"Who's the boss?" The role of dividend clienteles in banks' lending decisions

Petros Katsoulis* Eddie Gerba†

Jozef Baruník‡ Jonathan Acosta-Smith§

We study how dividend clienteles affect banks' lending behaviour in response to changes in payout policy. Using loan-level data covering the universe of UK small and medium-sized enterprises, we exploit a regulatory intervention during the Covid-19 pandemic that imposed a system-wide restriction on bank payouts to support credit provision to the real economy. We find that banks' supply of credit is inversely related to their exposure to dividend clienteles: institutions with greater exposure expand lending by less or not at all in response to the intervention. This heterogeneity arises because dividend clienteles react negatively to the change in payout policy leading to an increase in the required rate of return on banks' capital, thereby weakening their incentives to intermediate. This has real effects: firms that borrow from less exposed banks increase their capital expenditure by more.

Keywords: Cost of capital, intermediation capacity, payout policy, dividend clienteles, distribution restrictions

JEL Codes: C32, G21, G28, G35

*Bank of England, Threadneedle Street, EC2R 8AH, London, United Kingdom (Corresponding Author). Email: Petros.Katsoulis@bankofengland.co.uk

†Bank of England, Threadneedle Street, EC2R 8AH, London, United Kingdom. Email: Eddie.Gerba@bankofengland.co.uk

‡Charles University, Institute of Economic Studies, Opletalova 26, 110 00, Prague, Czech Republic. Email: Barunik@fsv.cuni.cz

§Organisation for Economic Co-operation and Development (OECD), 2, rue André Pascal - 75775 Paris Cedex 16, France. Email: Jonathan.Smith@oecd.org

The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or the OECD.

1 Introduction

Banks use capital as a basis to fulfill their key social role of lending to the real economy. Indeed, better capitalised banks tend to exhibit higher loan growth (Gambacorta and Shin, 2018). Banks also tend to distribute a significant portion of their earnings to shareholders via dividends and share buybacks (Gambacorta et al., 2023). While there is a voluminous literature examining these two aspects of banks' capital usage individually, there is relatively scant research looking at their interaction. This is surprising since banks are known to maintain their payouts even during times of stress (Acharya et al., 2011; Floyd et al., 2015), which could inhibit their ability to service the economy when most needed (Forti and Schiozer, 2015).

A key challenge in assessing how changes in banks' payout policies can affect their lending decisions lies with the reasons why banks make significant payouts. Payouts help banks signal their asset quality and future profitability to shareholders (Bhattacharya, 1980; Miller and Rock, 1985; Floyd et al., 2015; Forti and Schiozer, 2015), as well as reduce agency costs due to lower need for monitoring (Shleifer and Vishny, 1997; La Porta et al., 2000). Hence, a change in a bank's payout policy may be an indication of its diminished ability to provide credit to the real economy. However, banks may also pay out to satisfy dividend clienteles that have a preference for a specific payout policy (Black and Scholes, 1974; Graham and Kumar, 2006; Becker et al., 2011). If a bank reduces its payouts, these clienteles could react negatively purely because their demand is no longer met, which could increase the bank's funding costs and lower its ability to provide credit given the negative relationship between the two (Kovner and Van Tassel, 2022).

In this paper we isolate the impact of dividend clienteles on banks' funding costs as a result of a drastic change in their payout policy, and examine how this affects banks' lending decisions and real outcomes. To do this, we exploit a unique policy implemented during the Covid-19 pandemic that restricted banks' distributions in order to help them support the real economy. The policy was implemented in the face of the significant economic uncertainty brought by the pandemic, and provides an ideal setting for our analysis. This is because the regulatory intervention was explicitly designed to help banks support the real economy and was applied at a system-wide level to avoid providing signals about individual banks' resilience. Furthermore, it was explicitly communicated that the policy was not a necessary step for banks to maintain adequate capital positions, which would alleviate concerns about an undercapitalised banking system or private information held by supervisors.[1]

[1]This is seen in the messaging of the policy announcements which stressed that the additional capital headroom was not expected to be needed to meet capital requirements but rather to support the economy: https://www.bankofengland.co.uk/prudential-regulation/publication/2020/

In order to perform our analysis, we rely on an international sample of European banks to compare outcomes between those that restricted distributions (as the treated group) and those that either did not plan to make distributions regardless of whether they were restricted or not, or were legally obligated to complete already approved distributions (as the control group). We also obtain the holdings of these banks' shares by mutual funds, a subset of which provide income to their investors by investing in predominantly dividend-paying shares and hence act as a proxy for dividend clienteles in our analysis. We take several steps to ensure an appropriate identification of our effects. First, we match the treated and control groups of banks across various observable characteristics (such as size, capitalisation, profitability and funding profile) which could influence their propensity to make distributions as well as their funding costs. Second, we test for parallel trends, which hold for our results. Third, we include a host of control variables and fixed effects, which take into account bank-, fund- and country-specific characteristics.

Using a triple difference-in-differences setup we show that income-oriented funds reacted negatively to the change in payout policy, with a sizable impact on banks' valuations. Restricted banks whose shares were held in material quantities by these funds (i.e. they were significantly exposed to them) faced negative market pressure on their valuations, by, on average, 6-10 percentage points (pps) relative to the shares of banks that were less exposed.[2] In contrast, other funds did not differentiate between shares of banks that were restricted or not.

Next, we find that this pressure increased the required rate of return on equity (i.e. cost of equity) by up to 1.7 pps relative to banks that were less exposed to these mutual funds. Using a structural framework, we further showcase that this increase reflected shareholders' uncertainty about future dividends. On the other hand, debtholders reduced their required rate of return (i.e. cost of debt) by 0.7 pp, on average, for all restricted banks irrespective of their exposure to income-oriented funds, as a result of their higher capitalisation and lower leverage (Modigliani and Miller, 1958). However, this was not enough to fully offset the increase in shareholders' required rate of return, so the overall required rate of return on capital (i.e. cost of capital) for the most exposed restricted banks increased.

Subsequently, we document how this funding cost increase influenced lending outcomes. We use a confidential dataset containing all loans issued by ten large UK banking groups to national small and medium-sized enterprises (SMEs) (Hurley et al., 2021). We focus on this loan segment because SMEs were the most reliant on bank credit during the pandemic

pra-statement-on-deposit-takers-approach-to-dividend-payments-share-buybacks-and-cash-bonuses.

[2]For anecdotal evidence about the negative reaction of dividend clienteles see for example Financial Times (2020): retail investors in Hong Kong threatened legal action against HSBC due to its decision to postpone dividends following the regulatory request given their reliance on them for income.

(Acharya and Steffen, 2020). SMEs are also subject to greater lender discretion (Chodorow-Reich et al., 2022), which could play a role in our analysis if banks faced an increase in the required rate of return on their capital and had a choice on where to allocate it. We control for a number of other fiscal, monetary and prudential measures taken to support lending to the real economy, borrower and bank characteristics as well as credit demand via fixed effects. We find that the level of exposure to income-oriented funds mattered for their lending volumes. While less exposed banks that were affected by the policy increased their overall lending volumes by 40% relative to unaffected peers, this increase quickly dropped the more exposed a banks was, reaching 0% for those most exposed.

Finally, when aggregating loan-level data to the borrower level and applying appropriate fixed effects, we find that these lending outcomes affected firms' investment decisions: firms that borrowed from those same banks that were less exposed to dividend clienteles, increased their capital expenditure relative to firms borrowing from unaffected banks or those most exposed to dividend clienteles. Yet, we didn't find differences in firms' bank deposits or their headcount. This suggests that the additional lending was used for long-term investment and not just to help manage firms' immediate liquidity needs or to hire additional employees.

Together, the evidence indicates that the funding cost pressure from dividend clienteles, driven by the shift in payout policy, reduced banks' credit lines to the real economy compared to the counterfactual absent these clienteles. This highlights the tension between the private interests of some bank shareholders and banks' social role in supporting the economy that can be particularly important during times of stress (Gambacorta et al., 2023). Previous studies have advocated for the imposition of regulatory restrictions on payouts during stress to alleviate this tension (Acharya et al., 2011; Forti and Schiozer, 2015). Our results show that even with such restrictions in place, this tension may not be fully mitigated since dividend clienteles may still react negatively.

We review the related literature next. Section 2 describes the regulatory background and the development of our hypotheses. Section 3 describes the data used in the study while section 4 outlines the empirical strategy. Section 5 presents the results while section 6 concludes and discusses policy implications.

Related literature. We contribute to several strands of literature. First, there is a large literature examining firms' payout policies. The seminal work of Miller and Modigliani (1961) showed that in perfect and efficient capital markets dividends do not matter for share valuations. However, banks use dividends to reduce the information asymmetries between their management and stakeholders by signalling their assets' quality and future profitability (Morgan, 2002; Calomiris and Nissim, 2014; Forti and Schiozer, 2015). In the presence of deposit guarantees, dividends can also act as a counterbalance to the need for investors to

increase monitoring in order to mitigate agency costs (Demirgüç-Kunt and Huizinga, 2004). Aside from firm-specific factors, there are various investor-specific ones for why payouts matter. These include investor sentiment that is time-varying and causes managers to cater to existing demand (Baker and Wurgler, 2004; Li and Lie, 2006), traditional dividend clienteles (Black and Scholes, 1974; Graham and Kumar, 2006; Becker et al., 2011), or to smoothen consumption (Shefrin and Statman, 1984; Baker et al., 2007). Our experimental setup is uniquely placed to isolate the effect of investor-specific from firm-specific factors on banks' cost of funding following changes to payout policy. This is because the Covid-era distribution restrictions: i) were imposed by regulators rather than by the banks themselves; ii) were applied to a wide variety of banks rather than specific ones to avoid any stigma effects; and iii) were specifically designed to help banks support the economy rather than provide a signal about the banks' health. As a result, the policy was not expected to reveal any supervisory information about the banks' resilience.

Second, several papers have shown the positive correlation between bank capital and lending. Using a randomised experiment, Michelangeli and Sette (2016) find that better capitalised banks are more likely to accept mortgage applications and offer lower rates. Gambacorta and Shin (2018) find that better capitalised banks take advantage of lower borrowing costs to fund more loans. During times of stress, banks with higher capital headroom are less likely to constrain credit supply (Berrospide et al., 2024; Couaillier et al., 2024). Furthermore, a reduction of capital requirements helps banks increase lending and lower the cost of credit (Jiménez et al., 2017; Imbierowicz et al., 2018; Couaillier et al., 2022; Mathur et al., 2023; di Patti et al., 2023). However, the way in which banks become more capitalised matters for lending outcomes. Firms may prefer to raise new equity organically via retained earnings rather than via new issues to pursue profitable investments due to information asymmetry between better-informed management and less-informed outside investors (Myers and Majluf, 1984). Our results suggest that, even when this is the case, it can still affect banks' lending decisions when the equity rise is mandated by the regulatory authority and conflicts with banks' payout policy.

Third, there is an emerging literature on the effects of Covid-related distribution restrictions on banks' valuations and lending. Studies conducted in the euro area and the US found that banks facing restrictions experienced depressed valuations relative to their unrestricted peers, which could imply an increase in shareholders' required rate of return (Ampudia et al., 2023; Andreeva et al., 2023; Marsh, 2023). Kroen (2022) also finds that bond yields of restricted banks declined after the initial announcement. In a related study, Cáceres and Lamas (2023) find that income-oriented mutual funds sold more bank stocks than other funds after the introduction of the restrictions, and these stocks experienced more

negative abnormal returns as a result. Mücke (2023) further finds that these funds did not reverse the reduction of their holdings after the restrictions were lifted due to the uncertainty induced by the policy. On the lending side, Dautović et al. (2023) and Martínez-Miera and Vegas (2021) find that restricted banks in the euro area and Spain respectively increased lending to firms. Sanders et al. (2024) find no significant difference in euro area syndicated lending between banks that suffered a larger impact on their valuations and lesser impacted peers.

Our study goes beyond these papers by looking at the holistic impact of distribution restrictions on the required rate of return on banks' capital rather than share prices since it provides a more accurate measure of the overall funding costs banks face, which ultimately influence their lending decisions (Kovner and Van Tassel, 2022). Methodologically, our structural framework allows us to showcase that the policy led to a shift in expectations about future payouts. Furthermore, by linking to investor demand for dividends, we are able to showcase the heterogeneous policy impact on banks' funding costs and lending decisions depending on their exposure to such investors. Given the policy was largely agnostic to banks' funding costs, this study can serve as a basis for evaluating its effectiveness.

Finally, our analysis adds new evidence to the broader discussion on the role of banks as intermediaries. Acharya et al. (2011) find that during the Global Financial Crisis banks maintained or even increased dividend payments funded via higher leverage, which contributed to their reluctance to lend to the real economy. Dividend payouts, in particular, can create negative externalities in a tightly interconnected system of bank claims because banks with lower franchise value (as proxied by price-to-book ratios) have an incentive to pay out cash to shareholders today rather than to debtholders in a default state, which erodes the value of the claims held by other banks (Acharya et al., 2017). This supports the idea of regulatory distribution restrictions, both for the benefit of combined banks' shareholders and the real economy. The theoretical prediction and policy recommendation of Acharya et al. (2017) is supported by the empirical analysis of Gambacorta et al. (2023) which shows that banks with lower price-to-book ratios have stronger incentives to make payouts. This paper introduces a new dimension to the discourse on payout policies and regulatory constraints in the context of expanding banks' intermediation capacity: the role of dividend clienteles.

2 Regulatory background and hypotheses development

As the pandemic took hold in March 2020, many governments imposed social restrictions to contain its spread. In response, central banks and financial regulators took measures to limit the impact on the real economy and the financial system. These included distribution

restrictions, which limited or suspended banks' ability to pay dividends and conduct share buybacks, to increase their resilience and enhance their support to the real economy.

An important feature of these restrictions is that they varied across jurisdictions, both in terms of the timing of implementation and their scope. Most jurisdictions in Europe implemented the restrictions in March 2020, with the European Central Bank (ECB) recommending that all banks suspend dividends and share buybacks for the 2019 and 2020 financial years.[3] In the UK, the Prudential Regulation Authority (PRA) also called for restrictions on cash bonuses for bank employees, but the restrictions only applied to the seven largest deposit takers.[4] In Switzerland, the Financial Market Supervisory Authority (FINMA) suspended share buybacks but not dividends.[5] In the US, the Federal Reserve suspended share buybacks but only limited dividends following the publication of the stress test results in June 2020.[6] In Canada, the Office of the Superintendent of Financial Institutions (OSFI) limited both dividends and share buybacks.[7] In contrast, the Bank of Japan and the People's Bank of China did not impose any distribution restrictions.

Many authorities including the ECB and the PRA subsequently relaxed the restrictions and allowed banks to make limited distributions in 2021:H1 for 2020.[8] By September 2021, most jurisdictions had completely lifted their restrictions as concerns over the impact of the pandemic on banks' loss-bearing capacity eased. Subsequently, some supervisors expressed concerns about making system-wide distribution restrictions a formal tool to be used in a systemic crisis, given the potential negative impact on banks' valuations and their ability to raise capital in the future (ECB, 2022). Indeed, several empirical papers have found supportive evidence that the announcement of the policy led to a reduction in banks' stock prices (Ampudia et al., 2023; Andreeva et al., 2023; Marsh, 2023; Sanders et al., 2024), and part of that can be attributed to investors' search for income (Cáceres and Lamas, 2023). Dividend clienteles may thus have reacted negatively to the change in banks' payout policies. We can test this by examining the price impact of the policy on banks' shares depending on the degree of their exposure to dividend clienteles, proxied by income-oriented funds in our study. This leads to our first hypothesis:

[3] https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200327~d4d8f81a53.en.html

[4] https://www.bankofengland.co.uk/prudential-regulation/publication/2020/pra-statement-on-deposit-takers-approach-to-dividend-payments-share-buybacks-and-cash-bonuses

[5] https://www.finma.ch/en/news/2020/03/20200325-mm-garantiepaket/

[6] https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200625c.htm

[7] https://web.archive.org/web/20210420191445/https://www.osfi-bsif.gc.ca/Eng/osfi-bsif/med/Pages/nr_20200313.aspx

[8] https://www.bankofengland.co.uk/prudential-regulation/publication/2020/pra-statement-on-capital-distribution-by-large-uk-banks, https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200728_1~42a74a0b86.en.html

***H1**: Restricted banks with **greater** exposure to income-oriented funds faced more negative market valuations than the **less** exposed restricted banks, relative to unrestricted banks.*

Having examined a potentially negative impact of dividend clienteles on restricted banks' valuations, we then explore the impact on banks' funding costs. It is well-known that dividend cuts can exacerbate adverse information effects so a higher bank capitalisation can be accompanied by a higher shareholders' required rate of return without contradicting the second proposition of Modigliani and Miller (1958) (Miller, 1995). However, the distribution restrictions imposed by regulators during the pandemic were explicitly designed not to provide a signal about individual banks' resilience, to avoid stigma effects. Furthermore, Covid was an exogenous shock so the imposition of regulatory restrictions was not a response to an ex-ante weak banking system. As a result, it is reasonable to assume that these restrictions did not provide an adverse signal about the resilience of individual banks or the banking system as a whole. Instead, the heightened uncertainty regarding the impact of Covid (Batten et al., 2023) which exacerbated the uncertainty regarding the future path of the restrictions (i.e. timing of their lifting or whether they would be imposed again in the future) led dividend clienteles to demand a higher premium for holding bank shares, raising their required rate of return. In contrast, debtholders would have benefited from banks' higher capitalisation and lower leverage since the restrictions did not target their payouts. This would lead to a reduction of the required rate of return on debt, irrespective of the banks' exposure to dividend clienteles. Consequently, the overall required rate of return on capital would increase for more exposed banks relative to those less exposed. This leads to our second hypothesis:

***H2a**: Restricted banks with **greater** exposure to income-oriented funds experienced (i) a more pronounced increase in shareholders' required rate of return, (ii) a comparable decline in debtholders' required rate of return, and consequently (iii) a larger increase in the overall required return on capital than the **less** exposed restricted banks, relative to unrestricted banks.*

We further hypothesize that the imposition of distribution restrictions at the system-wide level prompted investors to reprice the risk associated with equity holdings across the entire banking sector. This repricing mechanism is expected to amplify interconnectedness among banks, whereby a shock to the required rate of return on equity for a given institution propagates to others through correlated shifts in investor expectations:

***H2b**: The adjustment in shareholders' required rate of return operates at the system-wide level, inducing greater interconnectedness across the banking sector through correlated repricing of equity risk.*

We then examine the impact of shareholder pressure on banks' lending decisions. Given

the negative relationship between the required rate of return on banks' capital and credit supply (Kovner and Van Tassel, 2022) as well as banks' lending discretion to SMEs (Chodorow-Reich et al., 2022), we hypothesize that those restricted banks more exposed to dividend clienteles increased their lending by less than their less exposed peers, relative to unrestricted banks:

***H3**: Restricted banks with **greater** exposure to income-oriented funds exhibited a smaller increase in the volume of SME lending than **less** exposed restricted banks, relative to unrestricted banks.*

If this hypothesis holds, it would imply that the adverse effect of dividend clienteles on banks' funding costs—induced by the change in payout policy—impacted their lending behaviour.

Finally, we examine the real effects of banks' lending decisions. The UK government introduced loan guarantee schemes to help firms manage their liquidity in the face of social restrictions. Given their co-existence in our sample period, we hypothesize that SMEs benefiting from higher (non-government guaranteed) lending volumes increased their capital expenditure, not their liquidity buffers:

***H4**: SMEs borrowing from **less** exposed restricted banks increased their capital expenditure compared to SMEs borrowing from **more** exposed restricted banks, relative to unaffected banks.*

3 Data & Variables construction

3.1 Banks' required rate of return on capital

We focus on European listed banks that were subject to similar restrictions during the Covid-19 crisis. We use S&P Capital IQ to identify a total of 194 such banks headquartered in 28 European countries. We exclude Swiss banks as they were only subject to share buyback restrictions. For each bank, we download its published 2020 annual report to understand whether it took any action to restrict distributions as a result of the regulatory requirement. Of these, 128 banks took such action and 66 did not. The inaction of the latter group is either because i) they did not plan to make distributions even though they may have been formally subject to restrictions, or ii) their distributions had been approved in an Annual General Meeting taking place prior to the introduction of the restrictions, which made them legally binding and hence were allowed to take place (Martínez-Miera and Vegas, 2021). We therefore assign the former banks to our treated group and the latter banks to our control

group.[9]

Our sample period stretches from January 2018 to September 2021, when restrictions were fully lifted in all countries. The main variables of interest are the required rates of return to shareholders and debtholders. As the shareholders' required rate of return is not directly observable, we use the class of implied cost of capital models proposed in the literature (see Lee et al. (2021) for an overview). These models relate the share price P_t to the discounted expected future cash flows (e.g. dividends) CF_{t+n}, where the discount rate is the 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 for testing the effects of the policy because it directly targeted dividends. Thus, these models capture the change 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 of 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, as this reduces measurement error (Mohanram and Gode, 2013). A detailed explanation of the methodology used to calculate each model is provided in Appendix A. For model calibration, we download banks' annual earnings per share (EPS), dividend per share (DPS) and return on equity (ROE) forecasts for the next five years on a daily basis from Refinitiv Workspace.[10]

For the required rate of return to debtholders we use the mid-yields of bank bonds traded in the secondary market with a residual 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 on other liabilities such as retail deposits covered by deposit insurance and non-traded debt, which would be less sensitive to distribution restrictions.[11]

[9] Some banks in the control group whose distributions had been pre-approved and were allowed to go ahead could subsequently become "treated" if they suspended another payout later in 2020. Our results are robust to removing these banks from our sample.

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

[11] As a robustness, we calculate the ratio of quarterly interest expenses to total debt as in Dick-Nielsen et al. (2022) which is more representative of the total return that is required by debtholders including depositors. Our analysis is robust to this alternative measure as explained in the Results section.

We then calculate the required rate of return on banks' capital $COC_{b,t}$ using a pre-tax weighted average:[12]

$$COC_{b,t} = \frac{E_{b,t}}{E_{b,t} + D_{b,t}} COE_{b,t} + \frac{D_{b,t}}{E_{b,t} + D_{b,t}} COD_{b,t}$$

where $E_{b,t}$ is the market capitalisation of bank b at time t, $D_{b,t}$ is the aggregate market value of the bank bonds, $COE_{b,t}$ is the shareholders' required rate of return and $COD_{b,t}$ is the debtholders' required rate of return.

Bank balance sheet characteristics are downloaded from S&P Capital IQ. Quarterly macroeconomic variables include the gross domestic product (GDP) growth which is downloaded from OECD data,[13] and the Consumer Price Index (CPI) and unemployment rates which are downloaded from Eurostat.[14] Daily number of new Covid-19 cases are obtained from the World Health Organization.[15] Finally, data on central bank policy rates are downloaded from BIS Statistics,[16] and quantitative easing (QE) holdings are downloaded from the respective central bank websites.

We manage to obtain control variable data for 146 out of 194 banks. We compare the banks in the treated and control groups across various dimensions using the following bank-specific variables: the logarithm of total assets as a proxy for size, the deposits to assets ratio as a proxy for funding profile, the loan loss provisions to gross loans ratio as a proxy for credit risk in the loan book, the return on equity as a proxy for profitability, the CET1 ratio as a proxy for capitalisation and the corporate-to-gross loans ratio as a proxy for the composition of banks' loan book. Comparing the mean values of the bank-specific variables between the treated and control groups before the start of the treatment (on 28 February 2020) via a t-test, we observe that treated banks were systematically larger, had a less stable funding profile and were more profitable (Panel A of Table B1 in Appendix B). To ensure that the treated and control groups are similar, we perform nearest neighbour matching based on these variables. The algorithm matches each treated bank to a control bank with similar characteristics (a control bank may be matched to several treated banks). In this way, the average values of the bank-specific control variables are statistically similar between the groups. After applying nearest neighbour matching, these differences are eliminated at the 5% confidence level (Panel B of Table B1). The matched sample contains 123 banks.

Finally, data limitations on the required rate of return to shareholders and debtholders means that our final sample consists of 98 banks, of which 85 were treated and 13 were not,

[12] Using a post-tax weighted average instead does not have any impact on our results.
[13] https://data.oecd.org/gdp/quarterly-gdp.htm
[14] https://ec.europa.eu/eurostat/data/database
[15] https://covid19.who.int/data
[16] https://www.bis.org/statistics/cbpol.htm

in 22 countries. We report the differences in the bank-specific variables for the final sample in Panel C of Table B1; there are no significant differences even at the 10% confidence level. We present the list of countries, the implementation dates of the restrictions, the ultimate authority issuing them and the number of treated and control banks in each country in Table B2 in Appendix B. The table also includes the reason for assigning the banks to the control group for each country, where applicable. Descriptive statistics for the variables are presented in Panel A of Table B3 in Appendix B.

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

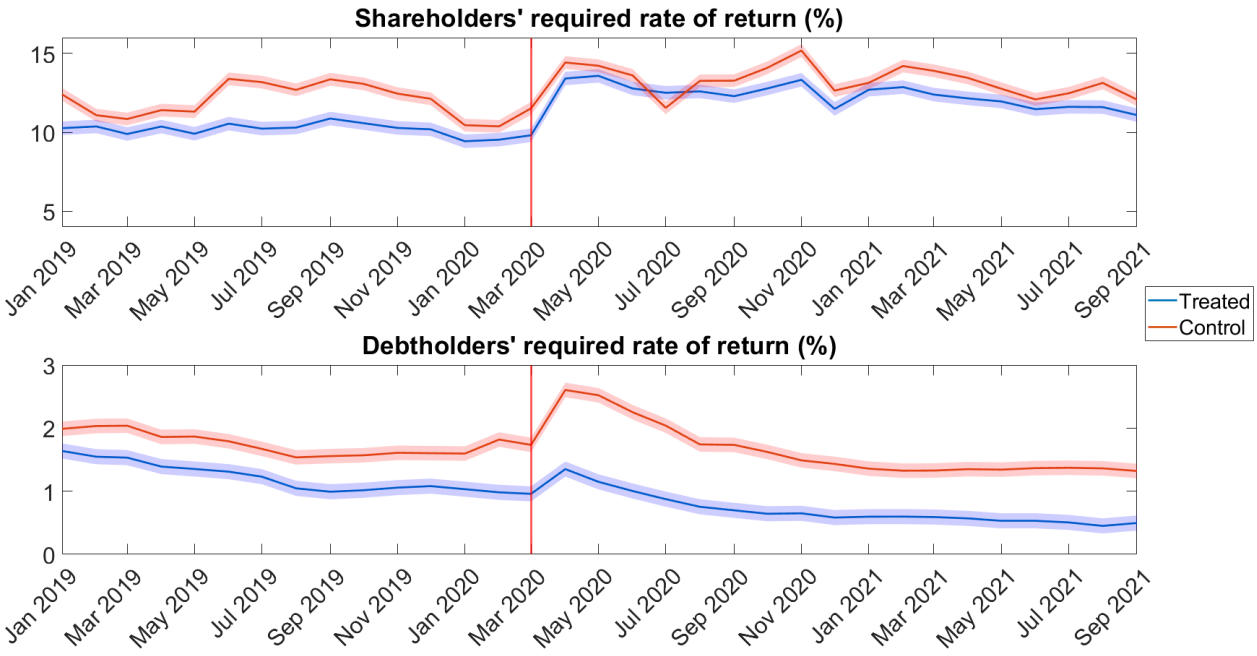


Figure 1: Monthly evolution of the average rate of return required by shareholders and debtholders for the treated and control groups of banks. The vertical red line denotes the introduction of distribution restrictions. Shaded areas denote 95% confidence intervals.

Focusing on the 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 of return for treated banks compared to control banks. However, after their introduction, the required rate of return on equity for both groups increased significantly, but more so for the treated group which reached similar levels to the control group. The increase from just prior to just after the introduction of restrictions (March-April 2020) for the treated group is substantial at 3.6 percentage points (pps), from 9.8% to 13.4%. This is 4.2 standard deviations of the differences of the required rate of return distribution. The change was slightly smaller for the control group at 2.9 pps, from 11.5% to 14.4% or 2.5 standard deviations of the differences distribution. Over time, the required rate of return decreased for

both groups but remained higher than the level prior to the introduction of the restrictions (11.1%/12.1% in September 2021 vs. 9.8%/11.5% in March 2020 for the treated/control group respectively).

Turning to the required rate of return on debt, throughout the sample we find that it was lower for the treated compared to control group. However, the difference between the two groups increased significantly from 54 basis points (bps) prior to the introduction to 94 bps afterwards, on average. Both groups experienced an increase in the required rate of return in April 2020, but the treated group did so to a lesser extent, with an increase of 39 bps from 0.96% to 1.35% or a 3.9 standard deviation increase, while the control group had an increase of 87 bps from 1.73% to 2.60% or a 4.6 standard deviation increase.

3.2 Mutual fund holdings

To test the impact of dividend clienteles, we download the data on mutual fund holdings of bank shares from Refinitiv Workspace. Specifically, for each bank in our sample, we download the list of mutual funds investing in the bank and their monthly holdings of its shares as a percentage of total shares outstanding. For each mutual fund, we additionally obtain information on whether it is income-oriented or not, i.e. whether it distributes the income it generates or retains it, similar to Cáceres and Lamas (2023).

As of end-December 2019, the data identify 4,407 mutual funds domiciled across 41 countries with holdings in the equity of banks included in our sample.[17] Of these, 1,724 (39%) were income-oriented funds. 72% of funds were categorised as "Equity" funds, 25% as "Mixed Assets" funds, and the rest as "Alternative" funds. Hence, the majority of mutual funds focused on equity investing. As seen in Panel A of Table B3 in Appendix B, each income-oriented fund held on average 0.09% of banks' total shares outstanding but the largest holding is 5.95%. When aggregating these holdings to the bank level, each bank in the treated group had 5.00% of its shares held by income-oriented funds on average, ranging from 0% up to 16.17%. However, banks in the control group had a much smaller average exposure of 3.03% to these funds, ranging from 0% up to 7.17%. This confirms that income-oriented funds have a preference for banks that make regular distributions, and that they could yield substantial influence over the banks most exposed to them.

[17] We observe significant concentration with 83% of the value of the holdings being in the top 5 countries, which are the United States, the United Kingdom, France, Singapore and Sweden.

3.3 Lending

We use data on the universe of UK SME loans issued by ten UK banking groups, provided confidentially to the Bank of England on a monthly basis by Experian, a private sector information services company. The dataset includes information on SME loan accounts, including balances and repayments, as well as SME information such as the registration number, sector (SIC code), region of head office and annual turnover. However, it does not have data on loan interest rates.

Our sample period is from January 2018 to June 2021, just prior to the lifting of restrictions by the PRA. Of the ten banking groups, five were subject to distribution restrictions and five were not.[18] We obtain the initial 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 amount of credit extended by a bank to a borrower, which is our variable of interest. We include accounts associated with loans, asset finance and leasing, and exclude credit cards and overdrafts which are much smaller in value and used to meet short-term liquidity needs.[19]

We further distinguish between loans issued under the Covid-19 government guarantee schemes and all other (non-guaranteed) loans. The UK government launched three such schemes targeted at different business sizes. The Bounce Back Loan Scheme (BBLS) offered a maximum loan amount of £50,000 100% guaranteed by the government, and was available to all UK businesses established before March 2020 adversely affected by Covid-19 although it was targeted at small and medium-sized ones.[20] The Coronavirus Business Interruption Loan Scheme (CBILS) offered a maximum loan amount of £5 million 80% guaranteed by the government, and was available to all small and medium-sized UK businesses with annual turnover of up to £45 million.[21] Finally, the Coronavirus Large Business Interruption Loan Scheme (CLBILS) offered a maximum loan amount of £200 million 80% guaranteed by the government, and was available to all medium and large-sized UK businesses with annual turnover of over £45 million.[22]

We use borrowers' registration numbers to obtain balance sheet data from the Bureau van Dijk's Orbis database, including total assets and capital, current assets and liabilities, and their profit and loss accounts. After merging the data, our final sample consists of 396,545

[18] While the five treated banks are all included in our final international sample detailed in Table B2, this only applies to one of the untreated banks due to unavailable data to estimate their shareholders' required rate of return.

[19] Credit cards and overdraft loans represent less than 0.1% of the total credit in our sample.

[20] https://www.gov.uk/guidance/apply-for-a-coronavirus-bounce-back-loan

[21] https://www.gov.uk/guidance/apply-for-the-coronavirus-business-interruption-loan-scheme

[22] https://www.gov.uk/guidance/apply-for-the-coronavirus-large-business-interruption-loan-scheme

loans, of which 277,319 were government guaranteed and issued from Q2 2020 onward (70%) and 119,226 were not and were issued throughout our sample period. We also use the database to obtain data on firms' capital expenditure (calculated as the change in fixed assets plus depreciation following Bahaj et al. (2020)), cash (proxied by bank deposits), and number of employees.

We drop observations at the 1% and 99% tails, corresponding to loans of less than £5,000 and more than £3,000,000 respectively. Descriptive statistics for the variables are presented in Panel B of Table B3 in Appendix B. We see that the majority of loans guaranteed by the government are up to £50,000. This suggests that most SMEs benefited from the BBLS, which offered a maximum loan amount of £50,000, rather than schemes offering higher amounts. The majority of businesses applying for the BBLS were small with turnover of less than £1 million, were more likely to have borrowed prior to the pandemic and were in sectors most affected by Covid, such as accommodation and food (Banks and Walker, 2021).

In Figure 2 we plot the quarterly evolution of the average SME lending volume of the two groups of banks (excluding government guaranteed loans). We observe that the control group is, on average, lending at higher volumes than the treated group. Following the introduction of the restrictions (marked by the vertical red line), the treated group exhibited a sustained increase in average loan volume—rising by 12% from £132,000 to £147,000 in the first quarter alone—whereas the control group experienced a decline of 11% from £345,000 to £305,000 in the same period.

4 Methodology

4.1 Price impact of mutual fund holdings

We start by examining whether mutual funds can meaningfully impact market pricing of banks' equity to assess their ability to influence banks' behaviour. We utilise a triple difference-in-differences (DiD) identification strategy using the bank-month panel in an event-study setting:[23]

$$CAR_{b,t} = \mu_b + \mu_t + \beta D_{b,t} + \xi D_{b,t} More_exposed_{b,t} + \gamma X_{b,t-1} + \zeta More_exposed_{b,t} + \epsilon_{b,t} \quad (1)$$

[23] A key feature of the policy is that it was introduced at different times in different countries. A number of recent econometric papers have shown that the standard two-way fixed effects estimator can produce biased estimates when applied in a setting with multiple treatment dates (de Chaisemartin and D'Haultfoeuille, 2023). However, as seen in Table B2, all countries in our sample introduced the restrictions in March 2020 and since we use a monthly frequency, the treatment date is the same.

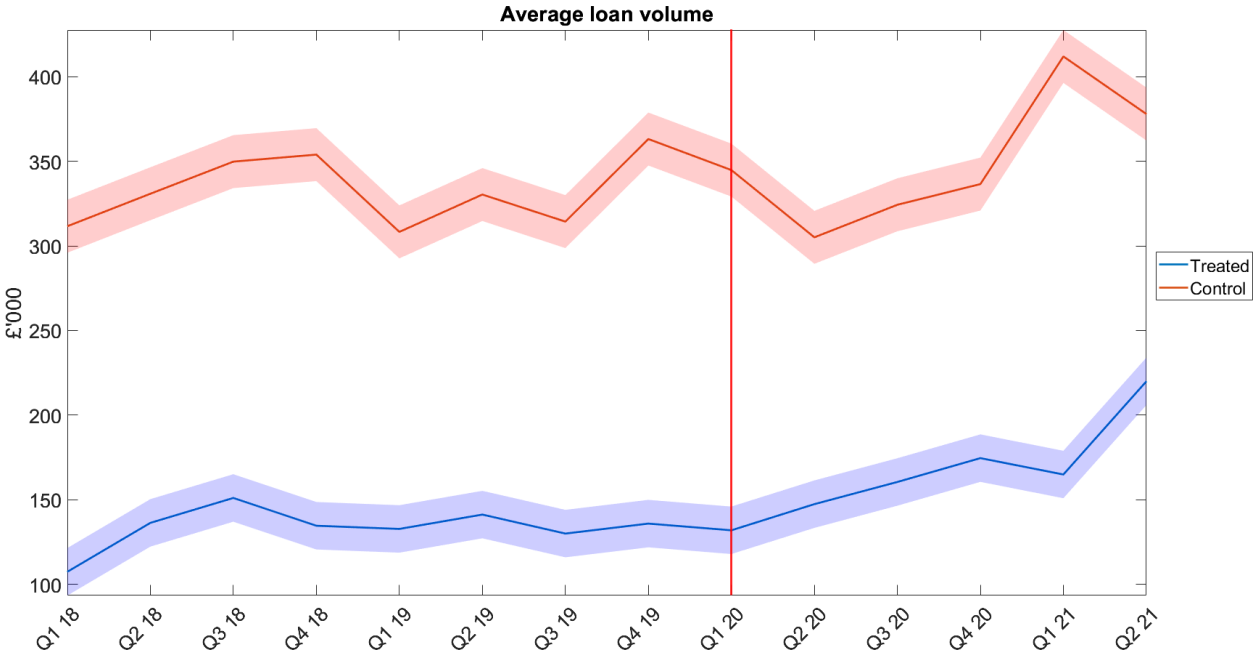


Figure 2: Quarterly evolution of the average SME lending volumes for the treated and control groups of banks. The vertical red line denotes the introduction of distribution restrictions. Shaded areas denote 95% confidence intervals. The data exclude government guaranteed loans.

where $CAR_{b,t}$ is the cumulative abnormal return of the stock of bank b in month t, μ_b are bank fixed effects to account for bank-specific unobservable time-invariant characteristics and μ_t are month fixed effects which control for all time-varying characteristics that affect banks equally. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group after the introduction of the restrictions. $More_exposed_{b,t}$ is a dummy variable that equals 1 for banks with significant exposure to income-oriented funds. To derive this dummy, we first calculate the aggregate monthly percentage of total shares outstanding held by income-oriented mutual funds for each bank, which measures the banks' exposure to these funds as discussed in subsection 3.2. The dummy variable then takes the value of 1 for values greater than a specific percentile of the distribution of this exposure.[24] $X_{b,t-1}$ is a matrix of lagged control variables that include the logarithm of banks' assets and the logarithm of banks' market capitalisation.

To derive $CAR_{b,t}$ we first calculate the abnormal return as the difference between the actual return and the expected return of the stock of bank b in month t:

$$AR_{b,t} = R_{b,t} - E[R_{b,t}]$$

The expected return $E[R_{b,t}]$ is estimated using the CAPM separately for each bank:[25]

[24] We report results for the 50th, 75th and 90th percentiles.

[25] We obtain similar, albeit slightly smaller results if we use the Fama-French 3-factor model instead.

$$E[R_{b,t}] = Rf_{b,t} + \beta_b(Rm_{b,t} - Rf_{b,t})$$

where $Rf_{b,t}$ is the risk-free rate proxied by the market mid-yield of 5-year national government bonds,[26] and $Rm_{b,t}$ is the market index return proxied using the national MSCI IMI indices that cover large, mid and small-cap companies. Finally, we calculate $CAR_{b,t}$ by summing the abnormal returns over an event window with the starting month being one period before the restrictions were imposed, i.e. the start of March 2020, and the last month being the end of our sample i.e. September 2021.

With specification (1) we are comparing the changes in cumulative abnormal returns of restricted vs. unrestricted bank shares, and separating the impact for banks more exposed to income-oriented funds. We hypothesize that ξ will be negative, indicating that, following the imposition of the restrictions, income-oriented funds exerted pressure on market valuations which affected banks more exposed to them to a greater extent than less exposed banks (*H1*).

We cluster standard errors by bank. While the number of banks in our international sample is sufficiently large for the purposes of clustering, recent econometric literature has suggested that the standard clustering estimator CV_1 may produce unreliable estimates when the number of treated vs. control units is significantly different in a DiD setting (MacKinnon et al., 2023a). For this reason, in our analysis we utilise a battery of different methodologies to ensure that our inferences are accurate. These are i) the jackknife wild cluster restricted bootstrap (WCR-S) (MacKinnon et al., 2023b), ii) the jackknife variance matrix estimator CV_3 (MacKinnon et al., 2023c) and iii) the modified CV_3 proposed by Hansen (2025) which is guaranteed to never be downward biased. In practice, all three methods produce almost identical estimates in our regressions. So in our results section, we report the t-statistics produced by the WCR-S for consistency which tend to be more conservative than those calculated under CV_1.

4.2 Required rate of return on capital

4.2.1 Magnitude

Next, we use a triple DiD regression to assess the impact of the investors' reaction to distribution restrictions on the required rate of return on bank capital depending on banks' exposure to income-oriented funds (*H2a*). Specifically, we utilise the bank-month panel and use as dependent variables the shareholders' required rate of return $COE_{b,t}$, the debtholders'

[26] For eurozone countries we use the euro benchmark which is based on German debt.

required rate of return $COD_{b,t}$ and the required rate of return on capital $COC_{b,t}$ for bank b in month t:

$$Y_{b,t} = \mu_b + \mu_t + \beta D_{b,t} + \xi D_{b,t} More_exposed_{b,t} + \gamma X_{b,t-1} + \delta Z_{b,t-1} + \zeta More_exposed_{b,t} + \epsilon_{b,t} \quad (2)$$

where $Y_{b,t}$ is one of the three dependent variables outlined above, μ_b and μ_t are bank and month fixed effects to account for bank-specific unobservable time-invariant characteristics as well as time-varying factors that affect all banks, and $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group after the introduction of the restrictions. $More_exposed_{b,t}$ is a dummy variable capturing banks more exposed to income-oriented funds defined in the previous subsection. We expect ξ to be positive for shareholders' required rate of return, meaning that restricted banks most exposed to income-oriented funds will face a proportionally higher increase than less exposed restricted banks, relative to unrestricted banks. In contrast, ξ should be insignificant for debtholders' required rate of return because the policy did not target their payouts. Finally, ξ should be positive for the overall required rate of return on capital, given the two prior anticipated effects.

We include a comprehensive set of controls that may affect investors' willingness to hold bank shares, their required rate of return and banks' propensity to pay dividends (Fama and French, 2001). Bank-specific lagged variables $X_{b,t-1}$ 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 as a proxy for capitalisation, the return on equity as a proxy for profitability, and the price-to-book ratio. In order to control for the potential impact of Covid-19 government guarantees on our dependent variables, we also include the ratio of corporate loans to gross loans. This is because Altavilla et al. (2021) find that banks that were larger, better capitalised, more liquid, and had pre-existing relationships with firms, were more likely to participate in the schemes. For the required rate of return to debtholders we also include the sovereign CDS spread as a proxy for sovereign risk and the volatility of country stock indices as a proxy for risk aversion, as in Arnould et al. (2022).

Country-specific lagged variables $Z_{b,t-1}$ include policy controls in the form of the key policy rate and the logarithm of central bank QE holdings. Macroeconomic controls include GDP growth, CPI and unemployment rates. Finally, we include the country-specific logarithm of the number of new Covid-19 cases as a proxy for the impact of the Covid-19 crisis on economic activity, which could affect investors' decisions and the required rate of return on banks' capital. Standard errors are clustered by bank and we report the t-statistics produced

by the WCR-S in the results section.

4.2.2 System-wide bank interconnectedness

In order to assess the system-wide impact of distribution restrictions on bank interconnectedness (*H2b*), we use a DiD specification of the form:

$$Y_{b,t} = \mu_b + \mu_t + \beta D_{b,t} + \gamma X_{b,t-1} + \delta Z_{b,t-1} + \epsilon_{b,t} \tag{3}$$

As dependent variables we use two bank-level measures of shock transmission that we construct at daily frequency. The first captures how much shocks to the required rate of return on a bank's equity are affected by shocks to these rates for other banks (we refer to this as *from*-connectedness). The second captures how much shocks to the required rate of return on a bank's equity affect the shocks to these rates for other banks (we refer to this as *to*-connectedness). In other words, the two measures capture the amount of shocks banks receive from, and transmit to the system, respectively. We include the same set of control variables as in the previous subsection.

To obtain the measures of shock transmission, we use a structural approach through a time-varying parameter vector autoregression, as the variance decomposition of such a model provides useful information about the transmission of shocks and hence about possible linkages (Diebold and Yilmaz, 2012). The intuition is that a shock to investors' required rate of return for one bank may be transmitted to other banks. Moreover, such shocks may be heterogeneously persistent and thus propagate across banks at different horizons, creating heterogeneously persistent linkages. Here, we follow Baruník and Křehlík (2018), who use the frequency response of shocks and identify the persistence of linkages.

We work with two levels of shock persistence. A transitory, rapidly dissipating shock to investors' expectations, and a more persistent shock, which in the case of equity is associated with persistent changes in expectations about future dividends (Balke and Wohar, 2002; Baruník and Křehlík, 2018). Hence, we expect β to be positive for persistent shocks indicating that, following the introduction of the restrictions, the persistent shocks became more intense for treated banks. Details about how we infer these measures from the data are provided in Appendix E.

4.3 Lending volumes

4.3.1 Baseline

To examine how banks react in the face of regulatory distribution restrictions and investors' pressure on their funding costs, we use a triple DiD regression using the bank-borrower-time panel. We start by regressing the logarithm of the loan volume issued by bank b to borrower i in quarter t on a treatment dummy $D_{b,t}$, which takes the value of 1 for banks in the treated group after they become treated (2020:Q2 onwards). We also include the $More_exposed_{b,t}$ dummy variable to assess whether restricted banks more exposed to income-oriented funds reacted differently compared to less exposed ones (*H3*):

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

where $More_exposed_{b,t}$ is a dummy variable that takes the value of 1 for banks with exposure to income-oriented funds higher than the median.[27] We expect β to be positive if restricted banks with less exposure to income-oriented funds increased their loan volumes following the introduction of distribution restrictions relative to unrestricted banks. Furthermore, we expect ξ to be negative if, relative to unrestricted banks, restricted banks with greater exposure to income-oriented funds—facing larger increases in their required return on capital—expanded lending volumes by less than their less exposed counterparts.

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-quarter fixed effects $\mu_{s,z,r,t}$ following Degryse et al. (2019). We are therefore 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 a UK region r have the same credit demand in quarter t.[28] Regions are defined according to the Classification of Territorial Units for Statistics (NUTS) of the UK.[29]

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

[27] We consider the median in the main results but in robustness we show that the effects become stronger when we use higher percentiles of the distribution.

[28] Although banks report loans at monthly frequency we group them by quarter because changes in borrower demand and bank lending strategy may not occur as frequently. Using month instead of quarter fixed effects has no significant impact on our results.

[29] 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.

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. We also include controls for other measures taken by the prudential and monetary authorities to support the real economy during the pandemic. From the prudential angle, to account for the impact of the UK Countercyclical Capital Buffer (CCyB) release,[30] 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.[31] From the monetary angle, we include the logarithm of bank cash deposited in central banks to control for the impact of QE. 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.[32]

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 liabilities to current assets as a proxy for liquidity (Martínez-Miera and Vegas, 2021).

We cluster standard errors by bank and borrowers' industry. In this panel we expect CV_1 to be severely biased because of the limited number of clusters (ten banks and nineteen industries) and the uneven number of observations (loans) within each cluster. Hence, once again we report results using WCR-S.

4.3.2 Loan and borrower characteristics

We run additional regressions to understand whether loan and borrower characteristics affected restricted banks' lending decisions. First, we test the impact of government guaranteed loans by including an additional interaction of the treatment dummy with the dummy variable $Gov_Loan_{i,b,t}$ that takes the value of 1 if the loan is government guaranteed:

[30] At the start of the pandemic the Financial Policy Committee of the Bank of England reduced the UK CCyB rate to 0% with immediate effect to support further the ability of banks to supply credit to the real economy: https://www.bankofengland.co.uk/-/media/boe/files/financial-policy-summary-and-record/2020/march-2020.pdf

[31] 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 percentage point (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.

[32] https://www.bankofengland.co.uk/markets/market-notices/2020/term-funding-scheme-market-notice-mar-2

$$Log(Volume_{i,b,t}) = \mu_b + \mu_{s,z,r,t} + \beta D_{b,t} + \xi_1 D_{b,t} More_exposed_{b,t} + \xi_2 D_{b,t} Gov_Loan_{i,b,t} + \gamma X_{b,t-1} + \delta Z_{i,t-1} + \theta_1 More_exposed_{b,t} + \theta_2 Gov_Loan_{i,b,t} + \epsilon_{i,b,t} \quad (5)$$

We expect ξ_2 to be zero if restricted banks issued government guaranteed loans of similar average volume as non-government guaranteed loans compared to unrestricted banks, or positive if they had incentives to issue larger volumes. This could occur for example if restricted banks facing higher funding costs issued larger government guaranteed loans that had low or zero credit risk for them and hence small capital impact.

Second, we test whether restricted banks reacted differently for smaller loans which would have a smaller capital impact. We interact the treatment dummy with the dummy variable $Large_Loan_{i,b,t}$ that takes the value of 1 if the loan is larger than £50,000:

$$Log(Volume_{i,b,t}) = \mu_b + \mu_{s,z,r,t} + \beta D_{b,t} + \xi_1 D_{b,t} More_exposed_{b,t} + \xi_2 D_{b,t} Gov_Loan_{i,b,t} + \xi_3 D_{b,t} Large_Loan_{i,b,t} + \gamma X_{b,t-1} + \delta Z_{i,t-1} + \theta_1 More_exposed_{b,t} + \theta_2 Gov_Loan_{i,b,t} + \theta_3 Large_Loan_{i,b,t} + \epsilon_{i,b,t} \quad (6)$$

We expect ξ_3 to be negative if restricted banks faced an increase in the required rate of return on their capital which could result in a smaller increase in the volume of larger loans (vis-a-vis smaller loans), compared to those issued by unrestricted banks.

Lastly, we examine whether banks extended differential credit to the cross-section of SMEs by categorising each firm to micro, small or medium according to the UK government's definition.[33] Specifically, we categorise a borrower as micro if it has less than 10 employees, and annual turnover or balance sheet total of less than €2 million; as small if it has less than 50 employees, and annual turnover or balance sheet total of less than €10 million; and as medium if it has less than 250 employees and annual turnover of less than €50 million or balance sheet total of less than €43 million.[34] We create dummies for each category and interact them with the treatment dummy:

[33] https://www.gov.uk/government/publications/beis-small-and-medium-enterprises-sme-action-plan-2022-t beis-small-and-medium-enterprises-smes-action-plan-2022-to-2025-accessible-webpage# definition-of-an-sme

[34] Note that not all firms strictly adhere to these criteria in our sample, so there are some that are larger (the largest firm has total assets of £174 million).

$$Log(Volume_{i,b,t}) = \mu_b + \mu_{s,z,r,t} + \beta D_{b,t} + \xi_1 D_{b,t} More_exposed_{b,t} + \xi_2 D_{b,t} Gov_Loan_{i,b,t} + \xi_3 D_{b,t} Large_Loan_{i,b,t} + \xi_4 D_{b,t} Micro_SME_{i,t} + \xi_5 D_{b,t} Small_SME_{i,t} + \xi_6 D_{b,t} Medium_SME_{i,t} + \gamma X_{b,t-1} + \delta Z_{i,t-1} + \theta_1 More_exposed_{b,t} + \theta_2 Gov_Loan_{i,b,t} + \theta_3 Large_Loan_{i,b,t} + \theta_4 Micro_SME_{i,t} + \theta_5 Small_SME_{i,t} + \theta_6 Medium_SME_{i,t} + \epsilon_{i,b,t} \quad (7)$$

We expect ξ_4 and potentially ξ_5 to be negative, given the fact that smaller firms tend to be riskier and their loans tend to incur higher capital charges for banks (Petersen and Rajan, 1994; Berger and Udell, 1995). Hence, restricted banks with higher required rate of return on their capital may have proportionally increased lending volumes to larger firms by more (Chodorow-Reich et al., 2022).

4.3.3 Real effects of banks' lending

In the final subsection we test whether banks' lending decisions affected firms' investment and hiring (*H4*). To do this, we aggregate the loan-level dataset to the borrower-quarter level. The vast majority of SMEs in our sample borrow from a single bank in any given quarter. We remove 1.4% of loan-level observations for which an SME borrows from multiple banks in the same quarter. This allows us to run the following regression:

$$Y_{i,t} = \mu_i + \mu_{z,t} + \mu_{r,t} + \beta D_{i,t} + \xi D_{i,t} More_exposed_{i,t} + \gamma X_{i,t-1} + \delta Z_{i,t-1} + \theta More_exposed_{i,t} + \epsilon_{i,t} \quad (8)$$

where $Y_{i,t}$ includes capital expenditure (in £million), the logarithm of cash and the logarithm of the number of employees of borrower i in quarter t. We include borrower, industry-quarter and region-quarter fixed effects following Bahaj et al. (2020), as well as the set of bank and borrower control variables defined previously.[35] Since each SME borrows from a single bank each quarter, which can be either in the control group, the treated less-exposed group or the treated more-exposed group with no overlap, we can include the treatment dummy and the interaction without needing to calculate the share of borrowing from each group. We run the regressions separately for loans that were government guaranteed vs. not, given that these can be issued by the same bank. We cluster standard errors at the borrower level. We

[35] We remove the borrower's liquidity when using the logarithm of cash as the dependent variable given that the latter is a subset of current assets, i.e. the denominator of the liquidity measure.

rely on the standard cluster estimator for this specification given that we have almost 50,000 borrowers in our sample.

5 Results

5.1 Price impact of mutual fund holdings

We report the results from specification (1) in Table 1, where in column (1) we show results for a simple DiD whereas in columns (2)-(4) we show results for the triple DiD for various levels of banks' exposure to income-oriented funds. The coefficient β for the treatment dummy $D_{b,t}$ is not statistically significant, which means that restricted banks less exposed to income-oriented funds did not face a differential price impact on their shares following the onset of the restrictions relative to unrestricted banks. However, the coefficient ξ for the interaction of the treatment dummy with the income-oriented fund dummy is negative and significant which means that restricted banks more exposed to income-oriented funds faced more negative abnormal returns (of between -5.9 and -10 pps) compared to less exposed restricted banks and relative to unrestricted banks over the implementation period. This effect is both economically and statistically significant. The results confirm *H1* and provide initial evidence that income-oriented investors induced a significant negative impact on banks' shares as a result of the change in the payout policy.

Table 1: This table reports the results for the cumulative abnormal return from specification (1) using different percentiles of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy with the bank-month panel. $CAR_{b,t}$ denotes the cumulative abnormal return for the share of bank b in month t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$CAR_{b,t}$			
	(1)	(2)	(3)	(4)
		Exposure > 50th percentile	Exposure > 75th percentile	Exposure > 90th percentile
$D_{b,t}$	−0.043	0.041	0.000	−0.002
	(−1.316)	(1.179)	(0.013)	(−0.064)
$D_{b,t}More_exposed_{b,t}$		−0.100***	−0.059**	−0.059**
		(−5.250)	(−2.198)	(−2.325)
Bank fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	
Observations	2,176	2,176	2,176	2,176
Adj. R^2	0.762	0.783	0.781	0.779

5.2 Required rate of return on capital

5.2.1 Magnitude

We report the results from specification (2) for shareholders' required rate of return in Table 2. The coefficient for the treatment dummy in column (1) is positive but not statistically significant, which indicates that, overall, shareholders' required rate of return for the restricted banks did not increase following the introduction of the restrictions relative to the unrestricted banks. However, the triple interaction coefficient is statistically significant across all three columns (2)-(4) which indicates that banks more exposed to income-oriented funds faced an increase in their shareholders' required rate of return by up to 1.7 pps compared to less exposed ones. This pattern is consistent with the results on the price impact presented in Table 1 where only banks more exposed to income-oriented funds faced a relative negative impact on their valuations.

Table 2: This table reports the results for the shareholders' required rate of return from specification (2) using different percentiles of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy (columns 2-4) with the bank-month panel. $COE_{b,t}$ denotes the shareholders' required rate of return for bank b in month t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$COE_{b,t}$			
	(1)	(2)	(3)	(4)
		Exposure > 50th percentile	Exposure > 75th percentile	Exposure > 90th percentile
$D_{b,t}$	0.024	0.012	0.016	0.017
	(2.886)	(1.427)	(1.748)	(1.895)
$D_{b,t}More_exposed_{b,t}$		0.013**	0.017***	0.017***
		(2.528)	(2.978)	(2.927)
Bank fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	1,699	1,699	1,699	1,699
Adj. R^2	0.717	0.724	0.730	0.728

Moving to debtholders' required rate of return in Table 3, we observe that the coefficient for the treatment dummy is negative and significant at the 10% level. This provides evidence that restricted banks faced a relaxation in their debt funding costs, of 0.7 pp relative to unrestricted banks. Further, separating the restricted banks into those less and more exposed to income-oriented funds reveals that there was no differential impact on their debt funding costs (as evidenced by the insignificant triple interaction coefficient in columns (2)-(4)).

Table 3: This table reports the results for the debtholders' required rate of return from specification (2) using different percentiles of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy (columns 2-4) with the bank-month panel. $COD_{b,t}$ denotes the debtholders' required rate of return for bank b in month t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$COD_{b,t}$			
	(1)	(2)	(3)	(4)
		Exposure > 50th percentile	Exposure > 75th percentile	Exposure > 90th percentile
$D_{b,t}$	−0.007*	−0.007*	−0.007*	−0.007*
	(−2.659)	(−2.104)	(−2.331)	(−2.292)
$D_{b,t}More_exposed_{b,t}$		0.001	−0.001	−0.001
		(0.311)	(−0.103)	(−0.833)
Bank fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	1,699	1,699	1,699	1,699
Adj. R^2	0.834	0.836	0.838	0.836

Finally, the results on the overall required rate of return on capital are reported in Table 4. The coefficient for the treatment dummy in column (1) is not significant, which suggests that, compared to unrestricted peers, the restricted banks did not face an increase in their overall funding costs. However, delving into those more exposed banks, in columns (2)-(4), reveals that they faced an increase in their overall funding costs by up to 2 pps relative to those less exposed.[36]

[36]In Table C1 in Appendix C we decompose the main effect into monthly leads and lags; for all three specifications the joint F-test fails to reject the null of no significance of the leads which provides support for parallel trends. In Appendix D we show for robustness the results when we use interest expenses over total debt as our measure for debtholders' required rate of return. Table D1 shows that, according to this broader measure of cost of debt, restricted banks did not benefit from a significant discount relative to their unrestricted peers. This confirms our assumption that other creditors like retail depositors were less sensitive to this policy. Since the market value of the bank bonds in our sample is on average only 17% of the book value of total debt, this drowns out the negative effects we report in Table 3. However, the results for the required rate of return on capital remain positive and significant despite the relatively larger weight placed on debt as seen in Table D2.

Table 4: This table reports the results for the required rate of return on capital from specification (2) using different percentiles of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy (columns 2-4) with the bank-month panel. $COC_{b,t}$ denotes the required rate of return on capital for bank b in month t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$COC_{b,t}$			
	(1)	(2)	(3)	(4)
		Exposure > 50th percentile	Exposure > 75th percentile	Exposure > 90th percentile
$D_{b,t}$	0.012	−0.001	0.002	0.004
	(1.146)	(−0.091)	(0.144)	(0.361)
$D_{b,t}More_exposed_{b,t}$		0.016*	0.020**	0.019***
		(1.939)	(3.017)	(3.659)
Bank fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	1,699	1,699	1,699	1,699
Adj. R^2	0.822	0.829	0.836	0.834

The evidence so far highlights the story that dividend clienteles exerted considerable pressure on banks' funding costs in reaction to the change in payout policy, consistent with *H2a*. These findings are pointing in the same direction as, for instance, Andreeva et al. (2023) and Sanders et al. (2024), who find that the Covid-19 dividend bans had a significant impact on the stock market valuation of banks in the Euro area. Our evidence goes further to show that this was due to a significant rise in the risk premium demanded by dividend clienteles. Uncertainty over future payouts, especially whether bank dividends could be repeatedly banned in the future created, in effect, a new risk premium component for which investors demanded additional compensation.

5.2.2 System-wide bank interconnectedness

We next examine whether the documented effect on shareholders' required rate of return has implications for system-wide bank interconnectedness. Specifically, we investigate the persistence and evolution of shock transmission mechanisms following the introduction of the restrictions. To do so, we analyse the aggregate dynamics of cross-bank spillovers within the treated and control groups, as captured by time-varying forecast error variance decompositions of the daily required return on equity. Our analysis distinguishes between transitory shocks (lasting up to 20 business days) and persistent shocks (extending beyond 20 business days), thereby allowing us to assess the temporal structure of interconnectedness in response

to the regulatory intervention.

In Figure 3, we plot the transitory and persistent interconnectedness of shareholders' required rate of return for the treated and control groups. Intuitively, we would expect that the linkages formed by transitory shocks would dominate in periods when financial markets process information rapidly, and shocks to one bank's required rate of return would only have a short-term impact on other banks. 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 shown in Figure 3, the persistent component of the required return on equity for treated banks is consistently dominated by the transitory component, with the former exhibiting approximately half the magnitude of the latter from the beginning of the sample period in 2018 up to the onset of the Covid-19 crisis in March 2020. Importantly, the role of persistent shocks changes in March 2020, when the impact of the pandemic hits the markets in the dash-for-cash episode. Interconnections based on persistent shocks became as important as those based on transitory shocks. In addition, the degree of interconnectedness tends to increase over time. In contrast, banks in the control group remain roughly unconnected throughout the sample period, which implies that there is very little shock transmission. This suggests that the restrictions increased the transmission of shocks between shareholders' required rate of return for the treated banks, in addition to their impact on the levels as documented in the previous subsection.

Next, we assess the significance of the change in linkages for the required rate of return observed in the plot. To do so, we estimate a DiD with the disaggregated shock transmission variables (*from*- and *to*-connectedness) introduced in subsection 4.2.2 as dependent variables for transitory and persistent shocks. The results for shareholders' required rate of return are reported in Table 5.

In general, the previously identified pattern remains. We observe a significant increase in the reception and transmission of persistent shocks to shareholders' required rate of return for the treated group. Measured against overall means (seen in Table B3), the DiD coefficients suggest an increase of 35% for recipients of persistent shocks, and 53% for transmitters. This is in line with *H2b* that dividend restrictions led to a higher long-term interconnectedness of restricted banks. This overall change in expectations about future dividends illustrates why the increase in the risk premium described in the previous section is so widespread and persistent in the European banking system during the sample period.

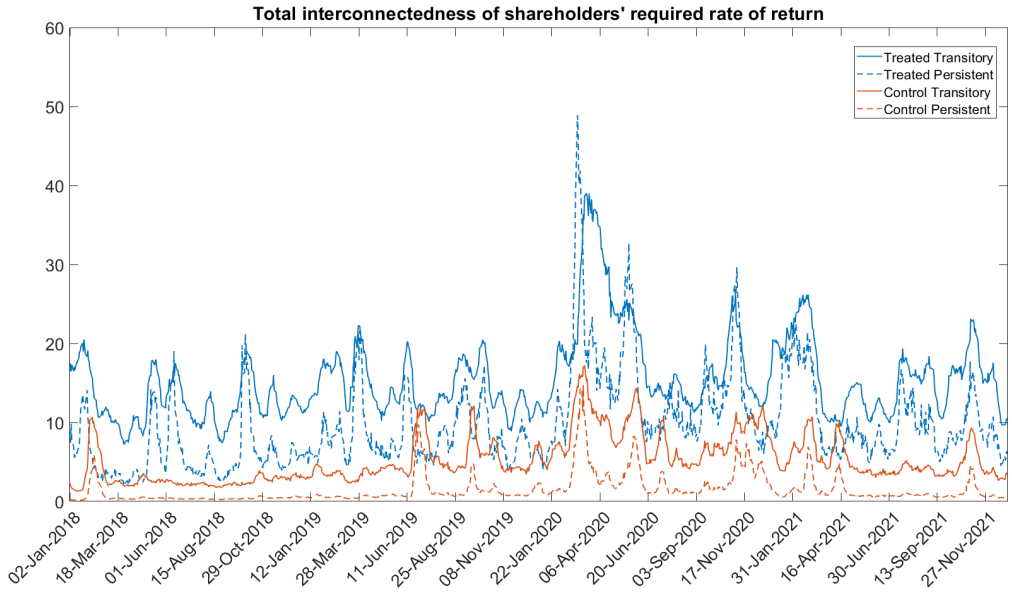


Figure 3: Total interconnectedness of shareholders' required rate of return. The graph presents the total interconnectedness measure for transitory (≤20 business days) and persistent (>20 business days) shock propagation, for treated and control groups of banks respectively.

Table 5: This table reports the results for the directional connectedness of banks' shareholders' required rate of return. $From_transitory_{b,t}$ and $From_persistent_{b,t}$ denote the transitory and persistent shocks on the shareholders' required rate of return received by bank b in day t from other banks. $To_transitory_{b,t}$ and $To_persistent_{b,t}$ denote the transitory and persistent shocks on the shareholders' required rate of return transmitted by bank b in day t to other banks. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$From_transitory_{b,t}$	$From_persistent_{b,t}$	$To_transitory_{b,t}$	$To_persistent_{b,t}$
	(1)	(2)	(3)	(4)
$D_{b,t}$	0.004	0.028***	0.012	0.016***
	(1.853)	(9.921)	(1.028)	(3.291)
Bank fixed effects	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	38,612	38,612	38,612	38,612
Adj. R^2	0.858	0.742	0.371	0.424

5.3 Lending volumes

5.3.1 Baseline

We start by reporting the results from specification (4) in Table 6. We find that restricted banks increased lending by more than unrestricted banks. In particular, in a simple DiD in

Table 6: This table reports the results for the lending volumes from specification (4) using the median of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy (column 2) with the bank-borrower-month panel. $Log(Volume_{i,b,t})$ denotes the logarithm of the volume of the loan issued to borrower i by bank b in quarter t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are double-clustered at the bank and borrowers' industry levels. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses and in the second panel. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$Log(Volume_{i,b,t})$	
	(1)	(2)
$D_{b,t}$	0.302**	0.403**
	(7.075)	(6.107)
$D_{b,t}More_exposed_{b,t}$		−0.188*
		(−2.675)
Sum of coefficients significance		$\beta + \xi = 0$ t-stat$_{(9)} = 3.156$ p-value $= 0.065$
Bank fixed effects	Yes	Yes
Size x Industry x Region x Quarter fixed effects	Yes	Yes
Controls	Yes	Yes
Observations	351,237	351,237
Adj. R^2	0.415	0.416

column (1), the coefficient β for the treatment dummy implies that following the introduction of the policy, restricted banks increased lending volumes by 30.2%, on average, compared to unrestricted ones.[37] This suggests that the policy fulfilled its purpose since restricted banks used the additional capital headroom to increase lending volumes. However, when we include the interaction with more exposed banks in column (2) (as described in specification (4)), we document a negative coefficient ξ for the triple interaction which is approximately half the magnitude of the baseline coefficient. This implies that more exposed restricted banks increased volumes by half as much as those less exposed relative to unrestricted banks. This is confirmed by the sum of the two coefficients in the second panel of column (2). In Table D3 in Appendix D we show that for higher percentiles of the distribution of exposure to income-oriented funds the two coefficients sum to zero, which indicates that the most exposed restricted banks did not increase their overall lending volumes compared to unrestricted banks. Hence, the results provide evidence in favour of *H3*, confirming the negative pressures that dividend clienteles exerted on banks' lending decisions.

[37] In Table C2 in Appendix C we include leads and lags for each quarter in our sample to test for the parallel trends assumption and the persistence of the effect. All leads are statistically insignificant, and the joint test for significance does not reject the null hypothesis of no significance (F-stat$_{(8,9)} = 2.03$, p-value $= 0.533$). This provides evidence for the validity of the parallel trends assumption. The lags are statistically significant at the 5% and 10% levels, and they have a similar magnitude throughout the implementation period of the restrictions.

5.3.2 Loan and borrower characteristics

In this subsection we investigate how loan and borrower characteristics influenced banks' lending decisions. First, we assess the impact of government guarantees, by reporting the results from specification (5) in column (1) of Table 7. The coefficient β for the treatment dummy is no longer significant, which suggests that less exposed restricted banks did not increase the volumes of non-government guaranteed loans compared to unrestricted banks. The coefficient ξ_2 for the triple interaction with the government guaranteed loan dummy is positive but not statistically significant. This implies that, relative to unrestricted banks, restricted banks with lower exposure to income-oriented funds issued government guaranteed loans in volumes comparable to those of non-guaranteed loans. However, the sum of the coefficients $\beta + \xi_2$ is statistically significant as seen in the second panel of column (1), suggesting that less exposed restricted banks increased the volume of government guaranteed loans compared to unrestricted banks. Interestingly, the coefficient for the triple interaction with banks more exposed to income-oriented funds, ξ_1, remains negative and significant, which means that these banks increased lending at a lower rate compared to less exposed banks and relative to unrestricted banks, including in the government guaranteed segment. This is seen in the second panel of column (1), where the sum of the coefficients $\beta + \xi_1 + \xi_2$ has lower statistical significance. This could be explained by larger loans worth more than £50,000 which were not 100% guaranteed by the government so they still carried credit risk and capital cost for the banks.

To examine this conjecture, in column (2) we further differentiate loans by size using specification (6). The coefficient β for the treatment dummy is now positive and significant, which indicates that less exposed restricted banks increased the volume of smaller non-government guaranteed loans worth up to £50,000 compared to unrestricted banks. The coefficient ξ_1 for the triple interaction with more exposed banks is no longer significant, which means that those restricted banks increased the volumes of smaller non-government guaranteed loans to a similar extent as less exposed restricted banks.[38] The coefficient ξ_3 for the triple interaction with large loans worth more than £50,000 is negative, significant and similar in size to β. This suggests that restricted banks did not increase the volumes of larger non-government guaranteed loans compared to unrestricted banks. This is confirmed by the sum of the coefficients $\beta + \xi_3$ in the second panel of column (2), which is insignificant. The sum $\beta + \xi_2 + \xi_3$ is still significant, which indicates that restricted banks increased the volumes of larger government guaranteed loans compared to the unrestricted banks, although at a lower rate to smaller government guaranteed loans.

[38] Although, in unreported results we find that for higher levels of exposure (75th and 90th percentiles), the coefficient ξ_1 remains negative and significant and completely counteracts the baseline coefficient β.

Finally, we report the results from specification (7) in column (3) where we differentiate between borrower size. Since we control for micro, small and medium-sized firms, the baseline is larger firms that do not strictly adhere to the UK government's definition of SMEs. The coefficient β for the treatment dummy is positive and significant, which indicates that less exposed restricted banks increased the volumes of smaller non-government guaranteed loans to large firms compared to unrestricted banks. The coefficients ξ_4 and ξ_5 for micro and small SMEs are negative and significant. This suggests that, relative to unrestricted banks, restricted banks did not expand the volume of smaller non-government-guaranteed loans to the same extent as they did for larger firms. In fact the sums of the coefficients $\beta + \xi_4$ and $\beta + \xi_5$ in the second panel of column (3) are insignificant, which means that these firms did not benefit from higher volumes of smaller non-government guaranteed loans (compared to unrestricted ones). In contrast, the coefficient ξ_6 for medium-sized SMEs is insignificant, which means that these firms benefited from higher volumes of smaller non-government guaranteed loans by restricted banks.

To summarise, our findings reveal that clientele pressure mattered less for loans that were smaller in size, even if not government guaranteed and when issued to larger firms, which tend to be more creditworthy. These are loans that carry smaller capital charges so the results indicate that clientele pressure led banks to selectively increase loan volumes in a way that would not be capital intensive.

5.3.3 Real effects of banks' lending

In the final subsection we examine the effects on firm planning, i.e. investment and hiring decisions. We report the results from specification (8) for the three variables of interest, capital expenditure, cash, and number of employees in Table 8. We first look at firms that obtained non-government guaranteed loans in Panel A. From column (1), the coefficient for the treatment dummy is positive and significant (at 0.032), meaning that firms that borrowed from less exposed restricted banks increased their capital expenditure by, on average, £32,000 relative to firms that borrowed from unrestricted banks. Given the sample average of £80,000, highlighted in Table B3, this is a significant increase. However, the triple interaction coefficient is negative and significant at -0.017, and the sum of the two is insignificant, as seen in the second panel. This implies that firms that borrowed from more exposed restricted banks did not increase their capital expenditure relative to firms that borrowed from unrestricted banks. These results are in line with the higher increase in lending volumes by less exposed restricted banks relative to more exposed ones, observed in Table 6. This suggests that firms used these additional funds to invest in long-term assets rather than to satisfy immediate liquidity needs, confirming *H4*. This is further confirmed by looking at column (2) where we

Table 7: This table reports the results for the lending volumes from specifications (5) - (7) in columns (1) - (3) respectively with the bank-borrower-month panel. $Log(Volume_{i,b,t})$ denotes the logarithm of the volume of the loan issued to borrower i by bank b in quarter t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. $More_exposed_{b,t}$ denotes banks more exposed to income-oriented funds than the median, $Gov_Loan_{i,b,t}$ denotes government guaranteed loans, $Large_Loan_{i,b,t}$ denotes loans lager than £50,000, and $Micro_SME_{i,t}$, $Small_SME_{i,t}$ and $Medium_SME_{i,t}$ denote micro, small and medium-sized SME borrowers respectively. Standard errors are double-clustered at the bank and borrowers' industry levels. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses and in the second panel. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$Log(Volume_{i,b,t})$		
	(1)	(2)	(3)
$D_{b,t}$	0.216	0.495*	0.551*
	(0.790)	(2.557)	(2.982)
$D_{b,t}More_exposed_{b,t}$	−0.190*	−0.024	−0.009
	(−2.548)	(−0.624)	(−0.193)
$D_{b,t}Gov_Loan_{i,b,t}$	0.413	0.661	0.785
	(2.458)	(3.681)	(3.998)
$D_{b,t}Large_Loan_{i,b,t}$		−0.449*	−0.477**
		(−2.492)	(−2.799)
$D_{b,t}Micro_SME_{i,t}$			−0.548**
			(−3.280)
$D_{b,t}Small_SME_{i,t}$			−0.298*
			(−2.613)
$D_{b,t}Medium_SME_{i,t}$			0.016
			(0.538)
Sum of coefficients significance	$\beta + \xi_2 = 0$	$\beta + \xi_3 = 0$	$\beta + \xi_4 = 0$
	$t\text{-stat}_{(9)} = 6.508$	$t\text{-stat}_{(9)} = 0.717$	$t\text{-stat}_{(9)} = 0.013$
	$p\text{-value} = 0.029$	$p\text{-value} = 0.529$	$p\text{-value} = 0.995$
	$\beta + \xi_1 + \xi_2 = 0$	$\beta + \xi_2 + \xi_3 = 0$	$\beta + \xi_5 = 0$
	$t\text{-stat}_{(9)} = 5.382$	$t\text{-stat}_{(9)} = 3.847$	$t\text{-stat}_{(9)} = 1.004$
	$p\text{-value} = 0.037$	$p\text{-value} = 0.081$	$p\text{-value} = 0.369$
Bank fixed effects	Yes	Yes	Yes
Size x Industry x Region x Quarter fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	351,237	351,237	351,237
Adj. R^2	0.418	0.670	0.675

observe no significant effect on firms' cash balances. Furthermore, firms did not use these funds to increase their headcount as seen in column (3), which is intuitive given the presence of the government furlough scheme at the time which provided funds to cover employees' salaries but only applied to existing employees.

In Panel B, we report the results for firms that obtained government-guaranteed loans. There was no difference in firms' capital expenditure or number of employees as a result of borrowing from less exposed restricted banks relative to unrestricted banks, or from more exposed restricted banks relative to less exposed. We observe a negative and insignificant coefficient for the treatment dummy and a positive and significant triple interaction coefficient when looking at cash balances. However, the sum of the two coefficients is not significant as seen in the second panel, which indicates that firms that borrowed from banks more exposed to dividend clienteles did not differentially alter their cash balances relative to firms that borrowed from unrestricted banks. Overall, the results indicate that government guaranteed loans benefited all firms to a similar degree irrespective of their lender since they had negligible capital impact.

6 Conclusion and policy implications

Banks prefer to maintain stable payouts to their shareholders to signal their financial strength and to cater to dividend clienteles. In this paper, we show that a change in their payout policy, even when mandated by the regulator, can lead to a negative reaction from dividend clienteles which in turn can influence how banks lend to the real economy.

Our findings show that the distribution restrictions imposed on banks during the Covid-19 pandemic led income-oriented funds, which act as a proxy for dividend clienteles, to exert negative pressure on the market valuation of these banks. Banks more exposed to these funds faced higher increases in the required rate of return on their capital. In response, their increase in overall lending to SMEs was smaller compared to less exposed banks. However, and similar to less exposed restricted banks, they increased volumes of smaller loans worth up to £50,000 that were issued to larger firms. This indicates that clientele pressure did influence banks' lending decisions, by prompting them to selectively increase loan volumes in a way that was not capital costly. We also show that these lending decisions had real effects: firms that borrowed from banks that were less exposed to dividend clienteles increased their capital expenditure by more relative to firms that borrowed from more exposed banks.

Our results have important policy implications. Several policies were introduced during the pandemic to increase banks' capital headroom to support the real economy. For example, regulatory authorities reduced capital requirements and existing evidence shows that this

Table 8: This table reports the results for borrowers' capital expenditure, logarithm of cash and logarithm of number of employees from specification (8) in columns (1) - (3) respectively with the borrower-quarter panel. Panel A presents results for the subsample of non-government guaranteed loans, while Panel B presents results for the subsample of government guaranteed loans. $Capital\ Expenditure_{i,t}$ denotes the capital expenditure of borrower i in quarter t calculated as the change in fixed assets plus depreciation (in £million). $Log(Cash_{i,t})$ denotes the logarithm of cash held in bank deposits by borrower i in quarter t. $Log(\#Employees_{i,t})$ denotes the logarithm of the number of employees employed by borrower i in quarter t. $D_{i,t}$ is a dummy variable taking the value of 1 for borrowers borrowing from banks in the treated group during the treatment period. $More_exposed_{i,t}$ denotes borrowers borrowing from banks more exposed to income-oriented funds than the median. Standard errors are clustered at the borrower level. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$Capital\ Expenditure_{i,t}$	$Log(Cash_{i,t})$	$Log(\#Employees_{i,t})$
	(1)	(2)	(3)
Panel A: Non-government guaranteed loans			
$D_{i,t}$	0.032**	−0.008	0.003
	(2.105)	(−0.150)	(0.295)
$D_{i,t}More_exposed_{i,t}$	−0.017*	0.004	−0.004
	(−1.746)	(0.125)	(−0.615)
Sum of coefficients significance	$\beta + \xi = 0$ $F\text{-stat}_{(1,20111)} = 0.98$ $p\text{-value} = 0.322$		
Borrower fixed effects	Yes	Yes	Yes
Region x Quarter fixed effects	Yes	Yes	Yes
Industry x Quarter fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	60,358	53,640	54,015
Adj. R^2	0.802	0.884	0.989
Panel B: Government guaranteed loans			
$D_{i,t}$	−0.000	−0.760	0.000
	(−0.002)	(−1.312)	(0.001)
$D_{i,t}More_exposed_{i,t}$	0.014	0.396**	−0.027
	(0.443)	(2.444)	(−0.677)
Sum of coefficients significance		$\beta + \xi = 0$ $F\text{-stat}_{(1,3587)} = 0.35$ $p\text{-value} = 0.553$	
Borrower fixed effects	Yes	Yes	Yes
Region x Quarter fixed effects	Yes	Yes	Yes
Industry x Quarter fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	8,955	7,192	7,857
Adj. R^2	0.838	0.952	0.993

helped banks to increase lending (Couaillier et al., 2022; Mathur et al., 2023). The rationale is that banks with higher capital headroom are less likely to constrain credit supply (Berrospide et al., 2024; Couaillier et al., 2024). However, while reduction in capital requirements does not directly affect banks' liability structure, this is not the case with distribution restrictions. Our results show the effect is material for credit supply, since investor pressure can determine banks' response to the policy. Policymakers need to consider how different policies affect banks' balance sheets in order to ensure that they achieve their intended purpose.

In addition, our findings shed light on the distributional effects of the policy. Restricted banks preferred to use the capital headroom to increase lending to larger firms, at the expense of smaller ones. Yet those are the ones that most rely on bank credit. While government guarantees were effective at unlocking credit to these firms, policymakers will need to carefully consider how to best incentivise banks to support smaller firms in a future crisis, especially if government guarantees are not available. At the same time, policymakers should consider how to broaden SMEs' access to credit during times of stress.

Our paper provides several avenues for future research. From a theoretical perspective, it would be beneficial to uncover the mechanisms through which regulatory distribution restrictions affect banks' business models, and quantify their welfare effects. While crisis-time restrictions imply a dividend deferral rather than cut (and hence a short-term effect on valuations (Ampudia et al., 2023)), if investors believe this policy may become a formal part of the regulatory toolkit, they could price in the probability of future payout restrictions (ECB, 2022), with potential impact on lending. From an empirical perspective, given that different countries implemented different distribution restriction strategies, it would be beneficial to assess whether a full ban vs. an upper limit to distributions works better to manage shareholder pressure and enables banks to support the real economy. We leave these questions for future research.

Acknowledgements

We would like to thank Paolo Fulghieri, James G. MacKinnon, Aakriti Mathur, Salvatore Miglietta, Eva Mulder, Ioana Neamtu, Anil Shivdasani, Frank Smets, Anjan Thakor, Neeltje van Horen and participants at the 2025 Money, Macro and Finance conference, the 2025 IBEFA Summer Meetings of the WEAI, the EFiC 2025 conference in Banking and Corporate Finance, the Royal Economic Society 2024 Annual Conference and the Conference on Frontier Risks, Financial Innovation and Prudential Regulation of Banks at Gothenburg University for their valuable comments.

References

Acharya, V. V., I. Gujral, N. Kulkarni, and H. S. Shin (2011). Dividends and bank capital in the financial crisis of 2007-2009. NBER Working Paper No. 16896.

Acharya, V. V., H. T. Le, and H. S. Shin (2017). Bank Capital and Dividend Externalities. *The Review of Financial Studies 30*(3), 988–1018.

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.

Ampudia, M., M. A. Muñoz, F. Smets, and A. Van der Ghote (2023). System-wide dividend restrictions: evidence and theory. BIS Working Paper No. 1131.

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.

Bahaj, S., A. Foulis, and G. Pinter (2020). Home values and firm behavior. *American Economic Review 110*(7), 2225–2270.

Baker, M., S. Nagel, and J. Wurgler (2007). The Effect of Dividends on Consumption. Brookings Papers on Economic Activity.

Baker, M. and J. Wurgler (2004). A catering theory of dividends. *Journal of Finance 59*(3), 1125–1165.

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.

Banks, W. and D. Walker (2021). What types of businesses have used government-guaranteed loan schemes? Available at https://www.bankofengland.co.uk/bank-overground/2021/what-types-of-businesses-have-used-government-guaranteed-loan-schemes. Bank Overground, Bank of England.

Baruník, J. and M. Ellington (2024). Persistence in financial connectedness and systemic risk. *European Journal of Operational Research 314*(1), 393–407.

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

Batten, J., T. Choudhury, H. Kinateder, and N. Wagner (2023). Volatility impacts on the European banking sector: GFC and COVID-19. *Annals of Operations Research 330*, 335–360.

Becker, B., Z. Ivković, and S. Weisbenner (2011). Local Dividend Clienteles. *Journal of Finance 66*(2), 655–683.

Berger, A. N. and G. F. Udell (1995). Relationship Lending and Lines of Credit in Small Firm Finance. *Journal of Business 68*(3), 351–381.

Berrospide, J. M., A. Gupta, and M. P. Seay (2024). The Usability of Bank Capital Buffers and Credit Supply Shocks at SMEs during the Pandemic. *International Journal of Central Banking 20*(3), 185–255.

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

Black, F. and M. Scholes (1974). The effects of dividend yield and dividend policy on common stock prices and returns. *Journal of Financial Economics 1*(1), 1–22.

Cáceres, E. and M. Lamas (2023). Dividend restrictions and search for income. Banco de España Working Paper No. 2332.

Calomiris, C. W. and D. Nissim (2014). Crisis-related shifts in the market valuation of banking activities. *Journal of Financial Intermediation 23*(3), 400–435.

Chodorow-Reich, G., O. Darmouni, S. Luck, and M. Plosser (2022). Bank liquidity provision across the firm size distribution. *Journal of Financial Economics 144*(3), 908–932.

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., M. L. Duca, A. Reghezza, and C. R. d'Acri (2024). Caution: Do Not Cross! Distance to Regulatory Capital Buffers and Corporate Lending in a Downturn. *Journal of Money, Credit and Banking*.

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.

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 (2023). Two-Way Fixed Effects and Differences-in-Differences with Heterogeneous Treatment Effects: A Survey. *Econometrics Journal 26*(3), C1–C30.

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).

Demirgüç-Kunt, A. and H. Huizinga (2004). Market discipline and deposit insurance. *Journal of Monetary Economics 51*(2), 375–399.

di Patti, E. B., M. Moscatelli, and S. Pietrosanti (2023). The impact of bank regulation on the cost of credit: Evidence from a discontinuity in capital requirements. *Journal of Financial Intermediation 53*, 101040.

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.

Financial Times (2020). Hong Kong investors warn of legal action over HSBC dividends. https://www.ft.com/content/3681a998-8164-4fd1-a5e5-ae54f56a3b70.

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.

Gambacorta, L., T. Oliviero, and H. S. Shin (2023). Low price-to-book ratios and bank dividend payouts: economic policy implications. *Economic Policy 38*(115), 675–701.

Gambacorta, L. and H. S. Shin (2018). Why bank capital matters for monetary policy. *Journal of Financial Intermediation 35*, 17–29.

Graham, J. R. and A. Kumar (2006). Do dividend clienteles exist? Evidence on dividend preferences of retail investors. *Journal of Finance 61*(3), 1305–1336.

Hansen, B. E. (2025). Standard errors for difference-in-difference regression. *Journal of Applied Econometrics*.

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.

Kovner, A. and P. Van Tassel (2022). Evaluating regulatory reform: Banks' cost of capital and lending. *Journal of Money, Credit and Banking 54*(5), 1313–1367.

Kroen, T. (2022). Payout Restrictions and Bank Risk-Shifting. Available at SSRN 4057374.

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. *The Review of Financial Studies 34*(4), 1907–1951.

Li, W. and E. Lie (2006). Dividend changes and catering incentives. *Journal of Financial Economics 80*(2), 293–308.

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

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

MacKinnon, J. G., M. Ø. Nielsen, and M. D. Webb (2023b). Fast and reliable jackknife and bootstrap methods for cluster-robust inference. *Journal of Applied Econometrics 38*(5), 671–694.

MacKinnon, J. G., M. Ø. Nielsen, and M. D. Webb (2023c). Leverage, influence, and the jackknife in clustered regression models: Reliable inference using summclust. *The Stata Journal 23*(4), 942–982.

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). Creditable capital: macroprudential regulation and bank lending in stress. Bank of England Staff Working Paper No. 1011.

Michelangeli, V. and E. Sette (2016). How Does Bank Capital Affect the Supply of Mortgages? Evidence from a Randomized Experiment. BIS Working Paper No. 557.

Miller, M. H. (1995). Do the M&M propositions apply to banks? *Journal of Banking & Finance 19*(3-4), 483–489.

Miller, M. H. and F. Modigliani (1961). Dividend Policy, Growth, and the Valuation of Shares. *The Journal of Business 34*(4), 411–433.

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.

Morgan, D. P. (2002). Rating banks: Risk and uncertainty in an opaque industry. *American Economic Review 92*(4), 874–888.

Mücke, C. (2023). Bank Dividend Restrictions and Banks' Institutional Investors. Available at SSRN 4498119.

Myers, S. C. and N. S. Majluf (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics 13*(2), 187–221.

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

Petersen, M. A. and R. G. Rajan (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance 49*(1), 3–37.

Petrova, K. (2019). A quasi-Bayesian local likelihood approach to time varying parameter VAR models. *Journal of Econometrics 212*(1), 286–306.

Sanders, E., M. Simoens, and R. V. Vennet (2024). Curse and blessing: the effect of the dividend ban on euro area bank valuations and syndicated lending. *Journal of Banking & Finance 163*, 107190.

Shefrin, H. M. and M. Statman (1984). Explaining investor preference for cash dividends. *Journal of Financial Economics 13*(2), 253–282.

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

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 98 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	85	10.28	0.62	0.001	0.09	0.16	0.43
Control	13	9.54	0.69	0.001	0.08	0.15	0.39
Δ		0.74	-0.07	0.000	0.01	0.01	0.04

Table B2: List of countries. The table illustrates the countries used in this study, their respective restrictions implementation dates, the authority issuing the restrictions, the number of banks in the treated and control groups and the reason for a bank being in the control group.

Country	**Restrictions implementation date**	**Regulatory authority issuing restrictions**	**# treated banks**	**# control banks**	**Reason for control***
Austria	27/03/2020	ECB	4	0	–
Belgium	27/03/2020	ECB	1	0	–
Czech Republic	16/03/2020	CNB	1	0	–
Denmark	16/03/2020	Finanstilsynet	3	2	No planned dividend
Estonia	27/03/2020	ECB	0	1	Dividend pre-approved
Finland	27/03/2020	ECB	2	1	Dividend pre-approved
France	27/03/2020	ECB	3	0	–
Germany	27/03/2020	ECB	5	2	Dividend pre-approved; No planned dividend
Greece	27/03/2020	ECB	0	1	No planned dividend
Hungary	19/03/2020	MNB	1	0	–
Italy	27/03/2020	ECB	12	0	–
Lithuania	27/03/2020	ECB	1	0	–
Malta	27/03/2020	ECB	1	0	–
Netherlands	27/03/2020	ECB	3	0	–
Norway	25/03/2020	Finanstilsynet	20	2	No planned dividend
Poland	26/03/2020	KNF	6	1	No planned dividend
Portugal	27/03/2020	ECB	1	0	–
Republic of Ireland	27/03/2020	ECB	2	1	No planned dividend
Romania	27/03/2020	NBR	2	0	–
Spain	27/03/2020	ECB	5	1	Dividend pre-approved
Sweden	26/03/2020	Finansinspektionen	2	0	–
United Kingdom	31/03/2020	PRA	10	1	No planned dividend

*Dividend pre-approved: The dividend was approved in the annual general meeting prior to the introduction of restrictions and hence was paid; No planned dividend: The bank did not plan to make any dividend payments and hence was not affected by the restrictions.

Table B3: Summary statistics for the variables used in the study. 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 (%)	1,825	10.96	3.29	2.11	8.58	10.94	13.43	19.57
Debtholders' required rate of return (%) (bond yields)	1,825	1.04	0.97	−0.47	0.31	0.82	1.70	5.35
Debtholders' required rate of return (%) (interest exp/total debt)	1,279	0.95	1.47	0.01	0.34	0.67	1.11	19.55
Required rate of return on capital (%)	1,825	6.97	3.59	0.29	3.83	6.72	9.44	16.60
Assets (£million)	1,825	378,312	536,456	470	31,632	115,726	543,937	2,384,009
Deposits (£million)	1,825	204,228	272,161	312	9,406	73,045	333,692	1,304,415
Loan loss provisions (£million)	1,784	220	461	−810	5	51	199	3,472
Gross loans (£million)	1,825	185,435	229,929	419	21,896	79,429	283,896	911,826
CET1 ratio (%)	1,825	15.05	2.37	10.98	13.40	14.63	16.51	24.80
CET1 capital (£million)	1,825	22,053	29,798	49	2,311	9,387	36,887	154,085
Return on Equity (%)	1,825	6.97	6.93	−44.39	4.26	7.62	10.37	62.94
Corporate loan ratio (%)	1,768	45.09	15.32	0.00	37.94	44.78	52.13	94.00
QE holdings (£million)	1,825	1,296,342	996,980	0	22,743	1,590,048	1,845,692	3,183,341
Policy rate (%)	1,825	−0.11	0.54	−0.75	−0.46	−0.36	0.48	2.25
GDP growth (%)	1,825	−0.05	6.03	−21.49	−2.10	0.89	2.04	24.60
CPI (%)	1,825	1.44	1.09	−2.32	0.72	1.43	2.14	5.22
Unemployment rate (%)	1,825	7.34	4.13	1.70	4.10	5.40	9.80	19.10
Sovereign CDS spread (%)	1,825	0.46	0.60	0.05	0.08	0.17	0.59	4.58
Country stock index volatility (%)	1,825	6.72	0.27	2.07	4.48	5.73	8.72	17.38
New Covid cases	1,825	2,085	5,766	0	0	0	783	61,654
Income-oriented fund share holdings (%)	118,852	0.09	0.29	0.00	0.002	0.01	0.04	5.95
Income-oriented fund banks' exposure (all) (%)	1,183	4.85	3.86	0.00	1.48	4.22	7.35	16.17
Income-oriented fund banks' exposure (treated) (%)	1,095	5.00	3.94	0.00	1.37	4.41	7.57	16.17
Income-oriented fund banks' exposure (control) (%)	88	3.03	2.00	0.00	1.58	2.23	4.11	7.17
From-connectedness (Transitory - Shareholders' RRoR)	43,159	0.13	0.06	0.009	0.10	0.13	0.16	0.49
From-connectedness (Persistent - Shareholders' RRoR)	43,159	0.08	0.06	0.001	0.03	0.06	0.11	0.49
To-connectedness (Transitory - Shareholders' RRoR)	43,159	0.08	0.08	0.001	0.03	0.05	0.10	0.50
To-connectedness (Persistent - Shareholders' RRoR)	43,159	0.03	0.04	0.001	0.01	0.02	0.04	0.48
From-connectedness (Transitory - Debtholders' RRoR)	67,825	0.15	0.07	0.01	0.11	0.14	0.18	0.50
From-connectedness (Persistent - Debtholders' RRoR)	67,825	0.10	0.09	0.001	0.02	0.06	0.15	0.50
To-connectedness (Transitory - Debtholders' RRoR)	67,825	0.09	0.09	0.001	0.03	0.06	0.12	0.50
To-connectedness (Persistent - Debtholders' RRoR)	67,825	0.04	0.05	0.001	0.01	0.02	0.05	0.48
Panel B: UK (Experian) sample								
Loan volume (all) (£)	396,545	76,016	169,282	5,001	22,810	50,000	50,000	2,988,570
Loan volume (government guaranteed) (£)	277,319	49,975	83,119	5,001	23,000	50,000	50,000	2,900,000
Loan volume (non-government guaranteed) (£)	119,226	136,586	272,022	5,001	22,691	50,000	126,281	2,988,570
SME total assets (£million)	396,545	1.034	2.504	0.001	0.046	0.204	0.904	174.000
Profit & Loss account (£million)	393,510	0.327	1.137	−57.923	0.000	0.028	0.243	75.341
Capital/Assets (%)	396,545	0.720	3.052	0.000	0.004	0.025	0.191	38.970
Log(Current liabilities/Current assets)	393,763	6.782	1.078	−6.786	6.251	6.744	7.155	15.378
Bank total assets (£million)	395,472	1,121,722	511,195	22	806,887	869,500	1,429,576	2,360,569
Deposits (£million)	395,472	569,176	311,376	17	427,773	462,400	494,593	1,304,415
Loan loss provisions (£million)	395,472	1,180	897	−797	284	1,430	2,056	3,472
Gross loans (£million)	395,472	465,014	205,606	15	341,126	382,088	518,718	911,826
CET1 ratio (%)	395,472	15.04	1.36	10.81	13.84	14.58	16.19	32.56
CCyB pass-through (%)	395,472	68.66	24.23	18.93	49.22	73.10	89.33	100.00
TFSME drawdown (£million)	395,472	403	1,310	0.000	0.000	0.000	0.000	7,000
Central bank deposits (£million)	395,472	111,575	68,079	4	73,998	82,959	151,000	292,000
Income-oriented fund banks' exposure (all) (%)	378,880	1.82	0.77	0.33	1.60	2.01	2.39	3.26
SME capital expenditure (£million)	345,382	0.08	0.28	−1.00	0.00	0.002	0.04	3.00
SME cash (£)	322,219	162.53	833.25	0.00	6.00	30.00	115.00	146,166
SME number of employees	305,942	17.77	69.95	1.00	2.00	5.00	16.00	9,525

C Difference-in-differences leads and lags

Table C1: This table reports the results for the shareholders' required rate of return $COE_{b,t}$ (column 1), the debtholders' required rate of return $COD_{b,t}$ (column 2) and the required rate of return on capital $COC_{b,t}$ (column 3) from the decomposition of the treatment dummy in specification (2) into monthly leads and lags from January 2018 to September 2021. $Treated_b$ is a dummy variable taking the value of 1 if bank b belongs to the treated group. Jan_18_t to Sep_21_t are dummy variables taking the value of 1 in the corresponding month. March 2020 acts as the baseline. Treatment starts in Apr_20_t. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)
Dependent Variable:	$COE_{b,t}$	$COD_{b,t}$	$COC_{b,t}$
$Treated_b$ * Jan_18_t	0.021	0.008	0.000
	(1.956)	(3.234)	(0.000)
$Treated_b$ * Feb_18_t	0.016	0.007	−0.000
	(1.499)	(2.860)	(−0.054)
$Treated_b$ * Mar_18_t	−0.023	0.008	−0.006
	(−2.203)	(2.869)	(−0.787)
$Treated_b$ * Apr_18_t	−0.006	0.005*	−0.001
	(−0.603)	(2.023)	(−0.145)
$Treated_b$ * May_18_t	−0.002	0.005*	−0.001
	(−0.196)	(1.957)	(−0.174)
$Treated_b$ * Jun_18_t	−0.006	0.005*	0.000
	(−0.354)	(1.807)	(0.049)
$Treated_b$ * Jul_18_t	−0.003	0.004	0.002
	(−0.177)	(1.704)	(0.316)
$Treated_b$ * Aug_18_t	0.004	0.003	−0.001
	(0.441)	(1.254)	(−0.204)
$Treated_b$ * Sep_18_t	−0.009	0.003	−0.009
	(−1.306)	(1.308)	(−1.096)
$Treated_b$ * Oct_18_t	−0.024*	0.003	−0.016
	(−2.856)	(1.033)	(−1.760)
$Treated_b$ * Nov_18_t	−0.026*	0.003	−0.015
	(−2.710)	(1.343)	(−1.192)
$Treated_b$ * Dec_18_t	−0.022*	0.004	−0.013
	(−2.524)	(1.334)	(−1.219)
$Treated_b$ * Jan_19_t	−0.033**	0.004	−0.012
	(−3.292)	(1.140)	(−0.956)
$Treated_b$ * Feb_19_t	0.000	0.003	0.006
	(0.015)	(0.544)	(0.865)
$Treated_b$ * Mar_19_t	0.009	0.002	0.011
	(0.566)	(0.545)	(1.139)
$Treated_b$ * Apr_19_t	−0.000	0.003	0.005
	(−0.028)	(1.120)	(1.014)
$Treated_b$ * May_19_t	−0.004	0.003	0.003
	(−0.243)	(0.892)	(0.614)
$Treated_b$ * Jun_19_t	−0.026*	0.003	−0.015
	(−3.305)	(0.753)	(−0.809)
$Treated_b$ * Jul_19_t	−0.026	0.004	−0.019
	(−2.321)	(1.039)	(−1.020)
$Treated_b$ * Aug_19_t	−0.016	0.004	−0.013
	(−0.839)	(1.229)	(−0.832)
$Treated_b$ * Sep_19_t	−0.017	0.004	−0.011
	(−0.859)	(1.353)	(−0.651)
$Treated_b$ * Oct_19_t	−0.010	0.005	−0.010
	(−0.620)	(1.223)	(−0.772)
$Treated_b$ * Nov_19_t	−0.008	0.005	−0.012
	(−0.478)	(1.014)	(−0.969)
$Treated_b$ * Dec_19_t	−0.001	0.004	−0.007
	(−0.065)	(0.946)	(−0.865)
$Treated_b$ * Jan_20_t	0.007	0.004	−0.010
	(1.402)	(0.889)	(−1.254)
$Treated_b$ * Feb_20_t	0.007	0.000	−0.001
	(1.474)	(0.256)	(−0.554)
$Treated_b$ * Apr_20_t	0.016	−0.007	0.011
	(0.959)	(−0.877)	(1.124)
$Treated_b$ * May_20_t	0.029	−0.008	0.012
	(1.518)	(−1.325)	(1.451)
$Treated_b$ * Jun_20_t	0.024	−0.007	0.009
	(1.139)	(−1.533)	(1.238)
$Treated_b$ * Jul_20_t	0.027	−0.005	0.006
	(1.429)	(−1.291)	(0.991)
$Treated_b$ * Aug_20_t	0.022	−0.003	0.007
	(1.218)	(−1.108)	(1.123)
$Treated_b$ * Sep_20_t	0.015	−0.003	0.006
	(0.781)	(−1.276)	(0.972)
$Treated_b$ * Oct_20_t	0.016	−0.003	0.008
	(0.774)	(−1.335)	(1.227)
$Treated_b$ * Nov_20_t	0.012	−0.002	0.010
	(0.489)	(−0.761)	(1.718)
$Treated_b$ * Dec_20_t	0.020	−0.002	0.002
	(1.119)	(−1.198)	(0.466)
$Treated_b$ * Jan_21_t	0.036	−0.003	0.010
	(1.711)	(−1.187)	(1.365)
$Treated_b$ * Feb_21_t	0.020	−0.003	0.004
	(0.918)	(−1.140)	(0.497)
$Treated_b$ * Mar_21_t	0.017	−0.003	0.002
	(1.004)	(−1.214)	(0.201)
$Treated_b$ * Apr_21_t	0.018	−0.002	0.006
	(1.652)	(−1.079)	(0.601)
$Treated_b$ * May_21_t	0.018	−0.002	0.004
	(1.476)	(−0.945)	(0.505)
$Treated_b$ * Jun_21_t	0.018	−0.003	0.002
	(1.370)	(−1.247)	(0.199)
$Treated_b$ * Jul_21_t	0.016	−0.003	−0.003
	(1.306)	(−1.037)	(−0.503)
$Treated_b$ * Aug_21_t	0.018	−0.004	0.001
	(1.502)	(−1.346)	(0.122)
$Treated_b$ * Sep_21_t	0.019	−0.003	−0.004
	(1.504)	(−0.986)	(−0.444)
Bank fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	1,727	1,727	1,699
Adj. R^2	0.710	0.845	0.835

Table C2: This table reports the results for the lending volumes from the decomposition of the treatment dummy in specification (4) into quarterly leads and lags from Q1 2018 to Q2 2021. $Log(Volume_{i,b,t})$ denotes the logarithm of the volume of the loan issued to borrower i by bank b in quarter t. $Treated_b$ is a dummy variable taking the value of 1 if bank b belongs to the treated group. $Q1_18_t$ to $Q2_21_t$ are dummy variables taking the value of 1 in the corresponding quarter. Q1 2020 acts as the baseline. Treatment starts in $Q2_20_t$. Standard errors are double-clustered at the bank and borrowers' industry levels. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$Log(Volume_{i,b,t})$
	(1)
$Treated_b$ * $Q1_18_t$	0.221
	(0.621)
$Treated_b$ * $Q2_18_t$	0.120
	(0.540)
$Treated_b$ * $Q3_18_t$	0.183
	(0.787)
$Treated_b$ * $Q4_18_t$	0.040
	(0.250)
$Treated_b$ * $Q1_19_t$	0.110
	(0.972)
$Treated_b$ * $Q2_19_t$	0.207
	(2.422)
$Treated_b$ * $Q3_19_t$	−0.069
	(−0.738)
$Treated_b$ * $Q4_19_t$	−0.064
	(−0.772)
$Treated_b$ * $Q2_20_t$	0.343**
	(6.036)
$Treated_b$ * $Q3_20_t$	0.340**
	(4.376)
$Treated_b$ * $Q4_20_t$	0.308*
	(3.159)
$Treated_b$ * $Q1_21_t$	0.399**
	(5.728)
$Treated_b$ * $Q2_21_t$	0.320*
	(3.590)
Bank fixed effects	Yes
Size x Industry x Region x Quarter fixed effects	Yes
Controls	Yes
Observations	351,237
Adj. R^2	0.416

D Further robustness

Table D1: This table reports the results for the debtholders' required rate of return, calculated as quarterly interest expenses over total debt, from specification (2) using different percentiles of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy (columns 2-4) with the bank-month panel. $COD_{b,t}$ denotes the debtholders' required rate of return for bank b in month t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$COD_{b,t}$			
	(1)	(2)	(3)	(4)
		Exposure > 50th percentile	Exposure > 75th percentile	Exposure > 90th percentile
$D_{b,t}$	0.000	−0.002	−0.003	−0.002
	(0.018)	(−0.597)	(−0.623)	(−0.424)
$D_{b,t}More_exposed_{b,t}$		0.004	0.004	0.003
		(1.223)	(1.214)	(0.975)
Bank fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	2,375	2,375	2,375	2,375
Adj. R^2	0.714	0.719	0.717	0.716

Table D2: This table reports the results for the required rate of return on capital, using quarterly interest expenses over total debt as the measure for debtholders' return, from specification (2) using different percentiles of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy (columns 2-4) with the bank-month panel. $COC_{b,t}$ denotes the required rate of return on capital for bank b in month t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are clustered at the bank level. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$COC_{b,t}$			
	(1)	(2)	(3)	(4)
		Exposure > 50th percentile	Exposure > 75th percentile	Exposure > 90th percentile
$D_{b,t}$	0.007	−0.001	0.001	0.002
	(2.077)	(−0.111)	(0.145)	(0.539)
$D_{b,t}More_exposed_{b,t}$		0.009**	0.009***	0.008***
		(2.594)	(3.008)	(2.733)
Bank fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	2,375	2,375	2,375	2,375
Adj. R^2	0.909	0.912	0.913	0.912

Table D3: This table reports the results for the lending volumes from specification (4) using the 75th and 90th percentiles of the banks' exposure to income-oriented funds to calculate the $More_exposed_{b,t}$ dummy with the bank-borrower-month panel. $Log(Volume_{i,b,t})$ denotes the logarithm of the volume of the loan issued to borrower i by bank b in quarter t. $D_{b,t}$ is a dummy variable taking the value of 1 for banks in the treated group during the treatment period. Standard errors are double-clustered at the bank and borrowers' industry levels. Jackknife wild cluster restricted bootstrap t-statistics are presented in parentheses and in the second panel. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable:	$Log(Volume_{i,b,t})$	
	(1)	(2)
	Exposure > 75th percentile	Exposure > 90th percentile
$D_{b,t}$	0.356***	0.391***
	(15.041)	(9.142)
$D_{b,t}More_exposed_{b,t}$	−0.466***	−0.539***
	(−7.261)	(−6.772)
Sum of coefficients significance	$\beta + \xi = 0$	$\beta + \xi = 0$
	t-stat$_{(9)} = -2.144$	t-stat$_{(9)} = -2.613$
	p-value = 0.288	p-value = 0.190
Bank fixed effects	Yes	Yes
Size x Industry x Region x Quarter fixed effects	Yes	Yes
Controls	Yes	Yes
Observations	351,237	351,237
Adj. R^2	0.417	0.417

E System-wide interconnectedness of banks: Estimation

E.1 Overview of the time-varying parameter VAR model

Since the behaviour of agents is highly dynamic, we infer bank interconnectedness from the time-varying parameter vector autoregression (TVP-VAR) model:

$$x_{t,T} = \phi_0\left(\frac{t}{T}\right) + \phi_1\left(\frac{t}{T}\right) x_{t-1,T} + \ldots + \phi_p\left(\frac{t}{T}\right) x_{t-p,T} + \epsilon_t, \tag{E.1}$$

estimated from vector of shareholders' required rate of return $x_{t,T} = (COE_{1,t,T}, \ldots, COE_{b,t,T}, \ldots, COE_{N,t,T})'$ or debtholders' required rate of return $x_{t,T} = (COD_{1,t,T}, \ldots, COD_{b,t,T}, \ldots, COD_{N,t,T})'$ for bank $b = 1, \ldots, N$ in day $t = 1, \ldots, T$ following the methodology of Baruník and Ellington (2024). Under appropriate conditions the model can be approximated locally by a stationary $x_{t,T} \approx x(u)$ for a given $t/T \approx u$ and importantly has a time-varying vector moving average representation:

$$x_t(u) = \sum_{h=-\infty}^{+\infty} \alpha\left(u, h\right) \epsilon_{t-h}, \tag{E.2}$$

where, at each fixed time u, the original process $x_{t,T}$ can be represented as a linear combination of uncorrelated innovations with time-varying impulse response (TV-IRF) functions $\alpha\left(u, h\right)$. The information contained in the impulse response functions allows the contribution of shocks in the system to be measured. Thus, their transformations over time determine the interconnectedness of banks.

We transform local impulse responses in the system into local impulse transfer functions using Fourier transformations. This allows us to identify the persistence dynamics of interconnectedness based on the 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 that captures how shocks propagate from a bank j to a bank k at a given time $u = t_0/T$ and horizon[39] $d_i \in \mathcal{H} = \{\mathrm{Tr}, \mathrm{Per}\}$, is formally defined as:

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

where $\widehat{\alpha}(u,\omega) = \sum_{h=0}^{H-1} \sum_h \widehat{\alpha}(u,h) e^{-i\omega h}$ is an impulse transfer function estimated from Fourier

[39] In the empirical investigation, 20 business days divides the transitory and persistent horizons.

frequencies ω of impulse responses covering a given horizon d_i frequencies.[40] Since the rows of the dynamic adjacency matrix do not necessarily sum to one, we normalise the element in each row by the corresponding row sum: $\left[\widetilde{\theta}(u,d)\right]_{j,k} = \left[\theta(u,d)\right]_{j,k} \Big/ \sum_{k=1}^{N} \left[\theta(u,d)\right]_{j,k}$. Equation (E.3) fully defines a dynamic horizon-specific link between banks.

To obtain the time-varying coefficient estimates $\widehat{\phi}_1(u), ..., \widehat{\phi}_p(u)$ and the time-varying covariance matrix $\widehat{\Sigma}(u)$ at a given point of time $u = t_0/T$, we estimate the approximating model in Equation (E.1) using Quasi-Bayesian Local-Likelihood (QBLL) methods (Petrova, 2019). We provide a detailed discussion of the estimation algorithm in Appendix E.2.

To evaluate the impact of distribution restrictions on the system of banks, we consider following three characteristics of shock transmission. First, we aggregate the pairwise interconnectedness between banks' j and k investor required rate of return to measure the total interconnectedness between all banks. This is defined as:

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

and measures the strength of system-wide interconnectedness attributable to all shocks in the system with a given persistence. Second, we are interested in directional measures that assess whether banks transmit or receive shocks in the system. Such horizon-specific from-directional connectedness, which measures how much of the variance of each bank's j investor return requirement is attributable to shocks to other banks' $i \in Z$ investor return requirements belonging to the set Z in the cross section, is defined as:

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

Third, a 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 returns in the set Z, is given by:

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

where $\mathcal{T}_{j \rightarrow \bullet}(u,d)$ 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.

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

We use the measures defined in (E.5) and (E.6) to assess whether there is a system-wide shift in the interconnectedness of banks following the implementation of the restrictions using DiD.

For the estimation 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.

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 diagonalise the covariance matrix because our objective is to focus on the connections controlled for possible contemporaneous correlation in residuals of the system. The $\alpha(u, d)$ matrix embeds the causal nature of connections, and the covariance matrix $\Sigma(u)$ contains contemporaneous covariances within the off-diagonal elements.

E.2 Estimation of the time-varying parameter VAR model

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

$$x_{t,T} = \phi_1(t/T)x_{t-1,T} + \ldots + \phi_p(t/T)x_{t-p,T} + \epsilon_{t,T}, \tag{E.7}$$

where $\epsilon_{t,T} = \Sigma^{-1/2}(t/T)\beta_{t,T}, \beta_{t,T} \sim NID(0, I_M)$ and $\phi(t/T) = (\phi_1(t/T), \ldots, \phi_p(t/T))^\top$ are the time varying autoregressive coefficients.

Note that all roots of the polynomial $\chi(z) = \det\left(I_N - \sum_{p=1}^{L} z^p x_{p,t}\right)$ lie outside the unit circle, and Σ_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 $\overline{x}_t^\top = (\mathrm{I}_N \otimes x_t)$, $x_t = \left(1, x_{t-1}^\top, \ldots, x_{t-p}^\top\right)$ and denoting the Kronecker product by $\otimes$, the model can be written as:

$$x_{t,T} = \overline{x}_{t,T}^\top \phi_{t,T} + \Sigma_{t/T}^{-\frac{1}{2}} \beta_{t,T} \tag{E.8}$$

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 (E.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:

$$\mathrm{L}_k\left(x|\theta_k,\Sigma_k,\overline{x}\right)\propto \tag{E.9}$$
$$|\Sigma_k|^{\mathrm{trace}(D_k)/2}\exp\left\{-\frac{1}{2}(x-\overline{x}^\top\phi_k)^\top\left(\Sigma_k\otimes D_k\right)(x-\overline{x}^\top\phi_k)\right\}$$

The D_k is a diagonal matrix whose elements hold the weights:

$$D_k = \mathrm{diag}(\varrho_{k1},\ldots,\varrho_{kT}) \tag{E.10}$$
$$\varrho_{kt} = \phi_{T,k}w_{kt}/\sum_{t=1}^{T}w_{kt} \tag{E.11}$$
$$w_{kt} = (1/\sqrt{2\pi})\exp((-1/2)((k-t)/H)^2),\quad \text{for } k,t\in\{1,\ldots,T\} \tag{E.12}$$
$$\zeta_{Tk} = \left(\left(\sum_{t=1}^{T}w_{kt}\right)^2\right)^{-1} \tag{E.13}$$

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 (E.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 $\phi_k|\,\Sigma_k$ for $k\in\{1,\ldots,T\}$:

$$\phi_k|\Sigma_k \backsim \mathcal{N}\left(\phi_{0k},(\Sigma_k\otimes\Xi_{0k})^{-1}\right) \tag{E.14}$$
$$\Sigma_k \backsim \mathcal{W}\left(\alpha_{0k},\Gamma_{0k}\right) \tag{E.15}$$

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

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

$$\phi_k|\Sigma_k,A,Y \backsim \mathcal{N}\left(\widetilde{\theta}_k,\left(\Sigma_k\otimes\widetilde{\Xi}_k\right)^{-1}\right) \tag{E.16}$$
$$\Sigma_k \backsim \mathcal{W}\left(\widetilde{\alpha}_k,\widetilde{\Gamma}_k^{-1}\right) \tag{E.17}$$

with quasi posterior parameters:

$$\widetilde{\phi}_k = \left(I_N \otimes \widetilde{\Xi}_k^{-1}\right)\left[\left(I_N \otimes A^\top D_k A\right)\hat{\phi}_k + \left(I_N \otimes \Xi_{0k}\right)\phi_{0k}\right] \tag{E.18}$$

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

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

$$\widetilde{\Gamma}_k = \Gamma_{0k} + Y' D_k Y + \Phi_{0k}\Gamma_{0k}\Phi_{0k}^\top - \widetilde{\Phi}_k \widetilde{\Gamma}_k \widetilde{\Phi}_k^\top \tag{E.21}$$

where $\widehat{\phi}_k = \left(I_N \otimes A^\top D_k A\right)^{-1}\left(I_N \otimes A^\top D_k\right) y$ is the local likelihood estimator for ϕ_k. The matrices Φ_{0k}, $\widetilde{\Phi}_k$ 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 100 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.