Bank of England

Moderation or indulgence? Effects of bank distribution restrictions during stress

Staff Working Paper No. 1,053
November 2023

Jonathan Acosta-Smith, Jozef Barunik, Eddie Gerba and Petros Katsoulis

Bank of England

Staff Working Paper No. 1,053

Moderation or indulgence? Effects of bank distribution restrictions during stress

Jonathan Acosta-Smith,[1] Jozef Barunik,[2] Eddie Gerba[3] and Petros Katsoulis[4]

Abstract

At the onset of the Covid-19 crisis, several regulatory authorities issued a recommendation or request to banks to restrict their dividend and share buyback distributions. The purpose of this action was to increase banks' resilience by not distributing retained earnings, and help them support the real economy given their unique role in doing so. These restrictions reflected the singular circumstances brought by Covid-19. We evaluate the impact of these restrictions on banks' resilience, lending and investors' required rate of return. First, using a difference-in-differences analysis on an international sample of European banks, we find that restricted banks increased their available Common Equity Tier 1 (CET1) capital and resilience in every quarter while the restrictions were fully in place, before gradually reducing it once they were partly lifted. Second, using a data set on the universe of UK small and medium-sized enterprise (SME) loans issued by nine UK banking groups, we find that restricted banks increased their lending volumes on smaller non-government guaranteed loans throughout the implementation period. Third, using the international sample of European banks, we find that the restrictions increased shareholders' required rate of return throughout the implementation period, with the impact on the required rate of return on capital partially offset by lower debtholders' required rate of return. The results indicate that distribution restrictions can be an effective crisis tool to increase banks' resilience and lending capacity.

Key words: Distribution restrictions, Covid-19, required rate of return, lending, pass-through.

JEL classification: C32, G21, G28, G35.

(1) Organisation for Economic Co-operation and Development (OECD). Email: jonathan.smith@oecd.org
(2) Institute of Economic Studies, Charles University. Email: barunik@fsv.cuni.cz
(3) Bank of England. Email: eddie.gerba@bankofengland.co.uk
(4) Bank of England. Email: petros.katsoulis@bankofengland.co.uk

The Bank's working paper series can be found at www.bankofengland.co.uk/working-paper/staff-working-papers

Bank of England, Threadneedle Street, London, EC2R 8AH
Email: enquiries@bankofengland.co.uk

ISSN 1749-9135 (on-line)

1 Introduction

The Covid-19 crisis was the first global systemic shock to test the regulatory framework enshrined in Basel III, which was put in place in the aftermath of the 2008-09 global financial crisis. Its goal was to enhance the resilience of the banking system and its ability to provide credit to the real economy during stress. As the Covid-19 market stress and social restrictions took hold in Europe in March 2020, several authorities issued a temporary distributions restriction recommendation or request, which urged banks to refrain from paying dividends, performing share buybacks and in some cases awarding staff cash bonuses (Svoronos and Vrbaski, 2020). The purpose of this action was to increase banks' resilience by not distributing retained earnings, and help them support the real economy given their unique role in doing so. This was in the context of the singular uncertainty prevalent at the time regarding the forthcoming very large impact of Covid-19, and the wide range of outcomes that could unfold. This uncertainty was reflected in the comprehensive range of measures taken by prudential and monetary authorities to support the real economy.[1]

In this paper, we empirically assess the impact of the distribution restrictions on banks' resilience, lending and investors' required rate of return throughout the entire implementation period. We adopt a holistic approach because the restrictions are likely to have affected both the assets and liabilities sides of banks' balance sheets. On the assets side, the restrictions may have led banks to utilise the surplus capital to increase lending. On the liabilities side, the restrictions may have increased banks' resilience if they decided to retain at least part of the surplus capital. However, they may also have impacted investors' required rate of return: on the one hand, since dividends and share buybacks affect investors' willingness to hold equity (DeAngelo et al., 2009), their cancellation could increase shareholders' required rate of return (i.e. cost of equity); on the other hand, increased capitalisation reduces the volatility of the share price and the riskiness of debt, lowering debtholders' required rate of return (i.e. cost of debt) (Modigliani and Miller, 1958). Those opposing impacts might be expected to have the net effect of raising the required rate of return on capital (i.e. cost of capital), given that the empirical literature has generally found that the impact of the Modigliani-Miller (MM) offset is imperfect for banks (Brooke et al., 2015).

We assess the impact on resilience and required rate of return on capital using an international sample of European banks. While some jurisdictions applied the restrictions to all banks (e.g. the European Central Bank - ECB), others applied them to only a subset of their banking system (e.g. the Prudential Regulation Authority - PRA). We use a difference-in-differences analysis to compare outcomes between banks that restricted distributions, and those that either were not subject to the restrictions, or did not plan to make distributions regardless of whether they were restricted or not. We measure resilience in terms of common

[1] https://www.bankofengland.co.uk/coronavirus

equity Tier 1 (CET1) capital. We estimate shareholders' required rate of return using the average of four commonly used dividend discount models in the literature (Claus and Thomas, 2001; Damodaran, 2022; Easton, 2004; Ohlson and Juettner-Nauroth, 2005), while debtholders' required rate of return is estimated using yields of bank bonds traded in the secondary market.

To assess the impact on lending we rely on Experian, a confidential dataset that provides all loans issued by nine UK banking groups to UK small and medium enterprises (SMEs) at a monthly frequency (Hurley et al., 2021). We focus on this loan segment since SMEs were the most reliant on bank credit during the pandemic. In contrast, large borrowers retained access to market-based finance and were less reliant on bank credit (Acharya and Steffen, 2020). We similarly utilise a difference-in-differences analysis and compare lending volumes between banks that were subject to the restrictions and those that were not. We control for a host of other policies that aimed to support lending to the real economy including countercyclical capital buffer (CCyB) release, quantitative easing, term funding to issue SME loans, and government-guaranteed lending.

Our findings can be summarised as follows. First, we find that the restricted banks increased their CET1 capital in every quarter of full restrictions implementation, peaking at 5.1% higher compared to the unrestricted banks in Q4 2020. This difference started decreasing and became insignificant from Q1 2021, when regulators partly lifted the restrictions and allowed banks to make limited distributions.

Second, we find that the restricted banks increased non-government guaranteed lending volumes to SMEs, although this effect was concentrated on loans smaller than £100,000, which nonetheless form the majority of our sample. Specifically, the average value of these loans issued by restricted banks increased by 34.2% compared to the unrestricted banks. This increase remained significant throughout the implementation period. We also find that distribution restrictions worked in tandem with fiscal policy measures in the form of government guarantees on loans, with restricted banks increasing lending by similar amounts in both segments. In addition, we find that the increase in lending volumes was not dependent on banks' capital positions, since even banks with lower capital provided similar lending volumes compared to their better capitalised peers.

Third, we find that the restrictions increased shareholders' required rate of return but reduced debtholders' one, in line with the MM theorem. Both effects persisted throughout the implementation period, with shareholders' required rate of return increasing on average by 2.7 percentage points (pp) and debtholders' one decreasing on average by 0.6 pp. This suggests an imperfect MM offset on the required rate of return on banks' capital, consistent with the empirical literature, although this does not account for any risk premia that investors may have demanded. However, we find no evidence of a pass-through of higher investors' required rate of return on to lending volumes, indicating that it did not lead to credit rationing.

Overall, the results provide evidence that the restrictions were effective at incentivising banks to use the restricted capital both to increase their resilience and lending volumes. Nonetheless, they also highlight the potential side-effects in terms of increasing investors' required rate of return. Our study focuses on the implementation period and does not attempt to assess any long-term effects of the restrictions. However, our results showcase that the higher required rate of return did not negatively impact the extension of credit to SMEs, which suggests that the benefits outweighed the costs, at least while the restrictions were in place. Nonetheless, distribution restrictions are unlikely to be able to substitute capital buffer releases as a way of promoting lending given their effectiveness on smaller loans only. Taken together, we believe that distribution restrictions were an effective tool to boost lending and strengthen banks' capital positions during the Covid-19 stress. However, their usage was justified due to the singular circumstances at the time, which are not likely to be applicable during normal economic downturns.

The rest of the paper is structured as follows. Section 2 describes the timeline of events and hypotheses development. Section 3 describes the data used in the study while section 4 presents the empirical strategy. Section 5 presents the results and finally section 6 concludes and discusses policy implications.

2 Timeline of events and hypotheses development

As the coronavirus pandemic took hold in March 2020, many governments imposed social restrictions to stem its spread. In response, central banks and regulatory authorities took action to limit the impact on the real economy and the financial system. This included distribution restrictions that limited or suspended banks' ability to pay dividends and perform share buybacks, to increase their resilience and help them support the real economy.

An important feature of these restrictions is that they varied across jurisdictions both in terms of the timing of the implementation, as well as their scope. Most jurisdictions in Europe implemented the restrictions in March 2020, with the ECB recommending all banks to suspend dividends and share buybacks for the financial years 2019 and 2020.[2] In the UK, the PRA additionally requested restrictions on bank staff cash bonuses, but the restrictions only applied to the seven largest deposit-takers.[3] In Switzerland, the Financial Market Supervisory Authority (FINMA) suspended share buybacks but not dividends.[4] In the US, the Federal Reserve suspended share buybacks but only placed a limit on dividends following the publication of the stress test results in June 2020.[5] In Canada, the Office of the Superintendent of Financial

[2] https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200327~d4d8f81a53.en.html
[3] https://www.bankofengland.co.uk/prudential-regulation/publication/2020/pra-statement-on-deposit-takers-approach-to-dividend
[4] https://www.finma.ch/en/news/2020/03/20200325-mm-garantiepaket/
[5] https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200625c.htm

Institutions (OSFI) limited both dividends and share buybacks.[6] In contrast, the Bank of Japan and the People's Bank of China did not impose any distribution restrictions.

Most jurisdictions lifted the restrictions by September 2021 when concerns about Covid's impact on banks' loss-bearing capacity eased. In the aftermath, some regulatory authorities raised concerns about making system-wide distribution restrictions a formal tool to be used during systemic crises, due to the potential negative implications for banks' valuations and ability to raise capital in the future (ECB, 2022). Indeed, studies conducted in the euro area and the US found that banks that faced restrictions experienced depressed valuations compared to the unrestricted peers, which could imply an increase in shareholders' required rate of return (Andreeva et al., 2023; Marsh, 2023). However, neither of these studies evaluated the impact on both shareholders' and debtholders' required rate of return, or its persistence throughout the implementation period. Our paper fills this gap by providing a comprehensive analysis of the impact of distribution restrictions on the required rate of return on banks' capital.

The theoretical literature has established various channels through which payouts affect firm valuations and shareholders' required rate of return. Payouts: i) affect investors' willingness to hold equity (DeAngelo et al., 2009), ii) provide positive signals about future earnings potential and resilience (Bhattacharya, 1980; Floyd et al., 2015; Miller and Rock, 1985), and iii) reduce agency costs and cost of capital via reputation and monitoring (Forti and Schiozer, 2015; La Porta et al., 2000; Shleifer and Vishny, 1997). Thus, blanket distribution restrictions could increase shareholders' required rate of return through these channels.

At the same time, the seminal work of Modigliani and Miller (1958) (MM) predicted that an increase in a firm's capital reduces the volatility of the share price and the riskiness and cost of debt. Given that distribution restrictions forced banks to conserve more capital and made them more solvent, this would imply a reduction in debtholders' required rate of return. Under idealised conditions, the MM theorem predicts that the overall required rate of return on capital would remain unchanged due to this offset. However, it has been found empirically that the MM offset applies only partially to banks, due to the presence of taxes and asymmetric information, as well as implicit government guarantees (Brooke et al., 2015). Hence, we hypothesize that distribution restrictions led to an increase in shareholders' required rate of return, and a lesser decrease in debtholders' required rate of return for the affected banks:

H1: Distribution restrictions increased shareholders' required rate of return, and decreased debtholders' required rate of return to a lesser extent for the affected banks.

Increases in the required rate of return on capital are typically associated with an increase in capital requirements (Brooke et al., 2015). Banks may respond to this in various ways. Commonly, they may reduce lending volumes, or increase the cost of lending. However, distribution restrictions in several cases followed a

[6] https://www.osfi-bsif.gc.ca/Eng/osfi-bsif/med/Pages/nr_20200313.aspx

reduction of capital requirements through the CCyB release, which gave banks strong incentives to direct the capital towards lending. Nonetheless, if the increase of the required rate of return on capital was substantial, banks may have decided to retain the surplus capital to boost their resilience and signal their commitment to distribute it as soon as the restrictions were lifted instead of lending it out (Matyunina and Ongena, 2022). We call this the *signalling channel*:

H2: Distribution restrictions increased affected banks' CET1 capital while they were fully in place.

Alternatively, banks may have decided to use the surplus capital to increase lending. A growing literature shows that banks respond to a loosening of capital requirements by increasing lending (Couaillier et al., 2022; Imbierowicz et al., 2018; Jiménez et al., 2017; Mathur et al., 2023). Dautović et al. (2023) and Martínez-Miera and Vegas (2021) find that restricted banks in the euro area and Spain respectively increased lending volumes compared to unrestricted ones. We call this the *lending channel*:

H3: Distribution restrictions increased affected banks' lending volume.

Yet, because of the two opposing effects, it is not *ex ante* clear which one will dominate. If the signalling channel dominates, then the pass-through from required rate of return on capital to lending volumes will be strong. If the lending channel dominates, then the bank is not bound by its funding constraints, so the pass-through is weak. In the extreme, banks may decide to retain all surplus capital, potentially leading to credit rationing (Baker and Wurgler, 2015; Berrospide and Edge, 2019; Favara et al., 2021), or lend it all out. A more probable reaction is that banks retain some of the surplus capital to signal their willingness to resume distributions when the restrictions are lifted, but also use a portion of it to increase lending. Hence, the two channels are not necessarily mutually exclusive so both *H2* and *H3* may hold.

3 Data & Variables construction

3.1 Required rate of return on capital

We focus on European listed banks that were subject to similar restrictions during Covid. We use S&P Capital IQ to identify a total of 194 such banks, which are headquartered in 28 European countries. We exclude Swiss banks because they were only subject to share buyback restrictions and not to dividend restrictions. For each bank, we download their 2020 published annual report to understand whether they took action to restrict distributions as a result of the regulatory request. Of these, 128 banks took such action and 66 didn't. The latter group's inaction is because either they were not subject to restrictions (e.g. smaller UK banks), or because they did not plan to make distributions even though they may have formally been under restrictions. Hence, we assign the former banks to our treated group and the latter banks to our control group.

Our sample period is from start of 2018 to end-September 2021 when the restrictions were lifted in all countries. The main variables of interest are shareholders' and debtholders' required rate of return. Since shareholders' required rate of return is not directly observable, we utilise the implied cost of capital class of models that has been proposed in the literature (see Lee et al. (2021) for an overview). These models link the stock price P_t to the discounted expected future cash flows (dividends) CF_{t+n}, where the discount rate is shareholders' required rate of return COE_t:

$$P_t = \sum_{n=1}^{\infty} \frac{CF_{t+n}}{(1 + COE_t)^n}$$

This class of models is appropriate to test the effects of the policy because it directly targeted dividends. Hence, these models capture the shift in investors' expectations about future dividends following the introduction of the restrictions, and hence the change in shareholders' required rate of return.

We estimate four dividend discount models commonly used in the literature (Altavilla et al., 2021; Dick-Nielsen et al., 2022), namely those by Damodaran (2022), Ohlson and Juettner-Nauroth (2005), Easton (2004) and Claus and Thomas (2001). We then follow common practice and calculate a simple average of the four estimates to obtain our central measure of shareholders' required rate of return, since this reduces measurement error (Mohanram and Gode, 2013). A detailed explanation of the methodology to calculate each model is provided in Appendix A. For model calibration we download banks' yearly earnings per share (EPS), dividend per share (DPS) and return on equity (ROE) forecasts for the next five years at a daily frequency from Refinitiv Eikon.[7]

For debtholders' required rate of return, we use mid yields of bank bonds that are traded in the secondary market and have a remaining maturity of at least one year. We then aggregate them at the bank level by taking the average of the corresponding mid yields weighted by market value as in Arnould et al. (2022). This excludes the required rate of return of other liabilities such as retail deposits and non-traded debt, which would be less sensitive to distribution restrictions.

Bank balance sheet characteristics are downloaded from S&P Capital IQ. Quarterly macroeconomic variables include GDP growth which is downloaded from OECD data,[8] and CPI and unemployment which are downloaded from Eurostat.[9] Daily number of new Covid cases are obtained from the World Health Organi-

[7] Shareholders are compensated for the risk they take in different ways (e.g. via dividends, share buybacks and capital appreciation). The models we use take this into account (e.g. via earnings forecasts), so they are suitable even for banks that do not pay dividends.

[8] https://data.oecd.org/gdp/quarterly-gdp.htm

[9] https://ec.europa.eu/eurostat/data/database

zation.[10] Finally, data on central bank policy rates are downloaded from BIS Statistics,[11] and quantitative easing (QE) holdings are downloaded from their respective websites.

We manage to obtain data on the control variables for 146 out of 194 banks. When comparing the mean values of the bank-specific variables between the treated and control groups on 28 February 2020 before the start of the treatment using a t-test, we observe that treated banks were systematically bigger in size, had a less stable funding profile and were more profitable (Panel A of Table B1 in Appendix B). In order to ensure that the treated and control groups are similar, we perform nearest neighbour matching based on the bank-specific control variables. The algorithm matches each treated bank to a control bank that has similar characteristics (a control bank may be matched to multiple treated ones). In this way, the average values of the bank-specific control variables between the groups are statistically similar. After applying the nearest neighbour matching these differences are eliminated at a 10% confidence level (Panel B of Table B1). The matched sample retains 123 banks.

Finally, we construct the shareholders' required rate of return estimates using the models detailed in Appendix A. Several banks in our sample do not have data on forecasts on EPS, DPS and ROE for all five years. We chose not to impute these values from averages given the uncertainty that permeated the Covid crisis, which could confound our results. Hence, our final sample consists of 80 banks, of which 70 were treated and 10 were not, in 21 countries. We provide the differences of the bank-specific variables for the final sample in Panel C of Table B1. The list of countries as well as the implementation dates of the restrictions and the number of treated and control banks in each country are presented in Table B2 in Appendix B. Descriptive statistics for the variables are provided in Panel A of Table B3 in Appendix B.

To motivate our analysis, we plot the monthly evolution of the average shareholders' and debtholders' required rate of return for the treated and control groups in Figure 1.

[10] https://covid19.who.int/data

[11] https://www.bis.org/statistics/cbpol.htm

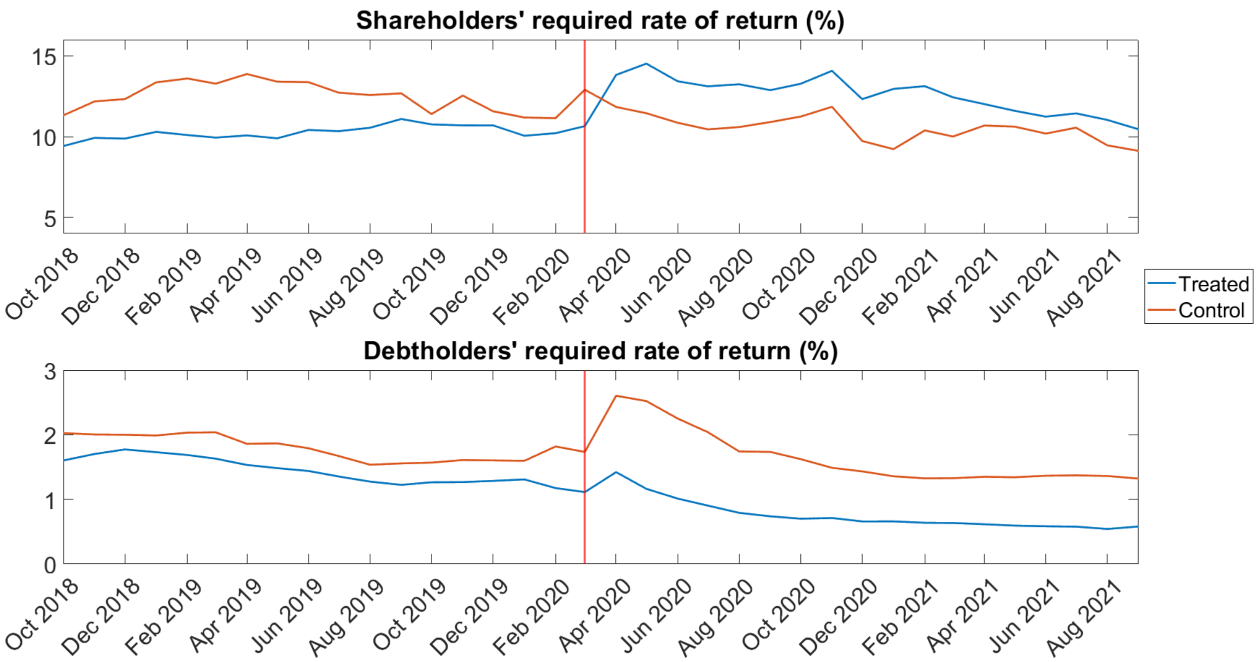

Figure 1: Monthly evolution of the average shareholders' and debtholders' required rate of return

Focusing on shareholders' required rate of return, we observe that prior to the introduction of restrictions (indicated by the vertical red line) shareholders demanded a lower rate for the treated group than the control group. However, after their introduction the required rate of return for the treated group's equity saw a significant increase, surpassing the control group's and remaining higher for the entire duration of the restrictions. Turning to debtholders' required rate of return, we observe that it was lower for the treated group compared to the control group throughout the sample. However, the difference significantly widened after the introduction of the restrictions.

We further zoom in on the period around the introduction of the restrictions in most jurisdictions in Figure 2 using daily frequency to look at the evolution of investors' required rate of return following regulatory announcements. Looking at shareholders' required rate of return, we observe that the difference between treated and control groups becomes positive for the first time and increases significantly after the 11th March 2020 (first vertical red line). This is when the Bank of England announced the measures to respond to the economic shock brought by Covid-19, which included a reduction of the Bank rate, the release of CCyB, and further supervisory guidance.[12] The ECB followed suit the next day with a similar announcement.[13] Importantly, while these measures applied to banks in both groups, the announcements included the provision that banks should refrain from increasing distributions following the capital buffer releases, which would affect the treated group only. We observe a gradual reduction of the difference from 23th March, but it picked up

[12] https://www.bankofengland.co.uk/news/2020/march/boe-measures-to-respond-to-the-economic-shock-from-covid-19
[13] https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200312~43351ac3ac.en.html

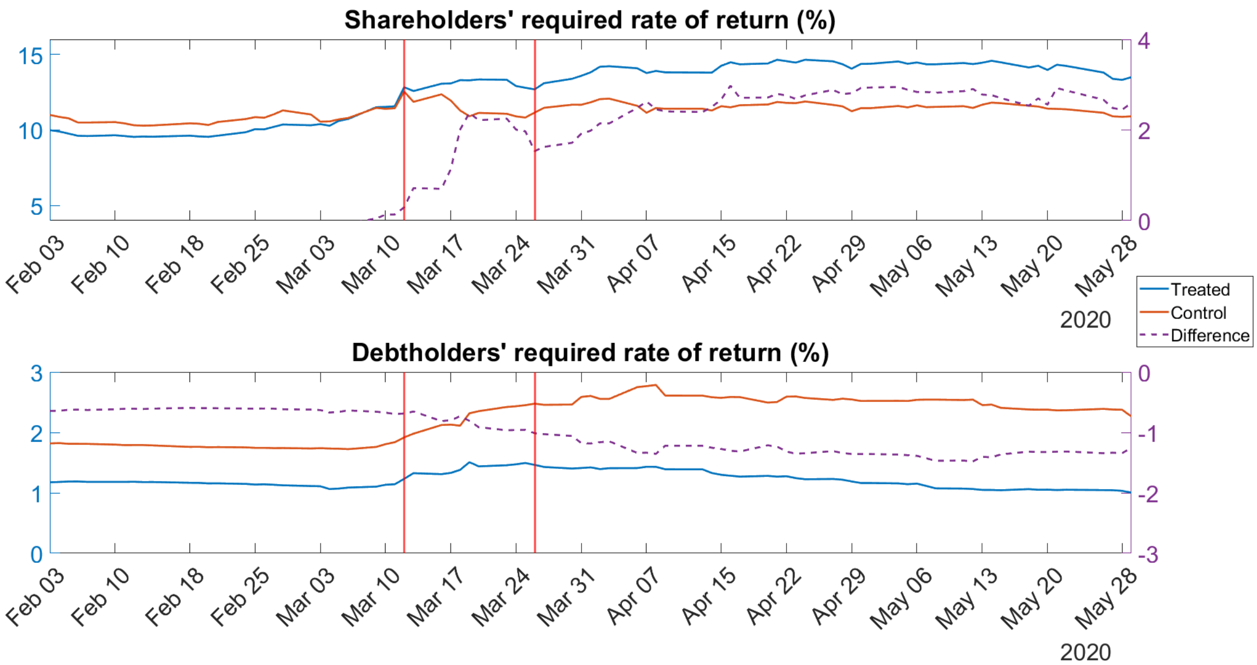

Figure 2: Daily evolution of the average shareholders' and debtholders' required rate of return

again following the ECB distributions restriction announcement on 27th March (second vertical red line), and remained higher thereafter.

Looking at debtholders' required rate of return, we similarly observe that the negative difference became larger following the announcements on 11th and 12th March, and it continued trending downwards following the announcement on 27th March. Overall, the descriptive analysis provides early support for our first hypothesis and indicates that distribution restrictions solidified the difference between the two groups that had started emerging following the initial recommendation not to increase distributions.

3.2 Lending

We use data on the universe of UK SME loans issued by nine UK banking groups, provided confidentially to the Bank of England at a monthly frequency by Experian, a private sector information services company. The dataset provides information on the loan accounts of SMEs including their balance and repayments, as well as SME information such as registration number, industry (SIC code), headquarters region and annual turnover. However, we do not have data on loan interest rates.

Our sample period is from January 2018 to June 2021, prior to the lifting of restrictions in July 2021. Of the nine banking groups, four were subject to distribution restrictions and five were not. We obtain the starting balance of each account, which corresponds to the loan amount, and sum across accounts for each borrower-bank relationship each month to obtain the total credit provided by a bank to a borrower, which is our variable of interest. We exclude credit card and overdraft loans which are likely to be used to cover short-term liquidity needs rather than for long-term investment. However, we differentiate between credit that was provided under the Covid-19 government guarantee schemes, and all other credit.

Our initial sample consists of 1,141,289 borrower-bank-month observations (loans for simplicity), of which 810,482 (71%) were government-guaranteed and issued from Q2 2020 onward, and 330,807 were non-government guaranteed and issued throughout the sample period. We then use borrowers' registration numbers to obtain from Bureau van Dijk's Orbis database balance sheet data including total assets and capital, current assets and liabilities, as well as their profit-loss account. We are only able to obtain this information for a subset of borrowers, so our final sample consists of 350,216 loans, of which 286,952 were government guaranteed and 63,264 were not.

We drop observations at the 1% and 99% tails, which correspond to loans less than £5,000 and more than £3,000,000 respectively. Descriptive statistics for the variables are provided in Panel B of Table B3 in Appendix B. We observe that the majority of government-guaranteed loans are up to £50,000 in value. This suggests that most SMEs benefited from the Bounce Back Loan Scheme (BBLS), which offered a maximum loan amount of £50,000, rather than schemes that offered higher amounts.[14] In addition, we observe that the standard deviation of loan volume is more than twice its mean, due to the presence of small and large borrowers in the dataset.

In Figure 3 we plot the quarterly evolution of banks' average SME lending volumes across the two groups for non-government guaranteed loans. We observe that the control group issues higher-value loans on average than the treated group. Although in the quarter after the introduction of the restrictions the former reduced the average loan volume while the latter increased it, both groups experienced an overall increase in volumes during the treatment period.

Given that the majority of loans in Experian are relatively small in value (less than £100,000), we repeat the plot for this subset of loans in Figure 4. We observe that they were moving in parallel in the year leading to the restrictions, and this continued in the first quarter after the restrictions were implemented. However, after that the control group reduced the average volume while the treated one increased it. This reversed in the last quarter of restrictions (Q2 2021), after restricted banks were allowed to make partial distributions.

[14] https://commonslibrary.parliament.uk/research-briefings/cbp-8906/

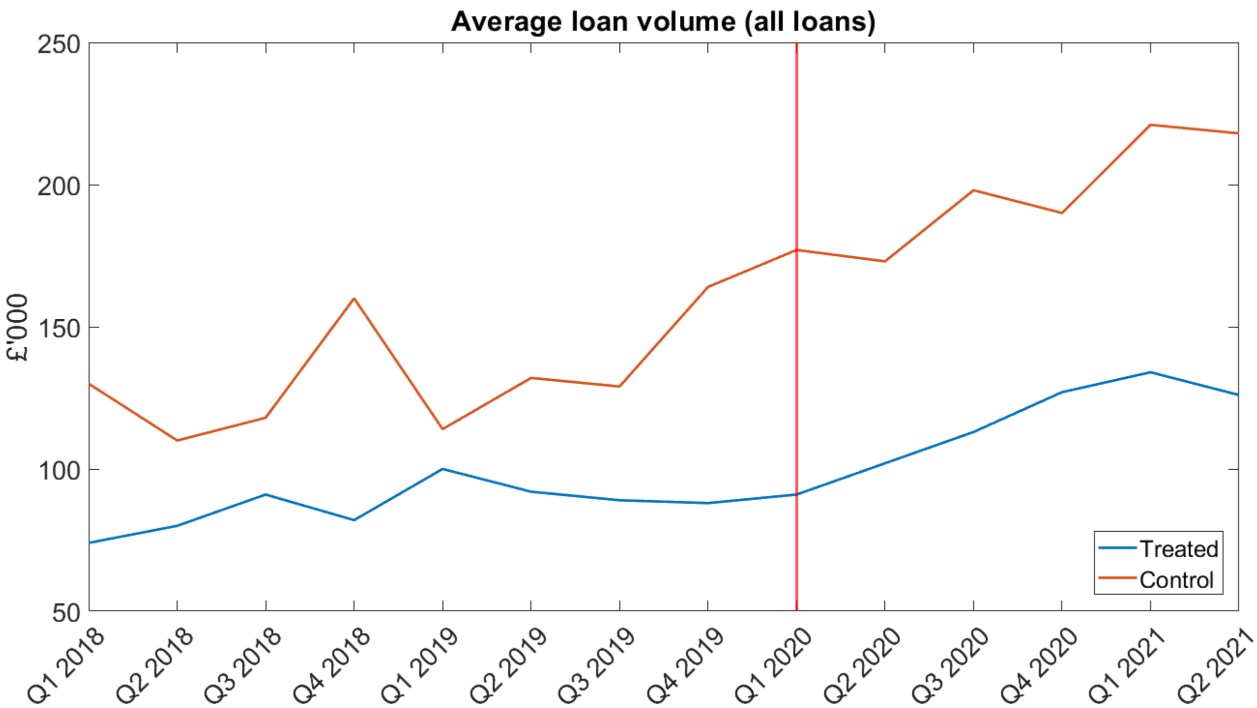

Figure 3: Quarterly evolution of banks' average SME lending volumes for non-government guaranteed loans

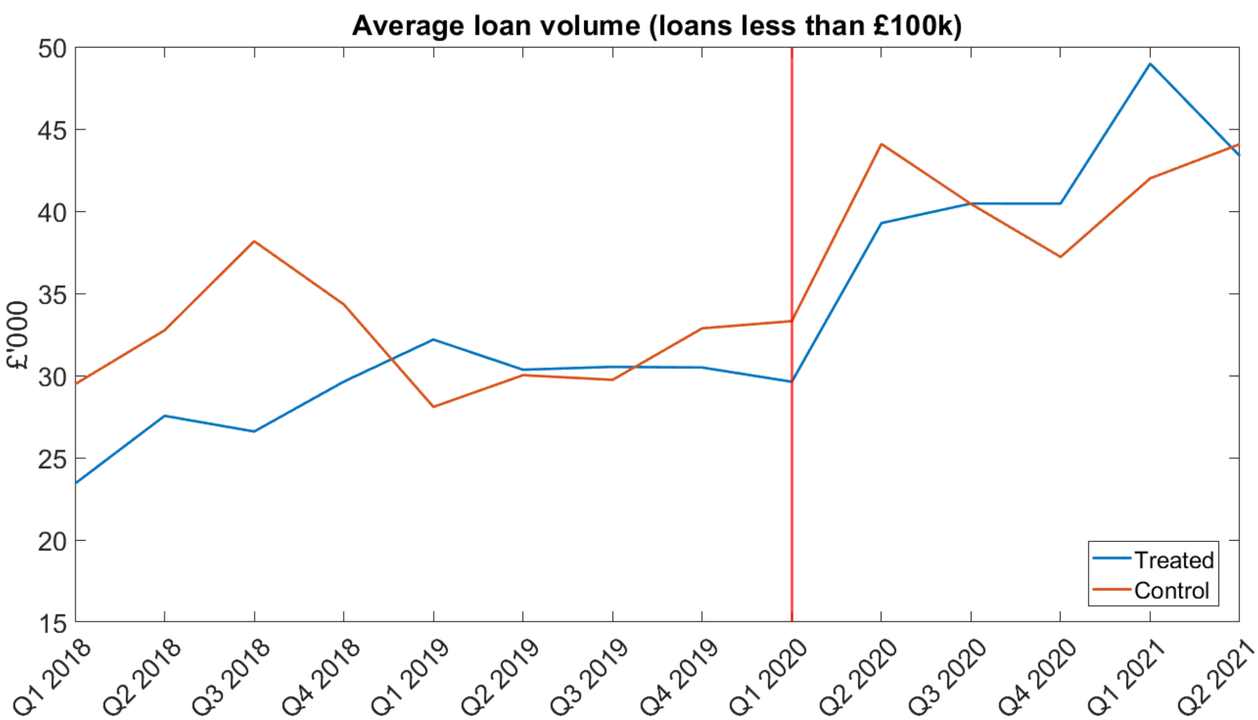

Figure 4: Quarterly evolution of banks' average SME lending volumes for non-government guaranteed loans less than £100,000

4 Methodology

4.1 Required rate of return on capital

4.1.1 Magnitude

In order to assess the impact of the distribution restrictions on the required rate of return on banks' capital, we utilise a difference-in-differences (DiD) approach. A key characteristic of the policy is that it was introduced at different dates in each jurisdiction. A number of recent econometric papers have shown that the standard two-way fixed effects estimator can yield biased estimates if applied in a setting with multiple treatment dates (see de Chaisemartin and D'Haultfoeuille (2021b) for a survey). For this reason, we use the DiD estimator proposed by de Chaisemartin and D'Haultfoeuille (2020) and expanded in de Chaisemartin and D'Haultfoeuille (2021a) to include dynamic effects, which is robust to multiple treatment dates. When including dynamic effects, the estimator compares the outcome evolution from time $t-1-l$ to t, between the group that first got treated at $t-l$ and the group that has not received treatment as of t. In other words, the estimator estimates the effect of having been treated for the first time l periods ago.[15]

We use shareholders' required rate of return $COE_{b,t}$ and debtholders' required rate of return $COD_{b,t}$ for bank b in month t as our dependent variables. Standard errors are clustered at the bank*time level and estimated using bootstrap. We include bank and time fixed effects to account for bank-specific unobservable time-invariant characteristics, as well as time-varying factors that affect all banks.

We also include a comprehensive set of controls that could affect investors' required rate of return and banks' propensity to pay dividends (Fama and French, 2001). Bank-specific lagged variables include the logarithm of total assets as a proxy for size, the ratio of retail deposits to total assets as a proxy for funding profile, the ratio of loan loss provisions to gross loans as a proxy for credit risk, the CET1 ratio for capitalisation, the return on equity as a proxy for profitability, as well as the price/book ratio. To control for the potential impact of government guarantees provided during Covid on our dependent variables, we also include the ratio of corporate loans to gross loans. This is because Altavilla et al. (2021) find that the banks that were larger, better capitalised, more liquid and had pre-existing relationships with firms were more likely to participate in the schemes.

Country-specific policy controls include the main policy rate and the logarithm of QE holdings held by central banks. Macroeconomic controls include GDP growth, CPI and unemployment; for debtholders' required rate of return we also include sovereign CDS spread as a proxy for sovereign risk, as well as the volatility of country stock indices as a proxy for risk aversion as in Arnould et al. (2022). Lastly, we include

[15] In practice, the results for the average treatment effect on the treated are similar when we use a standard two-way fixed effects estimator. Nonetheless, we chose not to use it to ensure the robustness of our results.

the country-specific logarithm of number of new Covid cases which proxies for the impact of Covid on economic activity which could affect the required rate of return on banks' capital.

4.1.2 Bank interconnectedness

Having estimated the impact of distribution restrictions on investors' required rate of return, our next objective is to consider their impact on banks' interconnections. More specifically, these shocks may be of heterogeneous persistence and may hence propagate across banks at various horizons, creating heterogeneously persistent interconnections. Hence our objective is to identify this interconnectedness due to shocks of a specific persistence across banks. The knowledge of how a shock to a bank j transmits to a bank k defines a direct link at a given period of time. As noted by Diebold and Yilmaz (2012), variance decompositions from an approximation model provide such information. Specifically, we can learn how much of the future variance of a variable j is due to shocks in a variable k.

While it may seem natural to choose a forecast horizon of interest to measure the persistence of shocks, the choice is costly in terms of information aggregation loss. In contrast to cumulative information with increasing horizon in variance decompositions, Baruník and Křehlík (2018) propose a far richer and more precise information containing alternative – frequency responses of shocks. As Baruník and Ellington (2020) illustrate in detail later, switching to frequency domain allows one to track connections stemming from transitory and persistent components of shocks that stay uncovered otherwise. Specifically, while short-term connectedness implies fast dissipation of shocks between investors' required rate of return on banks' capital, longer-term conenctedness implies more persistent changes in expectations about future dividends in the case of stock markets (Balke and Wohar, 2002). Hence Baruník and Křehlík (2018) and Baruník and Ellington (2020) show that such interconnections can be well characterised through frequency decomposition of variance decomposition from an approximation model. When inferred from a time-varying approximation model, such variance decompositions then show how connections evolve over time dynamically. We construct bank interconnectedness measures through the time-varying parameter vector autoregression (TVP-VAR) model estimated from shareholders' and debtholders' required rate of return for N banks following the methodology of Baruník and Ellington (2020) detailed in Appendix D. The TVP-VAR approach hence allows us to measure such changes due to the introduction of distribution restrictions.

4.2 Resilience

In order to assess the impact of distribution restrictions on banks' resilience, we use the same DiD identification strategy as for the required rate of return on banks' capital, but utilise the logarithm of CET1 capital of bank b in quarter t as our dependent variable (and remove the CET1 ratio from the list of independent variables). We also use the CET1 ratio and Risk-Weighted Assets (RWAs) as dependent variables for completeness.

4.3 Lending

Finally, for our lending analysis we rely on Experian, a dataset containing UK banks' lending to UK SMEs. Since we focus on one jurisdiction with a single announcement date, we utilise a standard two-way fixed effects DiD estimator at the bank-borrower-time level. Specifically, we regress the logarithm of the loan volume issued by bank b to borrower i in quarter t on a treatment dummy $D_{b,t}$ that takes the value of 1 for banks belonging to the treated group after they became treated (Q2 2020 onward).

$$Log(Volume_{i,b,t}) = \mu_b + \mu_{s,z,r,t} + \beta D_{b,t} + \gamma X_{b,t-1} + \delta Z_{i,t-1} + \epsilon_{i,b,t} \quad (1)$$

We include bank fixed effects μ_b to control for unobservable time-invarying bank characteristics. To control for credit demand, we utilise borrower industry-size-region-time fixed effects $\mu_{s,z,r,t}$ following Degryse et al. (2019). We are thus assuming that SMEs of similar size s (categorised according to their annual turnover) belonging to the same industry z (categorised according to their SIC code) and headquartered in UK region r have the same credit demand in quarter t. Regions are defined according to the Classification of Territorial Units for Statistics (NUTS) of the UK. Since the vast majority of SMEs in our sample have single-bank relationships, it is not feasible to use borrower-time fixed effects. Hence, using industry-size-region-time fixed effects strengthens the external validity of our analysis on the bank credit shock due to distribution restrictions.

Lagged bank controls $X_{b,t-1}$ include the logarithm of total assets as a proxy for size, the ratio of retail deposits to total assets as a proxy for funding profile, the ratio of loan loss provisions to gross loans as a proxy for credit risk, the CET1 ratio for capitalisation, and the return on equity as a proxy for profitability.

The unprecedented nature of the pandemic induced the response of prudential, monetary and fiscal authorities to support the real economy, which makes the identification of the impact of distribution restrictions on lending more challenging. We include controls for several of these responses in $X_{b,t-1}$ to isolate the channel of interest. From the prudential angle, to account for the impact of CCyB release, we include the UK CCyB pass-through rate of each bank, which is defined as the ratio of its UK risk-weighted credit exposures to its total risk-weighted credit exposures. The ratio can range from 0 if a UK bank does not have UK credit exposures and hence would not benefit from the UK CCyB release (not observed in practice), to 1 if a UK bank is fully exposed to the UK credit market and hence a 1 pp UK CCyB release would translate into a

1 pp reduction in its capital requirements. This allows us to control for the differential impact of the UK CCyB release in March 2020 on banks' capital requirements and their capacity to provide lending to the real economy.

From the monetary angle, we include the logarithm of bank cash deposited in central banks to control for the impact of quantitative easing. In addition, we include the logarithm of banks' drawdowns from the Term Funding Scheme for SMEs (TFSME), which was a funding scheme launched by the Bank of England in April 2020 to incentivise lending to SMEs by offering banks loans at or very close to the Bank rate.[16]

From the fiscal angle, we exclude all government-guaranteed loans in our baseline regression since the increase in lending in this segment by the treated group is unlikely to have occurred due to distribution restrictions. We include these loans when we test for interaction effects in subsection 5.3.3.

Lagged borrower controls $Z_{i,t-1}$ include the logarithm of total assets as a proxy for size, the capital to assets ratio as a proxy for funding profile, the profit-loss account as a proxy for profitability, and the ratio of current assets to current liabilities as a proxy for liquidity (Martínez-Miera and Vegas, 2021).

We cluster standard errors at the bank and borrowers' industry levels. A key econometric concern is the limited number of clusters (nine banks and nineteen industries), which may cause misleading inferences (Cameron and Miller, 2015). To remedy this, we use the wild cluster bootstrap which can provide robust inferences even with small and uneven clusters (MacKinnon and Webb, 2017, 2018; MacKinnon et al., 2023).

Finally, in order to assess the impact of the distribution restrictions on aggregate lending, i.e. the extensive margin of loan supply, we follow Khwaja and Mian (2008) and create two indicator variables, $Entry_{i,b,t}$ and $Exit_{i,b,t}$. $Entry_{i,b,t}$ takes the value of 1 for borrower i that starts borrowing after the restrictions were implemented, i.e. if it had no pre-existing relationship with bank b. Conversely, $Exit_{i,b,t}$ takes the value of 1 for borrower i that borrowed before the restrictions were implemented from bank b, but stopped afterwards. The two variables allow us to examine whether restricted banks significantly expanded or restricted their customer base following the restrictions respectively. We use them as dependent variables in specification (1).

We also follow Mathur et al. (2023) and aggregate the loans to the bank-region-quarter level. We use the logarithm of the total number of loans and total value of loans as dependent variables. We control for credit demand by including region-quarter fixed effects $\mu_{r,t}$, and differences in bank regional exposures and competition using bank-region fixed effects $\mu_{b,r}$. We use the lagged bank controls $X_{b,t-1}$ as before:

$$Log(\#Loans_{b,r,t}) = \mu_{r,t} + \mu_{b,r} + \beta D_{b,t} + \gamma X_{b,t-1} + \epsilon_{b,r,t} \quad (2)$$

[16] https://www.bankofengland.co.uk/markets/market-notices/2020/term-funding-scheme-market-notice-mar-2020

$$Log(Volume\ Loans_{b,r,t}) = \mu_{r,t} + \mu_{b,r} + \beta D_{b,t} + \gamma X_{b,t-1} + \epsilon_{b,r,t} \quad (3)$$

5 Results

5.1 Required rate of return on capital

5.1.1 Magnitude

We perform the DiD estimation for shareholders' and debtholders' required rate of return separately, and include placebo and dynamic effects to evaluate the parallel trends assumption as well as the persistence of the impact throughout the implementation period of the restrictions. We present the results in graphs for ease of readability. The estimated coefficients are included in Table C1 in Appendix C.

In Figure 5 we present the results for shareholders' required rate of return. The graph plots the DiD estimates for each month from the implementation of the restrictions ($t = 0$) until they are lifted, as well as for the months preceding the restrictions, denoted by negative values in the x-axis (pre and post periods are separated by the vertical blue line). The estimates include 95% confidence intervals, so they are significant at the 5% level if the red bands lie completely above or below the horizontal zero line.

As can be seen, before the implementation of the restrictions the DiD estimates are close to zero and insignificant, which validates the parallel trends assumption. Formally, the hypothesis that the pre-implementation coefficients are jointly equal to zero is not rejected (p-value = 0.319). From the month of implementation onward, the estimates increase and become statistically significant for most months. Specifically, on the first month of implementation ($t = 0$), shareholders' required rate of return increases for the restricted banks by 1.8 percentage points (pp) compared to the unrestricted banks. The difference increases in the subsequent months, peaking at 3.8 pp five months after the implementation. It subsides after twelve months (coinciding with March 2021 when most banks made limited distributions following the relaxation of restrictions), but remains significant at 1.8 pp in the last month of the restrictions. On average throughout the implementation period, we estimate a significant increase of shareholders' required rate of return by 2.7 pp for the treated group due to distribution restrictions (z-stat = 3.25, p-value = 0.001).

In Figure 6 we present the results for debtholders' required rate of return. The DiD estimates are positive and insignificant prior to the implementation of the restrictions (joint test for significance p-value = 0.112). They become negative from $t = 0$ onward, peaking at -1 pp on the second month after the implementation before reverting to around -0.5 pp by the eighth month and remaining at that level thereafter. The coefficients are statistically significant at the 10% level from month three and significant at the 5% level from month

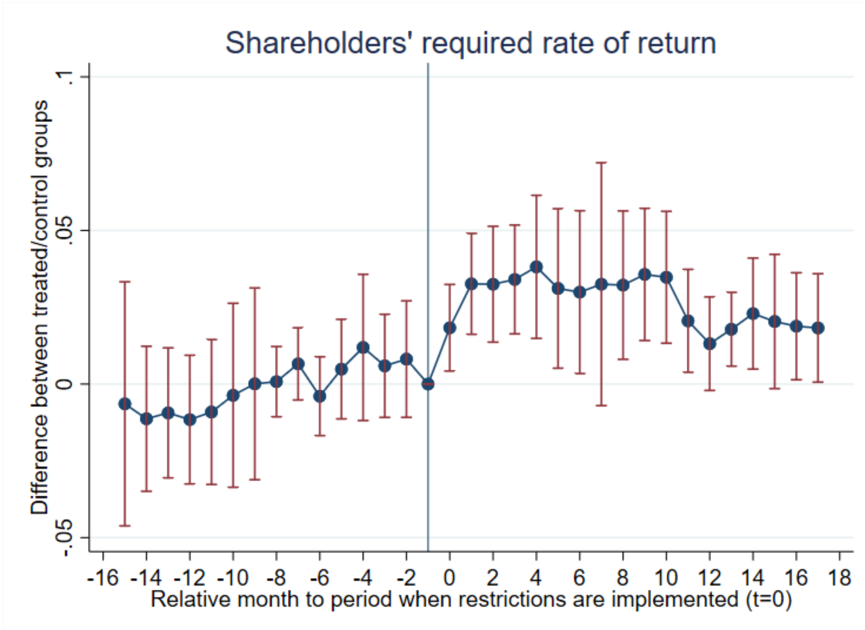

Figure 5: Difference-in-differences estimation for shareholders' required rate of return. The graph presents the DiD estimates for shareholders' required rate of return at a monthly frequency from the month of implementation (t=0) until the lifting of restrictions. Negative periods indicate months prior to implementation (separated by vertical blue line). Estimates include 95% confidence intervals.

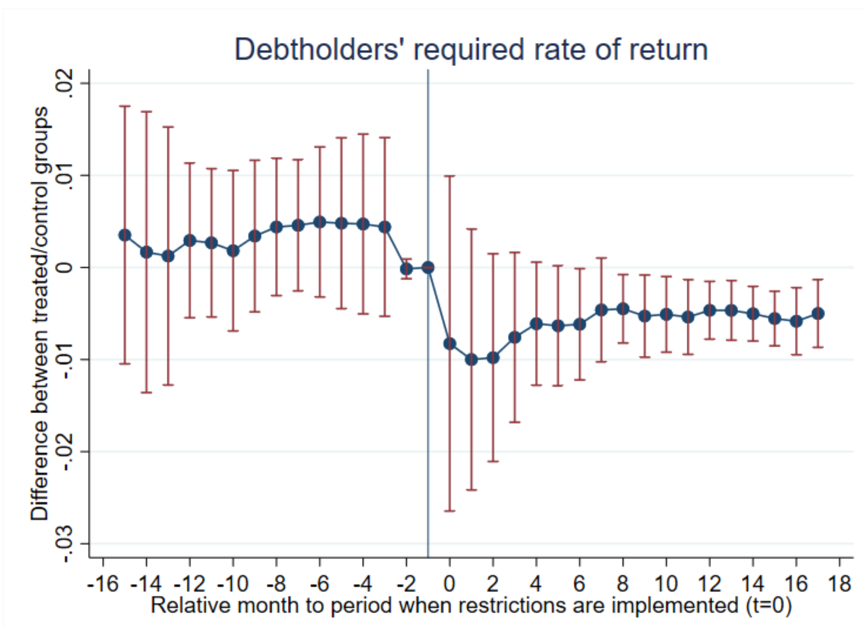

Figure 6: Difference-in-differences estimation for debtholders' required rate of return. The graph presents the DiD estimates for debtholders' required rate of return at a monthly frequency from the month of implementation (t=0) until the lifting of restrictions. Negative periods indicate months prior to implementation (separated by vertical blue line). Estimates include 95% confidence intervals.

seven. On average throughout the implementation period, we estimate a significant decrease of debtholders' required rate of return by -0.6 pp for the treated group due to distribution restrictions (z-stat $= -2.31$, p-value $= 0.021$). However, this reduction is lower than the increase in shareholders' required rate of return. On a weighted average basis, we estimate that the required rate of return on capital increased by 1 pp on average (z-stat $= 3.06$, p-value $= 0.002$), consistent with the empirical observation that the MM offset only applies partially.[17]

Overall, the results indicate that the distribution restrictions significantly increased shareholders' required rate of return but reduced debtholders' one, consistent with *H1*. The effects are persistent throughout the implementation period.[18] In the next subsection we investigate the impact in terms of interconnectedness and shock propagation between banks.

5.1.2 Persistence of banks' interconnections

Here we further explore the question if the persistent regulatory impact on investors' required rate of return that we document in the previous subsection influences banks' interconnections. We ask how persistent this transmission effect is as well as how the persistence of interconnections changed after the restrictions were introduced. More specifically, we assess the average interconnectedness of banks inferred from shock transmission to daily investors' required rate of return. The aggregate shock propagation is measured from time varying variance decompositions (section 4) of daily shareholders' and debtholders' required rate of return. We focus on the transitory and persistent interconnectedness due to shocks of up to 20 business days and greater than 20 business days, respectively.

We plot the transitory and persistent interconnectedness of shareholders' and debtholders' required rate of return in Figures 7 and 8 respectively, for both treated and control groups. Intuitively, we expect the interconnectedness formed on transitory shocks to dominate during periods when financial markets process information rapidly, and shocks to the required rate of return for one bank would have an impact on other banks only in the short term. On the other hand, persistent shocks tend to dominate during crises when uncertainty is high, or when there are fundamental changes in investors' expectations (Balke and Wohar, 2002; Baruník and Křehlík, 2018) and persistent interconnectedness should dominate.

As can be seen in Figure 7, the persistent interconnectedness of shareholders' required rate of return for the treated banks tends to be dominated by the transitory one from the start of the sample in 2018

[17] These estimates imply a MM offset of 1 - 1/2.7 = 63%, which is slightly higher than the offset of 53% calculated for the UK banking system only in Brooke et al. (2015).

[18] To assuage concerns that the results are driven by significant cross-country variation, we have repeated the analysis using a subsample of core Eurozone countries with more similar characteristics (Austria, Belgium, Finland, France, Germany, Italy, the Netherlands and Spain). The effects are even stronger than in the baseline analysis for shareholders' required rate of return with an average increase of 3.7 pp, while the average debtholders' required rate of return decreases by 0.4 pp. These are statistically significant at the 1% and 5% levels respectively.

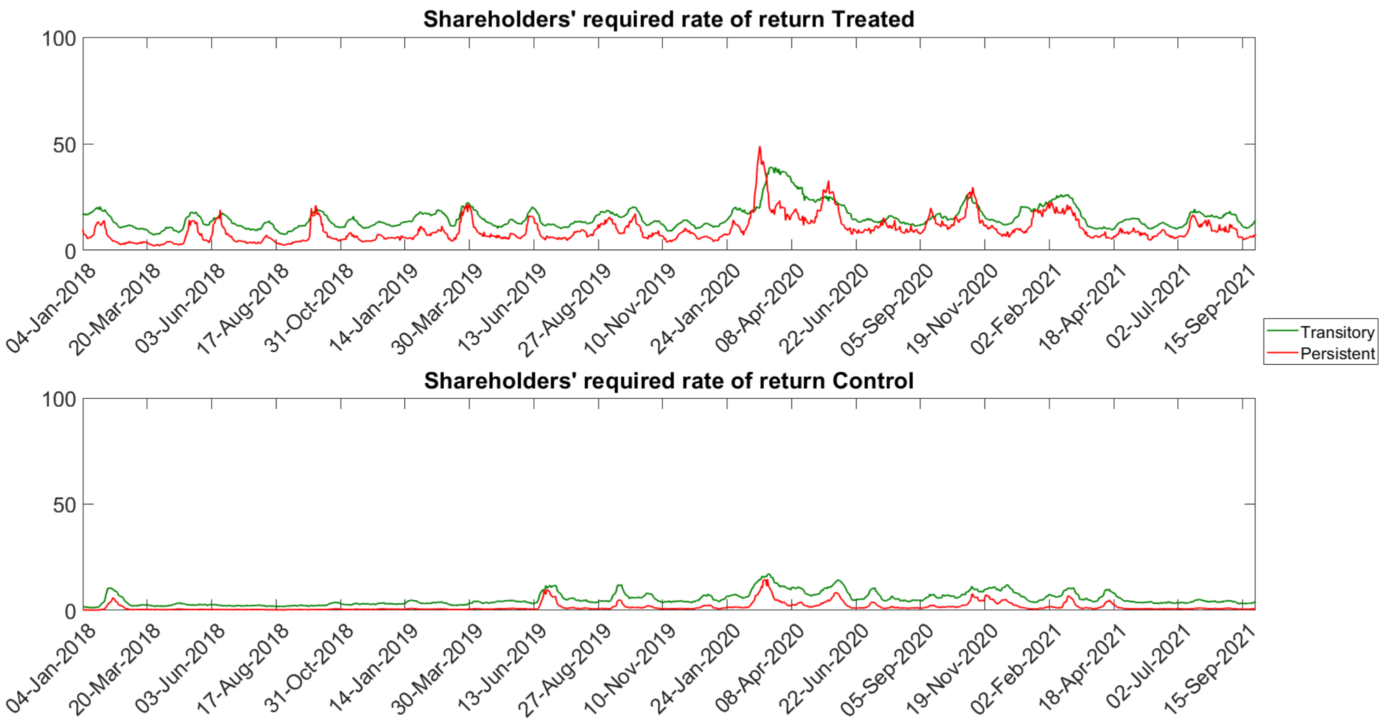

Figure 7: Total interconnectedness of shareholders' required rate of return. The graph presents the total interconnectedness measure for transitory ($\leq$20 business days) and persistent (>20 business days) shock propagation, for treated and control groups of banks respectively.

up until the Covid crisis in March 2020 with approximately half the strength. Importantly, the role of persistent shocks changes in March 2020 when the impact of the pandemic gripped the markets in the dash-for-cash episode. Interconnections based on persistent shocks became equally important to transitory ones. In addition, the level of interconnectedness tends to increase over time. In contrast, banks in the control group remain almost unconnected throughout the sample period meaning that there is very small shock transmission which is almost exclusively due to transitory shocks. This indicates that the restrictions increased the transmission of shocks between shareholders' required rate of return for the treated banks, in addition to persisting over time.

Moving to the interconnectedness of debtholders' required rate of return in Figure 8, we observe a different pattern. Interconnectedness between treated banks is dominated by both transitory and persistent connections, and there is a marked decrease in the role of persistent connections following the initial market turmoil due to Covid from July 2020 onward. Interconnectedness between banks in the control group remains low and dominated by transitory connections, similarly as in shareholders' required rate of return. The results indicate that debtholders' required rate of return became less sensitive to shocks from other banks, which could be an indication that other factors such as central bank action to stabilise financial markets became more important drivers instead.

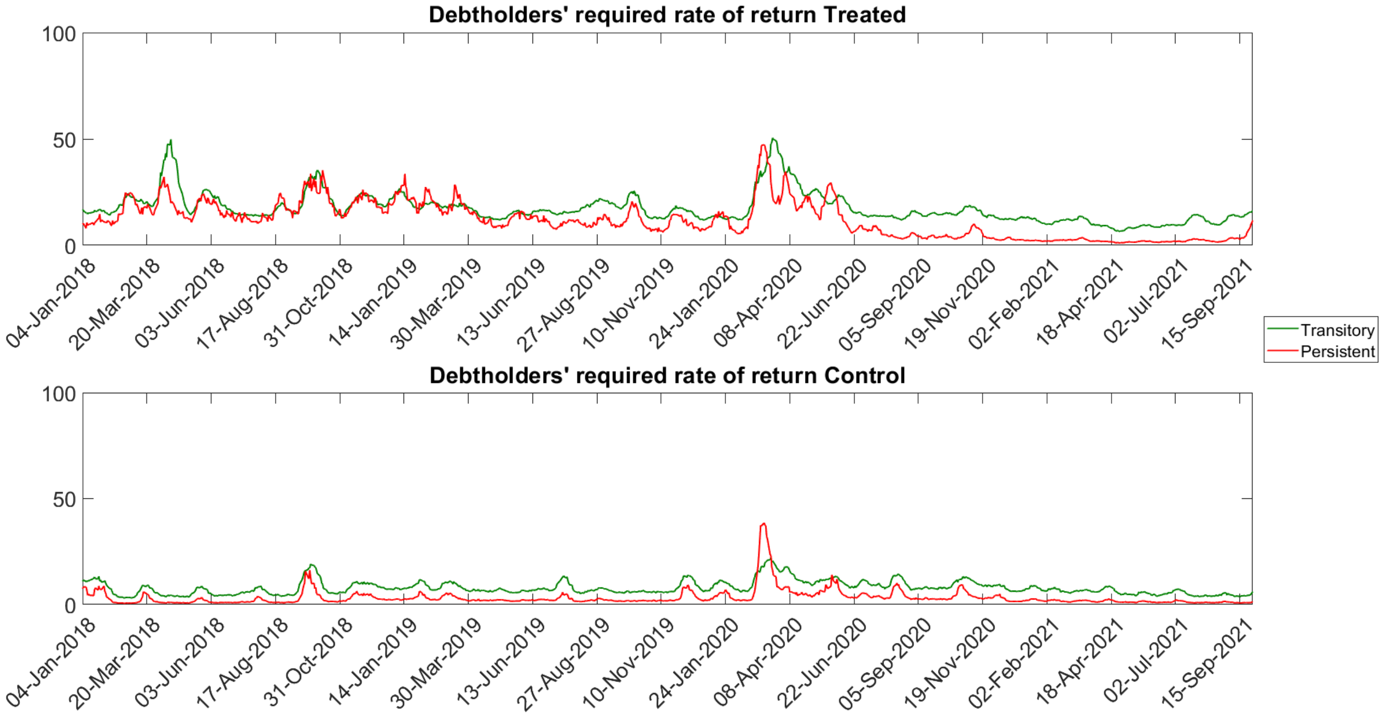

Figure 8: Total interconnectedness of debtholders' required rate of return. The graph presents the total interconnectedness measure for transitory (≤20 business days) and persistent (>20 business days) shock propagation, for treated and control groups of banks respectively.

5.2 Resilience

Having established the impact of the restrictions on the required rate of return on banks' capital, we now assess how banks utilised the surplus capital. If the signalling channel is strong, we expect to see an increase in banks' CET1 capital while the restrictions are fully in place, before reverting once they are partially lifted. We repeat the DiD estimation using the logarithm of CET1 capital, as well as the CET1 ratio and RWAs as dependent variables for completeness. The results for CET1 capital are presented in Figure 9, while the coefficients for all three dependent variables are provided in Table C2 in Appendix C.

Looking at Figure 9 on log CET1 capital, the hypothesis of joint pre-implementation coefficients insignificance is not rejected (p-value = 0.982). Following the introduction of the restrictions, we observe an immediate increase in the CET1 capital of treated banks, which is marginally significant at 3.1% in the first quarter (z-stat = 1.72, p-value = 0.086), increasing and becoming significant in the second quarter, and reaching 5.1% in the third quarter (z-stat = 2.62, p-value = 0.009). Thereafter, the difference decreased and became insignificant. This coincides with the relaxation of the restrictions for most banks which took effect in Q1 2021 ($t = 3$ in the graph), when banks were allowed to make partial distributions based on their capitalisation and profitability.[19] The results thus provide strong evidence in favour of the signalling channel,

[19] https://www.bankofengland.co.uk/prudential-regulation/publication/2020/pra-statement-on-capital-distribution-by-large-uk-ba

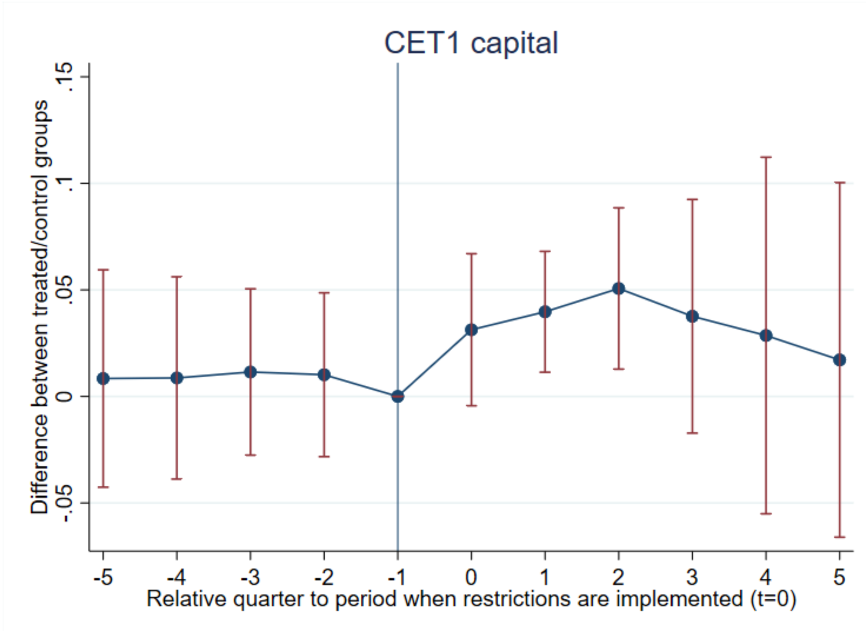

Figure 9: Difference-in-differences estimation for CET1 capital. The graph presents the DiD estimates for the logarithm of CET1 capital at a quarterly frequency from the quarter of implementation (t=0) until the lifting of restrictions. Negative periods indicate quarters prior to implementation (separated by vertical blue line). Estimates include 95% confidence intervals.

and confirm *H2*. Restricted banks increased their retained capital in every quarter of full restrictions, and reduced it as soon as distributions were allowed.

5.3 Lending

5.3.1 Baseline results

While we find evidence in favour of the signalling channel, this does not necessarily preclude the possibility that restricted banks used part of their surplus capital to increase lending. To test this, we focus on non-government guaranteed loans for our baseline results, given that the increase in the issuance of government-guaranteed loans by the treated group is unlikely to have occurred due to distribution restrictions. We report the results of the baseline regression (1) in columns (1) and (2) of Table 1, without and with borrower controls respectively. We observe that the coefficient β of the treatment dummy is similar in both specifications, even though including borrower controls reduces our sample substantially. However, the coefficient is not significant, which indicates that restricted banks did not increase their lending as a result of the restrictions when looking at the entire sample of loans.

If banks were hesitant to lend out all the surplus capital, they may have decided to increase lending on

https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr201215~4742ea7c8a.en.html smaller loans only, which would have a smaller impact on their available capital. In order to test this, we expand our baseline DiD specification to a tripe DiD by interacting the treatment dummy with the dummy variable *Large loan* that takes the value of 1 for loans larger than £100,000:

$$Log(Volume_{i,b,t}) = \mu_b + \mu_{s,z,r,t} + \beta D_{b,t} + \xi D_{b,t} Large\ loan_{i,b,t} + \gamma X_{b,t-1} + \delta Z_{i,t-1} + \epsilon_{i,b,t} \tag{4}$$

The results of regression (4) are presented in columns (3) and (4) of Table 1, without and with borrower controls respectively. Once we control for loan size, the treatment dummy becomes significant, indicating that restricted banks increased the average value of loans worth less than £100,000 by 34.2% as a result of the restrictions.[20] The coefficient ξ is negative, and the sum of β and ξ is not statistically different from zero ($t\text{-stat}_{(8)} = 0.29$, $p\text{-value} = 0.843$). The results hence indicate that restricted banks used the surplus capital to increase the value of smaller loans only, which form the majority of our sample.[21]

The findings support the lending channel and *H3*, but also indicate that banks may have been reluctant to increase lending volumes for the largest borrowers. This would be consistent with their preference to hoard a portion of the restricted capital for future payouts, consistent with our previous results.[22] Hence, we find that the two channels were not mutually exclusive, but the signalling channel may have offset any incentive to increase lending volumes for the largest loans. However, this translated into higher resilience, which remains beneficial if banks were to face large subsequent shocks.

5.3.2 Persistence results

We now examine the persistence of our baseline result by including leads and lags in our regression for each quarter in our sample, keeping the quarter prior to the restrictions as our reference period (Q1 2020). We multiply the dummy variable $Treated$, which takes the value of 1 for banks in the treated group, with dummy variables for each quarter.

The results including leads and lags are presented in columns (1) and (2) of Table 2, without and with borrower controls respectively. In both cases, the leads are not significant, consistent with the insignificant average treatment effect in columns (1) and (2) of Table 1. The lags are also insignificant, providing support for the parallel trends assumption. The joint test for significance of the lags does not reject the null hypothesis of no significance ($F\text{-stat}_{(8,8)} = 1.44$, $p\text{-value} = 0.690$).

Next, we focus on the leads and include additional interactions with *Large loan* to isolate persistence

[20] Both treated and control banks increased the unconditional average value of each loan after restrictions were introduced. Hence, we interpret the coefficient as a relative increase, rather than lesser decrease of the value of each loan.

[21] In Table C3 in Appendix C we present results when defining *Large loan* as loans worth at least £150,000 and £200,000. As expected, the coefficient β becomes marginally significant and insignificant respectively, which corroborates our main finding.

[22] Indeed, while loans less than £100,000 form the majority of our sample, larger loans issued by restricted banks were eight times larger in total value, so they would require significantly higher capital funding.

Table 1: Baseline results on lending volumes. This table reports the results of the baseline specification (1) without and with borrower controls in columns (1) and (2), and of the expanded specification (4) without and with borrower controls in columns (3) and (4). Standard errors are double-clustered at the bank and industry levels. Wild cluster bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	Log(Volume) (t)			
	(1)	(2)	(3)	(4)
Treatment (t)	0.270	0.316	0.322**	0.342**
	(1.162)	(1.318)	(3.771)	(4.602)
Treatment (t) * Large loan			−0.303*	−0.312*
			(−2.444)	(−2.400)
Log(SME Assets) ($t-1$)		0.418***		0.194***
		(19.592)		(17.518)
Capital/Assets ($t-1$)		0.206		0.106
		(1.159)		(1.158)
Profit ($t-1$)		−0.015		−0.014*
		(−1.468)		(−3.077)
Liquidity ratio ($t-1$)		0.062**		0.014**
		(4.580)		(3.879)
Log(Bank Assets) ($t-1$)	0.013	−0.061	−0.029	−0.121
	(0.026)	(−0.171)	(−0.175)	(−0.816)
Deposits/Assets ($t-1$)	−1.462	−0.689	−0.537	−0.297
	(−1.679)	(−1.081)	(−1.317)	(−1.021)
LLP/Loans ($t-1$)	−0.239	0.734	0.166	0.380*
	(−1.076)	(2.360)	(1.404)	(3.980)
CET1 ratio ($t-1$)	−0.044	−0.055	−0.023	−0.032*
	(−1.498)	(−1.610)	(−1.833)	(−2.149)
ROE ($t-1$)	0.013*	0.011*	0.004	0.003
	(1.925)	(3.620)	(1.456)	(1.842)
CCyB pass-through ($t-1$)	−0.014	−0.034	−0.011	−0.019*
	(−0.435)	(−1.638)	(−1.041)	(−3.479)
Log(TFSME) ($t-1$)	0.036	0.029*	0.008	0.002
	(2.219)	(2.644)	(2.005)	(0.470)
Log(CB cash) ($t-1$)	0.569**	0.661*	0.139*	0.159*
	(2.206)	(2.318)	(2.371)	(2.595)
Large loan			2.259***	2.042***
			(31.672)	(49.019)
Intercept	12.950*	8.720*	12.057***	11.008***
	(1.986)	(2.044)	(6.628)	(8.666)
Size x Industry x Region x Quarter fixed effects	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Observations	175,638	48,454	175,638	48,454
R^2	0.280	0.517	0.735	0.789

effects on loans smaller than £100,000. The results are presented in columns (3) and (4) of Table 2, without and with borrower controls respectively. The leads now become significant and persist throughout the implementation period. Specifically, in the first quarter of the restrictions restricted banks provided on average 33.5% higher loan values, which remained 32.6% higher in the last quarter (at the 10% level). Hence, we find that distribution restrictions effectively incentivised banks to increase lending throughout their implementation.

5.3.3 Interaction results

In this subsection we investigate the impact of other policies and banks' capital headroom and investors' required rate of return on our baseline results. In column (1) of Table 3, we present results when we include government-guaranteed loans and add an interaction term to assess whether fiscal support acted as a complement or a substitute to distribution restrictions. The *Gov guarantee* dummy takes the value of 1 if the loan was issued under a government guarantee scheme and 0 otherwise. We observe that the treatment dummy coefficient remains marginally significant at 34.6%, while the interaction coefficient is negative but insignificant (-18.9%). Hence, the results indicate that the two measures worked in tandem to support the real economy, with restricted banks increasing loan values by similar amounts in the two segments for loans less than £100,000 (which includes the vast majority of government-guaranteed loans in our sample issued under BBLS).

Next, in column (2) we examine the interaction of distribution restrictions with banks' capital ratios. We create the dummy variable *Lower capital*, which takes the value of 1 for banks whose CET1 ratio is on or below the 25th percentile of the distribution. These banks have lower capital positions, which could influence their decision to lend out the surplus capital. We find that the interaction of *Lower capital* with the treatment dummy is not significant (-0.2%), which indicates that banks which had lower capital positions increased lending to a similar degree as banks with higher positions. This is an indication of their ability to support the real economy during stress.

Finally, in column (3) we interact the treatment dummy with the shareholders' (COE) and debtholders' (COD) required rate of return, to understand whether they affected the availability of credit. Neither of the interaction coefficients are statistically significant. This indicates that, even though restricted banks experienced an increase in shareholders' required rate of return, this did not translate into a negative impact on the availability of credit. Hence, the pass-through from funding to lending is weak.

Table 2: Persistence results on lending volumes. This table reports the results from including leads and lags in the baseline specification (1) (columns (1) and (2)), and in the expanded specification (4) (columns (3) and (4)). Standard errors are double-clustered at the bank and industry levels. Wild cluster bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	Log(Volume) (t)			
	(1)	(2)	(3)	(4)
Treated * Q1 18	−1.586	−0.663		
	(−2.118)	(−1.594)		
Treated * Q2 18	−1.351	−0.762		
	(−1.805)	(−1.945)		
Treated * Q3 18	−1.380	−0.866		
	(−1.927)	(−2.749)		
Treated * Q4 18	−1.029	−1.010		
	(−1.965)	(−2.722)		
Treated * Q1 19	0.191	0.141		
	(1.067)	(0.918)		
Treated * Q2 19	0.203	−0.130		
	(1.415)	(−1.510)		
Treated * Q3 19	−0.512	−0.949*		
	(−1.683)	(−2.606)		
Treated * Q4 19	−0.246	−0.728		
	(−0.929)	(−2.165)		
Treated * Q2 20	−0.273	−0.353	0.295*	0.335***
	(−1.855)	(−2.527)	(2.975)	(6.346)
Treated * Q3 20	−0.091	−0.337	0.268*	0.265*
	(−0.384)	(−2.027)	(2.950)	(2.563)
Treated * Q4 20	0.273	0.029	0.299**	0.301**
	(1.182)	(0.211)	(5.144)	(3.981)
Treated * Q1 21	0.597	0.320	0.488*	0.459*
	(1.700)	(1.247)	(3.032)	(2.848)
Treated * Q2 21	0.213	−0.027	0.318**	0.326*
	(0.637)	(−0.156)	(3.467)	(3.684)
Treated * Large loan * Q2 20			−0.173	−0.193
			(−2.239)	(−3.245)
Treated * Large loan * Q3 20			−0.210**	−0.083
			(−7.086)	(−2.189)
Treated * Large loan * Q4 20			−0.234**	−0.186**
			(−6.013)	(−3.219)
Treated * Large loan * Q1 21			−0.530*	−0.511
			(−2.264)	(−2.293)
Treated * Large loan * Q2 21			−0.271**	−0.301**
			(−3.485)	(−4.195)
Log(SME Assets) ($t-1$)		0.416***		0.193***
		(20.084)		(17.384)
Capital/Assets ($t-1$)		0.201		0.106
		(1.148)		(1.162)
Profit ($t-1$)		−0.014		−0.014**
		(−1.400)		(−4.991)
Liquidity ratio ($t-1$)		0.062***		0.013*
		(4.633)		(3.477)
Log(Bank Assets) ($t-1$)	0.979	0.113	−0.035	−0.132
	(1.291)	(0.303)	(−0.194)	(−0.835)
Deposits/Assets ($t-1$)	−0.966	−0.950	−0.518	−0.239
	(−1.553)	(−2.229)	(−1.201)	(−0.776)
LLP/Loans ($t-1$)	−0.356	0.596	0.243	0.399*
	(−0.666)	(1.328)	(2.296)	(3.024)
CET1 ratio ($t-1$)	−0.049	−0.084	−0.025*	−0.034*
	(−2.201)	(−2.273)	(−1.887)	(−2.067)
ROE ($t-1$)	0.015	0.011*	0.004	0.003
	(2.125)	(3.589)	(1.417)	(1.796)
CCyB pass-through ($t-1$)	−0.010	−0.033	−0.012	−0.021*
	(−0.337)	(−1.645)	(−1.084)	(−3.409)
Log(TFSME) ($t-1$)	0.047**	0.036**	0.008	−0.001
	(3.993)	(4.480)	(1.558)	(−0.332)
Log(CB cash) ($t-1$)	0.870**	0.869**	0.149*	0.169*
	(2.665)	(3.025)	(2.338)	(2.775)
Large loan			2.259***	2.045***
			(31.650)	(48.538)
Intercept	3.238	6.876	12.225***	11.298***
	(0.430)	(1.473)	(6.237)	(8.578)
Size x Industry x Region x Quarter fixed effects	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Observations	175,638	48,454	175,638	48,454
R^2	0.283	0.519	0.736	0.789

Table 3: Interaction results on lending volumes. This table reports the results of the expanded specification (4) including interactions with government guarantees (column (1)), CET1 ratio (column (2)) and shareholders' and debtholders' required rate of return (column (3)). Standard errors are double-clustered at the bank and industry levels. Wild cluster bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	Log(Volume) (t)		
	(1)	(2)	(3)
Treatment (t)	0.346*	0.325**	0.248
	(3.322)	(4.366)	(2.308)
Treatment (t) * Large loan	−0.634**	−0.313*	−0.335
	(−5.859)	(−2.388)	(−2.296)
Treatment (t) * Gov guarantee	−0.189		
	(−4.379)		
Treatment (t) * Lower capital ($t-1$)		−0.002	
		(0.029)	
Treatment (t) * COE ($t-1$)			0.011
			(1.302)
Treatment (t) * COD ($t-1$)			−0.039
			(−1.329)
Log(SME Assets) ($t-1$)	0.123***	0.194***	0.197***
	(11.819)	(17.430)	(15.813)
Capital/Assets ($t-1$)	0.201**	0.107	0.080
	(3.381)	(1.182)	(0.947)
Profit ($t-1$)	0.011*	−0.014*	−0.014
	(3.130)	(−3.076)	(−2.738)
Liquidity ratio ($t-1$)	−0.006	0.014**	0.014**
	(−1.131)	(3.843)	(4.039)
Log(Bank Assets) ($t-1$)	0.070	−0.136	−0.152
	(0.502)	(−0.781)	(−0.778)
Deposits/Assets ($t-1$)	−0.221	−0.199	−0.579
	(−1.441)	(−0.770)	(−1.991)
LLP/Loans ($t-1$)	0.258	0.405*	20.126**
	(1.861)	(3.661)	(4.180)
CET1 ratio ($t-1$)	0.024	−0.031*	−0.077***
	(1.046)	(−2.204)	(−8.526)
ROE ($t-1$)	0.001	0.002	0.003
	(1.202)	(1.150)	(2.254)
CCyB pass-through ($t-1$)	−0.002	−0.018*	−0.021*
	(−0.437)	(−3.385)	(−3.228)
Log(TFSME) ($t-1$)	−0.006***	0.002	0.005
	(−4.141)	(0.641)	(1.163)
Log(CB cash) ($t-1$)	0.045	0.158*	0.226
	(0.704)	(2.541)	(2.090)
Large loan	2.149***	2.043***	2.056***
	(31.429)	(48.603)	(57.701)
Gov guarantee	0.269		
	(3.954)		
Lower capital ($t-1$)		−0.058	
		(−3.181)	
COE ($t-1$)			0.004
			(0.410)
COD ($t-1$)			−0.033
			(−2.170)
Intercept	8.168***	10.907***	9.260**
	(6.551)	(8.951)	(4.268)
Size x Industry x Region x Quarter fixed effects	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Observations	299,608	48,454	45,468
R^2	0.687	0.789	0.791

5.3.4 Extensive margin results

In the final subsection we examine the impact of distribution restrictions on aggregate lending, or the extensive margin. The results using $Entry_{i,b,t}$ and $Exit_{i,b,t}$ as dependent variables in the loan-level specification (1) are presented in columns (1) and (2) of Table 4 respectively. In both cases, we see that the treatment coefficient is not significant, which indicates that restricted banks were not more likely to increase or decrease their customer base. Next, the region-level results of specifications (2) and (3) are presented in columns (3) and (4) of Table 4. Again, the treatment coefficient is not significant which indicates that restricted banks did not increase the total number of loans or their aggregate value.[23]

Overall, the analysis indicates that restricted banks used the surplus capital to increase lending in the intensive, rather than extensive margin.

6 Conclusion and policy implications

In this paper we have examined the impact of the distribution restrictions made by several regulatory authorities during the Covid-19 crisis. The restrictions were made on the back of the singular uncertainty brought by the pandemic. We assessed the impact of the restrictions on banks' resilience, lending and investors' required rate of return.

Using an international sample of banks, we first find that banks increased their CET1 capital in all quarters they were under full restrictions, which increased their resilience. However, this increase diminished once they were allowed to make partial distributions. Nonetheless, a partial lifting of restrictions may provide a more gradual reduction of resilience than an immediate full lifting, which can be beneficial in cases where significant macroeconomic uncertainty persists.

Second, we find that UK banks increased non-government guaranteed lending to UK SMEs as a result of the restrictions. This increase was concentrated on smaller loans and on the intensive margin, and was not dependent on banks' capital positions. However, banks' incentive to retain part of the surplus capital may have offset any incentive to increase lending volumes for the largest loans. Hence, distribution restrictions are unlikely to be able to substitute other prudential measures such as capital buffer releases to promote lending.

Finally, we find that the distribution restrictions persistently increased shareholders' required rate of return, with the impact on the required rate of return on capital partially offset by lower debtholders' required rate of return. While the restrictions may have reduced the attractiveness of bank shares to shareholders due to deferred payments and uncertainty regarding future regulatory action, they were viewed positively by

[23]The results are also insignificant if we separate smaller loans as before.

Table 4: Extensive margin results. This table reports the results of the baseline specification (1) using *Entry* and *Exit* as dependent variables (columns (1) and (2)), as well as the results of specifications (2) and (3). Standard errors are double-clustered at the bank and industry levels in columns (1) and (2), and at the bank and region levels in columns (3) and (4). Wild cluster bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	Entry (t)	Exit (t)	Log(#Loans) (t)	Log(Volume Loans) (t)
	(1)	(2)	(3)	(4)
Treatment (t)	0.008	−0.017	−0.107	0.444
	(1.221)	(−1.127)	(−0.228)	(1.044)
Log(SME Assets) ($t-1$)	−0.001	−0.002*		
	(−1.134)	(−3.839)		
Capital/Assets ($t-1$)	−0.002	−0.008		
	(−0.096)	(−0.792)		
Profit ($t-1$)	−0.000	−0.000		
	(−1.110)	(−0.166)		
Liquidity ratio ($t-1$)	−0.000	−0.000		
	(−0.141)	(−1.065)		
Log(Bank Assets) ($t-1$)	−0.004	−0.047**	0.350	0.335
	(−0.587)	(−2.929)	(0.563)	(0.393)
Deposits/Assets ($t-1$)	0.040	0.057*	13.365**	16.299**
	(1.728)	(2.166)	(3.227)	(2.644)
LLP/Loans ($t-1$)	0.043	−0.015	3.254*	3.319
	(1.890)	(−0.864)	(3.879)	(2.616)
CET1 ratio ($t-1$)	−0.001	0.003	0.005	0.015
	(−0.611)	(1.300)	(0.114)	(0.274)
ROE ($t-1$)	0.000	−0.000	−0.006	0.009
	(0.232)	(−0.301)	(−0.405)	(0.468)
CCyB pass-through ($t-1$)	−0.001	−0.001*	0.062	−0.031
	(−2.473)	(−2.917)	(0.769)	(−0.537)
Log(TFSME) ($t-1$)	−0.001	−0.000	−0.029	0.005
	(−1.517)	(−0.323)	(−0.674)	(0.077)
Log(CB cash) ($t-1$)	0.008	−0.002	−0.844	−0.541
	(1.220)	(−0.269)	(−1.561)	(−1.089)
Intercept	0.506***	0.969***	−5.254	8.660
	(10.705)	(0.183)	(−0.708)	(0.825)
Size x Industry x Region x Quarter fixed effects	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	No	No
Region x Quarter fixed effects	No	No	Yes	Yes
Bank x Region fixed effects	No	No	Yes	Yes
Observations	48,454	48,454	956	956
R^2	0.972	0.972	0.882	0.810

bondholders as they increased banks' solvency and reduced the riskiness of debt. However, consistent with findings in the empirical literature, the Modigliani-Miller offset was not perfect such that the required rate of return on capital is estimated to have increased.

References

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*(3), 430–471.

Altavilla, C., P. Bochmann, J. D. Ryck, A.-M. Dumitru, M. Grodzicki, H. Kick, C. M. Fernandes, J. Mosthaf, C. O'Donnell, and S. Palligkinis (2021). Measuring the cost of equity of euro area banks. ECB Occasional Paper No. 254.

Altavilla, C., A. Ellul, M. Pagano, A. Polo, and T. Vlassopoulos (2021). Loan Guarantees, Bank Lending and Credit Risk Reallocation. Available at SSRN 3963246.

Andreeva, D., P. Bochmann, J. Mosthaf, and J. Schneider (2023). Evaluating the impact of dividend restrictions on euro area bank market values. ECB Working Paper No. 2787.

Arnould, G., G. Avignone, C. Pancaro, and D. Zochowski (2022). Bank funding costs and solvency. *European Journal of Finance 28*(10), 931–963.

Baker, M. and J. Wurgler (2015). Do Strict Capital Requirements Raise the Cost of Capital? Bank Regulation, Capital Structure, and the Low-Risk Anomaly. *American Economic Review 105*(5), 315–320.

Balke, N. S. and M. E. Wohar (2002). Low-Frequency Movements in Stock Prices: A State-Space Decomposition. *Review of Economics and Statistics 84*(4), 649–667.

Baruník, J. and M. Ellington (2020). Dynamic networks in large financial and economic systems. *arXiv preprint arXiv:2007.07842*.

Baruník, J. and T. Křehlík (2018). Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk. *Journal of Financial Econometrics 16*(2), 271–296.

Berrospide, J. M. and R. M. Edge (2019). The Effects of Bank Capital Buffers on Bank Lending and Firm Activity: What Can We Learn from Five Years of Stress-Test Results? Finance and Economics Discussion Series No. 2019-050, Federal Reserve Board.

Bhattacharya, S. (1980). Nondissipative Signaling Structures and Dividend Policy. *Quarterly Journal of Economics 95*(1), 1–24.

Brooke, M., O. Bush, R. Edwards, J. Ellis, B. Francis, R. Harimohan, K. Neiss, and C. Siegert (2015). Measuring the macroeconomic costs and benefits of higher UK bank capital requirements. Bank of England Financial Stability Paper No. 35.

Cameron, A. C. and D. L. Miller (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources 50*(2), 317–372.

Claus, J. and J. Thomas (2001). "Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets. *Journal of Finance 56*(5), 1629–1666.

Couaillier, C., A. Reghezza, C. R. d'Acri, and A. Scopelliti (2022). How to release capital requirements during a pandemic? Evidence from euro area banks. ECB Working Paper No. 2720.

Dahlhaus, R. (1996). On the kullback-leibler information divergence of locally stationary processes. *Stochastic processes and their applications 62*(1), 139–168.

Dahlhaus, R., W. Polonik, et al. (2009). Empirical spectral processes for locally stationary time series. *Bernoulli 15*(1), 1–39.

Damodaran, A. (2022). Equity Risk Premiums (ERP): Determinants, Estimation, and Implications – The 2022 Edition. Available at SSRN 4066060.

Dautović, E., L. Gambacorta, and A. Reghezza (2023). Supervisory policy stimulus: evidence from the euro area dividend recommendation. ECB Working Paper No. 2796.

de Chaisemartin, C. and X. D'Haultfoeuille (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review 110*(9), 2964–2996.

de Chaisemartin, C. and X. D'Haultfoeuille (2021a). Difference-in-Differences Estimators of Intertemporal Treatment Effects. Available at SSRN 3731856.

de Chaisemartin, C. and X. D'Haultfoeuille (2021b). Two-Way Fixed Effects and Differences-in-Differences with Heterogeneous Treatment Effects: A Survey. Available at SSRN 3980758.

DeAngelo, H., L. DeAngelo, and D. J. Skinner (2009). *Corporate Payout Policy*. Now Publishers Inc.

Degryse, H., O. D. Jonghe, S. Jakovljević, K. Mulier, and G. Schepens (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation 40*(100813).

Dick-Nielsen, J., J. Gyntelberg, and C. Thimsen (2022). The Cost of Capital for Banks: Evidence from Analyst Earnings Forecasts. *Journal of Finance 77*(5), 2577–2611.

Diebold, F. X. and K. Yilmaz (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting 28*(1), 57–66.

Easton, P. D. (2004). PE Ratios, PEG Ratios, and estimating the implied expected rate of return on equity capital. *Accounting Review 79*(1), 73–95.

ECB (2022). ECB response to the European Commission's call for advice on the review of the EU macroprudential framework.

Fama, E. F. and K. R. French (2001). Disappearing dividends: changing firm characteristics or lower propensity to pay? *Journal of Financial Economics 60*(1), 3–43.

Favara, G., I. Ivanov, and M. Rezende (2021). Do Strict Capital Requirements Raise the Cost of Capital? Bank Regulation, Capital Structure, and the Low-Risk Anomaly. *Journal of Financial Economics 142*(3), 1426–1443.

Floyd, E., N. Li, and D. J. Skinner (2015). Payout policy through the financial crisis: The growth of repurchases and the resilience of dividends. *Journal of Financial Economics 118*(2), 299–316.

Forti, C. and R. F. Schiozer (2015). Bank dividends and signaling to information-sensitive depositors. *Journal of Banking & Finance 56*, 1–11.

Hurley, J., S. Karmakar, E. Markoska, E. Walczak, and D. Walker (2021). Impacts of the Covid-19 crisis: evidence from 2 million UK SMEs. Bank of England Staff Working Paper No. 924.

Imbierowicz, B., J. Kragh, and J. Rangvid (2018). Time-Varying Capital Requirements and Disclosure Rules: Effects on Capitalization and Lending Decisions. *Journal of Money, Credit and Banking 50*(4), 573–602.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2017). Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments. *Journal of Political Economy 125*(6), 2126–2177.

Kadiyala, K. R. and S. Karlsson (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics 12*(2), 99–132.

Khwaja, A. I. and A. Mian (2008). Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *American Economic Review 98*(4), 1413–1442.

La Porta, R., F. L. de Silanes, A. Shleifer, and R. W. Vishny (2000). Agency Problems and Dividend Policies around the World. *Journal of Finance 55*(1), 1–33.

Lee, C. M. C., E. C. So, and C. C. Y. Wang (2021). Evaluating Firm-Level Expected-Return Proxies: Implications for Estimating Treatment Effects. *Review of Financial Studies 34*(4), 1907–1951.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

MacKinnon, J. G., M. O. Nielsen, and M. D. Webb (2023). Cluster-robust inference: A guide to empirical practice. *Journal of Econometrics 232*(2), 272–299.

MacKinnon, J. G. and M. D. Webb (2017). Wild bootstrap inference for wildly different cluster sizes. *Journal of Applied Econometrics 32*, 233–254.

MacKinnon, J. G. and M. D. Webb (2018). The wild bootstrap for few (treated) clusters. *Econometrics Journal 21*, 114–135.

Marsh, W. B. (2023). Supervisory stringency, payout restrictions, and bank equity prices. *Journal of Banking & Finance 154*, 106936.

Martínez-Miera, D. and R. Vegas (2021). Impact of the dividend distribution restriction on the flow of credit to non-financial corporations in Spain. Banco de España Economic Bulletin 1/2021.

Mathur, A., M. Naylor, and A. Rajan (2023). Useful, usable, and used? Buffer usability during the Covid-19 crisis. Bank of England Staff Working Paper No. 1011.

Matyunina, A. and S. Ongena (2022). Bank capital buffer releases, public guarantee programs, and dividend bans in COVID-19 Europe: an appraisal. *European Journal of Law and Economics 54*, 127–152.

Miller, M. H. and K. Rock (1985). Dividend policy under asymmetric information. *Journal of Finance 40*(4), 1031–1051.

Modigliani, F. and M. H. Miller (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *American Economic Review 48*(3), 261–297.

Mohanram, P. and D. Gode (2013). Removing predictable analyst forecast errors to improve implied cost of equity estimates. *Review of Accounting Studies 18*, 443–478.

Ohlson, J. and B. E. Juettner-Nauroth (2005). Expected EPS and EPS Growth as Determinants of Value. *Review of Accounting Studies 10*, 349–365.

Pesaran, H. H. and Y. Shin (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters 58*(1), 17–29.

Petrova, K. (2019). A quasi-Bayesian local likelihood approach to time varying parameter VAR models. *Journal of Econometrics*.

Shleifer, A. and R. W. Vishny (1997). A survey of corporate governance. *Journal of Finance 52*(2), 737–783.

Svoronos, J.-P. and R. Vrbaski (2020). Banks' dividends in Covid-19 times. FSI Briefs 6, Bank for International Settlements.

A Shareholders' required rate of return models

The description in this Appendix largely follows Appendix A4 in Altavilla et al. (2021).

A.1 Damodaran (2022) model

The free cash flow to equity method of Damodaran (2022) adopts a standard discount factor model with constant growth of earnings from year 6 onward:

$$P_t = \sum_{n=1}^{5} \frac{FCFE_n}{(1+COE_t)^n} + \frac{FCFE_6}{(COE_t - g^L)(1+COE_t)^5} \tag{A.1}$$

where P_t is the stock price at time t, COE_t is the shareholders' required rate of return at time t and $FCFE_n$ is the expected free cash flow to equity of a bank for future years n. $FCFE_6$ is expected to grow at a constant rate g^L for the rest of the bank's life, which is assumed to be equal to the corresponding country's GDP growth.

$FCFE_n$ is proxied using earnings per share (EPS) forecasts. Specifically:

$$FCFE_n = \begin{cases} (1-RE)(1-\tau)EPS_n, \text{ if } EPS_n > 0 \\ EPS_n, \text{ if } EPS_n \leq 0 \end{cases}, n = 1, 2, ..., K \tag{A.2}$$

where RE is the percentage of earnings retained by the bank for reinvestment (assumed to be equal to 10% as in Altavilla et al. (2021)) and τ is the marginal tax rate on dividends.

Since we only observe EPS_n up to $n = 5$, we assume that year-to-year growth rates increase at a constant rate of α such that the growth rate at year 6 is equal to the long-term growth rate g^L. Hence: $1 + g^L = (1 + g^S)\alpha^{6-K+i}$ and $FCFE_{K+i} = FCFE_K \prod_{j=1}^{i}(1 + \alpha^j g^s)$, where $\alpha = (\frac{1+g^L}{1+g^S})^{\frac{1}{6-K+i}}$ for $i = 1$ and $g^S = (\frac{EPS_5}{EPS_1})^{\frac{1}{4}} - 1$ is the short-term growth rate. The shareholders' required rate of return COE_t is derived by solving (A.1) numerically.

A.2 Ohlson and Juettner-Nauroth (2005) model

The model proposed by Ohlson and Juettner-Nauroth (2005) is of the form:

$$P_t = \frac{EPS_{t+1}}{COE_t} \frac{g^S + COE_t \frac{DPS_{t+1}}{EPS_{t+1}} - (g^L - 1)}{COE_t - (g^L - 1)} \tag{A.3}$$

where EPS_{t+1} and DPS_{t+1} are the forecast one-year ahead earnings per share and dividends per share respectively.

The shareholders' required rate of return is the solution of the quadratic equation given P_t:

$$COE_t = A + \sqrt{A^2 + \frac{EPS_{t+1}}{P_t}(g^S - (g^L - 1))} \tag{A.4}$$

where $A = \frac{1}{2}\left[(g^L - 1) + \frac{DPS_{t+1}}{P_t}\right]$.

A.3 Easton (2004) model

Easton (2004) derives a simplified version of the Ohlson and Juettner-Nauroth (2005) model by setting $g^L = 1$ and ignoring dividends:

$$COE_t = \sqrt{\frac{EPS_{t+1}}{P_t} g^S} \tag{A.5}$$

A.4 Claus and Thomas (2001) model

Claus and Thomas (2001) propose the following model:

$$P_t = B_t + \sum_{n=1}^{5} \frac{(ROE_n - COE_t)B_{n-1}}{(1 + COE_t)^n} + \frac{(ROE_5 - COE_t)(1 + g^L)B_4}{(COE_t - g^L)(1 + COE_t)^4} \tag{A.6}$$

where B_t is equity book value whose future values are calculated using clean surplus accounting $B_{t+1} = B_t + EPS_{t+1} - DPS_{t+1}$, and ROE_n are forecast n-year ahead returns on equity. The shareholders' required rate of return COE_t is derived by solving the equation numerically.

B Data description

Table B1: Nearest neighbour matching results. This table reports the mean values of bank-specific variables and their differences for the treated and control groups before matching (Panel A) and after matching (Panel B) as of 28 February 2020. Panel C provides statistics for the final sample of 80 banks used in this study. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	# Banks	Log(Assets)	Deposits/Assets	Provisions/Loans	ROE	CET1 ratio	Corp. lend ratio
Panel A: Unmatched sample							
Treated	111	9.78	0.63	0.001	0.09	0.16	0.44
Control	35	8.75	0.76	0.002	0.02	0.15	0.42
Δ		1.03**	-0.13***	-0.001	0.07*	0.01	0.02
Panel B: Matched sample							
Treated	104	9.73	0.64	0.001	0.08	0.16	0.44
Control	19	9.18	0.72	0.001	0.06	0.16	0.37
Δ		0.55	-0.08*	0.000	0.02	0.00	0.07
Panel C: Final matched sample							
Treated	70	10.47	0.62	0.001	0.08	0.16	0.44
Control	10	10.35	0.73	0.001	0.03	0.15	0.36
Δ		0.12	-0.11*	0.000	0.06	0.01	0.08

Table B2: List of countries. The table illustrates the countries used in this study, their respective restrictions implementation dates, as well as the number of banks in the treated and control groups corresponding to each country.

Country	**Restrictions implementation date**	**# treated banks**	**# control banks**
Austria	27/03/2020	4	0
Belgium	27/03/2020	1	0
Czech Republic	16/03/2020	1	0
Denmark	16/03/2020	1	0
Estonia	27/03/2020	0	1
Finland	27/03/2020	2	1
France	27/03/2020	3	0
Germany	27/03/2020	5	1
Greece	27/03/2020	0	1
Hungary	19/03/2020	1	0
Italy	27/03/2020	9	0
Lithuania	27/03/2020	1	0
Malta	27/03/2020	1	0
Netherlands	27/03/2020	3	0
Norway	25/03/2020	15	0
Poland	26/03/2020	6	2
Republic of Ireland	27/03/2020	1	1
Romania	15/07/2020	2	0
Spain	27/03/2020	5	1
Sweden	26/03/2020	1	0
United Kingdom	31/03/2020	8	2

Table B3: Summary statistics for the variables used in the study (monthly frequency). Columns denote, respectively, the name of the variable, number of observations, mean value, standard deviation, minimum value, 25th, 50th, 75th percentiles and maximum value.

Variable	*N*	Mean	SD	Min	25th	50th	75th	Max
Panel A: International sample								
Shareholders' required rate of return (%)	2,431	10.77	3.25	2.11	8.54	10.34	12.93	19.98
Debtholders' required rate of return (%)	2,961	1.24	1.07	−0.47	0.47	0.98	1.93	6.83
Assets (£million)	2,431	359,430	547,698	633	15,128	55,872	525,884	2,384,009
Deposits (£million)	2,431	186,337	263,628	337	8,953	41,592	331,385	1,304,415
Loan loss provisions (£million)	2,326	172	459	−797	5	35	160	7,959
Gross loans (£million)	2,431	164,357	221,281	91	8,620	37,271	275,899	911,826
CET1 ratio (%)	2,418	15.29	2.97	8.15	13.40	14.63	16.77	31.53
CET1 capital (£million)	2,379	15,565	21,234	49	1,301	4,220	28,321	103,738
Return on Equity (%)	2,428	8.05	9.29	−44.39	4.28	7.94	11.98	48.63
Corporate loan ratio (%)	2,317	46.15	17.70	0.00	37.84	46.04	58.19	94.00
QE holdings (£million)	2,408	1,106,878	964,234	0	23,008	922,271	1,639,598	3,183,341
Policy rate (%)	2,431	0.20	0.78	−0.48	−0.45	0.00	0.71	2.50
GDP growth (%)	2,431	1.31	6.08	−21.49	−0.34	1.87	3.85	24.77
CPI (%)	2,431	1.88	1.17	−1.96	1.17	1.88	2.52	7.45
Unemployment rate (%)	2,431	5.88	2.88	1.70	4.00	5.00	6.60	17.30
Sovereign CDS spread (%)	2,426	0.43	0.41	0.07	0.13	0.27	0.63	2.59
Country stock index volatility (%)	2,482	1.36	0.51	0.55	0.95	1.17	1.77	2.90
New Covid cases	2,431	2,078	6,320	0	0	0	588	61,654
Panel B: UK (Experian) sample								
Loan volume (£)	350,216	67,959	153,928	5,001	22,475	50,000	50,000	2,980,625
Loan volume - government guaranteed (£)	286,952	50,677	83,744	5,001	24,000	50,000	50,000	2,900,000
Loan volume - non-government guaranteed (£)	63,264	146,349	303,078	5,001	20,000	47,613	125,460	2,980,625
SME total assets (£million)	350,216	0.681	1.855	0.001	0.037	0.144	0.579	113.778
Profit & Loss account (£million)	350,216	0.188	0.844	−59.055	0.000	0.014	0.130	75.341
Capital/Assets (%)	350,216	0.741	3.089	0.000	0.004	0.030	0.210	38.998
Log(Current liabilities/Current assets)	350,216	8.109	10.225	−7.423	6.207	6.750	7.199	15.378
Bank total assets (£million)	350,216	1,162,844	523,062	22	806,887	872,994	1,444,296	2,360,569
Deposits (£million)	350,216	557,272	307,838	17	427,773	466,913	487,570	1,304,415
Loan loss provisions (£million)	350,216	1,196	787	−797	470	1,430	2,056	3,095
Gross loans (£million)	350,216	438,167	170,319	15	341,126	382,088	450,493	911,826
CET1 ratio (%)	350,216	15.08	1.40	10.81	13.84	14.58	16.22	32.56
CCyB pass-through (%)	350,216	63.36	24.03	18.93	49.22	72.57	89.33	100.00
TFSME drawdown (£million)	350,216	516	1,464	0.000	0.000	0.000	0.000	7,000
Central bank deposits (£million)	350,216	128,426	66,313	4	75,747	99,189	190,455	292,415

C Difference-in-differences results

Table C1: Monthly difference-in-differences estimates for required rate of return on capital. This table presents the monthly DiD estimates for shareholders' and debtholders' required rate of return. Months -14 to -1 indicate placebo effects to assess parallel trends assumption. Month 0 is implementation month, and months 1 to 17 indicate dynamic effects to assess persistence. Standard errors are clustered at the bank*month level. Bootstrap z-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2018 to September 2021.

	(1)	(2)
Dependent Variable:	Shareholders' required rate of return	Debtholders' required rate of return
Month -14	−0.006	0.004
	(−0.318)	(0.493)
Month -13	−0.011	0.002
	(−0.939)	(0.214)
Month -12	−0.009	0.001
	(−0.869)	(0.174)
Month -11	−0.012	0.003
	(−1.083)	(0.685)
Month -10	−0.009	0.003
	(−0.757)	(0.650)
Month -9	−0.004	0.002
	(−0.240)	(0.409)
Month -8	0.000	0.003
	(0.004)	(0.812)
Month -7	0.001	0.004
	(0.133)	(1.156)
Month -6	0.007	0.005
	(1.094)	(1.259)
Month -5	−0.004	0.005
	(−0.604)	(1.188)
Month -4	0.005	0.005
	(0.588)	(1.014)
Month -3	0.012	0.005
	(0.982)	(0.948)
Month -2	0.006	0.004
	(0.692)	(0.889)
Month -1	0.008	−0.000
	(0.840)	(−0.285)
Month 0	0.018**	−0.008
	(2.548)	(−0.890)
Month 1	0.033***	−0.010
	(3.893)	(−1.384)
Month 2	0.032***	−0.010*
	(3.376)	(−1.701)
Month 3	0.034***	−0.008*
	(3.765)	(−1.613)
Month 4	0.038***	−0.006*
	(3.212)	(−1.790)
Month 5	0.031**	−0.006*
	(2.349)	(−1.904)
Month 6	0.030**	−0.006**
	(2.212)	(−2.001)
Month 7	0.033	−0.005
	(1.611)	(−1.604)
Month 8	0.032***	−0.004**
	(2.614)	(−2.366)
Month 9	0.036***	−0.005**
	(3.252)	(−2.318)
Month 10	0.035***	−0.005**
	(3.174)	(−2.431)
Month 11	0.021**	−0.005***
	(2.408)	(−2.602)
Month 12	0.013*	−0.005***
	(1.691)	(−2.910)
Month 13	0.018***	−0.005***
	(2.909)	(−2.822)
Month 14	0.023**	−0.005***
	(2.488)	(−3.322)
Month 15	0.020*	−0.006***
	(1.827)	(−3.664)
Month 16	0.019**	−0.006***
	(2.118)	(−3.142)
Month 17	0.018**	−0.005***
	(2.028)	(−2.661)
Observations	1,712	1,759
N banks	51	56

Table C2: Quarterly difference-in-differences estimates for resilience. This table presents the quarterly DiD estimates for logged CET1 capital, CET1 ratio and logged RWAs. Quarters -4 to -1 indicate placebo effects to assess parallel trends assumption. Quarter 0 is implementation quarter, and quarters 1 to 5 indicate dynamic effects to assess persistence. Standard errors are clustered at the bank*quarter level. Bootstrap z-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from Q1 2018 to Q3 2021.

	(1)	(2)	(3)
Dependent Variable:	Log(CET1 capital)	CET1 ratio	Log(RWAs)
Quarter -4	0.008	0.000	0.004
	(0.323)	(0.084)	(0.190)
Quarter -3	0.009	0.008	−0.321
	(0.358)	(1.148)	(−0.960)
Quarter -2	0.011	0.000	0.108
	(0.575)	(0.049)	(0.635)
Quarter -1	0.010	0.004	−0.001
	(0.519)	(0.783)	(−0.045)
Quarter 0	0.031*	0.003	0.017
	(1.719)	(1.333)	(1.076)
Quarter 1	0.040***	0.008***	−0.006
	(2.745)	(3.084)	(−0.458)
Quarter 2	0.051***	0.006*	0.020
	(2.622)	(1.660)	(0.895)
Quarter 3	0.038	0.007	0.006
	(1.344)	(1.635)	(0.236)
Quarter 4	0.029	0.011*	−0.020
	(0.669)	(1.656)	(−0.493)
Quarter 5	0.017	0.008	−0.023
	(0.403)	(1.232)	(−0.672)
Observations	1,581	1,603	1,579
N banks	117	118	117

Table C3: Results on alternative large loan thresholds. This table reports the results of the expanded specification (4) using a *Large Loan* threshold of £150,000 (column (1)) and £200,000 (column (2)). Standard errors are double-clustered at the bank and industry levels. Wild cluster bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	Log(Volume) (t)	
	(1)	(2)
Treatment (t)	0.353*	0.358
	(2.781)	(2.271)
Treatment (t) * Large loan	−0.402	−0.409
	(−1.659)	(−1.403)
Log(SME Assets) ($t-1$)	0.217***	0.240***
	(19.105)	(20.608)
Capital/Assets ($t-1$)	0.007	0.130
	(0.048)	(0.888)
Profit ($t-1$)	−0.020*	−0.024*
	(−3.600)	(−4.265)
Liquidity ratio ($t-1$)	0.014	0.017*
	(2.839)	(3.332)
Log(Bank Assets) ($t-1$)	−0.139	−0.053
	(−0.721)	(−0.217)
Deposits/Assets ($t-1$)	−0.430	−0.464
	(−1.548)	(−1.179)
LLP/Loans ($t-1$)	0.559	0.562
	(2.935)	(2.325)
CET1 ratio ($t-1$)	−0.025	−0.040*
	(−1.815)	(−2.396)
ROE ($t-1$)	0.004	0.005*
	(2.045)	(2.846)
CCyB pass-through ($t-1$)	−0.026*	−0.031
	(−3.137)	(−2.485)
Log(TFSME) ($t-1$)	0.002	0.006
	(0.471)	(1.128)
Log(CB cash) ($t-1$)	0.316**	0.442**
	(2.797)	(2.694)
Large loan	2.144***	2.178***
	(80.101)	(59.685)
Intercept	10.650***	9.902***
	(6.671)	(4.224)
Size x Industry x Region x Quarter fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
Observations	48,454	48,454
R^2	0.769	0.744

D Banks' interconnectedness estimation

We consider a locally stationary TVP-VAR of a lag order p describing the dynamics as

$$\mathbf{CF}_{t,T} = \mathbf{\Phi}_1(t/T)\mathbf{CF}_{t-1,T} + \ldots + \mathbf{\Phi}_p(t/T)\mathbf{CF}_{t-p,T} + \boldsymbol{\epsilon}_{t,T}, \tag{D.1}$$

where $\mathbf{CF}_{t,T} = \left(\mathrm{CF}^{(1)}_{t,T}, \ldots, \mathrm{B}^{(N)}_{t,T}\right)^\top$ is a doubly indexed N-variate time series of investors' required rate of return measures , $\boldsymbol{\epsilon}_{t,T} = \mathbf{\Sigma}^{-1/2}(t/T)\boldsymbol{\eta}_{t,T}, \boldsymbol{\eta}_{t,T} \sim NID(0, \boldsymbol{I}_M)$ and $\mathbf{\Phi}(t/T) = (\mathbf{\Phi}_1(t/T), \ldots, \mathbf{\Phi}_p(t/T))^\top$ are the time varying autoregressive coefficients. Note that t refers to a discrete time index $1 \leq t \leq T$ and T is an additional index indicating the sharpness of the local approximation of the time series by a stationary process. Rescaling time such that the continuous parameter $u \approx t/T$ is a local approximation of the weakly stationary time-series (Dahlhaus, 1996), we approximate $\mathbf{CF}_{t,T}$ in a neighborhood of $u_0 = t_0/T$ by a stationary process:

$$\widetilde{\mathbf{CF}}_t(u_0) = \mathbf{\Phi}_1(u_0)\widetilde{\mathbf{CF}}_{t-1}(u_0) + \ldots + \mathbf{\Phi}_p(u_0)\widetilde{\mathbf{CF}}_{t-p}(u_0) + \boldsymbol{\epsilon}_t. \tag{D.2}$$

The TVP-VAR process has a time varying Vector Moving Average VMA(∞) representation (Dahlhaus, Polonik, et al., 2009; Baruník and Ellington, 2020) $\mathbf{CF}_{t,T} = \sum_{h=-\infty}^{\infty} \mathbf{\Psi}_{t,T}(h)\boldsymbol{\epsilon}_{t-h}$, where parameter vector $\mathbf{\Psi}_{t,T}(h) \approx \mathbf{\Psi}(t/T, h)$ is a time varying impulse response function characterized by a bounded stochastic process.[24] Information contained in $\mathbf{\Psi}_{t,T}(h)$ permits the measurement of the contribution of shocks in the system. Hence, its transformations over time will determine the interconnectedness of banks. Since a shock to a variable in the model does not necessarily appear alone, an identification scheme is crucial in identifying the connectedness. We adapt the extension of the generalized identification scheme of Pesaran and Shin (1998) to locally stationary process as proposed by Baruník and Ellington (2020).

We transform local impulse responses in the system to local impulse transfer functions using Fourier transformations. This allows us to measure the horizon specific dynamics of the connectedness based on heterogeneous persistence of shocks in the system. A dynamic representation of the variance decomposition of shocks from bank j to bank k then establishes a dynamic horizon specific adjacency matrix, which is central to our measures.

Specifically, the element of such a matrix, which captures how shocks from a bank j are propagated to a

[24] Since $\mathbf{\Psi}_{t,T}(h)$ contains an infinite number of lags, we approximate the moving average coefficients at $h = 1, \ldots, H$ horizons.

bank k at a given point of time $u = t_0/T$ and a given horizon[25] $d_i \in \mathcal{H} = \{\mathrm{Tr}, \mathrm{Per}\}$, is formally defined as:

$$\Big[\boldsymbol{\theta}(u, d_i)\Big]_{j,k} = \frac{\widehat{\sigma}_{kk}^{-1} \sum\limits_{\omega \in d_i} \left(\Big[\widehat{\boldsymbol{\Psi}}(u,\omega)\widehat{\boldsymbol{\Sigma}}(u) \Big]_{j,k} \right)^2}{\sum\limits_{\omega \in \mathcal{H}} \Big[\widehat{\boldsymbol{\Psi}}(u,\omega)\widehat{\boldsymbol{\Sigma}}(u)\widehat{\boldsymbol{\Psi}}^{\top}(u,\omega) \Big]_{j,j}}, \tag{D.3}$$

where $\widehat{\boldsymbol{\Psi}}(u,\omega) = \sum_{h=0}^{H-1} \sum_h \widehat{\boldsymbol{\Psi}}(u,h)e^{-i\omega h}$ is an impulse transfer function estimated from Fourier frequencies ω of impulse responses that cover a specific horizon d_i frequencies.[26] It is important to note that $\Big[\boldsymbol{\theta}(u,d)\Big]_{j,k}$ is a natural disaggregation of traditional variance decompositions to a time-varying and h-horizon adjacency matrix. This is because the portion of the local error variance of the j-th variable at horizon h due to shocks in the k-th variable is scaled by the total variance of the j-th variable. As the rows of the dynamic adjacency matrix do not necessarily sum to one, we normalize the element in each by the corresponding row sum: $\Big[\widetilde{\boldsymbol{\theta}}(u,d)\Big]_{j,k} = \Big[\boldsymbol{\theta}(u,d)\Big]_{j,k} \Big/ \sum\limits_{k=1}^{N} \Big[\boldsymbol{\theta}(u,d)\Big]_{j,k}$. Equation (D.3) defines a dynamic horizon specific interconnectedness completely. Naturally, our adjacency matrix is filled with weighted links showing strengths of the connections. The links are directional, meaning that the j to k link is not necessarily the same as the k to j link. In sum, the adjacency matrix is asymmetric, horizon specific and evolves dynamically.

To obtain the time-varying coefficient estimates $\widehat{\boldsymbol{\Phi}}_1(u), ..., \widehat{\boldsymbol{\Phi}}_p(u)$ and the time-varying covariance matrix $\widehat{\boldsymbol{\Sigma}}(u)$ at a given point of time $u = t_0/T$, we estimate the approximating model in Equation (D.2) using Quasi-Bayesian Local-Likelihood (QBLL) methods (Petrova, 2019). Specifically, we use a kernel weighting function, which gives larger weights to those observations surrounding the period whose coefficient and covariance matrices are of interest. Using conjugate priors, the (quasi) posterior distribution of the parameters of the model are available analytically. This alleviates the need to use a Markov Chain Monte Carlo (MCMC) simulation algorithm and permits the use of parallel computing. We provide a detailed discussion of the estimation algorithm in Appendix D.

Finally, the variance decompositions of the forecast errors from the VMA(∞) representation require a truncation of the infinite horizon with a H horizon approximation. As $H \to \infty$ the error disappears (Lütkepohl, 2005). We note here that H serves as an approximating factor and has no interpretation in the time-domain. We obtain horizon specific measures using Fourier transforms and set our truncation horizon H=100; the results are qualitatively similar for $H \in \{50, 100, 200\}$. In computing our measures, we also diagonalize the covariance matrix because our objective is to focus on the connections controlled for possible contemporaneous correlation in residuals of the system. The $\boldsymbol{\Psi}(u,d)$ matrix embeds the causal nature of

[25] In the empirical investigation, 20 business days divide the transitory and persistent horizons.

[26] Note that $i = \sqrt{-1}$.

connections, and the covariance matrix $\mathbf{\Sigma}(u)$ contains contemporaneous covariances within the off-diagonal elements.

To evaluate a time-varying and frequency specific banks interconnectedness from the estimated model, we use several definitions that focus on aggregate characteristics as well as disaggregate connections between banks. We focus on measures revealing when an individual bank is a transmitter or a receiver of shocks.

First, we aggregate the pairwise connectedness between banks' j and k investor required rate of return to measure the total connectedness between all banks. This is defined as the ratio of the off-diagonal elements sum to the sum of the entire matrix:

$$\mathcal{IC}(u,d) = 100 \times \sum_{\substack{j,k=1 \\ j \neq k}}^{N} \left[\widetilde{\boldsymbol{\theta}}(u,d)\right]_{j,k} \Bigg/ \sum_{j,k=1}^{N} \left[\widetilde{\boldsymbol{\theta}}(u)\right]_{j,k} \tag{D.4}$$

This measures the contribution of forecast error variance attributable to all shocks in the system, minus the contribution of own shocks over frequency band d and infers system-wide connectedness over such frequency band in the spirit of Diebold and Yilmaz (2012). In our context, it captures the % of future variability in investors' required rate of return that is explained by shocks to the required rate of return for other banks. Note that $\mathcal{IC}(u,d)$ is defined for each time and frequency such that we can obtain a time-frequency dynamics of total conenctedness.

Finally, in order to measure directional connections to test *H4*, we construct a horizon-specific directional connectedness measures for each bank j. First, a horizon-specific from-directional connectedness, which measures how much of each bank's j investor required rate of return variance is due to shocks of other banks' $i \in Z$ investor required rate of return belonging to the set Z in the cross-section, is defined as:

$$\mathcal{F}_{j \leftarrow \bullet}(u,d) = \sum_{i \in Z} \left[\widetilde{\boldsymbol{\theta}}(u)\right]_{j,i} \Bigg/ \sum_{\substack{k=1 \\ k \neq j}}^{N} \left[\widetilde{\boldsymbol{\theta}}(u,d)\right]_{j,k} \quad d \in \mathcal{H} = \{\text{Tr}, \text{Per}\}\,. \tag{D.5}$$

Second, horizon-specific to-directional connectedness, which measures the contribution of each bank's j investor required rate of return variance to variances of other banks' investor required rate of return in the set Z, is given by:

$$\mathcal{T}_{j \to \bullet}(u,d) = \sum_{i \in Z} \left[\widetilde{\boldsymbol{\theta}}(u)\right]_{i,j} \Bigg/ \sum_{\substack{k=1 \\ k \neq j}}^{N} \left[\widetilde{\boldsymbol{\theta}}(u,d)\right]_{j,k} \quad d \in \mathcal{H} = \{\text{Tr}, \text{Per}\}\,, \tag{D.6}$$

where $\mathcal{T}_{j \to \bullet}(u,d)$ is the transmission of shocks from bank j to banks belonging to the set Z, and $\mathcal{F}_{j \leftarrow \bullet}(u,d)$ is the reception of shocks of bank j from other banks in Z. These are defined correspondingly as the sum of rows and columns of the normalised variance decomposition matrix, divided by the sum of the off-diagonal elements of the matrix.

One can interpret these measures as dynamic to-degrees and from-degrees that associate with the nodes of the weighted directed network captured by a variance decomposition matrix. These two measures show how other banks' investor required rate of return contribute to the investor required rate of return of a bank j, and vice versa how a bank's j investor required rate of return contributes to the investor required rate of return of others, respectively, in a time-varying fashion at a horizon d. Note that one can simply add these measures across all horizons to obtain total time-varying measures.

We use equations (D.5) and (D.6) to assess respectively: i) whether there is a structural shift in the total interconnectedness between banks' investor required rate of return following the implementation of the restrictions, and ii) whether there exist spill-over effects between jurisdictions due to different restriction timings.

D.1 Estimation of the time-varying parameter VAR model

Let $\mathbf{CF}_t$ be an $N \times 1$ vector generated by a stable time-varying parameter (TVP) heteroskedastic VAR model with p lags:

$$\mathbf{CF}_{t,T} = \mathbf{\Phi}_1(t/T)\mathbf{CF}_{t-1,T} + \ldots + \mathbf{\Phi}_p(t/T)\mathbf{CF}_{t-p,T} + \boldsymbol{\epsilon}_{t,T}, \tag{D.7}$$

where $\boldsymbol{\epsilon}_{t,T} = \mathbf{\Sigma}^{-1/2}(t/T)\boldsymbol{\eta}_{t,T}, \boldsymbol{\eta}_{t,T} \sim NID(0, \boldsymbol{I}_M)$ and $\mathbf{\Phi}(t/T) = (\mathbf{\Phi}_1(t/T), \ldots, \mathbf{\Phi}_p(t/T))^\top$ are the time varying autoregressive coefficients. Note that all roots of the polynomial $\chi(z) = \det\left(\mathbf{I}_N - \sum_{p=1}^{L} z^p \mathbf{CF}_{p,t}\right)$ lie outside the unit circle, and $\mathbf{\Sigma}_t^{-1}$ is a positive definite time-varying covariance matrix. Stacking the time-varying intercepts and autoregressive matrices in the vector $\phi_{t,T}$ with $\overline{\mathbf{CF}}_t^\top = (\mathbf{I}_N \otimes x_t)\,, x_t = \left(1, x_{t-1}^\top, \ldots, x_{t-p}^\top\right)$ and denoting the Kronecker product by $\otimes$, the model can be written as:

$$\mathbf{CF}_{t,T} = \overline{\mathbf{CF}}_{t,T}^\top \phi_{t,T} + \mathbf{\Sigma}_{t/T}^{-\frac{1}{2}} \boldsymbol{\eta}_{t,T} \tag{D.8}$$

We obtain the time-varying parameters of the model by employing the Quasi-Bayesian Local-Likelihood (QBLL) approach of Petrova (2019). The estimation of Equation (D.7) requires re-weighting the likelihood function. The weighting function gives higher proportions to observations surrounding the time period whose parameter values are of interest. The local likelihood function at time period k is given by:

$$\begin{gathered} \mathrm{L}_k\left(\mathbf{CF}|\theta_k, \mathbf{\Sigma}_k, \overline{\mathbf{CF}}\right) \propto \\ |\mathbf{\Sigma}_k|^{\mathrm{trace}(\mathbf{D}_k)/2} \exp\left\{-\frac{1}{2}(\mathbf{CF} - \overline{\mathbf{CF}}^\top \phi_k)^\top \left(\mathbf{\Sigma}_k \otimes \mathbf{D}_k\right)\left(\mathbf{CF} - \overline{\mathbf{CF}}^\top \phi_k\right)\right\} \end{gathered} \tag{D.9}$$

The $\mathbf{D}_k$ is a diagonal matrix whose elements hold the weights:

$$\mathbf{D}_k = \mathrm{diag}(\varrho_{k1}, \ldots, \varrho_{kT}) \tag{D.10}$$

$$\varrho_{kt} = \phi_{T,k} w_{kt} / \sum_{t=1}^{T} w_{kt} \tag{D.11}$$

$$w_{kt} = (1/\sqrt{2\pi}) \exp((-1/2)((k-t)/H)^2), \quad \text{for } k, t \in \{1, \ldots, T\} \tag{D.12}$$

$$\zeta_{Tk} = \left(\left(\sum_{t=1}^{T} w_{kt} \right)^2 \right)^{-1} \tag{D.13}$$

where ϱ_{kt} is a normalised kernel function. w_{kt} uses a Normal kernel weighting function. ζ_{Tk} gives the rate of convergence and behaves like the bandwidth parameter H in (D.12). The kernel function puts a greater weight on the observations surrounding the parameter estimates at time k relative to more distant observations.

We use a Normal-Wishart prior distribution for $\phi_k | \, \mathbf{\Sigma}_k$ for $k \in \{1, \ldots, T\}$:

$$\phi_k | \mathbf{\Sigma}_k \backsim \mathcal{N}\left(\phi_{0k}, (\mathbf{\Sigma}_k \otimes \mathbf{\Xi}_{0k})^{-1}\right) \tag{D.14}$$

$$\mathbf{\Sigma}_k \backsim \mathcal{W}\left(\alpha_{0k}, \mathbf{\Gamma}_{0k}\right) \tag{D.15}$$

where ϕ_{0k} is a vector of prior means, $\mathbf{\Xi}_{0k}$ is a positive definite matrix, α_{0k} is a scale parameter of the Wishart distribution ($\mathcal{W}$), and $\mathbf{\Gamma}_{0k}$ is a positive definite matrix.

The prior and weighted likelihood function implies a Normal-Wishart quasi posterior distribution for $\phi_k | \, \mathbf{\Sigma}_k$ for $k = \{1, \ldots, T\}$. Formally, let $\mathbf{A} = (\overline{x}_1^\top, \ldots, \overline{x}_T^\top)^\top$ and $\mathbf{Y} = (x_1, \ldots, x_T)^\top$, then:

$$\phi_k | \mathbf{\Sigma}_k, \mathbf{A}, \mathbf{Y} \backsim \mathcal{N}\left(\widetilde{\theta}_k, \left(\mathbf{\Sigma}_k \otimes \widetilde{\mathbf{\Xi}}_k\right)^{-1}\right) \tag{D.16}$$

$$\mathbf{\Sigma}_k \backsim \mathcal{W}\left(\widetilde{\alpha}_k, \widetilde{\mathbf{\Gamma}}_k^{-1}\right) \tag{D.17}$$

with quasi posterior parameters

$$\widetilde{\phi}_k = \left(\mathbf{I}_N \otimes \widetilde{\mathbf{\Xi}}_k^{-1}\right) \left[\left(\mathbf{I}_N \otimes \mathbf{A}^\top \mathbf{D}_k \mathbf{A}\right) \hat{\phi}_k + \left(\mathbf{I}_N \otimes \mathbf{\Xi}_{0k}\right) \phi_{0k} \right] \tag{D.18}$$

$$\widetilde{\mathbf{\Xi}}_k = \widetilde{\mathbf{\Xi}}_{0k} + \mathbf{A}^\top \mathbf{D}_k \mathbf{A} \tag{D.19}$$

$$\widetilde{\alpha}_k = \alpha_{0k} + \sum_{t=1}^{T} \varrho_{kt} \tag{D.20}$$

$$\widetilde{\mathbf{\Gamma}}_k = \mathbf{\Gamma}_{0k} + \mathbf{Y}' \mathbf{D}_k \mathbf{Y} + \mathbf{\Phi}_{0k} \mathbf{\Gamma}_{0k} \mathbf{\Phi}_{0k}^\top - \widetilde{\mathbf{\Phi}}_k \widetilde{\mathbf{\Gamma}}_k \widetilde{\mathbf{\Phi}}_k^\top \tag{D.21}$$

where $\widehat{\phi}_k = \left(\mathbf{I}_N \otimes \mathbf{A}^\top \mathbf{D}_k \mathbf{A}\right)^{-1} \left(\mathbf{I}_N \otimes \mathbf{A}^\top \mathbf{D}_k\right) y$ is the local likelihood estimator for ϕ_k. The matrices $\mathbf{\Phi}_{0k}$, $\widetilde{\mathbf{\Phi}}_k$

are conformable matrices from the vector of prior means, ϕ_{0k}, and a draw from the quasi posterior distribution, $\widetilde{\phi}_k$, respectively.

The motivation for employing these methods are threefold. First, we are able to estimate large systems that conventional Bayesian estimation methods do not permit. This is typically because the state-space representation of an N-dimensional TVP VAR (p) requires an additional $N(3/2+N(p+1/2))$ state equations for every additional variable. Conventional Markov Chain Monte Carlo (MCMC) methods fail to estimate larger models, which in general confine one to (usually) fewer than 6 variables in the system. Second, the standard approach is fully parametric and requires a law of motion. This can distort inference if the true law of motion is misspecified. Third, the methods used here permit direct estimation of the VAR's time-varying covariance matrix, which has an inverse-Wishart density and is symmetric positive definite at every point in time.

In estimating the model, we use p=2 and a Minnesota Normal-Wishart prior with a shrinkage value $\varphi = 0.05$ and centre the coefficient on the first lag of each variable to 0.1 in each respective equation. The prior for the Wishart parameters are set following Kadiyala and Karlsson (1997). For each point in time, we run 500 simulations of the model to generate the (quasi) posterior distribution of parameter estimates. Note we experiment with various lag lengths, $p = \{2, 3, 4, 5\}$; shrinkage values, $\varphi = \{0.01, 0.25, 0.5\}$; and values to centre the coefficient on the first lag of each variable, $\{0, 0.05, 0.2, 0.5\}$. Network measures from these experiments are qualitatively similar. Notably, adding lags to the VAR and increasing the persistence in the prior value of the first lagged dependent variable in each equation increases computation time.