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The impact of G-SIB identification on bank lending: evidence from syndicated loans

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Abstract

This paper uses granular data on syndicated loans to analyse the impact of international reforms for Global Systemically Important Banks (G-SIBs) on bank lending behaviour. Using a difference-in-differences estimation strategy, we find no effect of the reforms on overall credit supply, while at the same time documenting a substantial decline in borrower- and loan-specific risk factors for the affected banks. Moreover, we detect a significant decline in the pricing gap between interest rates charged by G-SIBs and other banks, which we interpret as indirect evidence for a reduction in funding cost subsidies. Overall, our results suggest that the G-SIB reforms have helped to mitigate moral hazard problems associated with systemically important banks, while the consequences for the real economy have been limited.

Keywords: bank regulation, bank lending, systemically important banks

JEL classification: G20, G21, G28

Non-technical summary

In this paper, we use granular data on the global market for syndicated loans to examine how the G-SIB reforms after 2012 affected the lending behaviour of the designated institutions. The reforms are expected to have a positive impact on financial intermediation in the long-run, since better capitalised and more resilient institutions should be better able to absorb shocks while sustaining the provision of key services to the real economy. In the short-term, however, banks could constrain credit supply as they adapt to the higher regulatory requirements associated with the new framework. Moreover, if the reforms credibly mitigate the 'too-big-to-fail' problem, G-SIBs may experience a reduction in implicit funding cost subsidies that reflect bailout probabilities, and they could partially pass on the resulting increase in funding costs to their borrowers. Finally, the reforms may have an effect on G-SIBs' risk taking, in line with the framework's intention to reduce moral hazard and make banks internalize both up- and downside risks of their investments.

Our findings illustrate that G-SIB designation did not exert a significant impact on overall credit supply of the affected banks. This holds true in a variety of specifications that control for both observed and unobserved factors affecting bank lending, including factors relating to credit demand. At the same time, G-SIB designation significantly affected the banks' risk appetite, leading to changes in portfolio composition. Relative to the control group, G-SIBs shifted lending towards better-rated companies in the period following the reforms, and also increased the share of collateralised lending – even within the same risk class of borrowers. Our estimates further show that other banks decreased their interest rates on loans more than G-SIBs after 2012, which suggests more conservative loan pricing by G-SIBs relative to the banks in the control group. Finally, we do not find any impact of G-SIB designation on the geographical composition of loans or on loan maturities.

Overall, our results provide suggestive evidence that the post-crisis reforms have effectively limited excessive risk taking and reduced funding cost subsidies for G-SIBs, while potential side effects for the real economy that could be associated with a potential reduction in credit supply have been contained. The documented decline in borrower- and loan-specific risk factors for G-SIBs indicates a more liable risk management, in line with the intention of stricter loss absorbance requirements and resolution reforms. Moreover, the decline in competitive pricing advantages is consistent with a reduction in implicit funding cost subsidies for G-SIBs, which may be seen as indirect evidence that the reforms credibly reduced bailout expectations associated with 'too-big-to-fail' considerations. At the same time, we do not see a reduction in the overall credit supply provided by G-SIBs, indicating that the delayed and gradual implementation of the framework gave G-SIBs sufficient time to adapt without excessively restricting the provision of key services to the economy. This suggests that negative effects for the real sector are likely to be contained.

1 Introduction

The collapse of Lehman Brothers in September 2008 vividly demonstrated that the failure of an individual large institution can create significant stress in the financial system as a whole, with severe implications for economic growth and welfare. The failure was an exemplification of the so called 'too-big-to-fail' problem, whereby the system-wide costs of the failure of a systemically important bank oftentimes outweigh the social costs related to a bailout. 'Too-big-to-fail' considerations in turn create severe moral hazard problems within the affected banks, which take on more risk than socially optimal in the expectation of being bailed out in a stress event. In the aftermath of the financial crisis, policy makers around the world adopted a series of reforms that were meant to address such problems by inducing banks to better internalise the negative externalities associated with their business activities. Key elements of the framework comprised additional loss absorbency and resolution requirements for Global Systemically Important Banks (G-SIBs), aimed at making these institutions less likely to fail and at making potential failures less costly for society.

In this paper, we examine how the G-SIB reforms after 2012 affected the lending behaviour of the designated institutions. The reforms are expected to have a positive impact on financial intermediation in the long-run, since better capitalised and more resilient institutions should be better able to absorb shocks while sustaining the provision of key services to the real economy (see, e.g., Gambacorta & Shin 2018, Begenau 2020, or Bahaj & Malherbe 2020). In the short-term, however, banks could constrain credit supply as they adapt to the higher regulatory requirements associated with the new framework (see, e.g., Behn *et al.* 2016, Fraisse *et al.* 2019, Gropp *et al.* 2019). Moreover, if the reforms credibly mitigate the 'too-big-to-fail' problem, G-SIBs may experience a reduction in implicit funding cost subsidies that reflect bailout probabilities (see, e.g., Berndt *et al.* 2019), and they could partially pass on the resulting increase in funding costs to their borrowers. Finally, the reforms may have an effect on G-SIBs' risk taking, in line with the framework's intention to reduce moral hazard and make banks internalize both up- and downside risks of their investments.

While we cannot analyse the long-run effects of the reforms, our paper studies potential short-term adjustments for the affected banks, using a difference-in-differences estimation methodology that distinguishes between G-SIBs and other banks. We rely on granular data on the global market for syndicated loans to the non-financial private sector, obtained from Dealogic Loanware. For the companies that are active in this market, syndicated loans represent a major source of funding and are therefore of high importance for the smooth functioning of their business operations (see, e.g., Sufi 2007). The high granularity of the loan-level data enables us to study potential effects along the various dimensions spelled out above, including effects of the reforms on loan volumes, portfolio composition, loan pricing, pricing sensitivity to borrower risk, and loan maturity. Moreover, the inclusion of multi-dimensional fixed effects allows us to systematically control for a large variety of factors that could also exert an influence on the variables of interest.

Our findings illustrate that G-SIB designation did not exert a significant impact on overall credit supply of the affected banks. This holds true in a variety of specifications that control for both observed and unobserved factors affecting bank lending, including factors relating to credit demand. At the same time, G-SIB designation significantly affected the banks' risk appetite, leading to changes in portfolio composition. Relative to the control group, G-SIBs shifted lending towards better rated companies in the period following the reforms, and also increased the share of collateralised lending – even within the same risk class of borrowers. Our estimates further show that other banks decreased their interest rates on loans by 7.3 percent more than G-SIBs after 2012, which suggests more conservative loan pricing by G-SIBs and may be interpreted as indirect evidence for a reduced implicit funding cost subsidy. This effect is most pronounced in the segment of less risky borrowers, whereas we do not see significant differences in the pricing of loans to riskier borrowers. Finally, we do not find any impact of G-SIB designation on the geographical composition of loans or on loan maturities.

Overall, our results provide suggestive evidence that the post-crisis reforms have effectively limited excessive risk taking and reduced funding cost subsidies for G-SIBs, while potential side effects for the real economy that could be associated with a potential reduction in credit supply have been contained. The documented decline in borrower- and loan-specific risk factors for G-SIBs indicates a more liable risk management, in line with the intention of stricter loss absorbance requirements and resolution reforms. Moreover, the decline in competitive pricing advantages is consistent with a reduction in implicit funding cost subsidies for G-SIBs, which may be seen as indirect evidence that the reforms credibly reduced bailout expectations associated with 'too-big-to-fail' considerations. At the same time, we do not see a reduction in the overall credit supply provided by G-SIBs, indicating that the delayed and gradual implementation of the framework gave G-SIBs sufficient time to adapt without excessively restricting the provision of key services to the economy. This suggests that negative effects for the real sector are likely to be contained, even before considering possible substitution effects that may arise if other banks take up the slack in cases where G-SIBs reduce certain business activities.

Our paper adds to the literature on the role of 'too-big-to-fail' considerations and government guarantees in the banking sector, with particular focus on the lending process. Most closely related is the paper by Degryse *et al.* (2020), which was developed in parallel to our own and also studies the effect of G-SIB designation on corporate lending. The two papers complement each other as they are relying on different data sets and study different borrower characteristics, and also differ in the way in which credit risk is measured. Further, we add to their analysis by considering additional dimensions, such as pricing sensitivity to risk and geographical composition of the loan portfolio, and by using a broader sample of banks. While the findings of the two papers are broadly consistent with each other, Degryse *et al.* (2020) tend to find a slightly more pronounced effect of G-SIB designation on overall credit supply. Two other closely related papers are those by Gropp *et al.* (2014) and Beck *et al.* (2020). The former shows that the removal of *explicit* government guarantees in the German banking sector in the early 2000s induced banks to reduce credit risk by cutting off the riskiest borrowers from credit. Our findings suggest that the post-crisis G-SIB reforms credibly reduced *implicit* government guarantees relating to 'too-big-to-fail' considerations, with similar effects on credit risk taking of the affected banks. The latter paper examines the real effects of the bail-in of a major Portuguese institution in 2014. While that paper examines credit supply effects relating to an *application* of the post-crisis 'too-big-to-fail' framework (i.e., the resolution of a significant institution), our paper focuses on potential effects relating to the *implementation* of the new framework. Besides these papers focusing on credit supply, there are a number of studies examining the evolution of implicit funding cost subsidies for G-SIBs in the post-reform period (see, e.g., Ueda & Weder di Mauro 2013, Gudmundsson 2016, Schich & Toader 2017, Cetorelli & Traina 2018, Berndt *et al.* 2019). Generally, these papers tend to find evidence for a reduction in funding cost subsidies – consistently with the relative increase in loan interest rates which we document – while the subsidies remain positive also after the implementation of the G-SIB reforms.[1]

In addition, our paper also relates to the literature examining the relation between bank regulation and lending, which often focuses on capital regulation. As mentioned above, there is an emerging consensus in the literature that better capitalised institutions are better able to lend in the long-term, while the transition to higher capital requirements may induce short-term costs as banks constrain lending while adapting their balance sheets to the new rules (see also Van den Heuvel 2008, Admati & Hellwig 2013, Mendicino *et al.* 2019, in addition to the papers cited above). Recently, a number of papers examine the effects of higher macroprudential capital requirements on bank lending, mostly focusing on the Basel III Countercyclical Capital Buffer that is meant to be varied over time (e.g., Aiyar *et al.* 2014, Jimenez *et al.* 2017, Basten 2020). Cappelletti *et al.* (2019) use bank balance sheet data to study the impact of higher capital buffers for systemic banks in a European context, finding limited effects on overall credit supply and a decrease in aggregate risk weights, which is consistent with our own findings. Compared with their paper, we focus on the G-SIB framework and a more international sample, while using much more granular data and thus significantly improving on identification. Moreover, we examine not only the

[1] In addition, some papers examine the effects of the reforms on bank behaviour more broadly, for example analysing the evolution of G-SIB balance sheets or window dressing behaviour (e.g., Violon *et al.* 2017, Behn *et al.* 2019).

effects on aggregate loan volumes and risk weights, but also study the effects of reforms on loan pricing and portfolio composition more broadly.

The remainder of the paper is structured as follows. In the following Section 2 we present details on the regulatory framework that comes along with G-SIB designation. Section 3 gives an overview of the dataset we use in our empirical analysis. In Section 4 we outline our empirical strategy that we use to analyse the effect of the regulatory changes on lending behaviour. Section 5 presents the main findings. After presenting additional robustness tests in Section 6, we conclude in Section 7.

2 The international G-SIB framework

The 2008-09 financial crisis had illustrated that problems in individual large institutions can impose substantial stress on the financial system as a whole. Many banks were considered as 'too-big-to-fail', which generated severe moral hazard problems and eventually imposed significant costs on taxpayers, as massive public sector interventions where necessary in order to reinstate confidence in the banking sector. A clear lesson from the crisis was that measures needed to be taken in order to address the systemic and moral hazard risks associated with the existence of systemically important financial institutions.

A key element of the post-crisis regulatory framework that was designed in order to tackle these issues is the international framework for Global Systemically Important Banks (G-SIBs). The framework imposes additional capital requirements on G-SIBs and thereby increases their resilience against shocks (see Basel Committee on Banking Supervision 2011). The identification of G-SIBs rests on an indicator-based approach that aggregates information from five individual risk categories, capturing banks' systemic importance through their size, interconnectedness, cross-jurisdictional activity, complexity, and the substitutability of financial infrastructure or services they provide. Each of the five risk categories is broken down further into two or three risk indicators that are then aggregated into the G-SIB score. Banks for which the score exceeds a specific threshold are designated as G-SIBs and sorted into five different buckets associated with different additional capital requirements (ranging from 1 to 3.5 percent of risk-weighted assets). Moreover, G-SIBs need to fulfill minimum Total Loss Absorbing Capacity (TLAC) requirements and are subjected to more intense supervisory oversight as well as specific resolution planning requirements (see, e.g., Financial Stability Board 2011b,a, 2015 for the key elements of the framework).

The post-crisis framework for G-SIBs aims to reduce both the probability of a G-SIB failure (by imposing additional capital requirements) and the cost resulting from such a failure (by ensuring that G-SIBs can be resolved without severe systemic disruption or exposing taxpayers to loss). Thus, in the long-run the reforms should make G-SIBs and the banking sector as a whole more resilient and better able to absorb shocks while keeping up lending to the real economy. In the short-run, however, G-SIBs may feel pressure to adjust their balance sheets in response to the new framework, and such adjustments could involve reductions in loan supply or substitution of riskier loans with safer ones. For example, a credible resolution framework could reduce implicit funding cost subsidies for G-SIBs, which could in turn translate into lower lending if G-SIBs pass on (part of) this increase to their borrowers by increasing the interest rates on loans. Moreover, G-SIBs could adjust their risk taking behaviour as the new framework is intended to reduce excessive risk taking by making it more likely that losses are imposed on G-SIB shareholders and creditors in case of a failure. Our paper aims to study these potential short-term adjustments in response to the new framework, while an analysis of the long-run effects mentioned above is out of scope.

The post-crisis reforms for G-SIBs have been implemented in a gradual manner, so that splitting the sample into pre- and post-reform periods is challenging. In particular, different reform elements followed different implementation timelines, were first announced globally and then implemented at national level, and usually included phase-in arrangements that further delayed the application of the final standard. Given these challenges, we follow a simple approach and split the sample into pre- and post-reform periods by using the Financial Stability Board's first publication of the G-SIB list in November 2011 as an event date (see Financial Stability Board 2011b). Although the post-crisis framework was not yet fully implemented from 2012 onward, key elements of the future framework were published in parallel and gave banks an idea of how the new requirements would look like. Moreover, following the publication of the list banks knew for the first time whether or not they would be subjected to the new requirements for G-SIBs. For both reasons, banks may have started to adapt their lending behaviour from 2012 onward in response to the reforms.

3 Data

3.1 Loan-level data on syndicated loans

Our empirical analysis relies on data from the international syndicated loan market. A syndicated loan is granted jointly by a group of banks, including one or more lead banks and several participating banks. Before the loan agreement is signed the lead banks have to assess the quality of the borrower and negotiate the conditions. Once the main conditions are set, lead banks offer parts of the loan to participating banks, while remaining responsible for monitoring the borrower. Typically, a deal over a loan syndication is issued in several tranches, which can be seen as separate lines of credit that vary by volume, terms and conditions. Since the composition of the syndicate may also change across tranches within a given deal, we choose the tranche as the main unit of observation in our analysis.

Our primary source of data is Dealogic Loanware, which has been widely used for studying the evolution of the global syndicated loan market (see, e.g. Esty & Megginson 2003, Carey & Nini 2007, Popov & Van Horen 2015). The data contains tranche-level information on loan-specific characteristics such as volume, margin and maturity. Since it does not contain information on the amount lent by each participant in a tranche, we follow previous literature and allocate the entire tranche volume to the lead banks (see, e.g., Ivashina & Scharfstein 2010, Giannetti & Laeven 2012), where the allocation takes place based on an equal weight whenever a given loan is extended by more than one lead bank.[2] To focus on the real economy, we restrict the estimation sample to include only loans to the non-financial private sector. That is, we exclude interbank loans and loans granted to the public sector since the latter might be reflecting subsidised credit, special agreements or hidden guarantees. Moreover, Figure 1 illustrates how aggregate syndicated loan volumes for G-SIBs and other banks have evolved over time. Over the last 20 years, G-SIBs have issued substantially higher volumes than the group of all other banks. The ratio between volumes issued by both groups indicates strongly diverging trends in the run-up to and during the Global Financial Crises (GFC), where G-SIBs reduced loan volumes both in absolute and in relative terms. To avoid issues with the parallel trends assumption in a difference-in-differences setup, we focus on the period between 2010 and 2018 in the empirical analysis. In robustness checks, we have also estimated all specifications on the full sample ranging from 2000 to 2018 (see Section 6).

[Figure 1 here]

Table 1 shows descriptive statistics for the 160,000 tranche-level observations that are included in our sample, covering a total of 20,232 distinct borrowing firms from 149 countries. The average tranche size for G-SIBs is USD 88 million, which compares with an average tranche size of USD 60 million for other banks, while both groups of banks charge similar interest rates on the loans.[3] G-SIBs tend to lend with a shorter average maturity and with a lower share of collateralised loans. Furthermore, we have information on the credit

[2]Dealogic Loanware does not provide sufficient information on how the tranche volume is distributed among the lead banks, nor on what proportion of the tranche is allocated to the participating banks. However, according to Simons (1993) lead banks keep a substantial stake of the loan in their own portfolio. Our estimates could be biased if either G-SIBs or other banks systematically changed their roles after the reforms, e.g. increasingly acting as lead banks rather than participating banks or vice versa (since we consider only the former in our analysis). However, as shown in Figure C.1 the share of G-SIBs in total lead banks and participating banks is relatively stable over time and did not change after 2012, which mitigates this concern.

[3]The information on interest rates is available for slightly less than half of the sample. For the baseline setting we use the overall margin, which includes all incurred costs. Later on we also distinguish between the fee and the pure interest rate margin component. Moreover, in the context of syndicated loans, it is common practice for interest rates to be expressed as premiums on base rates (e.g., LIBOR, EURIBOR, HKIBOR). We also run robustness checks where we include these base rates.

ratings of $1,476$ firms at the time of the signing of the deal, representing around 25 percent of the observations in our overall sample.[4] G-SIBs lend to slightly better-rated borrowers on average. Moreover, and not surprisingly, G-SIBs are more involved in foreign lending, with almost 53 percent of tranches being granted to borrowers abroad, compared with 40 percent for other banks. The last row indicates that the average tranche structure does not substantially differ across both groups of banks. On average, a tranche is originated by 4.7-4.8 lead banks.

[Table 1 here]

Further information on the type of loans included in the sample is shown in Figure 2, which provides an overview of the predominant borrowing countries and industries. In addition, Figure 3 illustrates the lending allocation with respect to the borrower's credit rating for the subsample of observations for which this information is available. Generally, most of the loans are granted to medium-graded as well as non-investment speculative and highly speculative graded companies. Reflecting the better average rating, the distribution for G-SIBs is somewhat shifted to the left relative to the distribution for other banks. Nevertheless, there is significant overlap between the two distributions, which is important for identification purposes in the empirical analysis. Descriptive information on the pricing of loans is shown in Figure 4, which illustrates that interest rates vary substantially across risk-classes. Both groups of banks demand higher interest rates from poorly-rated borrowers.[5] Thus, banks are clearly demanding compensation for taking on more risk.

[Figures 2 to 4 here]

[4]We take a simple average of the credit rating from Moody's and Standard & Poor's. Where one of them is missing, we rely solely on the other (non-missing) rating. Firms for which we are unable to obtain any information on the rating are excluded from the corresponding regressions on borrower risk.

[5]Interestingly, the interest rates for extremely poorly rated borrowers seem to be stagnating or, in some cases, even slightly declining. Possible explanations for this inter alia include cross-subsidisation of other products sold to the same borrower or evergreening of exposures to the respective borrower. Given the extremely low credit volumes for these risk classes (recall Figure 3) we do not think that this pattern constitutes a severe challenge for our empirical analysis.

3.2 Bank-level data on balance sheets and income statements

We match the syndicated loan data with bank balance sheet and income statement information from SNL Financial (provided by S&P Global Market Intelligence). Unfortunately, Dealogic Loanware and SNL Financial do not share a common identifier, which makes the matching process quite challenging as the only commonality lies in the name of the bank. To improve the matching, we make use of a web search-based matching method in the spirit of Autor *et al.* (2016) (see Annex A for further details). Our final sample comprises 683 banks (34 G-SIBs and 649 Non-G-SIBs) from 80 different countries, which account for 86 percent of total lending in the Dealogic Database. As quarterly bank characteristics are often missing we use bank controls at the annual frequency to account for time-varying differences across banks in the empirical analysis.

In Table 2 we provide summary statistics for the banks in our matched sample. Not surprisingly, G-SIBs are much larger: total assets of the median G-SIB exceed the median counterpart of the control group by a factor of 29. Moreover, G-SIBs are relatively less involved in providing loans which is evident by the consistently lower Loan-to-Deposit (or Loan-to-Asset) ratio and the lower Net Interest Income relative to Total Assets. The problem of non-performing loans is also less severe. Finally, syndicated loans account for approximately 6.5 percent of the total loan portfolio of the median G-SIB, while this share is at about one percent for the median Non-G-SIB.

[Table 2 here]

4 Empirical strategy

This section describes the difference-in-differences methodology that we use to assess whether banks that were designated as G-SIBs have adjusted their lending behaviour relative to other banks after the reforms. The focus in this respect is on loan volumes, portfolio composition, loan pricing and maturity, and the sensitivity of loan pricing to loan risk.

4.1 Effect on lending volumes

The way in which our data set is constructed requires aggregation of data at various levels in order to draw conclusions about lending behaviour. Specifically, the data set records each loan tranche only once – at the time of issuance – so that it is not possible to track the evolution of a specific firm-bank relationship over time (as it is often done in the credit supply literature relying on credit register data). While running regressions at tranche level would allow to assess how average tranche size has evolved, it would ignore the fact that banks can also change the number of loans granted. The latter, however, is particularly important for the evolution of total bank lending in the syndicated loan market, as e.g. shown by Giannetti & Laeven (2012). For this reason, we start the empirical analysis by aggregating lending volumes at the bank × quarter level and then estimate the following equation:

$$\mathit{Log(Lending}_{i,t}) = \beta_1 GSIB_i \times Post2012_t + \beta_2 \mathit{Bank\text{-}Controls}_{i,t} + \lambda_i + \lambda_t + u_{i,t} \qquad (1)$$

The dependent variable $\mathit{Log(Lending}_{i,t})$ is the logarithm of the total loan volume that was originated by bank i in quarter t. $GSIB_i$ is a dummy variable taking the value of 1 if the bank was designated as G-SIB at least once between 2012 and 2016, and zero otherwise.[6] $Post2012_t$ is another binary variable, which is equal to 1 for all observations occurring after $2011Q4$, and otherwise equal to zero. The coefficient of interest is β_1 which indicates how G-SIBs have adjusted their average loan volumes after 2012, relative to banks in the control group. To account for time-varying heterogeneity between banks, the specification includes measures of bank size, profitability and capital adequacy as control variables. Moreover, bank fixed effects, λ_i, control for both observed and unobserved structural differences between different banks, including differences in size, complexity and systemic importance that relate to G-SIB designation itself. In the same manner, the quarterly dummies, λ_t, control for

[6] We also conduct robustness checks where we include only the banks designated in November 2011 as G-SIBs, while excluding the five banks that were first designated at a later point from the analysis. All our results are robust to this change.

heterogeneity over time. Finally, the stochastic error terms $u_{i,t}$ are clustered at the bank-level.

While results for Equation 1 can provide insights on the evolution of aggregate loan volumes for G-SIBs and other banks, the specification cannot control for possible differences in credit demand that could also affect the results. For example, G-SIBs could be lending to firms in different countries or industries with different economic conditions, and such differences would complicate the identification of supply side effects in Equation 1. To address this issue, we estimate a modified version of the Khwaja & Mian (2008) estimator that is widely used in the credit supply literature (see, e.g., Behn *et al.* 2016, Jimenez *et al.* 2017, Fraisse *et al.* 2019). Specifically, we aggregate lending volumes by bank, time and country-industry ('*natind*') of the borrowing firm and include country-industry × quarter fixed effects to account for time-varying credit demand shocks and other types of heterogeneity that are specific to a given country-industry. In principle, the disaggregated structure of our data would have allowed us to go even more granular and conduct analysis at the level of the individual borrower, while including firm fixed effects. However, we choose the country-industry level instead since the average number of syndicated loans granted to a specific firm is relatively small, particularly when looking at the same time period (see, e.g. Berg *et al.* 2016a, Acharya *et al.* 2017, or Gropp *et al.* (2019) for similar approaches).[7] Taking all this into account, our second specification is the following:

$$
\begin{aligned}
\mathit{Log(Lending}_{i,t,natind}) = & \beta_1 GSIB_i \times Post2012_t + \beta_2 \mathit{Bank\text{-}Controls}_{i,t} \\
& + \lambda_i + \lambda_{t,natind} + u_{i,t,natind}
\end{aligned} \tag{2}
$$

The dependent variable $\mathit{Log(Lending}_{i,t,natind})$ is the logarithm of the total loan volume which a specific bank i grants over quarter t to a specific country-industry *natind*. Besides the different level of aggregation and the inclusion of more granular fixed effects, all other variables in the regressions are defined as above. Moreover, standard errors in these and the

[7] Reassuringly, Degryse *et al.* (2019) show that borrower fixed effects based on firm clusters yield bank credit supply shocks that are comparable to those obtained using firm fixed effects.

subsequent regressions are double-clustered at the bank and country-quarter level.

4.2 Effect on portfolio composition

The high granularity of our data also allows analysing whether the reforms had any differential effects on portfolio composition for G-SIBs relative to other banks. Specifically, we can test whether there are any differential effects with respect to borrower risk, the amount of secured lending, and the amount of domestic versus foreign lending.

4.2.1 Borrower risk

To analyse potential effects of the reforms on borrower risk, we aggregate tranche volumes by bank i, quarter t, company rating rat and borrower country c and then estimate the following regression equation:[8]

$$\begin{aligned} \mathit{Log(Lending}_{i,t,rat,c}) =& \beta_1 GSIB_i \times Post2012_t \times Rating_{rat} \\ &+ \lambda_{i,t} + \lambda_{t,rat,c} + \lambda_{i,rat,c} + u_{i,t,rat,c} \end{aligned} \tag{3}$$

The dependent variable $\mathit{Log(Lending}_{i,t,rat,c})$ is the amount of all loans which a given bank i grants to companies with rating rat in country c at time t. The *Rating* variable is a categorial variable that separates the observations in our sample into five risk classes based on the borrowers' credit rating, where a lower value of this variable corresponds to a riskier rating (see Annex B for further information). All other variables are defined as above. The coefficient β_1 for the triple interaction term indicates whether G-SIBs differentially adjusted their lending relative to the control group after 2012, depending on the riskiness of the borrower. A positive coefficient would indicate that the reform has encouraged G-SIBs, relative to other banks, to shift more lending from riskier towards safer borrowers (or to

[8] As explained in Section 3, the information on the borrower's credit ratings is missing for about 75 percent of the tranche level observations in our sample, so that this aggregation is based on a reduced sample. Since the introduction of the rating dimension adds an additional level of aggregation which further thins out the number of identifying observations within a fixed effect cluster, we additionally aggregate at the country rather than the country-industry level in these tests, to not lose too much explanatory power.

shift less lending from safer towards riskier borrowers). The use of multi-dimensional fixed effects allows us to shut down a multitude of possible channels which could have had an effect on the risk-taking behaviour of banks. Bank × quarter fixed effects absorb all time-varying bank-specific factors that affect loans in different risk classes to the same extent.[9] Quarter × rating × country fixed effects control for time-varying demand shocks on the country-rating level. These are particularly relevant if there were changes in the demand for credit that are specific to firms in a given rating class within a given country. Finally, bank × rating × country fixed effects absorb all structural differences in the banks' preferences for specific risk-profiles within a geographical destination.

4.2.2 Secured vs unsecured lending

While the company rating is a firm-specific risk indicator, the riskiness of an individual loan is also affected by the loan-specific terms and conditions, e.g. the amount of collateralisation. To test whether G-SIBs have adjusted the share of collateralised lending after 2012, we make use of loan tranche specific information that indicates whether the respective loan tranche is secured with collateral or not.[10] We aggregate lending volumes by bank i, quarter t, status of collateralisation sec and borrowing country c, and then estimate a modified version of Equation 3, where we replace the rating classification with the binary variable that indicates the status of collateralisation. Furthermore, to account for the possibility that the status of collateralisation depends on the riskiness of the respective borrower, we also aggregate lending volumes by bank, quarter, status of collateralisation and credit rating, and estimate

[9] As some banks extend loans only to a single rating class within a given quarter (so that these observations are absorbed by the bank × quarter FEs and do not help to identify β_1), we also estimate an alternative specification that includes bank control variables instead of bank × quarter fixed effects and thus increases the number of identifying observations. Alternatively, we also aggregate our data at annual rather than quarterly level to obtain more variation within a given bank-time period.

[10] The data set does not include information on the value of the respective collateral, or on the fraction of the loan tranche that is secured. It only indicates whether the loan tranche is secured or not.

the effect on secured lending within a particular risk class:[11]

$$
\begin{aligned}
Log(Lending_{i,t,sec,rat}) = & \beta_1 GSIB_i \times Post2012_t \times Secured_{sec} \\
& + \lambda_{i,t} + \lambda_{t,sec,rat} + \lambda_{i,sec,rat} + u_{i,t,sec,rat}
\end{aligned} \tag{4}
$$

The dependent variable $Log(Lending_{i,t,sec,rat})$ is the amount of all loans which a given bank i grants to companies with collateralisation status sec and rating rat at time t. The *Secured* variable indicates collateralisation status, and all other variables are defined as above. A positive coefficient for β_1 would indicate that the reform has encouraged G-SIBs, relative to other banks, to require a higher share of collateralisation for loans to firms in a given rating class. Multi-dimensional fixed effects account for time-varying heterogeneity across banks, time-varying heterogeneity between the amount of secured lending that is obtained by firms in a specific rating class, and bank-specific heterogeneity with respect to the amount of secured lending for loans to firms in a specific risk class.

4.2.3 Domestic vs foreign lending

To test whether G-SIBs have altered the geographical composition of their lending activities relative to other banks in the post reform era, we aggregate lending volumes at the bank $\times$ quarter $\times$ borrower country level and estimate the following equation:

$$
\begin{aligned}
Log(Lending_{i,t,c}) = & \beta_1 GSIB_i \times Post2012_t \times Domestic \\
& + \lambda_{i,t} + \lambda_{t,c} + \lambda_{i,c} + u_{i,t,c}
\end{aligned} \tag{5}
$$

$Log(Lending_{i,t,c})$ specifies the amount of all loans which a given bank i granted to companies in a given country c at time t. *Domestic* is a binary variable which is equal to 1 if the home country of the bank coincides with the home country of the borrower. The regression includes bank $\times$ quarter, country $\times$ quarter and bank $\times$ country fixed effects to improve

[11] Ignoring borrower risk could lead to an omitted variable problem, for example if banks generally require more collateral for riskier borrowers. We omit the country dimension in this regression since otherwise the number of identifying observations within a given fixed effect cluster becomes too small.

identification. In this equation, the coefficient β_1 captures whether G-SIBs differentially adjusted their shares of domestic and foreign lending activities relative to banks in the control group. A positive coefficient for β_1 would imply that G-SIBs have increased the share of domestic lending since 2012.

4.3 Effect on interest rate and maturity

We also analyse whether and how G-SIBs have adjusted their pricing behaviour and the maturity of their loans in the post-reform period. This issue can be examined directly at tranche level, i.e. the most granular level of observation in our data set.[12] This is because in these tests we are interested in how average margins and maturities for the originated loans have evolved, in contrast to the loan volume regressions where we were interested in the evolution of total bank lending and not in average loan volumes. Our most saturated regression equation in this section takes the following form:

$$\begin{aligned} X_{i,tranche} = & \beta_1 GSIB_i \times Post2012_t + \beta_2 Controls_{tranche} \\ & + \beta_3 Bank\text{-}Controls_{i,t} + \lambda_i + \lambda_{t,natind} + u_{i,tranche} \end{aligned} \tag{6}$$

with $X \in$ (*Log(Margin), Maturity*).[13] The coefficient β_1 measures how G-SIBs have changed their pricing behaviour and the average maturity of originated tranches after the reforms when compared with other banks. Bank control variables are the same as above, and the specification further includes bank and country-industry $\times$ quarter fixed effects. Moreover, we control for a number of tranche and firm characteristics which might have an effect on the contractual interest payment and the maturity. These are the tranche amount, the status of collateralisation, the credit rating of the borrowing firm and the tranche maturity (in the

[12] As one tranche could be originated by more than one lead bank, our precise unit of observation is the tranche-bank level, where the allocation among lead banks takes place based on an equal weight (see Section 3).

[13] To better capture the right-skewed distribution of interest rate margins, we take logarithm for this dependent variable. Results are very similar when we use the margin in absolute terms instead. We cannot include bank $\times$ quarter fixed effects in these regressions, since they would absorb the coefficient of interest, β_1.

case where we use the margin as dependent variable; when the maturity is the dependent variable, we include the interest rate margin as a control). To account for possible correlation across tranches within a particular deal we also double-cluster standard errors at bank and deal level in alternative specifications for the tranche level regressions (in addition to the usual clustering at bank and country-quarter level).[14]

4.4 Effect on the pricing sensitivity to risk

Finally, we investigate whether G-SIBs have changed their behaviour when pricing borrower risk. Specifically, we estimate the following regression equation:

$$\begin{aligned} Log(Margin_{i,tranche}) =& \beta_1 GSIB_i \times Post2012_t \times Rating_{rat} + \beta_2 Controls_{tranche} \\ &+ \lambda_{i,t} + \lambda_{t,rat,c} + \lambda_{i,rat,c} + u_{i,tranche} \end{aligned} \tag{7}$$

All variables are defined as above. A positive coefficient for β_1 would imply that G-SIBs have more strongly increased (or less strongly decreased) the margins for better rated companies than for lower rated companies when compared with banks in the control groups (i.e., they have reduced the pricing differential for risk in relative terms). The regression includes tranche-level control variables and multiple high-dimensional fixed effects to control for other factors, in the same way as specified above.[15]

5 Results

This section presents our main findings on the effects of reforms on G-SIBs' lending behaviour, including loan volumes, portfolio composition, loan pricing, pricing sensitivity to borrower risk, and loan maturity.

[14] As the borrowing company does not change within a given deal, credit conditions of tranches within a deal could possibly depend on each other.

[15] To increase the number of identifying observations, we also replace bank $\times$ quarter fixed effects with bank controls and estimate Equation 7 again.

5.1 Effect on lending volumes

Table 3 shows the results for a variety of specifications analysing the impact of the reforms on loan volumes. We do not identify a significant differential effect for G-SIBs relative to the control group in any of these specifications. Column 1 shows the results for Equation 1, where we aggregate lending volumes at the bank $\times$ quarter level. The remaining columns include the results for the Khwaja & Mian (2008)-type estimator outlined in Equation 2, where loan volumes are aggregated at the bank $\times$ quarter $\times$ country-industry level in order to control for time-varying credit demand shocks at the country-industry level. Column 2 focuses on the intensive lending margin and includes only non-zero observations, while column 3 includes also quarters in which the respective bank did not extend any loans to firms in the respective country-industry and thus captures both the intensive and the extensive lending margin.[16] Results continue to be insignificant when we use the number of deals instead of the lending volume as a dependent variable (column 4). In the last column, we test for possible effects at the extensive margin only by estimating a Linear Probability Model that uses as dependent variable a dummy equal to one if the respective bank extended a loan to the respective country-industry in the relevant quarter, and zero otherwise. The coefficient of interest remains insignificant.

[Table 3 here]

5.2 Effect on portfolio composition

This subsection examines whether the reforms had any effects on the banks' portfolio composition, including differentiation by borrower risk, status of collateralisation, and borrower location (domestic vs. foreign).

[16] That is, the sample in column 3 is a balanced panel in which we assign the value of zero to bank $\times$ quarter $\times$ country-industry observations that did not record positive lending volumes. We omit bank $\times$ country-industry clusters that never record any positive lending volumes throughout the sample period.

5.2.1 Borrower risk

Figure 5 illustrates that the (weighted) average borrower credit rating (at origination) continuously declined for both G-SIBs and other banks in the period until 2012. Thereafter, the average rating stabilised for G-SIBs, while the declining trend continued for other banks.

[Figure 5 here]

Table 4 complements the descriptive evidence in Figure 5 with a formal regression analysis. In Panel A, columns 1-3, we aggregate lending volumes by bank, quarter, credit rating and borrower country. Column 1 includes the full set of multidimensional fixed effects (Equation 3) and is therefore our most stringent specification. The significant coefficient for the triple interaction term indicates that G-SIBs shifted less lending to borrowers with worse credit ratings in the post-reform period when compared with other banks, consistent with the patterns documented in Figure 5. Column 2 estimates a less stringent specification by replacing bank $\times$ quarter fixed effects with bank control variables, using the same sample as in column 1. The coefficient of interest remains significantly positive. For this less stringent specification we can increase the number of identifying observations by including also loans from banks that only lend to firms in a single rating class within a given quarter.[17] The triple interaction term on this expanded sample is still positive, but loses statistical significance (column 3). As an alternative way to obtain more rating variation within a given bank-time, we also aggregate lending volumes by bank, year (instead of quarter), credit rating and borrower country and apply exactly the same estimation procedure as before. Results are presented in columns 4-6 of Panel A and show a positive and significant coefficient for the triple interaction term in all three specifications. Overall, although not significant in all specifications, the results in this panel suggest that G-SIBs shifted lending towards less risky companies when compared with the control group in the post-reform period.

[Table 4 here]

[17]The number of banks in this specification more than doubles, while the number of observations increases only by about eight percent. For the specification in column 1, the additional observations are absorbed by the bank $\times$ quarter fixed effect.

To test whether differential adjustments between G-SIBs and other banks are stronger in any specific segment of loans, Panel B of Table 4 splits the sample into more and less risky borrowers, where we consider borrowers with an investment grade credit rating as less risky (these are all firms with ratings of *BBB*- or better). Results reveal that the relative adjustment mainly took place in the segment of less risky (investment grade) borrowers, i.e. for loans to companies in the top two of our five risk classes. The coefficient in column 1 indicates that after the reforms G-SIBs have granted 27.5 percent more loans to investment grade firms in a given country, relative to banks in the control group. We do not detect any significant differences in the more risky segment (column 2), and the same pattern emerges when using yearly instead of quarterly data in columns 3 and 4.

5.2.2 Secured vs unsecured lending

Next, we analyse the role of collateralised lending. In general, requiring collateral helps to address frictions arising from asymmetric information and mitigates the impact of possible borrower defaults, thus reducing the risk of the loan portfolio. Figure 6 shows that for most of the sample period G-SIBs collateralise around 20-25 percent of their loans by volume. From 2015 onwards, however, there is a sharp increase in the collateralisation ratio to about 40 percent. This increase also occurred for banks in the control group, but earlier and to even higher levels than for G-SIBs. Specificially, other banks started to request more collateral already during the financial crisis, while G-SIBs did not adjust at that time. Thus, G-SIBs have been catching up with other banks in the post-reform period.

[Figure 6 here]

Table 5 analyses this issue in more detail by presenting results for the regression analysis. In columns 1-3, we aggregate lending volumes by bank, quarter, borrower country and status of collateralisation (i.e., secured vs unsecured lending), and otherwise follow an estimation procedure that is similar to the one for Table 4. Column 1 makes use of the full set of multidimensional fixed effects and is therefore our preferred specification. According to the coefficient for the triple interaction term, G-SIBs have increased the proportion of new loans that are secured by roughly 21 percent after 2012 when compared with the control group. The effect weakens and becomes insignificant when we replace bank $\times$ quarter fixed effects with bank control variables (with column 2 using the same sample as in column 1, and column 3 expanding the sample in a similar manner as explained in the previous section).

[Table 5 here]

Albeit illustrative, the results in columns 1-3 of Table 5 might suffer from an omitted variable problem. Specifically, the majority of secured tranches are issued to borrowers with low credit ratings, so that a borrower's credit rating may simultaneously determine the amount of lending and the requirement for collateral. In the previous section we have shown that in relative terms G-SIBs have increased their lending to better-rated companies after the reforms, which should bias against finding a positive effect for the triple interaction term in Table 5. Nevertheless, to systematically address this issue and fully isolate the effect of reforms on collateralised lending, we additionally condition on the borrower's credit rating. That is, we aggregate loan volumes by bank, quarter, status of collateralisation and credit rating, and then estimate the effect on collateralised lending within a given risk class (Equation 4). Results are shown in columns 4-6 and illustrate that after the reforms G-SIBs have increased the proportion of collateralised lending within a given risk class when compared with banks in the control group. Coefficients are significant in all three columns and have more than doubled in magnitude relative to the ones in columns 1-3, in line with the intuition for the direction of the potential bias in these columns that we provided above.[18]

[18]Columns 4-6 include only loans to rated companies, so that the sample in these specifications is reduced relative to columns 1-3. To make sure that the more pronounced effect in columns 4-6 is not driven by differences in sample composition, we also estimate column 1 while including only loans to rated companies in the estimation. We obtain a point estimate for the triple interaction term of 0.27, which is somewhat higher than in column 1, but considerably lower than in column 4.

5.2.3 Domestic lending vs foreign lending

We also examine whether G-SIBs have adjusted cross-border lending in response to the regulatory changes. Cross-jurisdictional activity is one of the categories determining systemic importance in the G-SIB framework, and it could be that G-SIBs have tried to reduce their global footprint in the aftermath of the reforms. To analyse this graphically, Figure 7 plots the evolution of the share of domestic loans in total loans for G-SIBs and other banks over the sample horizon. In line with intuition, the figure shows that G-SIBs are generally much more involved in foreign activities, with the share of domestic loans being consistently lower than the one for other banks (between 35 and 45 percent for G-SIBs, and between 60 and 70 percent for other banks). The most striking development can be observed in the run-up to the global financial crisis, where G-SIBs considerably decreased the proportion of domestic lending, while other banks displayed the opposite trend. Since then, however, the share of domestic lending has been relatively stable for both groups of banks.

[Figure 7 here]

Our regression analysis in Table 6 confirms this pattern, as we do not obtain a clear direction for the triple interaction term in Equation 5 (which is in any case always insignificant). In columns 1-3, we aggregate lending volumes by bank, quarter and borrower country. The order of specifications shown in the table is the same as in previous sections. Column 1 is our most conservative specification and includes the entire set of two-dimensional fixed effects. In column 2 we use the sample from column 1 and replace bank $\times$ quarter fixed effects with bank control variables, while column 3 additionally includes loans from banks that lend to only foreign or only domestic firms within a given quarter (which cannot contribute to identification of coefficients in Equation 5). For robustness, we also use a broader aggregations of lending volumes by bank, quarter and domestic-or-foreign exposures. Coefficients for the triple interaction term in this alternative specification remain insignificant (columns 4-6).

[Table 6 here]

5.3 Effect on pricing behaviour

Besides loan volumes and composition it is also possible that G-SIBs have adjusted their loan pricing after the reforms. For example, to the extent that the reforms helped to mitigate too-big-to-fail considerations they may have reduced (implicit) funding cost subsidies for G-SIBs (see, e.g., Cetorelli & Traina 2018, Berndt *et al.* 2019). If G-SIBs (partially) passed on the resulting increase in funding costs to their borrowers, this could have an effect on loan pricing. Figure 8 gives descriptive evidence on average interest rate margins before and after the reforms, broken down by risk class of the borrower. Overall, interest rate margins have declined universally after 2012, reflecting the low interest rate environment in the recent period which also had an impact on the pricing of corporate loans. Furthermore, G-SIBs charged on average lower margins than other banks, both before and after 2012. However, as shown in the lower panel this pricing gap has narrowed after 2012, in particular for the best-rated borrowers.

[Figure 8 here]

To further examine this pattern, we use the panel dimension in our data and run various versions of the regression model specified in Equation 6. Since our observational unit is the tranche-level now, we include tranche characteristics as additional control variables (comprising the loan amount, maturity, borrower rating, and status of collateralisation). Including these control variables is important for attributing observed changes to a potential reduction in funding cost subsidies, since unconditional adjustments in loan pricing could also be due to relative changes in borrower composition, status of collateralisation, or other loan characteristics.

Regression results are presented in Table 7. In columns 1-3, we successively decrease the coarseness of the fixed effect clusters, using quarter fixed effects in column 1, quarter-country fixed effects in column 2, and quarter-country-industry fixed effects in column 3. The coefficient for the interaction term between the G-SIB and the reform dummies is positive in all specifications (though statistically insignificant in the most stringent specification in column 3). The coefficient in column 2 indicates that G-SIBs decreased the average interest rate margin by 7.3 percent less than other banks after the reforms, after controlling for possible differences in loan terms and borrower risk. Columns 4-6 repeat the estimations in columns 1-3 while using a different level of clustering that accounts for possible correlation in error terms for observations within the same deal (see Section 4.3 for further details). Results are statistically significant in all three columns with this alternative level of clustering. Overall, the results in Table 7 suggest that G-SIBs have become more conservative in pricing their loans in the period after 2012, which is consistent with a potential reduction in funding cost subsidies.[19]

[Table 7 here]

Next, we examine the sensitivity of pricing to risk. As shown in Figure 8, after 2012 other banks had decreased their interest rates margins in particular for the safest borrowers, i.e. in a risk sensitive manner. To analyse this more formally, we estimate Equation 7 and show the results in Table 8. The first column of Panel A is the most saturated specification as it contains the full set of multidimensional fixed effects. The positive coefficient for the triple interaction suggests that other banks have increased differentiation between safe and risky borrowers when pricing their loans in the post-reform period, relative to G-SIBs. Column 2 and 3 replace bank-quarter fixed effects with bank control variables, where column 2 uses the same sample as in column 1 and column 3 includes additional observations that were previously absorbed by the bank-quarter fixed effects. Results remain very stable. Finally, columns 4-6 repeat the estimations in columns 1-3 while using the alternative level of clustering. While the coefficient in the most stringent specification remains statistically significant (column 4), it becomes insignificant in columns 5 and 6.

[19] As shown by Berg *et al.* (2016b), an important part of syndicated loan pricing comes in the form of fees. The granularity of our data allows us to further decompose the interest rate charged by the banks into a fee component and a pure interest rate component. We find suggestive evidence that the less pronounced decrease in interest rate margins relative to other banks was mainly due to the pure interest rate component, whereas fee structures were adjusted in a similar manner. Specifically, coefficients for the interaction term remain relatively stable when using the pure interest rate component as a dependent variable in Equation 6, while they become insignificant when using the fee component. Detailed regression results are available upon request.

[Table 8 here]

In a final step, we want to ascertain where in the risk scale an adjustment of interest rate margins has been made. In order to examine this issue, we perform a sample split (investment vs. non-investment grade) and estimate the effect on the interest rate margin for each risk segment separately. Panel B of Table 8 shows that the relative adjustment mainly took place in the segment of investment grade borrowers (in line with Figure 8), while we do not detect any differential effects for the borrowers with worse credit ratings. The coefficient in column 1 indicates that other banks decreased the margins on investment grade loans by 12.6 percent when compared with G-SIBs.[20]

While it is difficult to take definite conclusions, one possible explanation for these differential effects on pricing could be that prime borrowers are more eager to do business with G-SIBs, so that G-SIBs have more pricing power with them and therefore do not have to reduce interest rates on their loans so much for firms in this category. Such demand-side effects would make it difficult for other banks to gain market share in the safe borrower segment and could hence also explain the volume effects discussed in Section 5.2.1 (which illustrated that other banks gained market share on the risky segments, in relative terms). Of course, this is just one potential explanation and others are possible as well. Pinning down the exact mechanism behind our findings would require further information and is beyond the scope of this paper.

5.4 Effect on maturity

Figure 9 illustrates the evolution of the weighted average loan maturity for both groups of banks over the sample horizon. In general, G-SIBs grant loans with shorter maturities, with an apparent structural break at the time of the global financial crisis, where G-SIBs considerably shortened average loan maturities. Since then, however, there have not been any differential patterns for the two groups of banks, at least not at this aggregate level.

[20] In the more saturated specifications shown in columns 3 and 4 we lose statistical significance. However, coefficient are of similar magnitudes as in columns 1 and 2.

[Figure 9 here]

Using the tranche-level data we formally investigate this issue by estimating Equation 6. Indeed, the results in Table 9 do not reveal any significant differences between G-SIBs and other banks for the period after 2012. As before, columns 1-3 successively decrease the coarseness of the fixed effect clusters, while columns 4 and 5 include additional robustness tests. Specifically, column 4 uses a logarithmic version of the dependent variable, while column 5 omits the credit rating as control variable, which allows us to more than double our sample size (the inclusion of the interest rate margin as a control variable in this specification allows to still (at least partially) control for counterparty credit risk). All estimates are insignificant and the coefficient of interest varies in sign, which leads us to conclude that there has been no differential adjustment in tranche maturities in the post-reform era.

[Table 9 here]

6 Robustness

This section provides a number of robustness tests and alternative specifications. The first set of robustness tests concerns the effects on credit supply. Columns 1 and 2 of Table C.1 re-estimate Equation 2 while using different estimation samples. In column 1, we include loans to public entities and loans to the financial sector in addition to loans to the non-financial private sector and continue to find an insignificant coefficient for the interaction term. In column 2, we extend the pre-treatment period up to the year 2000. The coefficient of interest is now negative and weakly significant, reflecting differential developments for G-SIBs and other banks in the run-up to and during the global financial crisis (recall Figure 1). As noted in Section 3, we think that these differential developments may create issues with the parallel trends assumption in a difference-in-differences setting, which is why our preferred specification is the one where the sample is restricted to the years from 2010 to 2018. In column 3 and 4 we use a Poisson Pseudo-Maximum Likelihood (PPML) Estimator to estimate the effect on loan volumes and the number of deals.[21] The coefficient of interest remains insignificant.

Table C.2 presents results for several robustness tests for the regressions on portfolio allocation. Columns 1-3 refer to borrower risk. In order to show that our results do not depend on a specific classification of the rating variable, columns 1 and 2 show the results for alternative classifications: column 1 is based on a binary rating variable that distinguishes between firms with investment grade ratings and firms with non-investment grade ratings, whereas column 2 groups credit ratings into deciles.[22] In both cases, the coefficient for the interaction term remains significantly positive. The coefficient turns insignificant in column 3, where we start the sample period in 2000 instead of 2010. As noted before, this is not our preferred specification, given diverging trends for G-SIBs and other banks ahead of 2010. In columns 4-6 of Table C.2 we present a number of robustness tests relating to the impact of the reforms on secured lending. In column 4, we extend the sample to the years from 2000 to 2018 and continue to find a positive and significant coefficient for the triple interaction term. In columns 5 and 6, we conduct tranche-level regressions, using as dependent variable a dummy variable that is equal to one when the respective tranche is secured and zero otherwise. Consistently with the main findings the estimates show that tranches issued by G-SIBs are relatively more likely to be secured after the reforms, both in a linear probability (column 5) and in a logit model (column 6). The coefficient in column 5 indicates that since 2012 the probability that G-SIBs require collateral increased by 13.4 percent relative to the control group. Overall, the results support the empirical findings in the main text. G-SIBs shifted more lending to less risky borrowers and also increased the

[21]As stressed by Silva & Tenreyro (2006, 2011), the PPML Estimator yields unbiased and robust results for log-linearized models in the presence of many zero observations and of heteroscedastic error terms. When applied to credit exposure data this estimator has already been used in the literature (see, e.g., Popov & Van Horen 2015). To include multiple levels of fixed effects we rely on Correia *et al.* (2020). The reduced number of identifying observations in these regressions (in comparison to column 3 and 4 in Table 3) is due to separation in the context of Poisson models (see Correia *et al.* 2019).

[22]Using the rating in absolute levels (i.e., a very refined rating scale) is not possible, since we would end up with very few identifying observations for some credit ratings, given the differences between G-SIBs and Non-G-SIBs with respect to the distribution of loans across risk categories (recall Figure 3). Also for the regression in column 2, we construct deciles based on the borrower's credit rating for G-SIBs and Non-G-SIBs separately and aggregate credit volumes at annual rather than quarterly level, to obtain a greater overlap of observations within the fixed effect clusters.

demand for collateral relative to the control group.

The last set of robustness checks in Table C.3 concerns the effects on the pricing behaviour. Columns 1 and 2 are about the average effect on interest rate margins, where we extend the pre-treatment period to 2000 in column 1 and include the base rate on which the margin is added in column 2.[23] The positive coefficients for the interaction term in both columns are in line with the main results in Table 7 and suggest a more conservative pricing of loans by G-SIBs in the post-reform period. Columns 3-5 analyse the pricing sensitivity to risk. In column 3 the pre-treatment period starts in 2000, in column 4 we add up margins and base rates and use the logarithm of the sum as dependent variable (similar to column 2), and column 5 replaces the rating variable with a binary rating classification in the same way as column 2 in Table C.2. All the results support the findings in Table 8, Panel A, indicating a less risk sensitive pricing for G-SIBs since 2012 in relative terms.

7 Conclusion

In this paper, we use granular data on syndicated loans to analyse the impact of the post-crisis reforms for G-SIBs on bank lending behaviour. We find that – compared with other banks – G-SIBs have reduced credit risk taking after the reforms, with respect to both borrower- and loan-specific risk factors. Specifically, G-SIBs shifted lending towards better-rated companies and also increased the amount of secured lending in the post-reform period. The latter is a catch-up effect relative to other banks, which already increased the amount of secured lending during and immediately after the global financial crisis. When analysing interest rate margins, we find evidence for more conservative pricing behaviour by G-SIBs in the post-reform period. While the interest rates charged by G-SIBs were considerably lower than those charged by other banks before the reforms, this pricing gap has narrowed after 2012. The narrowing is consistent with a relative increase in funding costs for G-SIBs – potentially due to a reduction in implicit funding cost subsidies – which was then at least

[23] We consider the following four base rates: LIBOR, EURIBOR, HKIBOR and US Prime. These four base rates cover 90 percent of the observations in our sample.

partially passed on to the banks' borrowers.

Overall, our findings suggest that the post-crisis reforms at least partially mitigated moral hazard problem associated with systemically important banks. They effectively limited excessive risk taking and reduced funding cost subsidies for G-SIBs. The latter may be seen as indirect evidence for a credible reduction in bailout expectations associated with 'too-big-to-fail' considerations (see also Berndt *et al.* 2019 and the papers cited above on this point). At the same time, potential side effects that could be associated with tighter regulation appear to be limited, since we do not detect significant effects on overall credit supply or cross-border lending of G-SIBs. While the findings in our paper suggest that the reforms were going into the right direction, the extent to which they have solved the 'too-big-to fail' problem remains an interesting topic for further research.

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Figures

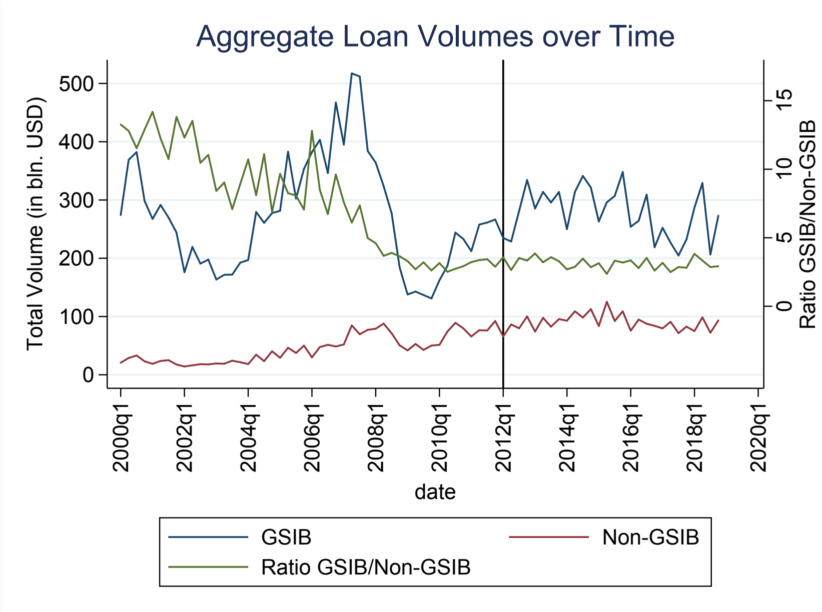

Figure 1: We aggregate lending volumes by quarter and group of G-SIBs/Non-G-SIBs. For the ratio, we divide both volumes in a given quarter.

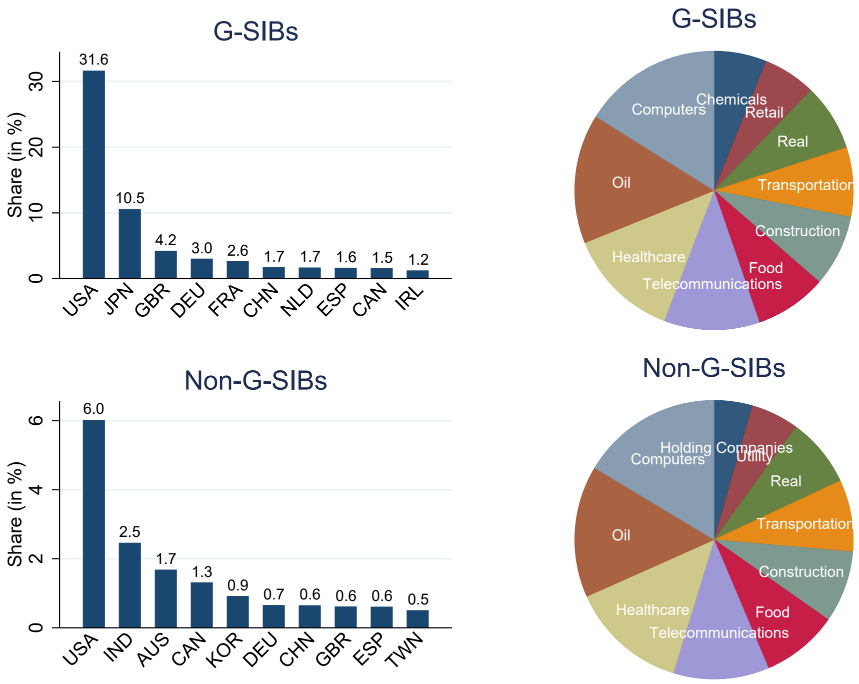

Figure 2: The left panel shows the geographical breakdown of lending volumes for G-SIBs (top) and Non-G-SIBs (bottom) for the period 2010-2018. The right panel illustrates lending volumes by industry for G-SIBs (top) and Non-G-SIBs (bottom) for the same period. For illustration purposes we focus on the 10 largest countries/industries in each panel.

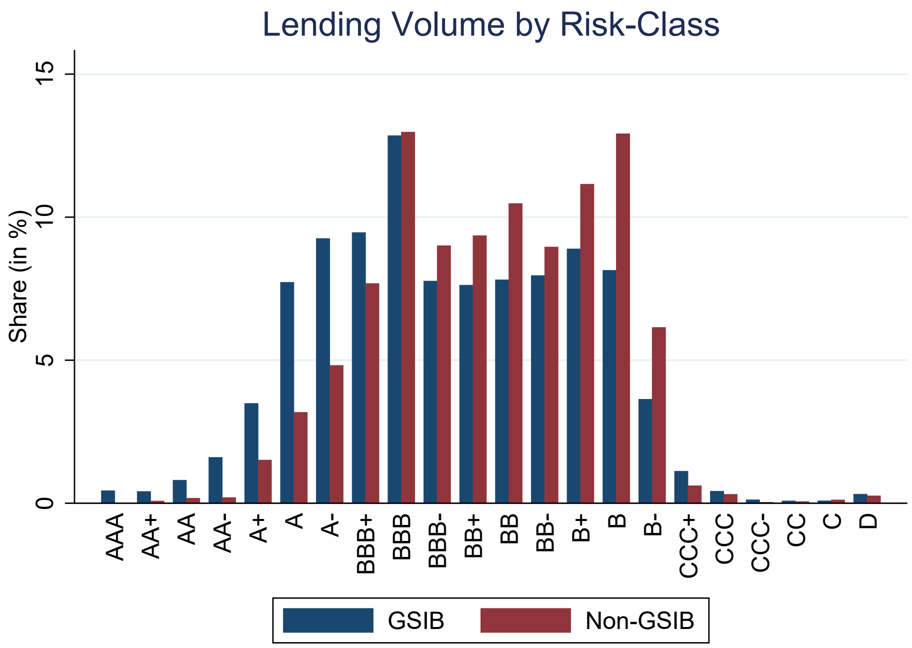

Figure 3: We aggregate lending volumes by credit rating and group of G-SIBs/Non-G-SIBs. If the ratings from Moody's Corporation and S&P Financial Services LLC differ by an odd number of notches, we round the average to the next lower rating notch. Then, we calculate the respective portfolio share for each group of banks.

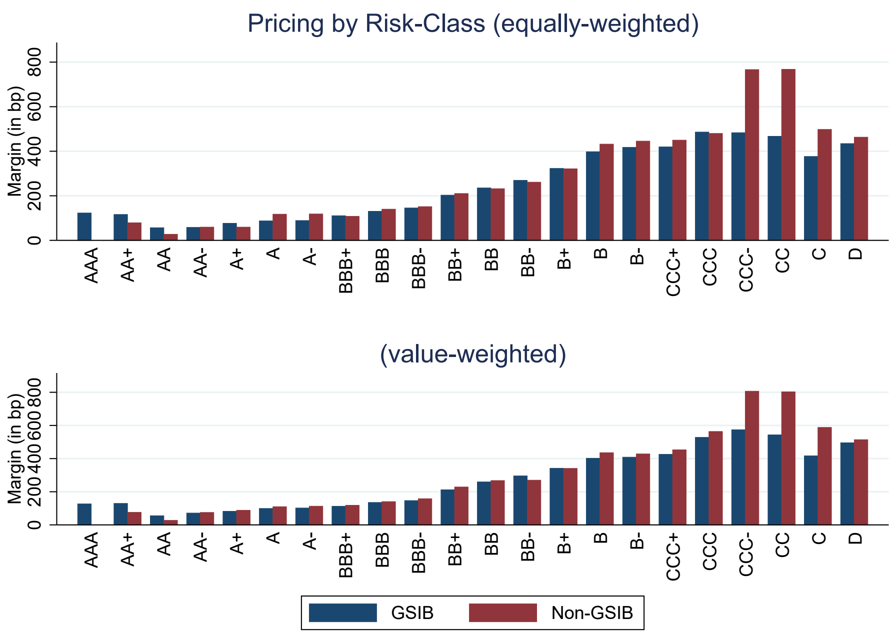

Figure 4: For each group of banks, we calculate the margin per credit rating by applying an unweighted mean in the top panel and a value-weighted average in the bottom panel. If the ratings from Moody's Corporation and S&P Financial Services LLC differ by an odd number of notches, we round the average to the next lower rating notch.

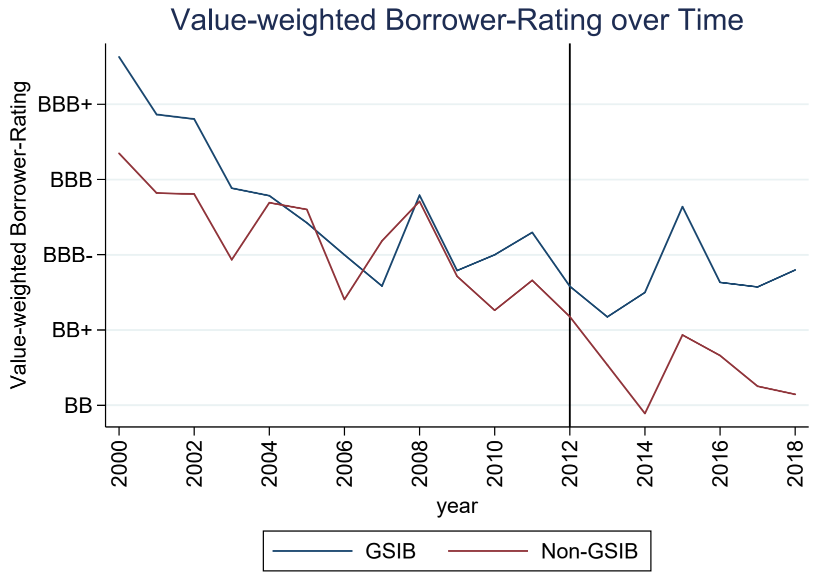

Figure 5: For both G-SIBs and Non-G-SIBs we calculate the share of funds which is attributed to a specific rating class in a given year. We transform the credit ratings to a numerical Standard & Poor's scale with "0" representing "D" up to "22" representing "AAA" and compute a weighted average. For illustration purpose, we leave the labels of the y-axis with the original rating classification.

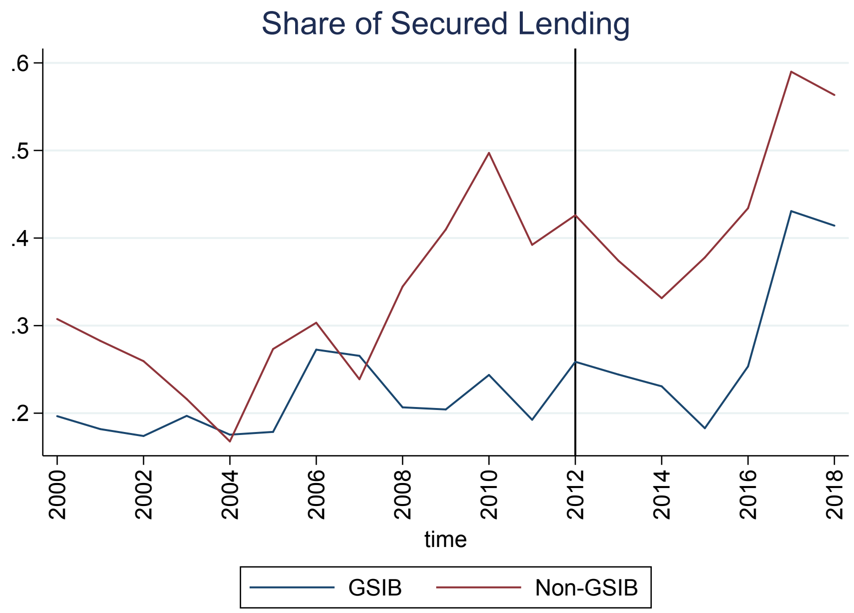

Figure 6: For both G-SIBs and Non-G-SIBs we calculate the share of funds which is secured by collateral in a given year.

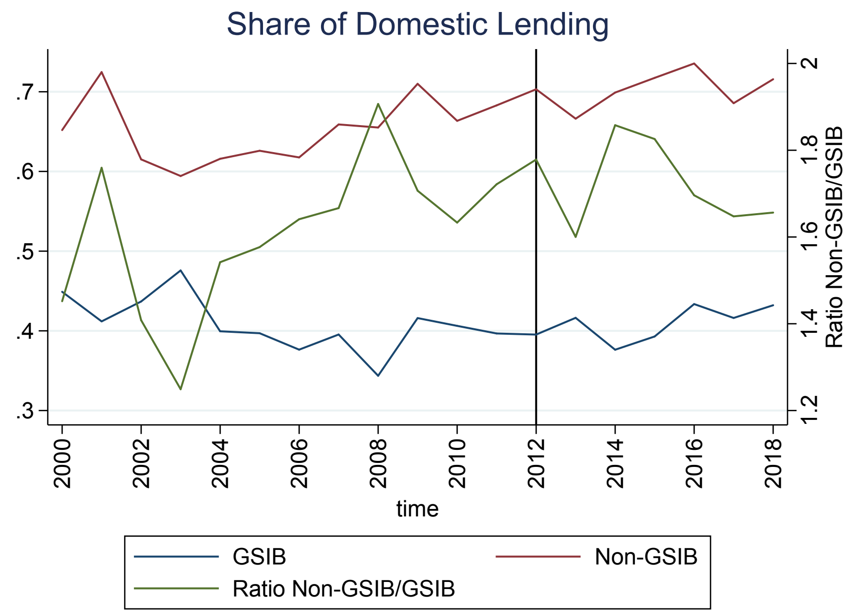

Figure 7: For each bank, we compute the domestic loan share by dividing the amount of domestic loans issued by the total loan volume. We then calculate an average across the individual banks.

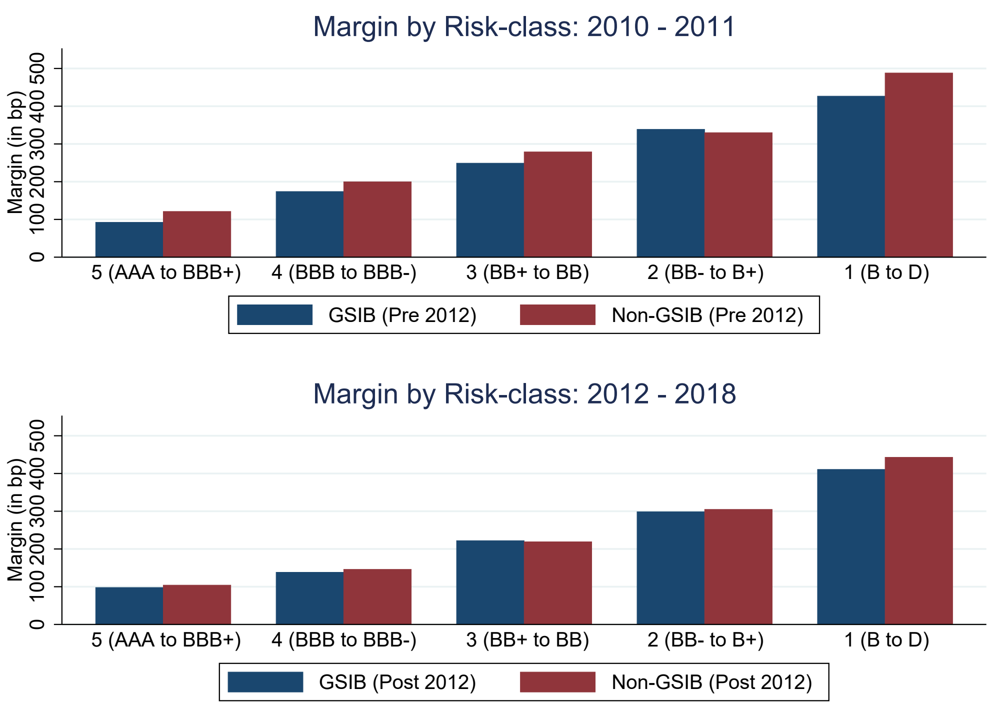

Figure 8: Each bar represents the average margin for a given risk segment. We aggregate tranche margins by calculating an equal (unweighted) average for each group of banks.

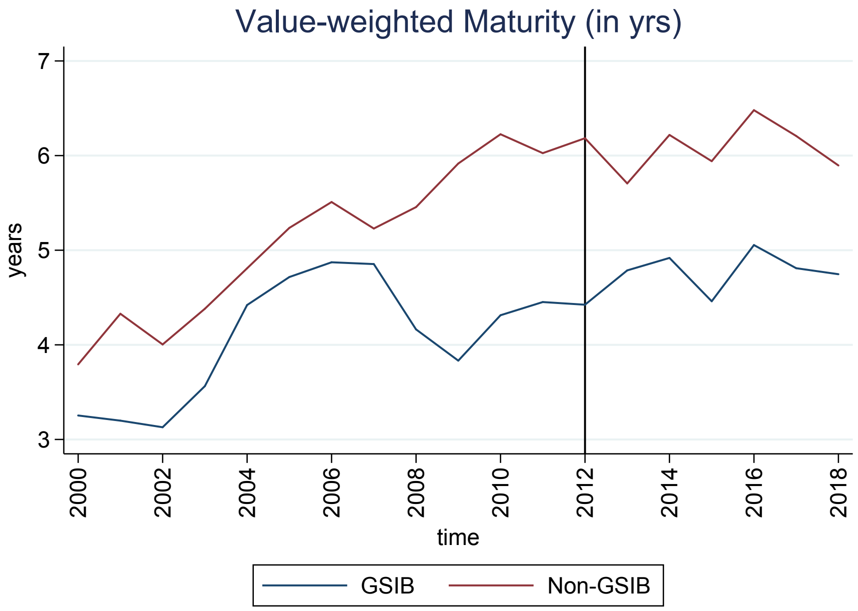

Figure 9: For both G-SIBs and Non-G-SIBs we calculate the share of funds which is attributed to a specific maturity in a given year. We then use these weights to compute a value-weighted maturity for each group of banks.

Tables

Table 1: Syndicated Loan Market - Tranche-Level Information

	G-SIBs			Non-G-SIBs		
	N	Mean	Std. dev.	*N*	Mean	Std. dev.
Tranche Size (in Tsd. US-$)	108,929	88230.1	142901.7	52,354	59527.5	104141.6
Margin (in bp)	51,251	270.01	154.52	20,646	264.13	163.61
Maturity (in yrs)	106,051	5.0036	3.3155	49,941	5.6395	4.1000
Rating	33,223	10.5550	3.3146	7,838	10.0995	3.0446
Secured Y/N	108,818	0.3240	0.4680	52,331	0.4481	0.4973
Domestic Y/N	108,929	0.4792	0.4996	52,354	0.6071	0.4884
Number of Lead Banks	108,929	4.8064	4.6359	52,354	4.6796	4.3375

Note: This table summarizes our tranche level data for the period 2010-2018. We calculate summary statistics for the rating variable by transforming the S&P rating scale to a numerical scale starting with ”0” representing ”D” up to ”22” representing ”AAA”. A rating of ”10” corresponds to ”BB”.

Table 2: Sum Stats of Balance Sheet Items and P&L metrics

(a) G-SIBs

G-SIBs	N	Mean	P10	P50	P90	Std. dev.
Total Assets (in Bln. US-$)	289	1598.6	663.50	1578.5	2589.8	756.93
Total Net Loans (in Bln. US-$)	286	673.39	125.72	700.63	1040.3	380.52
Total Deposits (in Bln. US-$)	286	819.53	187.82	721.94	1668.0	552.39
Net Interest Income (in Bln. US-$)	266	24.634	6.3566	18.534	49.483	16.903
Loan-to-Deposit Ratio	286	0.9099	0.5670	0.7681	1.2551	0.4909
Leverage Ratio	44	0.07848	0.05760	0.08135	0.09450	0.01354
Tier 1 Capital Ratio	248	0.1369	0.1088	0.1319	0.1722	0.02503
NPL Ratio	198	0.01377	0.001728	0.008733	0.02831	0.01570
Return on Average Assets (in %)	287	0.4978	-0.02963	0.4433	1.1692	0.4926
Return on Average Equity (in %)	287	7.0174	-0.5670	7.4592	14.022	6.8253
Synd Loan Volume to Total Net Loans (in %)	286	12.868	1.0359	6.5342	23.462	20.201
Synd Loan Volume to Total Assets (in %)	289	3.4121	0.3251	2.6795	7.6815	2.6075

(b) Non-G-SIBs

Non-G-SIBs	N	Mean	P10	P50	P90	Std. dev.
Total Assets (in Bln. US-$)	2,805	135.14	8.2008	53.814	379.85	218.44
Total Net Loans (in Bln. US-$)	2,709	77.103	4.0488	32.262	208.64	126.85
Total Deposits (in Bln. US-$)	2,557	78.459	5.8299	37.117	212.24	124.54
Net Interest Income (in Bln. US-$)	2,651	2.5750	0.1677	0.9744	6.0348	4.3862
Loan-to-Deposit Ratio	2,557	1.0701	0.6237	0.8994	1.6136	0.6461
Leverage Ratio	277	0.09203	0.08090	0.09190	0.1063	0.009003
Tier 1 Capital Ratio	2,406	0.1283	0.08667	0.1232	0.1764	0.03406
NPL Ratio	1,999	0.02042	0.002344	0.01291	0.05191	0.02149
Return on Average Assets (in %)	2,713	0.8745	0.09135	0.8140	1.9729	0.7408
Return on Average Equity (in %)	2,692	9.0532	1.3918	9.2618	17.631	6.9655
Synd Loan Volume to Total Net Loans (in %)	2,709	5.9465	0.2964	1.0227	7.8790	18.504
Synd Loan Volume to Total Assets (in %)	2,805	2.8941	0.1530	0.5678	4.1643	10.983

Note: Both panels show summary statistics for annual bank-specific financial indicators obtained from SNL Financial for the period 2010-2018. For the last two rows in each panel, we sum up tranche volumes of syndicated loans (provided by Dealogic Loanware) by bank-year and divide them by the respective SNL item.

Table 3: Effects of the G-SIB reforms on Lending Volumes

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(# of Deals)	(5) 1(Lending > 0)
Post2012 × GSIB	0.0595	-0.0229	0.0246	0.00761	0.000875
	(0.0972)	(0.0513)	(0.123)	(0.00542)	(0.00651)
Observations	6,145	52,820	693,996	693,996	693,996
R-squared	0.801	0.656	0.215	0.138	0.215
Bank Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	No	No	No	No
Qtr x Ctr x Ind FE	No	Yes	Yes	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Ind x Qtr
Margin	Int	Int	Ext & Int	Ext & Int	Ext
Model	Log w/o zeros	Log w/o zeros	Log w/ zeros	Log w/ zeros	LPM
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Unit of Obs	Bank x Qtr	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind
Nr. of Banks	377	375	541	541	541

Note: Table 3 estimates the effect on lending volumes. Column 1 includes quarter FE, columns 2-5 make us of quarter, borrower-country, industry FE. While column 1 and 2 capture the intensive margin only, column 3 and 4 focus on both intensive and extensive margin. Column 4 uses number of deals as dependent variable and column 5 estimates a Linear Probability Model. Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table 4: Effects of the G-SIB reforms on Portfolio riskiness

(a) Lending Sensitivity to Risk

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)	(5) Log(Lending)	(6) Log(Lending)
Post2012 × GSIB × Rat	0.219**	0.160*	0.124	0.203*	0.227**	0.203**
	(0.0976)	(0.0933)	(0.0835)	(0.106)	(0.0928)	(0.0882)
Post2012 × GSIB		-0.594	-0.425		-0.806***	-0.625**
		(0.365)	(0.328)		(0.300)	(0.300)
Observations	9,525	9,525	10,297	6,284	6,284	6,542
R-squared	0.850	0.814	0.815	0.826	0.802	0.803
Bank Controls	No	Yes	Yes	No	Yes	Yes
Bank x Time FE	Yes	No	No	Yes	No	No
Rat x Ctr x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank x Rat x Ctr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Yr	Bank & Ctr x Yr	Bank & Ctr x Yr
Frequency	Quarterly	Quarterly	Quarterly	Yearly	Yearly	Yearly
Sample	Full	Condensed	Full	Full	Condensed	Full
Unit of Obs	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Yr x Rat x Ctr	Bank x Yr x Rat x Ctr	Bank x Yr x Rat x Ctr
Nr. of Banks	58	58	119	68	68	119

(b) Breakdown by Risk Segment

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)
Post2012 × GSIB	0.275**	-0.118	0.405**	0.0952
	(0.127)	(0.158)	(0.159)	(0.170)
Observations	5,186	4,459	3,320	2,892
R-squared	0.697	0.683	0.558	0.595
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Country x Time FE	Yes	Yes	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Yr	Bank & Ctr x Yr
Frequency	Quarterly	Quarterly	Yearly	Yearly
Risk Segment	Safe	Risky	Safe	Risky
Unit of Obs	Bank x Qtr x Ctr	Bank x Qtr x Ctr	Bank x Yr x Ctr	Bank x Yr x Ctr
Nr. of Banks	102	114	102	113

Note: Panel A estimates the effect on the lending sensitivity to risk. In columns 1-3 we aggregate lending volumes by bank, risk class, borrowing country and quarter, in columns 4-6 we aggregate by bank, risk class, borrowing country and year. *Rat* is our own-created, five-bin rating variable. In Panel B we estimate the effect for a particular risk segment, where the safe segment includes all investment grade credit ratings, i.e. ratings equal to or greater than *BBB-*. The risky segment contains all the remaining credit ratings (i.e. less than *BBB-*). Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table 5: Effects of the G-SIB reforms on Secured Lending

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)	(5) Log(Lending)	(6) Log(Lending)
Post2012 × GSIB × Sec	0.207**	0.144	0.107	0.436**	0.477*	0.532**
	(0.0956)	(0.0949)	(0.0906)	(0.213)	(0.243)	(0.236)
Post2012 × GSIB		-0.0588	0.0172		-0.141	-0.126
		(0.0775)	(0.0721)		(0.139)	(0.141)
Observations	27,409	27,409	30,075	6,447	6,447	7,186
R-squared	0.725	0.671	0.668	0.696	0.580	0.593
Bank Controls	No	Yes	Yes	No	Yes	Yes
Bank x Quarter FE	Yes	No	No	Yes	No	No
Sec x Ctr x Qtr FE	Yes	Yes	Yes	No	No	No
Bank x Sec x Ctr FE	Yes	Yes	Yes	No	No	No
Sec x Rat x Qtr FE	No	No	No	Yes	Yes	Yes
Bank x Sec x Rat FE	No	No	No	Yes	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Rat x Qtr	Bank & Rat x Qtr	Bank & Rat x Qtr
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Sample	Full	Condensed	Full	Full	Condensed	Full
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Unit of Obs	Bank x Qtr x Sec x Ctr	Bank x Qtr x Sec x Ctr	Bank x Qtr x Sec x Ctr	Bank x Qtr x Sec x Rat	Bank x Qtr x Sec x Rat	Bank x Qtr x Sec x Rat
Nr. of Banks	173	173	344	65	65	125

Note: Table 5 estimates the effect on secured lending. In columns 1-3 we aggregate lending volumes by bank, quarter, status of collateralisation and borrower country and estimate the effect within a given borrower country. In columns 4-6 we aggregate by bank, quarter, status of collateralisation and rating class and estimate the effect within rating class. *Sec* is a binary variable, which is one, if lending volumes are secured and zero otherwise. Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table 6: Effects of the G-SIB reforms on Foreign Lending

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)	(5) Log(Lending)	(6) Log(Lending)
Post2012 × GSIB × Dom	-0.0517	-0.0700	-0.0542	0.0670	0.0670	0.101
	(0.0776)	(0.0833)	(0.0814)	(0.128)	(0.128)	(0.131)
Post2012 × GSIB		0.00787	0.0459		0.0204	-0.0117
		(0.0663)	(0.0642)		(0.118)	(0.117)
Observations	21,963	21,963	25,199	5,452	5,452	8,852
R-squared	0.707	0.653	0.645	0.898	0.783	0.766
Bank Controls	No	Yes	Yes	No	Yes	Yes
Bank x Qtr FE	Yes	No	No	Yes	No	No
Dom x Qtr FE	No	No	No	Yes	Yes	Yes
Bank x Dom FE	No	No	No	Yes	Yes	Yes
Ctr x Qtr FE	Yes	Yes	Yes	No	No	No
Bank x Ctr FE	Yes	Yes	Yes	No	No	No
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank	Bank	Bank
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Sample	Full	Condensed	Full	Full	Condensed	Full
Unit of Obs	Bank x Qtr x Ctr	Bank x Qtr x Ctr	Bank x Qtr x Ctr	Bank x Qtr x Dom	Bank x Qtr x Dom	Bank x Qtr x Dom
Nr. of Banks	141	141	361	162	162	368

Note: Table 6 estimates the effect on foreign lending. In columns 1-3 we aggregate lending volumes by bank, quarter and borrower country. In columns 4-6 we aggregate by bank, quarter and domestic/foreign lending. *Dom* is a binary variable, which is one if the nationality of the parent bank is the same as the country of credit exposure and zero otherwise. Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table 7: Effects of the G-SIB reforms on the Pricing of Tranches

VARIABLES	(1) Log(Margin)	(2) Log(Margin)	(3) Log(Margin)	(4) Log(Margin)	(5) Log(Margin)	(6) Log(Margin)
Post2012 $\times$ GSIB	0.0874**	0.0727**	0.0359	0.0874***	0.0727***	0.0359*
	(0.0387)	(0.0351)	(0.0321)	(0.0326)	(0.0264)	(0.0213)
Amount	0.0218***	0.0208***	0.0135***	0.0218***	0.0208***	0.0135***
	(0.00582)	(0.00552)	(0.00488)	(0.00534)	(0.00467)	(0.00430)
Maturity	0.0460***	0.0502***	0.0519***	0.0460***	0.0502***	0.0519***
	(0.00699)	(0.00601)	(0.00642)	(0.00629)	(0.00513)	(0.00514)
Rating	-0.149***	-0.141***	-0.137***	-0.149***	-0.141***	-0.137***
	(0.00619)	(0.00506)	(0.00512)	(0.00546)	(0.00374)	(0.00344)
Secured	0.0270	0.00732	-0.00516	0.0270	0.00732	-0.00516
	(0.0219)	(0.0226)	(0.0227)	(0.0215)	(0.0219)	(0.0224)
Observations	25,177	25,118	24,978	25,177	25,118	24,978
R-squared	0.656	0.748	0.827	0.656	0.748	0.827
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	No	No	Yes	No	No
Qtr x Ctr FE	No	Yes	No	No	Yes	No
Qtr x Ctr x Ind FE	No	No	Yes	No	No	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Deal	Bank & Deal	Bank & Deal
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Nr. of Banks	119	119	118	119	119	118

Note: Table 7 estimates the effect on charged interest rates. In column 1 we include quarter FE, in column 2 quarter, borrower-country FE and in column 3 quarter, borrower-country, industry FE. In column 4-6 we double-cluster standard errors at bank and deal level and follow, apart from that, the same estimation procedure as in column 1-3. Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table 8: Effects of the G-SIB reforms on the Pricing Sensitivity to Risk

(a) Pricing Sensitivity to Risk

VARIABLES	(1) Log(Margin)	(2) Log(Margin)	(3) Log(Margin)	(4) Log(Margin)	(5) Log(Margin)	(6) Log(Margin)
Post2012 × GSIB × Rat	0.0734***	0.0530*	0.0503*	0.0734**	0.0530	0.0503
	(0.0241)	(0.0312)	(0.0291)	(0.0344)	(0.0400)	(0.0368)
Post2012 × GSIB		-0.0766	-0.0751		-0.0766	-0.0751
		(0.0578)	(0.0547)		(0.0892)	(0.0826)
Amount	0.0214***	0.0217***	0.0217***	0.0214***	0.0217***	0.0217***
	(0.00519)	(0.00533)	(0.00531)	(0.00505)	(0.00506)	(0.00506)
Maturity	0.0499***	0.0506***	0.0505***	0.0499***	0.0506***	0.0505***
	(0.00662)	(0.00658)	(0.00656)	(0.00533)	(0.00538)	(0.00535)
Secured	-0.0157	-0.0200	-0.0206	-0.0157	-0.0200	-0.0206
	(0.0234)	(0.0238)	(0.0237)	(0.0253)	(0.0252)	(0.0250)
Observations	24,240	24,240	24,461	24,240	24,240	24,461
R-squared	0.795	0.783	0.786	0.795	0.783	0.786
Bank Controls	No	Yes	Yes	No	Yes	Yes
Bank x Quarter FE	Yes	No	No	Yes	No	No
Rat x Ctr x Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank x Rat x Ctr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Deal	Bank & Deal	Bank & Deal
Sample	Full	Condensed	Full	Full	Condensed	Full
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Nr. of Banks	102	102	111	102	102	111

(b) Breakdown by Risk Segment

VARIABLES	(1) Log(Margin)	(2) Log(Margin)	(3) Log(Margin)	(4) Log(Margin)
Post2012 × GSIB	0.126*	0.0405	0.0927	0.0300
	(0.0679)	(0.0314)	(0.0608)	(0.0306)
Observations	7,131	18,031	7,098	17,970
R-squared	0.449	0.374	0.789	0.455
Bank Controls	Yes	Yes	Yes	Yes
Tranche Characteristics	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	No	No
Quarter x Country FE	No	No	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Risk Segment	Safe	Risky	Safe	Risky
Nr. of Banks	86	97	86	97

Note: Panel A estimates the effect on the pricing sensitivity to risk. *Rat* is our own-created, five-bin rating variable. In columns 1-3 we double-cluster standard errors at bank and quarter-country level, in columns 4-6 at bank and deal level. In Panel B we estimate the effect for a particular risk segment, where the safe segment includes all investment grade credit ratings, i.e. ratings equal to or greater than *BBB-*. The risky segment contains all the remaining credit ratings (i.e. less than *BBB-*). In column 1 and 2 we include quarter fixed effects, column 3 and 4 uses quarter, borrower-country FE. Tranche characteristics include trance amount, maturity, borrower rating and status of collateralisation. Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table 9: Effects of the G-SIB reforms on the Tranche Maturity

VARIABLES	(1) Maturity	(2) Maturity	(3) Maturity	(4) Log(Maturity)	(5) Maturity
Post2012 × GSIB	0.0280	-0.00238	-0.0634	-0.0194	0.00952
	(0.125)	(0.0705)	(0.0515)	(0.0173)	(0.0691)
Amount	0.0169	0.0134	0.0573**	-0.00990	0.121***
	(0.0245)	(0.0241)	(0.0222)	(0.00610)	(0.0269)
Margin	0.00205***	0.00222***	0.00231***	0.000252**	0.00214***
	(0.000308)	(0.000305)	(0.000335)	(0.000101)	(0.000251)
Rating	-0.0583***	-0.0533***	-0.0685***	-0.0307***	
	(0.0172)	(0.0151)	(0.0153)	(0.00492)	
Secured	0.582***	0.481***	0.435***	0.110***	0.553***
	(0.0921)	(0.0909)	(0.0984)	(0.0311)	(0.0956)
Observations	25,177	25,118	24,978	24,978	63,935
R-squared	0.193	0.352	0.513	0.480	0.589
Bank Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	No	No	No	No
Qtr x Ctr FE	No	Yes	No	No	No
Qtr x Ctr x Ind FE	No	No	Yes	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Nr. of Banks	119	119	118	118	271

Note: Table 9 estimates the effect on tranche maturities. In column 1 we include quarter FE, in column 2 quarter, borrower-country FE and in column 3 quarter, borrower-country, industry FE. In column 4 we use the logarithmized maturity (in yrs) as dependent variable. In column 5 we omit the credit rating as control variable. Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Appendices

A Web-based matching procedure

Given the absence of common identifier between Dealogic Loanware and SNL Financial, we have to match the two data sets based on the name of the bank. In doing so, we have to deal with the 'classical' string match problem, where the name of the same banks in the two data sets may be different in its spelling. For example, the Bavarian state bank is listed as "BayernLB" in Dealogic Loanware and as "Bayerische Landesbank AöR" in SNL Financial. In addition, complex ownership structures and the existence of holding companies can further complicate the matching (e.g., Dealogic Loanware provides syndicated loan data for NatWest Markets, which is the investment banking arm of The Royal Bank of Scotland (RBS), whereas in SNL Financial only information for RBS is available). In both of the examples mentioned, traditional methods of fuzzy string matching would lead to a poor result.

Against this background, we apply the following matching algorithm: In a first round, we match banks by their punctuation-free names. This traditional method already gives us 441 matches between the two data sets. In further rounds, we match banks based on common URL addresses. That is, we collect the URLs of the top 5 hits when running an internet search engine with the bank's name and look for cases where cleaned URL addresses coincide. We consider a bank pair as matched when at least one particular combination of the top 5 URLs matches. In this manner, we are able to match an additional amount of 242 banks. In a last step, we check all matches for plausibility by hand.

B Classification of borrower risk

For the baseline specification on borrower risk we divide the sample into five risk classes based on the borrowers' credit rating. This is done in a way that captures the distribution of credit ratings in our sample, which is quite uneven across the Standard & Poor's rating scale (recall Figure 3; e.g., 84 percent of all companies share a rating between *BBB+* and *B-*). An overview of the allocation of ratings into the five risk classes is provided in Table B.1. Reflecting the thinner tails of the distribution, the top and and bottom eight rating bins in the Standard & Poor's rating scale are assigned to the best- and worst-rated risk classes, respectively. The remaining six rating bins are assigned to the inner three risk classes, with each of these classes including two bins. Notably, our classification captures the cut-off between investment grade (*BB+* or higher) and non-investment grade (*BBB-* or lower) ratings, which is between buckets 3 and 4 and also forms the basis for the sample splits in Tables 4 and 8. Figure B.1 displays the distributions of observations across the five risk classes. In order to show that our results do not depend on the specific classification of the rating variable that is outlined above, we provide results for alternative specifications in Section 6.

Table B.1: Summary of the own-created rating scale

Five-bin scale	Standard & Poor's scale
5	AAA, AA+, AA, AA-, A+, A, A-, BBB+
4	BBB, BBB-
3	BB+, BB
2	BB-, B+
1	B, B-, CCC+, CCC, CCC-, CC, C, D

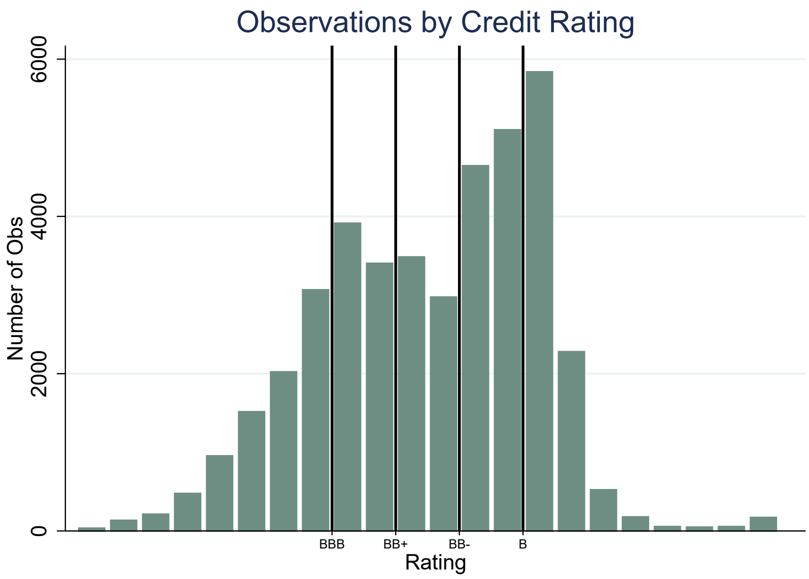

Figure B.1: This figure plots a histogram with respect to the credit rating. Each bar represents one of 22 rating bins ranging from AAA to D. The vertical lines indicate the four cut-off points for the own-created rating scale.

C Additional figures and tables

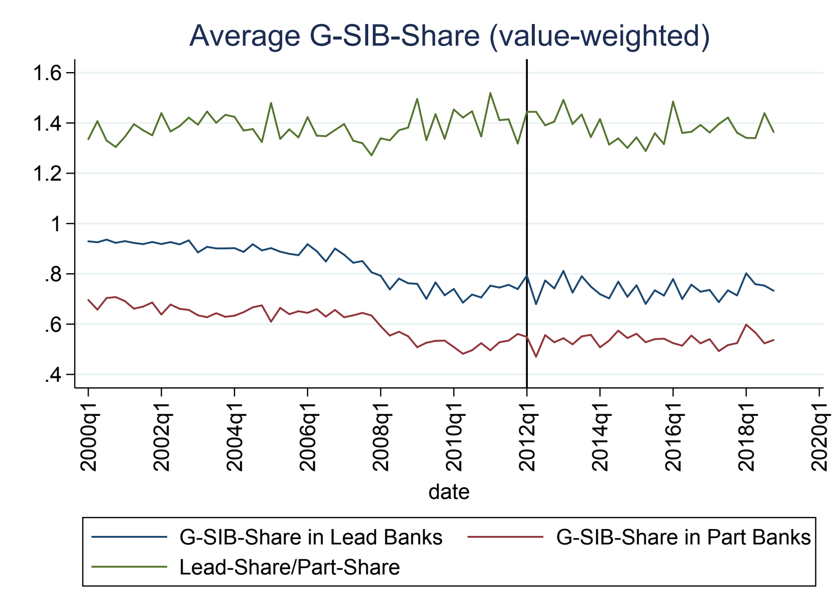

Figure C.1: For each quarter, we calculate the share of the lending volume originated by G-SIBs in the total number of leading banks (blue) and participating banks (red). The green line indicates the ratio between the two lines.

Table C.1: Credit supply - alternative Specifications

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Lending Volume	(4) # of Deals
Post2012 × GSIB	-0.00740	-0.243*	0.124	0.0954
	(0.131)	(0.130)	(0.143)	(0.125)
Observations	924,532	1,069,880	344,762	344,762
R-squared	0.203	0.212		
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Qtr x Ctr x Ind FE	Yes	Yes	Yes	Yes
Firms	All	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2000 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Margin	Int & Ext	Int & Ext	Int & Ext	Int & Ext
Model	Log w/ zeros	Log w/ zeros	PPML	PPML
Frequency	Quarterly	Quarterly	Quarterly	Quarterly
Unit of Obs	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind
Nr. of Banks	598	542	477	477
Pseudo R2			0.427	0.262

Note: Table C.1 estimates the effect on lending volumes. In column 1 we include all borrowing parties in the sample, column 2 extends the pre-treatment period to 2000. In column 3 and 4 we estimate the relationship using a Poisson Pseudo-Maximum Likelihood (PPML) Estimator, where the number of deals is the dependent variable in column 4. Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table C.2: Portfolio riskiness - alternative Specifications

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)	(5) Sec Dummy	(6) Sec Dummy
Post2012 × GSIB × Rat	0.512**	0.115*	0.123			
	(0.239)	(0.0646)	(0.111)			
Post2012 × GSIB × Sec				0.344*		
				(0.175)		
Post2012 × GSIB					0.134***	0.671***
					(0.0500)	(0.246)
Amount					-0.0167***	-0.0898***
					(0.00424)	(0.0125)
Maturity					0.0280***	0.164***
					(0.00248)	(0.0134)
Margin					0.175***	1.024***
					(0.0178)	(0.0888)
Observations	8,911	7,129	12,959	9,188	64,695	64,362
R-squared	0.845	0.837	0.857	0.716	0.248	
Bank Controls	No	No	No	No	Yes	Yes
Bank x Time FE	Yes	Yes	Yes	Yes	No	No
Rat x Ctr x Time FE	Yes	Yes	Yes	No	No	No
Bank x Rat x Ctr FE	Yes	Yes	Yes	No	No	No
Sec x Rat x Time FE	No	No	No	Yes	No	No
Bank x Sec x Rat FE	No	No	No	Yes	No	No
Bank FE	No	No	No	No	Yes	Yes
Quarter FE	No	No	No	No	Yes	Yes
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2000 - 2018	2000 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Rat x Qtr	Bank & Ctr x Qtr	Bank
Frequency	Quarterly	Yearly	Quarterly	Quarterly	-	-
Rating	Binary	Deciles	Five-bin scale	Five-bin scale	-	-
Unit of Obs	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Qtr x Sec x Rat	Bank x Tranche	Bank x Tranche
Model	OLS	OLS	OLS	OLS	LPM	Logit
Nr. of Banks	65	67	61	66	271	194

Note: Table C.2 estimates the effect on portfolio riskiness. Column 1-3 studies the effect with respect to borrower risk. In column 1 we use a binary risk classification (IG vs. non-IG) as rating variable, in column 2 the rating classification is based on deciles, in column 3 we extend the sample period to 2000. In columns 4-6 we investigate the effect on secured lending. In column 4 the pre-treatment period starts in 2000. In column 5 and 6 we use the information, whether a tranche is secured or not, as dependent binary variable and estimate tranche-level regressions (LPM in column 5 and Logit-Regression in column 6). Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

Table C.3: Pricing of Tranches - alternative Specifications

VARIABLES	(1) Log(Margin)	(2) Log(Margin)	(3) Log(Margin)	(4) Log(Margin)	(5) Log(Margin))
Post2012 × GSIB	0.0505*	0.0633**			
	(0.0290)	(0.0318)			
Amount	0.00597	0.0171***	0.0214***	0.0196***	0.00372
	(0.00554)	(0.00492)	(0.00519)	(0.00433)	(0.00516)
Maturity	0.0494***	0.0349***	0.0499***	0.0368***	0.0588***
	(0.00433)	(0.00550)	(0.00662)	(0.00584)	(0.00724)
Rating	-0.162***	-0.109***			
	(0.00639)	(0.00452)			
Secured	0.0516**	-0.0345	-0.0157	-0.00966	0.0183
	(0.0204)	(0.0219)	(0.0234)	(0.0218)	(0.0192)
Post2012 × GSIB × Rat			0.0734***	0.0598***	0.118***
			(0.0241)	(0.0177)	(0.0427)
Observations	37,598	24,337	24,240	23,504	24,524
R-squared	0.786	0.722	0.795	0.779	0.713
Bank Controls	Yes	Yes	No	No	No
Bank x Quarter FE	No	No	Yes	Yes	Yes
Rat x Ctr x Qtr FE	No	No	Yes	Yes	Yes
Bank x Rat x Ctr FE	No	No	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No	No
Qtr x Ctr FE	Yes	Yes	No	No	No
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2000 - 2018	2010 - 2018	2000 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Margins	excl Base-Rate	incl Base-Rate	excl Base-Rate	incl Base-Bate	excl Base-Rate
Rat Class	-	-	Five-bin scale	Five-bin scale	Binary
Nr. of Banks	129	107	102	96	102

Note: Table C.3 estimates the effect on the pricing behaviour. Column 1-2 study the average effect on margins irrespective of borrower risk. In column 1 we extend the pre-treatment period to 2000, in column 2 we add up margins with base rates and use the logarithm of the sum as dependent variable. Columns 3-5 analyse the pricing sensitivity to risk. In column 3 the pre-treatment period starts in 2000, column 4 includes the sum of margins and base rates as dependent variable (similar to column 2) and column 5 uses a binary rating classification (IG vs non-IG). Significance levels are indicated by stars with *** $p < 0.01$, ** $p < 0.05$, * < 0.1.

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