays a map of the sample countries (European Union, Norway, and United Kingdom) and their S&P's long-term issue credit ratings if at least one short position disclosed in the period July 2019 to June 2020. The Portuguese authority has published short positions in this period but does not provide their history once a short seller reduces their size to below the disclosure threshold of 0.5% of a stock's shares outstanding.

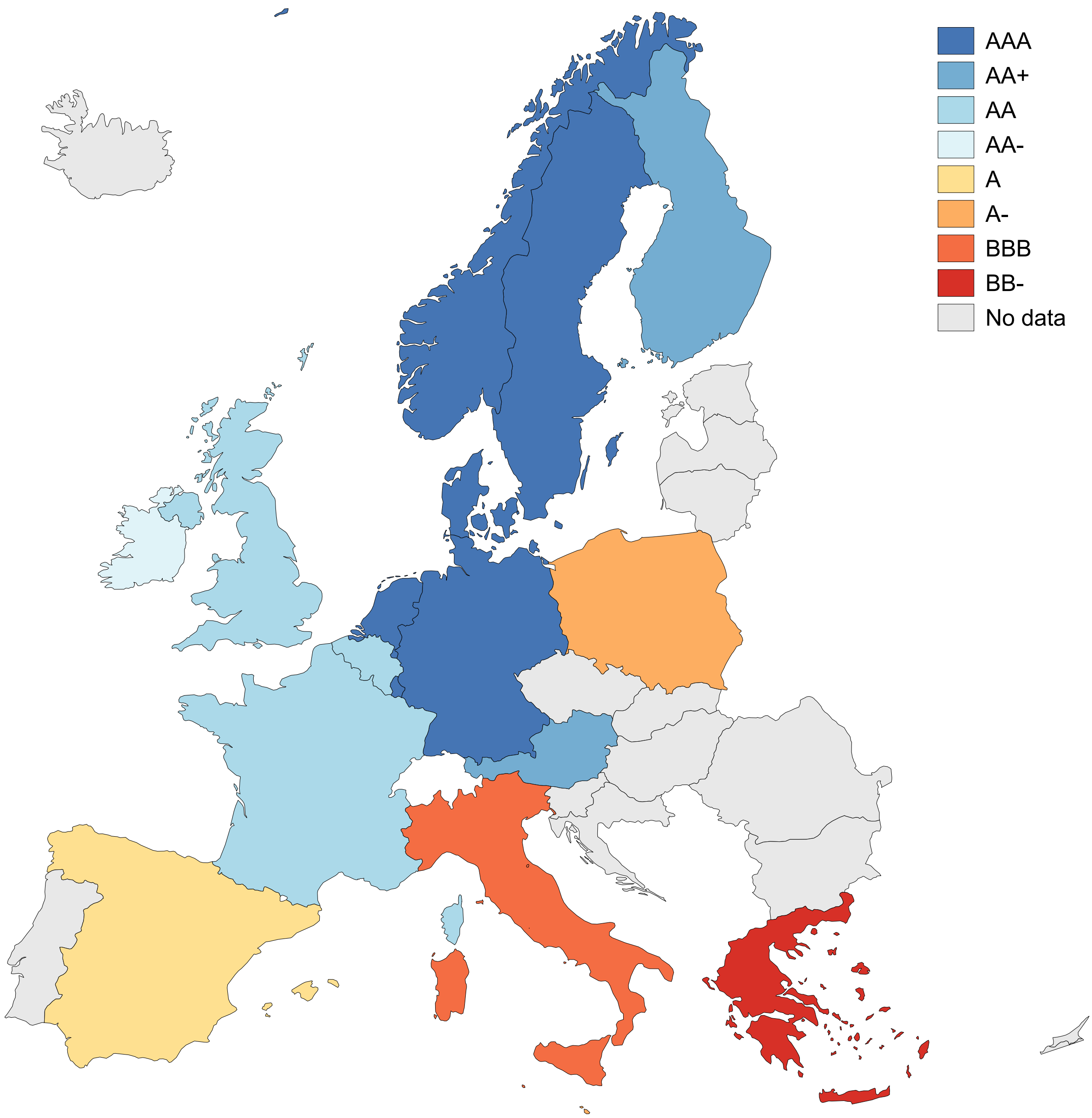

Figure OA.3

Disclosed short positions in liquid and illiquid companies during the COVID-19 crisis

This figure shows the number of disclosed short positions 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). We split the sample of firms using the median of the industry-adjusted quick ratio as break point. 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 dashed vertical line marks 24 February 2020, which represents the beginning of the stock market crash associated with the COVID-19 crisis. The sample period is June 01, 2019 - June 26, 2020.

Figure OA.4 Panel A: Countries with low credit rating

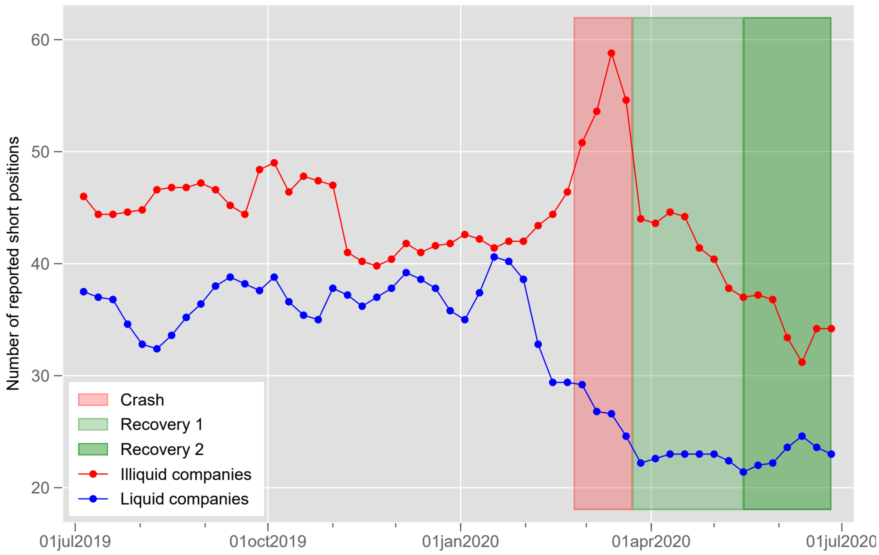

Figure OA.5 Panel B: Countries with high credit rating

Figure OA.6
Triple interaction for different country credit ratings
This figure displays the triple interaction coefficient $D(Crash) \times D(Country\ Rating_r) \times Company\ illiquidity$ of the following regression model:

$$\begin{aligned} D(Short\ position_{i,j,t}) &= \sum_r \sum_p \beta_1^{r,p} D(Period_p) \times D(Country\ Rating_r) \times Company\ illiquidity_i + \\ &\sum_r \sum_p \beta_2^{r,p} D(Period_p) \times Company\ illiquidity_i + \\ &\mathbf{X}'_{i,t-1}\gamma + \alpha_{c,t} + \alpha_{ind,t} + \alpha_{j,t} + \alpha_{i,j} + \epsilon_{i,j,t}, \end{aligned}$$

where $D(Country\ Rating_r)$ is a dummy that equals 1 if the country's credit rating equals the respective rating group, with $Country\ Rating_r = \{AAA; AA; A; \leq BBB\}$. $D(Period_p)$ are a dummy variables indicating different time periods, where $Period_p = \{Crash; Recovery\ 1; Recovery\ 2\}$. The $Crash$ period is from February 24 to March 23, the $Recovery$ 1 period is from March 24 to May 14, and the $Recovery$ 2 period is from May 15 to June 26, 2020. All other variables are defined as in Equation (2). We plot each coefficient $\beta_1^{r,Crash}$ with a 90% confidence interval of the respective rating group. The reference group, which is by construction zero, are countries with a AAA credit rating. The sample period is July 2019 to June 2020.

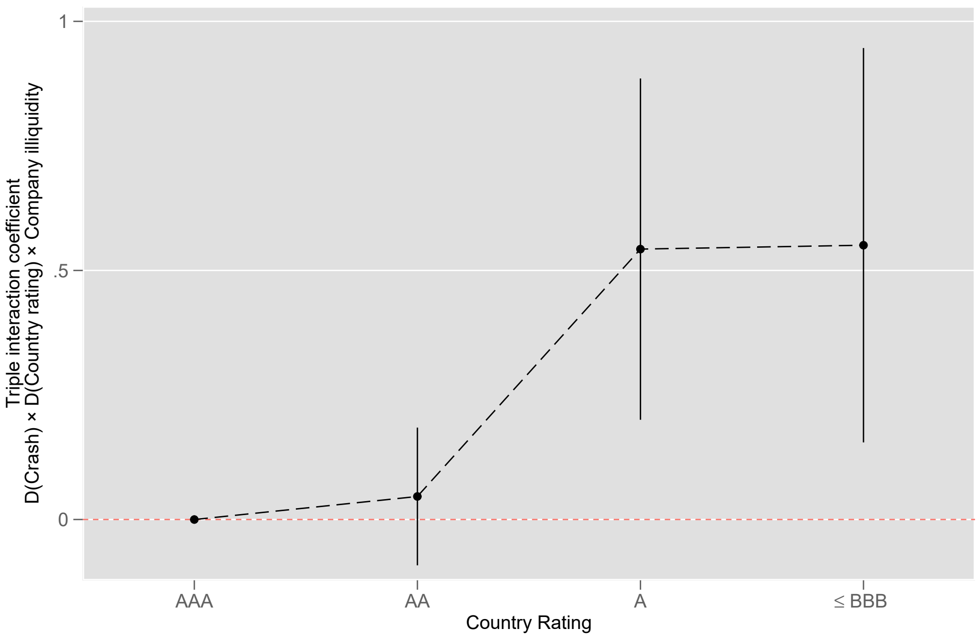

Table OA.1
Definitions of variables

Variable	Description	Source
Dependent variables:		
D(Short position)	Dummy variable equal to 1 for all days on which an investor has a significant short position ($\geq 0.5\%$) open for a given stock.	NCA
D(Short entry)	Dummy variable equal to 1 for the day on which an investor enters a significant short position ($\geq 0.5\%$) for a given stock.	NCA
Key explanatory variables:		
D(Crash)	Dummy variable equal to 1 for the stock market crash period (February 24, 2020 – March 23, 2020), and zero otherwise.	
D(Recovery 1)	Dummy variable equal to 1 for the first stock market recovery period (March 24, 2020 – May 17, 2020), and zero otherwise.	
D(Recovery 2)	Dummy variable equal to 1 for the second stock market recovery period (May 18, 2020 – June 26, 2020), and zero otherwise.	
D(Pre-Crash)	Dummy variable equal to 1 for the period after the PHEIC and prior to the stock market crash (January 30, 2020 - February 23, 2020), and zero otherwise.	
D(Low country rating)	Dummy variable equal to 1 if a company's headquarters country is rated below AA- according to S& P's methodology, and zero otherwise.	Eikon
Rating notch	A country's long-term sovereign debt rating by S& P's at the end of 2019, ranging between 0 (AAA) up to 12 (BB-).	Eikon
CDS5y	Daily average of a country's 5-year sovereign CDS spread in year 2019.	Eikon
Company illiquidity	Percentile rank of company illiquidity, ranging from 0 (liquid) to 1 (illiquid). Company liquidity is measured by three-year median of the industry-adjusted quick ratio (fiscal years 2016-2018). The quick ratio is defined as Total Current Assets excluding Total Inventories to Total Current Liabilities. The yearly ratios are provided by the Eikon variable *TR.QuickRatio*.	Eikon

Table OA.1

Variable	Description	Source
D(Disclosure)	Dummy variable equal to 1 if there was a new short position disclosure for a particular stock in the last three trading days.	NCA
Main control variables:		
Cases	Daily confirmed COVID-19 cases per million people.	OxCGRT, Eurostat
Deaths	Daily confirmed COVID-19 deaths per million people.	OxCGRT, Eurostat
Government response	Government Response Stringency Index provided by the Oxford COVID-19 Government Response Tracker. The index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response).	OxCGRT
Health expenditure	Countries' expenditure on health (all functions) per captia (in USD) as of 2017.	OECD
Hospital beds	Countries' total hospital beds per 1,000 population as of 2017.	OECD
ICU beds	Countries' intensive care (ICU) and intermediate care beds (IMCU) beds per 100,000 population as of 2011.	Rhodes et al. (2012)
Liquid to total assets	Banks liquid assets as a percentage of total assets, aggregated on country level. No data available for Norway. Variable name: *CBD2.A.[COUNTRYCODE].W0.11._Z._Z.A.A.I3018._Z._Z._Z._Z._Z._Z.PC*	ECB data warehouse
Tier 1 capital ratio	Banks core tier 1 capital — that is, equity capital and disclosed reserves — to total risk-weighted assets, aggregated on country level. No data available for Norway. Variable name: *CBD2.A.[COUNTRYCODE].W0.11._Z._Z.A.A.I4002._Z._Z._Z._Z._Z._Z.PC*	ECB data warehouse
Loan-to-deposit ratio	Ratio between the banks total loans and total deposits, aggregated on country level. No data available for Norway. Variable name: *CBD2.A.[COUNTRYCODE].W0.11._Z._Z.A.A.I3006._Z._Z._Z._Z._Z._Z.PC*	ECB data warehouse

Table OA.1

Variable	**Description**	**Source**
Undrawn revolving credit	A firm's industry-adjusted USD amount of undrawn revolving credit relative to its total assets. The ratio is transformed into percentile ranks. Variable name: *UndrawnCrdtPortionRevolvingCrdt*.	Capital IQ
Total undrawn credit	A firm's industry-adjusted USD amount of total undrawn credit relative to its total assets. The ratio is transformed into percentile ranks. Variable name: *TotUndrawnCredit*.	Capital IQ
ROE	The three-year median of the industry-adjusted Net Income Before Extraordinary Items to the Average Total Equity. Average Total Equity is the average of Total Equity at the beginning and the end of the year. The ratio is transformed into percentile ranks. The yearly ratios are provided by the Eikon variable *TR.ReturnonAvgTotEqtyPctNetIncomeBeforeExtraItems*.	Eikon
ROA	The three-year median of the industry-adjusted ratio of Income After Taxes to the Average Total Assets. Average Total Assets is the average of Total Assets at the beginning and the end of the year. The ratio is transformed into percentile ranks. The yearly ratios are provided by the Eikon variable *TR.ROATotalAssetsPercent*.	Eikon
Price-to-book	The three-year median of the industry-adjusted ratio of price to book value per share. It is calculated by dividing a company's closing price by its book value per share. Book value per share is calculated by dividing total equity from latest fiscal period by current total shares outstanding. The final ratio is transformed into percentile ranks. The yearly ratios are provided by the Eikon variable *TR.PriceToBVPerShare*.	Eikon
Z-score	The three-year median of the industry-adjusted Z-score. The Z-score is defined as in Altman et al. (2017) by the following equation: Z-score= 3.25+ $6.56\times X_1$+$3.26\times X_2$ + $6.72\times X_3$+ 1.05 $\times X_4$, where X_1=Working Capital/Total Assets, X_2 = Retained Earnings/Total Assets; X_3 = Earnings before Interest and Taxes/Total Assets, and X_4 = Market Value of Equity/Book Value of Total Liabilities. The Z-score is transformed into percentile ranks.	Eikon

Table OA.1

Variable	Description	Source
Interest coverage ratio	The three-year median of the ratio of EBITDA to total net interest expenses. EBITDA is LTM Earnings before Interest, Taxes, Depreciation and Amortization. The yearly ratios are provided by the Eikon variable $TR.EBITDAInterestCoverage$.	Eikon
Synthetic credit rating	Synthetic credit ratings are estimated from companies' three-year median Interest coverage ratio based on Standard & Poor's categories and data provided by Aswath Damodaran. For more details, see http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datacurrent.html. A value of 1 represents the highest credit rating. Higher values represent a lower credit rating.	Eikon, Aswath Damodaran's website
D(Zombie)	Dummy variable equal to 1 for companies with a *Synthetic credit rating* equal or lower than BB and a negative *ROA*, and zero otherwise.	Eikon, Aswath Damodaran's website
Net debt-to-EBITDA	The three-year median of industry-adjusted net debt to EBITDA. Net debt is Total Debt minus Cash and Short Term Investments. EBITDA is LTM Earnings before Interest, Taxes, Depreciation and Amortization. The ratio is transformed into percentile ranks. The yearly ratios are provided by the Eikon variable $TR.NetDebtToEBITDA$.	Eikon
ST Debt-to-T Assets	The industry-adjusted ratio of short-term debt & current portion of long-term debt to total assets for the fiscal year 2019. The ratio is transformed into percentile ranks. The yearly ratios are provided by the Eikon variable $TR.PCSTDebtAndCurrPrtnOfLTDebtToTotAsstPct$.	Eikon
ST Debt-to-T Debt	The industry-adjusted ratio of short-term debt & current portion of long-term debt to total debt for the fiscal year 2019. The ratio is transformed into percentile ranks. The yearly ratios are calculated by combining the Eikon variable $TR.PCSTDebtAndCurrPrtnOfLTDebtToTotAsstPct$ and $TR.PCTotDebtToTotAsstPct$.	Eikon
DN resilience	The variable 'teleworkable_manual_wage' as defined by Dingel and Neiman (2020) at the 2-digit NAICS industry level. It is the fraction of wages to jobs that can be done from home based on manual classification by the authors.	Dingel and Neiman (2020)

Table OA.1

Variable	**Description**	**Source**
KP resilience	The variable 'affected_share' as defined by Koren and Pető (2020) at the 3-digit NAICS industry level. It is the percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others	Koren and Pető (2020)
HLR resilience	The variable 'dur_workplace' as defined by Hensvik et al. (2020) at the 4-digit NAICS industry level. It is the hours worked at workplace per day.	Hensvik et al. (2020)
Local share 1	The three-year median of a company's revenue share generated in the headquarter country if the country is mentioned as a single, separate segment in the company's reporting. Local share equal to zero if segment data available but no single headquarter country segment. Otherwise set to missing. The yearly segment data are provided by the Eikon variable *TR.BGS.GeoTotalRevenue*.	Eikon
Local share 2	The three-year median of a company's revenue share generated in the headquarter country. If a firm's headquarter country is part of a larger geographic segment with multiple mentioned markets, share is split across all mentioned markets equally. Local share equal to zero if segment data available but no headquarter country segment. Otherwise set to missing. The yearly segment data are provided by the Eikon variable *TR.BGS.GeoTotalRevenue*.	Eikon
Local share 3	The three-year median of a company's revenue share generated in the headquarter country. If a firm's headquarter country is part of a larger geographic segment with multiple mentioned markets, share is split across all mentioned markets equally. Local share set to missing if segment data not available or if segment data available but no headquarter country segment. The yearly segment data are provided by the Eikon variable *TR.BGS.GeoTotalRevenue*.	Eikon
No. of employees	A company's headquarter country-adjusted total number of employees. The infornation is provided by the Eikon static variable *TR.Employees*	Eikon
Total assets	A company's three-year median of the headquarter country-adjusted total assets in USD. The yearly data are provided by the Eikon variable *TR.TotalAssetsReported*.	Eikon

Table OA.1

Variable	**Description**	**Source**
Revenue	A company's three-year median of the headquarter country-adjusted total revenue in USD. The yearly data are provided by the Eikon variable *TR.Revenue*.	Eikon

Stock-level control variables:

$ret_{t-h,t-l}$	Daily return over the time period $t-H$ to $t-l$	Datastream
Amihud	$\lvert\mathrm{ret}_t\rvert/(VO \times P) \times 10^6$, where ret_t is the return, VO is the number of shares traded (in thousands), and P is the price (Amihud, 2002). We winsorize the Amihud illiquidity ratio at 1% at the upper tail and then average it over the last 5 trading days, requiring at least 3 valid observations.	Datastream
BidAsk	$(PA-PB)/P$, expressed in percentage terms, where P is the stock's price, PA is the ask price, and PB is the bid price, all provided by Datastream. We winsorize the bid-ask spread at 1% at the upper tail and then average it over the last 5 trading days, requiring at least 3 valid observations.	Datastream
ISVola	Standard deviation of daily residual returns computed over the last 60 trading days, requiring at least 10 valid observations. Residual returns are computed using the Capital asset pricing model, over the last 250 trading days, requiring at least 100 valid observations.	Datastream, Kenneth French
β^{MKTRF}(*Market beta*)	Stock's exposure to the market portfolio computed using the capital asset pricing model (CAPM), over the last 250 trading days, requiring at least 100 valid observations.	Datastream, Kenneth French

Table OA.2 Overview of short-selling bans
This table lists the short-selling bans enacted in 2020 during the COVID-19 pandemic in Europe. The regulations prohibited the talking of net short positions or the increase of existing net short positions, regardless of where the transaction was executed. Market-making activities were exempted from the short-selling bans.

Country	Announcement	Start	End	Coverage
Austria	18 March	18 March	18 May	All instruments that trade on the Wiener Börse and where the FMA is the relevant competent authority.
Belgium	16 March	17 March	17 March	Temporary ban for a list of 17 instruments.
Belgium	17 March	18 March	18 May	All instruments listed on Euronext Brussels or Euronext Growth and where the FSMA is the relevant competent authority
France	16 March	17 March	17 March	Temporary ban for a list of 92 instruments.
France	17 March	18 March	18 May	Ban for a list of 793 firms.
Greece	17 March	18 March	18 May	All instruments that trade on the Athens Stock Exchange and where the HCMC is the relevant competent authority
Italy	12 March	13 March	13 March	Temporary ban for a list of 85 of instruments.
Italy	14 March	17 March	17 March	Temporary ban for a list of 20 instruments.
Italy	17 March	18 March	18 May	Ban for a list of 237 instruments.
Spain	16 March	17 March	18 May	All instruments that trade on a Spanish stock exchange and where the CNMV is the relevant competent authority

Table OA.3 Triple difference regression with countries' rating notch as fiscal space proxy
Table OA.3 shows the result for the fixed effects panel regression described in equation (1). The dependent variable is $D(Short\ position)$, which is a dummy variable equal to 1 if investor j holds a short position in stock i on day t and is zero otherwise. The main explanatory variables are: *D(Crash)*, which is a dummy variable that equals 1 for the stock market crash period (February 24 – March 23, 2020) and zero otherwise; *D(Recovery 1)*, which is a dummy variable that equals 1 for the first stock market recovery period (March 24 – May 17, 2020) and zero otherwise; *D(Recovery 2)*, which is a dummy variable that equals 1 for the second stock market recovery period (May 18 – June 26, 2020) and zero otherwise; *Rating notch*, which is the S&P rating notch (ranging from 0 (AAA) to 12 (BB-) end of year 2019; $Company\ illiquidity_i$, which is the percentile rank (ranging between 0 and 1) of firm illiquidity based on the industry-adjusted quick ratio. Stock-level controls contain a shorting ban dummy, lagged stock returns at different horizons, stock liquidity proxies, idiosyncratic volatility, and market beta. Detailed definitions of all stock-level control variables can be found in Table OA.1. 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)	(4)	(5)
	Dependent variable: $D(Short\ position)$				
D(Crash) × Rating notch × Company illiquidity	0.0657***	0.0662***	0.0802***	0.0685***	0.0681***
	(3.03)	(2.90)	(3.39)	(2.74)	(2.73)
D(Recovery 1) × Rating notch × Company illiquidity	0.0577**	0.0536**	0.0753***	0.0598**	0.0597**
	(2.41)	(2.22)	(2.99)	(2.22)	(2.22)
D(Recovery 2) × Rating notch × Company illiquidity	0.0393	0.0303	0.0451*	0.0303	0.0295
	(1.45)	(1.16)	(1.66)	(1.08)	(1.06)
D(Crash) × Company illiquidity	-0.0869*	-0.0848*	-0.1001*	-0.1129*	-0.1122*
	(-1.68)	(-1.68)	(-1.78)	(-1.96)	(-1.95)
D(Recovery 1) × Company illiquidity	-0.0692	-0.0619	-0.0889	-0.0885	-0.0882
	(-1.06)	(-1.00)	(-1.34)	(-1.38)	(-1.38)
D(Recovery 2) × Company illiquidity	-0.0585	-0.0471	-0.0513	-0.0707	-0.0728
	(-0.80)	(-0.68)	(-0.67)	(-0.99)	(-1.03)
D(Crash) × Rating notch	-0.0036	–	–	–	–
	(-0.75)				
D(Recovery 1) × Rating notch	-0.0062	–	–	–	–
	(-1.05)				
D(Recovery 2) × Rating notch	-0.0155***	–	–	–	–
	(-2.73)				
adj. R^2	0.004	0.245	0.245	0.247	0.244
adj. within R^2	0.004	0.005	0.004	0.003	0.002
Nobs	708,177	707,931	705,043	680,669	680,669
Stock-level control variables	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	–
Investor FE	Yes	Yes	Yes	–	–
Time FE	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

Table OA.4 Triple difference regression with countries' 5-year sovereign CDS spread as fiscal space proxy

Table OA.4 shows the result for the fixed effects panel regression described in equation (1). The dependent variable is $D(\textit{Short position})$, which is a dummy variable equal to 1 if investor j holds a short position in stock i on day t and is zero otherwise. The main explanatory variables are: *D(Crash)*, which is a dummy variable that equals 1 for the stock market crash period (February 24 – March 23, 2020) and zero otherwise; *D(Recovery 1)*, which is a dummy variable that equals 1 for the first stock market recovery period (March 24 – May 17, 2020) and zero otherwise; *D(Recovery 2)*, which is a dummy variable that equals 1 for the second stock market recovery period (May 18 – June 26, 2020) and zero otherwise; *CDS5y*, which is a country's average 5-year sovereign CDS spread in year 2019; $\textit{Company illiquidity}_i$, which is the percentile rank (ranging between 0 and 1) of firm illiquidity based on the industry-adjusted quick ratio. Stock-level controls contain a shorting ban dummy, lagged stock returns at different horizons, stock liquidity proxies, idiosyncratic volatility, and market beta. Detailed definitions of all stock-level control variables can be found in Table OA.1. 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)	(4)	(5)
	Dependent variable: $D(\textit{Short position})$				
D(Crash) × CDS5y × Company illiquidity	0.0057***	0.0056***	0.0067***	0.0056**	0.0056**
	(2.90)	(2.77)	(3.05)	(2.35)	(2.34)
D(Recovery 1) × CDS5y × Company illiquidity	0.0051**	0.0046**	0.0064***	0.0048*	0.0048*
	(2.42)	(2.23)	(2.86)	(1.95)	(1.93)
D(Recovery 2) × CDS5y × Company illiquidity	0.0023	0.0017	0.0035	0.0019	0.0020
	(1.04)	(0.79)	(1.52)	(0.76)	(0.81)
D(Crash) × Company illiquidity	-0.1086*	-0.1047*	-0.1282**	-0.1362**	-0.1350**
	(-1.87)	(-1.84)	(-2.00)	(-2.03)	(-2.01)
D(Recovery 1) × Company illiquidity	-0.0914	-0.0826	-0.1177	-0.1052	-0.1042
	(-1.31)	(-1.25)	(-1.65)	(-1.47)	(-1.45)
D(Recovery 2) × Company illiquidity	-0.0524	-0.0443	-0.0743	-0.0816	-0.0870
	(-0.68)	(-0.61)	(-0.95)	(-1.09)	(-1.17)
D(Crash) × CDS5y	-0.0004	–	–	–	–
	(-0.94)				
D(Recovery 1) × CDS5y	-0.0004	–	–	–	–
	(-0.97)				
D(Recovery 2) × CDS5y	-0.0008*	–	–	–	–
	(-1.86)				
adj. R^2	0.2431	0.2438	0.2463	0.2428	0.4905
adj. within R^2	0.0043	0.0037	0.0028	0.0022	0.0033
Nobs	694,002	693,756	690,868	666,509	666,509
Stock-level control variables	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	–
Investor FE	Yes	Yes	Yes	–	–
Time FE	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

Table OA.5 Triple difference regression with current ratio as liquidity proxy

Table OA.5 shows the result for the fixed-effects panel regression described in equation (1). The dependent variable is $D(Short\ position)$, which is a dummy variable equal to 1 if investor j holds a short position in stock i on day t and is zero otherwise. The main explanatory variables are: *D(Crash)*, which is a dummy variable that equals 1 for the stock market crash period (February 24 – March 23, 2020) and zero otherwise; *D(Recovery 1)*, which is a dummy variable that equals 1 for the first stock market recovery period (March 24 – May 17, 2020) and zero otherwise; *D(Recovery 2)*, which is a dummy variable that equals 1 for the second stock market recovery period (May 18 – June 26, 2020) and zero otherwise; *D(Low country rating)*, which is a dummy variable that equals 1 if the country of headquarters has a rating below AA- and zero otherwise; $Company\ illiquidity_i$, which is the percentile rank (ranging between 0 and 1) of firm illiquidity based on the industry-adjusted current ratio. Stock-level controls contain a shorting ban dummy, lagged stock returns at different horizons, stock liquidity proxies, idiosyncratic volatility, and market beta. Detailed definitions of all stock-level control variables can be found in Table OA.1. 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)	(4)	(5)
	Dependent variable: $D(Short\ position)$				
D(Crash) × D(Low country rating) × Company illiquidity	0.4548***	0.4540***	0.4857***	0.4044**	0.4041**
	(3.02)	(2.67)	(2.74)	(2.17)	(2.16)
D(Recovery 1) × D(Low country rating) × Company illiquidity	0.3276**	0.3101**	0.3580**	0.3033*	0.3037*
	(2.36)	(2.05)	(2.15)	(1.65)	(1.66)
D(Recovery 2) × D(Low country rating) × Company illiquidity	0.2341	0.2140	0.2714	0.2204	0.2256
	(1.47)	(1.32)	(1.52)	(1.14)	(1.17)
D(Crash) × Company illiquidity	-0.0073	-0.0096	-0.0031	-0.0298	-0.0299
	(-0.17)	(-0.23)	(-0.07)	(-0.62)	(-0.62)
D(Recovery 1) × Company illiquidity	-0.0035	-0.0059	-0.0015	-0.0134	-0.0135
	(-0.07)	(-0.12)	(-0.03)	(-0.26)	(-0.26)
D(Recovery 2) × Company illiquidity	-0.0129	-0.0144	-0.0032	-0.0281	-0.0293
	(-0.23)	(-0.26)	(-0.05)	(-0.50)	(-0.52)
D(Crash) × D(Low country rating)	-0.0152	–	–	–	–
	(-0.50)				
D(Recovery 1) × D(Low country rating)	-0.0125	–	–	–	–
	(-0.37)				
D(Recovery 2) × D(Low country rating)	-0.0585*	–	–	–	–
	(-1.74)				
adj. R^2	0.2446	0.2451	0.2469	0.2438	0.4904
adj. within R^2	0.0042	0.0038	0.0027	0.0021	0.0031
Nobs	708,177	707,931	705,043	680,669	680,669
Stock-level control variables	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	–
Investor FE	Yes	Yes	Yes	–	–
Time FE	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

Table OA.6 Trading against local demand stimulus or direct liquidity support? Estimation with quadruple interactions

Table OA.6 shows the result for the fixed effects panel regression described in equation (2) augmented with interactions of all effects with a dummy variable $D(Var)$. The dependent variable is $D(Short\ position)$, which is a dummy variable equal to 1 if investor j holds a short position in stock i on day t and is zero otherwise. The main explanatory variables are: *D(Crash)*, which is a dummy variable that equals 1 for the stock market crash period (February 24 – March 23, 2020) and zero otherwise; *D(Recovery 1)*, which is a dummy variable that equals 1 for the first stock market recovery period (March 24 – May 17, 2020) and zero otherwise; *D(Recovery 2)*, which is a dummy variable that equals 1 for the second stock market recovery period (May 18 – June 26, 2020) and zero otherwise; *D(Low country rating)*, which is a dummy variable that equals 1 if the country of headquarters has a rating below AA- and zero otherwise; $Company\ illiquidity_i$, which is the percentile rank (ranging between 0 and 1) of firm illiquidity based on the industry-adjusted quick ratio. $D(Var)$ is defined by the median split of the following variables: Three different definitions of the share of the revenue generated in the headquarter country, as well as the number of employees, total assets and revenue adjusted by the country median. In Column (1), we only calculate the revenue share of the headquarter 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 headquarter country is reported, we assume that the headquarter country is less likely to be an important sales market and define the share as 0. In Column (2), we alter the first definition by also calculating the local revenue share if the headquarter 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 headquarter country and split the share across all mentioned markets equally. In Column (3), we relax the assumption that headquarter 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 Columns (4) to (6) are conducted using the median of the previous three fiscal years of the number of employees, total assets and revenue adjusted by the country median. All regressions include stock-level controls as 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)	(4)	(5)	(6)
	Dependent variable: D(Short position)					
D(Var)=	D(Local company)			D(Low company relevance)		
	Above median			Below median		
	Local $share_1$	Local $share_2$	Local $share_3$	Employees	Total assets	Revenue
D(Crash) × D(Low country rating) × Company illiquidity × D(Var)	0.6716**	0.9738***	0.9966***	-0.1370	-0.0937	-0.2269
	(2.03)	(3.07)	(2.84)	(-0.43)	(-0.29)	(-0.69)
D(Crash) × D(Low country rating) × Company illiquidity	0.0434	-0.0338	0.2042	0.7227***	0.6012**	0.7062***
	(0.19)	(-0.18)	(1.08)	(2.75)	(2.34)	(2.64)
D(Crash) × D(Low country rating) × D(Var)	0.0255	-0.0181	-0.0858	0.1506***	0.0878	0.0197
	(0.40)	(-0.29)	(-1.31)	(2.69)	(1.50)	(0.32)
D(Crash) × Company illiquidity × D(Var)	0.0481	0.0670	-0.1085	-0.2115**	-0.1396	-0.1409
	(0.43)	(0.60)	(-0.91)	(-2.39)	(-1.43)	(-1.45)
D(Recovery 1) × D(Low country rating) × Company illiquidity × D(Var)	0.5457	0.8921**	0.9814**	-0.2904	-0.2131	-0.5413
	(1.49)	(2.54)	(2.56)	(-0.84)	(-0.59)	(-1.54)
D(Recovery 1) × D(Low country rating) × Company illiquidity	-0.0030	-0.1108	0.0390	0.6594**	0.5484*	0.7882***
	(-0.01)	(-0.54)	(0.18)	(2.35)	(1.93)	(2.75)
D(Recovery 1) × D(Low country rating) × D(Var)	0.0235	-0.0293	-0.1031	0.1153*	0.0459	-0.0159
	(0.34)	(-0.44)	(-1.54)	(1.79)	(0.65)	(-0.23)
D(Recovery 1) × Company illiquidity × D(Var)	0.0276	0.0518	-0.1880	-0.1454	-0.1050	-0.0741
	(0.23)	(0.42)	(-1.51)	(-1.36)	(-0.92)	(-0.67)
D(Recovery 2) × D(Low country rating) × Company illiquidity × D(Var)	0.5521	0.9384**	0.8196**	-0.7068**	-0.5416	-0.9627***
	(1.39)	(2.49)	(2.02)	(-2.06)	(-1.53)	(-2.80)
D(Recovery 2) × D(Low country rating) × Company illiquidity	-0.1760	-0.3145	-0.0156	0.8381***	0.6583**	0.9529***
	(-0.63)	(-1.27)	(-0.06)	(3.05)	(2.45)	(3.58)
D(Recovery 2) × D(Low country rating) × D(Var)	0.0264	-0.0315	-0.1186	0.1279*	0.0073	-0.0226
	(0.36)	(-0.44)	(-1.60)	(1.89)	(0.10)	(-0.31)
D(Recovery 2) × Company illiquidity × D(Var)	-0.0210	0.0238	-0.2318*	-0.0425	-0.1530	0.0197
	(-0.16)	(0.18)	(-1.68)	(-0.37)	(-1.33)	(0.16)
adj. R^2	0.4849	0.4853	0.4899	0.4925	0.4909	0.4911
adj. within R^2	0.0040	0.0048	0.0054	0.0048	0.0042	0.0047
Nobs	574,287	574,287	493,987	650,049	680,669	679,916
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