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Does regulation only bite the less profitable? Evidence from the too-big-to-fail reforms

Tirupam Goel, Ulf Lewrick and Aakriti Mathur

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Does regulation only bite the less profitable? Evidence from the too-big-to-fail reforms

Tirupam Goel,[(1)] Ulf Lewrick[(2)] and Aakriti Mathur[(3)]

Abstract

Profitability shapes banks' responses to higher capital requirements. It underpins the opportunity cost of downsizing and the ability to generate capital. We assess its role based on a major reform, using textual analysis to identify the timing of banks' responses. Consistent with our model, less profitable banks contract in response to higher capital surcharges. Banks near the regulatory thresholds that determine the surcharges shrink further. More profitable banks, conversely, continue to increase their systemic importance. The reallocation of activity to these banks can improve efficiency. However, these banks have also been more exposed to tail risk during the Covid crisis.

Key words: Global systemically important bank (G-SIB), textual analysis, capital regulation, systemic risk, bank profitability, difference-in-differences (DD).

JEL classification: G21, G28, L51.

(1) Bank for International Settlements. Email: tirupam.goel@bis.org (corresponding author)
(2) Bank for International Settlements and a research fellow at the University of Basel. Email: ulf.lewrick@bis.org
(3) Bank of England. Email: aakriti.mathur@bankofengland.co.uk

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

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1 Introduction

Banks' responses to changes in regulation have received significant scrutiny, particularly since the reforms following the 2008 financial crisis (e.g. Admati *et al.* (2013)). A bank's pre-reform capitalisation plays a key role in determining how it adjusts to new regulation and the attendant impact on lending (e.g. Berger *et al.*, 2008; Gropp *et al.*, 2019; Jimenéz *et al.*, 2017). Yet, little is known about how pre-reform profitability shapes banks' balance sheet adjustment in response to regulation. Instead, much more attention has been dedicated to studying how regulation affects profitability (e.g. Ahmad *et al.*, 2020).

Profitability is key to the trade-off banks face when reacting to tighter regulation. It not only determines the opportunity cost of shrinking business activities, but also underpins the ability to raise capital organically, i.e. by retaining profits. Understanding how profitability affects banks' responses to new capital requirements is therefore crucial for understanding how regulation works. This matters particularly for the regulation of large banks whose resilience is critical for the stability of the financial system.

In this paper, we examine how profitability determines banks' adjustments to regulation. We assess a cornerstone of the too-big-to-fail reforms: the framework for Global Systemically Important Banks (G-SIBs). The framework imposes additional capital surcharges on some – but not all – large internationally active banks, which therefore create incentives for these banks to reduce their systemic importance.[1] Notably, the calibration of the capital surcharges is exogenous to the banks' pre-reform profitability. It thus provides an ideal setup to evaluate the role of bank profitability in an international context using publicly available data.

Our main contribution is to show empirically that profitability plays a determining role in shaping banks' response to changes in capital requirements, even after controlling

[1]The G-SIB framework defines systemic importance as the weighted average of a bank's market share in various financial activities. Systemic importance is thus tightly linked to the size of the bank and provides an estimate of the impact a bank's failure would have on the financial system (BCBS, 2021).

for bank capitalisation. Our difference-in-differences (DD) approach reveals that the framework caused the less profitable G-SIBs, i.e. those with pre-treatment return on assets (ROA) below the sample median, to cut back their systemic importance relative to the less profitable Non G-SIBs (i.e. banks not subject to the framework). Exploiting discontinuities in the calibration of the rules, we show that the contraction was even stronger for those G-SIBs that were close to the regulatory thresholds that determine their capital surcharges. By contrast, the more profitable G-SIBs continued to raise their systemic importance in sync with the more profitable Non G-SIBs. Including profitability as a third interaction term in the difference-in-differences approach, we establish that the wedge between more and less profitable G-SIBs, as compared with the corresponding wedge between more and less profitable Non G-SIBs, has increased significantly.

We present a theoretical framework to rationalise our empirical results. The model predicts that in response to higher capital requirements a more profitable bank shrinks its balance sheet by less (or expands it by more) than a less profitable bank – this is because the opportunity cost of shrinking is higher for a more profitable bank. To fund the relatively larger balance sheet, the more profitable bank raises more capital. Consistent with this mechanism, we show empirically that more profitable G-SIBs responded to the G-SIB framework by raising more capital than their less profitable peers.

What do these findings imply for policy? In addition to supporting G-SIBs' resilience by raising their capital ratios, the framework promotes a reallocation of banking activity towards the more profitable banks. This could enhance intermediation efficiency. However, the reallocation can raise financial stability concerns if higher profitability is based on greater risk taking. We test this hypothesis using the Covid-19 crisis as an experiment. Our results indicate that the more profitable G-SIBs experienced a larger increase in systemic risk during the pandemic, suggesting that higher profitability in good times may reflect greater exposure to tail risks (e.g. Meiselman *et al.* (2020)).[2]

Taken together, our findings suggest that the impact of regulation can vary considerably across banks. This underscores the value of complementary policy measures, such as enhanced supervision and resolution requirements, to contain banks' exposure to tail events and help address systemic risk.

A methodological contribution of our paper is the identification of regulatory treatments based on textual analysis. Identifying treatment dates is challenging since major reforms are generally announced long before their implementation, and they are phased-in over multiple years. The G-SIB framework is no exception: it was announced in 2011, while the implementation of higher capital requirements was phased in from 2016 to 2018 (BCBS, 2013). We use word-count analysis, and also distinguish between action-oriented versus general discussions of the G-SIB framework in banks' annual reports, to identify 2015 as the year when G-SIBs started incorporating the framework into their strategic planning. Annual reports originate from decision makers within banks, and contain valuable information about how regulatory reforms affect a bank's strategy. Despite these benefits, academic research has thus far made little use of the text contained in annual reports to assess the effects of regulatory reforms.

Several robustness checks confirm that bank profitability, rather than other factors such as banks' domicile or business model, is the main determinant of banks' response to the framework. We also consider a variety of alternative measures of profitability or alternative estimation approaches, such as matching. Furthermore, we exploit the flexibility of our textual analysis to consider the possibility of varying treatment dates across G-SIBs. For this, we use recent advances in staggered difference-in-differences approaches (e.g. Callaway and Sant'Anna (2021)). Our conclusions prove robust both quantitatively and in terms of statistical significance in all these experiments.

[2]We measure systemic risk based on the widely used SRISK measure (Acharya *et al.*, 2012; Brownlees and Engle, 2016). Our measure of systemic importance explains close to half of the variation in SRISK.

Related literature Our paper makes three contributions to the banking literature. First, it advances a growing literature on the determinants of how banks adjust to regulatory reforms. Most of the literature has focused on the role of capital, i.e. banks' *present* ability to meet capital requirements. For instance, Berger *et al.* (2008) and Gropp *et al.* (2019) show that poorly capitalised banks respond more quickly and strongly than their peers to tighter regulatory targets, and typically pursue balance sheet adjustments rather than raising capital via retaining earnings. This conclusion accords with Kashyap *et al.* (2010), who underscore that frictions in raising capital externally have a material impact on banks' response to higher requirements. In a similar vein, Jimenéz *et al.* (2017) conclude that the impact of dynamic provisioning requirements depends on banks' capitalisation. Complementing this line of research, our paper shows that even after controlling for capitalisation levels, pre-treatment profitability, i.e. the ability to generate capital in the future, proves to be a key driver of banks' responses to changes in capital requirements.

Our finding relates to that of Cohen and Scatigna (2016), who report that the more profitable banks expanded lending by more amid rising regulatory requirements after the 2007–08 crisis. Fang *et al.* (2020), for the case of emerging markets, and De Jonghe *et al.* (2020), for banks in Belgium, document that weaker banks contract credit supply by more when faced with higher capital requirements. Our work is also related to Peek and Rosengren (1995) who establish that banks facing binding regulatory requirements in response to negative shocks to capital are likely to shrink by more. Relatedly, Goel *et al.* (2020) use a theoretical model to show that banks' internal reallocation of capital in response to regulatory changes depends on the relative profitability of their business units.

Second, we propose a new methodology to identify regulatory treatments. Previous research has relied on announcement dates, such as the publication of the assessment methodology or banks' initial G-SIB designation (eg, Financial Stability Board (2021) or Violon *et al.* (2020)). It is, however, far from obvious when banks would start to incorporate future requirements into their capital planning. Our approach uses banks' annual reports which contain key insights around when and how banks respond to regulatory reforms. Several previous studies have relied on annual reports as a source of information about *non-financial* firms. For instance, keyword searches on 10-K filings of U.S. firms have been used, for example, by Hoberg and Maksimovic (2015) and Buehlmaier and Whited (2018) to assess financial constraints, Friberg and Seiler (2017) to construct measures of risk and ambiguity, and Hoberg and Moon (2017) for measuring offshoring activities. Hassan *et al.* (2019), in turn, use earnings conference calls to measure the effect of firms' exposure to political risk. Our paper builds on this line of research by adopting a two-step approach, in which we first perform a keyword search and then evaluate the context of the keyword occurrences to sharpen the interpretation of the search results.

Finally, this paper furthers our understanding of the effectiveness of post-crisis reforms aimed at addressing the too-big-to-fail problem, which remains a policy priority. While an established literature assesses the effects of capital requirements on banks' balance sheets or risk-taking (see Adrian *et al.* (2018) for a discussion), less is known about the effect of regulation on the systemic importance of banks.[3,4] Violon *et al.* (2020), for instance, find that relative to Non G-SIBs, G-SIBs cut back on asset growth and leverage, whereas other measures, such as ROA, were little affected. Goel *et al.* (2019) point to an acceleration of G-SIBs' balance sheet adjustments after the G-SIB framework was introduced. Behn and Schramm (2021) assess the impact of G-SIB designation on syndicated lending, and find no effect, while Degryse *et al.* (2020) point to an adverse effect on lending volumes. In a

[3]Few papers assess size-dependent bank regulation quantitatively, including Corbae and D'Erasmo (2021), Passmore and von Hafften (2019), and Goel (2016).

[4]In contrast to our focus on the medium-term impact, a different strand of the literature studies the immediate market response to the disclosure of G-SIB designations (e.g. Moenninghoff *et al.* (2015), Bongini *et al.* (2015) or the effect of the G-SIB framework on intermittent window dressing by banks (e.g. Behn *et al.* (2019), Garcia *et al.* (2021)).

similar vein, Favara *et al.* (2021) find that G-SIBs in the United States reduced corporate lending relative to other large U.S. banks. By contrast, our focus is on the framework's impact on the overall systemic importance of G-SIBs. Our analysis thus complements the ongoing evaluation of reforms to address the too-big-to-fail impasse.

We organise the remainder of this paper as follows. In Section 2, we outline the main features of the G-SIB framework and discuss how we take advantage of textual analysis to identify the regulatory treatment. Section 3 introduces the data before we turn to our empirical methodology in Section 4. We discuss our main empirical results in Section 5 and present a model in Section 6 to rationalise our findings. Section 7 assesses the robustness of our findings and considers the financial stability implications. We conclude with Section 8. The online appendix contains additional background information on the G-SIB framework and the textual analysis. It also provides additional results and robustness checks.

2 Institutional details and identifying treatment

2.1 The G-SIB framework

We use the G-SIB framework, a cornerstone of the too-big-to-fail reforms, to study the potentially differential impact of capital regulation on more and less profitable banks.

The goal of the framework is to induce large internationally active banks to internalise the negative externalities they impose on the global banking system (see Chapter SCO40 in BCBS (2021)). To this end, the framework imposes capital requirements that are proportional to banks' systemic importance. Systemic importance is measured based on the G-SIB *score*, which is equal to the weighted average of banks' market share in various financial activities (see Appendix A for more details on the framework). The score thus approximates the systemic impact of a bank's failure (BCBS, 2021).

Banks with scores above a certain threshold are designated as *global systemically important banks* or "G-SIBs". We refer to all other banks in the sample of large internationally active banks that the framework assesses as "Non G-SIBs". The framework does not impose any additional requirements on Non G-SIBs. By contrast, G-SIBs are grouped into different "buckets" based on their scores, and those with higher scores have to meet higher capital requirements. As a result, the framework creates incentives for G-SIBs to reduce their systemic importance depending on how much costlier capital is relative to debt (Kashyap *et al.*, 2010).

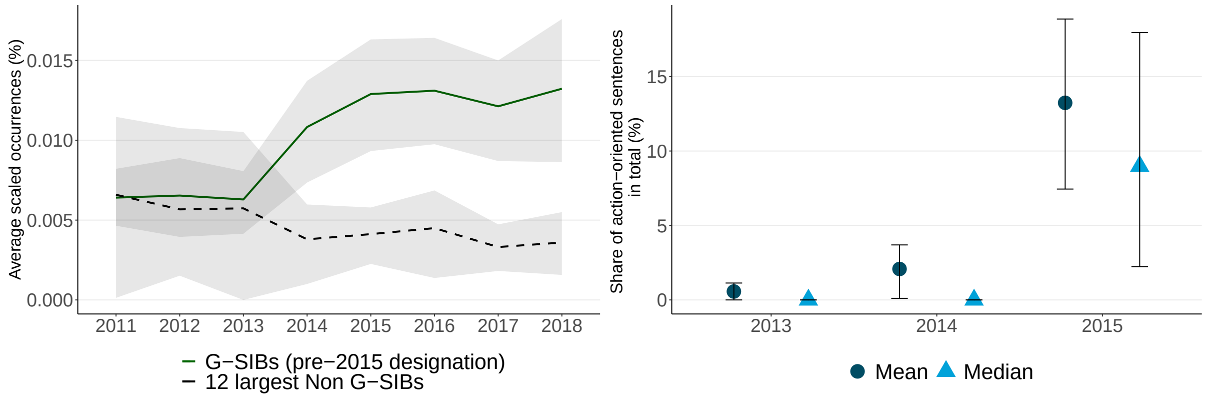
Several features of the framework facilitate our analysis. For one, the regulatory treatment is not directly related to banks' profitability, which we exploit in our empirical analysis. In addition, the framework applies across jurisdictions on a consistent basis and relevant underlying data are made publicly available. This allows us to draw conclusions in an international context and in a fully transparent manner. Moreover, the rules-based framework makes the identification of the treated banks (G-SIBs) and control banks (Non G-SIBs) straightforward.

2.2 Applying textual analysis to identify the treatment date

Identifying precisely when banks respond to the G-SIB framework is challenging for several reasons. Like other major reforms, the G-SIB framework was announced (2011) long before its implementation (2016). In addition, the implementation was phased-in gradually (from 2016 to 2018). While existing studies on the evaluation of regulatory reforms in general or the G-SIB framework in particular tend to use the announcement or implementation date as the *treatment* date, it is not obvious as to how much in advance banks adjust.[5]

[5] Event studies around key announcement dates (such as the publication of the G-SIB methodology or the list of G-SIBs) are not subject to these challenges because their goal is to assess the immediate market impact. These studies, however, are mute on the impact of the framework on banks' medium term strategic adjustments – the focus of our study.

Figure 1: Framework references in G-SIBs' annual reports: Word counts and keywords-in-context



(A) Average scaled word count occurrences

(B) Share of action-oriented sentences

Note: The left-hand panel plots the average occurrences of keywords (see Appendix B.1) for banks that have G-SIB framework-related discussions in their annual reports, with 95% bootstrapped confidence intervals. The total G-SIB-related keywords for each bank-year are scaled by the total length of the annual report. The 12 largest Non G-SIBs are based on 2013 scores. We exclude from the control sample those banks that were designated as G-SIBs in 2011 but dropped from the G-SIB list thereafter. The right-hand panel plots the average and median share of action-oriented sentences between 2013 and 2015, calculated after exclusion of outliers. The graph further shows the 95% bootstrapped confidence intervals for the mean and median. Outliers are defined as observations 1.5 times the distribution's inter-quartile range below (above) the first (third) quartile. In both panels, the sample is restricted to G-SIBs based on pre-2015 designation.

We leverage banks' annual reports – a pivotal source of information about a bank's strategic response to new regulation – to identify the *de-facto* treatment date for the G-SIB framework. We first count the number of times keywords related to the G-SIB framework (e.g. "gsib" or "systemically relevant bank") appear in banks' annual reports (see Appendix B.1 for the full list of keywords). Following Baker *et al.* (2016), we then scale the keyword count by the total number of words in the annual report to adjust for changes in the length of the reports over time or across banks.

The evolution of scaled occurrences highlights a significant increase in framework-related discussions by G-SIBs during 2014 and 2015 – in contrast to a decline observed for Non G-SIBs (see left-hand panel, Figure 1).[6] Furthermore, the number of G-SIBs

[6]The increase in the average scaled occurrences of G-SIBs from 2013 to 2014 and from 2014 to 2015 is statistically significant at the 5% level, based on a regression of scaled word counts on bank, country, and year dummies. Using a normalised version of the scaled word counts as in Husted *et al.* (2020)

mentioning the framework increased from two-thirds in 2011 to the full sample in 2015. The pattern thus suggests that G-SIBs began incorporating the G-SIB framework in their strategic considerations most actively during 2014 and 2015, suggesting these years as potential treatment dates.

To pin down the exact treatment date, we assess the context in which keywords appear in the annual report. We extract sentences in G-SIBs' annual reports that contain a keyword and then categorise them in their order of relevance to banks' capital planning. Guided by the pattern in the left-hand panel of Figure 1, we focus on the reports of the years from 2013 to 2015, which comprise 1,255 sentences in total.

Next, each author independently classifies sentences into three categories. Sentences in the first category are *action-oriented* and discuss active responses by the bank to the G-SIB framework – and are therefore of key interest to us – such as: *"In the last year, we took some dramatic actions to reduce our G-SIB capital surcharge ..."* (JP Morgan, 2015).[7] Sentences in the second category comprise *general discussions* of the framework, for example: *"RBS has been provisionally allocated a G-SII buffer of 1.5%" (RBS, 2014).* The third category consists of irrelevant sentences, or cases where the keyword is used out of context. The authors' tags are highly correlated, with disagreement between at least two authors in less than 7% of the sentences, and a statistically significant pair-wise correlation of more than 0.85. For each annual report, we then compute the average number of sentences in each category across authors to mitigate any potential biases.

We find that the number of action-oriented sentences is highest in 2015. The average share of action-oriented sentences relative to all relevant sentences (i.e. action-oriented

yields a similar pattern. A word count analysis using banks' earnings call reports also yields the same conclusion. However, earnings call reports are available only for a small subset of banks in our sample and for a limited number of years, and thus, cannot serve as a complementary basis for our analysis.

[7]Appendix B.2 lists several examples of action-oriented sentences. We note that majority of these sentences discuss plans initiated or completed by the bank in the previous year, rather than being of a forward-looking nature. Appendix B.3 shows a word cloud of the 70 most frequent words (after excluding articles and other basic words) in the relevant sentences.

and general discussion) across annual reports is also the highest in 2015. Moreover, the median share is zero in 2013 and 2014 (close to zero for the mean), whereas it is significantly higher in 2015 (Figure 1, right-hand panel).

This suggests that most G-SIBs took action to meet the G-SIB requirements in 2015, one year before the regulatory phase-in of the surcharges. 2015 thus serves as the treatment year for our main empirical analysis.

3 Data

The main source of our analysis is the bank-level dataset of the G-SIB framework published by the Basel Committee on Banking Supervision (BCBS). The main variable of interest is the G-SIB score. The score is available for 84 large global banks from 21 jurisdictions at an annual frequency since 2013. A major advantage of the dataset is that the score is computed using a common template and on a consistent basis across banks and over time. In addition, the BCBS and the national supervisors review these data for consistency. The data are publicly available. Moreover, the scores are computed for both G-SIBs as well as Non G-SIBs – which is ideal for our empirical analysis.

We complement the G-SIB dataset with bank balance sheet and income statement items from Fitch (see Table 1). Our main proxy for bank profitability is the return on assets (ROA), defined as the ratio of operating profit to total assets.[8] Throughout our analysis, we focus on the time period from 2013 to 2018, i.e. from the first year for which G-SIB scores are available up to the completion of the phase-in of the framework.

Adjusting the G-SIB score There are challenges in terms of directly using the official G-SIB score to study the impact of the G-SIB framework. We discuss how we address

[8]An advantage of using ROA as opposed to, for example, return on equity (ROE), is that ROA is independent of banks' leverage. Also, ROA is less susceptible than ROE to differences in national tax regimes across banks in our global sample.

Table 1: Summary statistics of main variables

	Mean	Stdev	P10	P25	P50	P75	P90	N
GSIB Score (official, bps)	128.53	107.30	28.93	47.52	85.80	186.08	284.03	443
GSIB Score (adjusted, bps)	134.68	115.08	29.42	52.67	89.63	188.33	288.82	443
Close to bucket threshold (binary)	0.20	0.40	0.00	0.00	0.00	0.00	1.00	348
Return on assets (%)	0.95	0.58	0.31	0.51	0.89	1.31	1.69	492
CET1 capital ratio (%)	12.12	2.99	8.78	10.16	11.64	13.56	15.80	486
Density ratio (%)	47.12	17.54	26.15	33.10	43.79	61.25	70.66	485
Non-performing loan ratio (%)	2.77	2.99	0.52	0.94	1.64	3.35	7.04	478
Cash to total assets (%)	7.04	5.59	1.34	2.53	5.94	10.13	13.71	492
Deposits to total liabilities (%)	56.41	17.91	30.34	41.73	59.01	70.21	79.24	486
Debt-service ratio gap (percentage points)	0.13	1.45	−1.59	−0.64	−0.01	0.83	1.69	498
Credit-to-GDP gap (percentage points)	−1.32	14.79	−17.93	−9.88	0.76	7.60	18.65	504
ΔSRISK% (percentage points)	0.63	1.48	0.02	0.08	0.19	0.58	1.00	70
ΔSRISK (US$ billion)	21.34	23.59	4.96	8.90	14.05	22.40	52.20	70

Note: The table shows summary statistics for the variables used in the analysis. Statistics are based on 2013 to 2018 data on an unbalanced sample of 84 banks from 21 jurisdictions. For the scores, the units are basis points (bps). For the bank characteristics, the units are displayed alongside the name of the variables. Closeness to bucket threshold is a binary indicator variable equal to 1 if the official G-SIB score in the previous year is in a range of 20 bps from one of the bucket thresholds. Return on assets (ROA): the ratio of operating profits to total assets. CET1 capital ratio: Common Equity Tier-1 (CET1) capital over risk-weighted assets. Density ratio: risk-weighted assets over total assets. Non-performing loan ratio: the ratio of non-performing loans to total loans. Cash to total assets: total cash holdings as a share of total assets. Deposits to total liabilities: total deposits as a share of total liabilities. Debt service ratio gap: difference between the ratio of interest payments plus amortisations to income and the ratio's long-term trend. Credit-to-GDP gap: difference between the credit-to-GDP ratio and its long-term trend. ΔSRISK%: the change in the percent contribution of a bank to total systemic risk of the financial system (see Brownlees and Engle, 2016 and Acharya *et al.*, 2012). ΔSRISK: the change in the expected capital shortfall in a crisis in US$ billions. For both SRISK measures, changes are given by the difference between the bank's maximum monthly value in 2020 and the corresponding mean value for the three months preceding the March 2020 turmoil.

these challenges below.

First, the scores are relative. This means that a ceteris paribus increase in the financial activities of one bank mechanically leads to a decline in the official score of all other banks. This violates the Stable Unit Treatment Value Assumption (SUTVA) which underpins a causal difference-in-difference analysis. To make the scores non-relative, we recompute the score as the weighted average of market shares relative to 2013. We thus decouple the evolution of banks' scores over time.

Second, since the indicator values are denominated in euro, exchange rate fluctuations can affect banks' scores over time. The appreciation of the U.S. dollar against the euro in 2014, for example, is likely to have increased U.S. banks' scores above and beyond the actual evolution of their financial activities. To get around this issue, we purge the indicators of exchange rate effects by converting the indicator values back into the banks' reporting currency and restate all indicators in euro based on the 2013 exchange rates.[9]

Third, the official scores are subject to a regulatory override wherein a bank's market share in some relatively skewed financial activities is capped to limit biases. We abstract away from this cap to avoid masking any changes in banks' actual scores.

With these adjustments, we obtain an *adjusted* G-SIB score, which is our main variable of interest. Yet, to show that our conclusions are not driven by these adjustments, we compare the results obtained from using the official and adjusted scores in our main regressions. We also note that the official and adjusted scores have a high correlation of 0.98. Table 1 presents the summary statistics for the official and adjusted G-SIB scores.

4 Empirical methodology

Our goal is to estimate the effect of the framework on more and less profitable G-SIBs. To this end, we employ a difference-in-differences framework.

Baseline specification and identification assumptions Our first main specification is as follows:

$$Score_{i,t} = \gamma \left[Post_t \times G\text{-}SIB_i\right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}, \tag{1}$$

where $Score_{i,t}$ represents either the adjusted or official G-SIB score of bank i in year t, the measure of its systemic importance. $Post_t$ is a dummy variable that equals 1 in the post-treatment period (2015–18) and 0 during the pre-treatment period (2013–14), whereas $G\text{-}SIB_i$ equals 1 (zero otherwise) for banks that have officially been designated a G-SIB before 2015, i.e. pre-treatment.[10] $X_{i,t-1}$ accounts for time-varying bank-specific

[9]We note that Benoit *et al.* (2019) recommend that such an adjustment also be applied in the BCBS' official G-SIB methodology to improve the measurement of banks' systemic importance.

[10]By restricting the treated sample to those banks designated as G-SIBs in the pre-treatment period, we ensure that banks' behavior in the post-treatment period does not affect their treatment status.

characteristics: the CET1 capital ratio, the density ratio as well as the ratios of cash to assets, deposits to liabilities and non-performing loans to total loans (see Table 1 for the variable definitions). Throughout our analysis, we use the first lag of these variables to address any potential endogeneity concerns. α_i controls for a bank's unobserved time-invariant characteristics. $\delta_{c,t}$, in turn, accounts for time-varying characteristics of country c where bank i is headquartered, such as changes to the macroeconomic or regulatory environment. $\varepsilon_{i,t}$ is the error term. We cluster the standard errors at the bank-level. Our interest is in the coefficient $\hat{\gamma}$ which captures the treatment effect.

Our main identifying assumption is that G-SIBs and Non G-SIBs followed parallel trends before the treatment. A visual inspection of the pre-treatment trend in the scores of G-SIBs' and Non G-SIBs' supports this assumption (see Figure 2, left-hand panel). To formally test this, we examine whether the difference in the score of G-SIBs and Non G-SIBs in 2014 (the last pre-treatment period) is significantly different from that in 2013 (the first period in our sample). We find the difference to be statistically insignificant (with a p-value greater than 0.50) irrespective of whether we control for bank fixed effects, meaning that the parallel trends hypothesis cannot be rejected.[11]

To further validate our approach, we ensure that Non G-SIBs were not treated (i.e. only G-SIBs were affected by the treatment). We keep the treatment and control groups clearly separated based on a time-invariant definition of G-SIB status. This helps avoid any bias that could arise from banks switching between G-SIB and Non G-SIB status. We also note that by adjusting the official score we avoid changes in one bank's activity from

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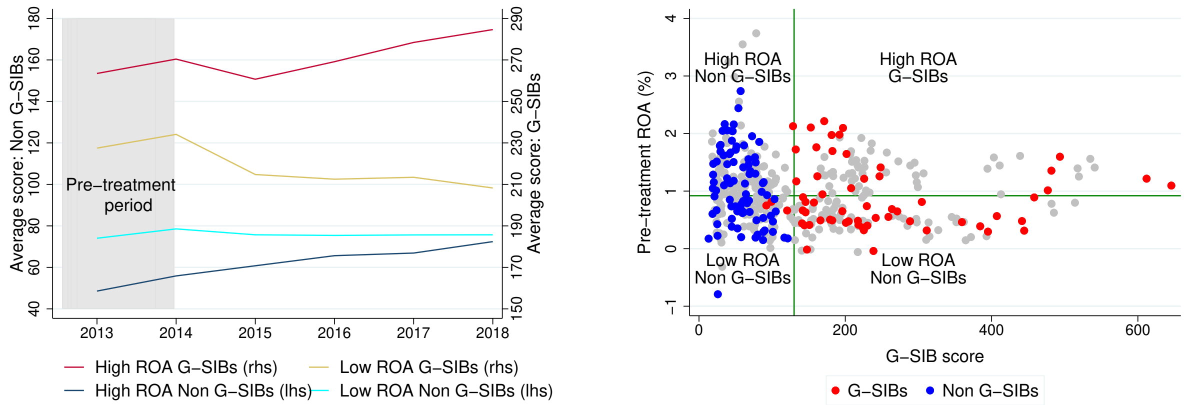
Consequently, banks designated as G-SIBs for the first time after 2015 are dropped from the sample.

[11]The comparatively small number of pre-treatment observations limits our ability to test for parallel trends. G-SIB scores prior to 2013 are not available, and proxies cannot be computed as banks typically do not report the data that are needed to calculate the G-SIB score. However, total assets – one of the key inputs to the score – of G-SIBs and Non G-SIBs evolved in parallel before treatment based on quarterly data from 2010 to 2014. To test this, we run equation (1) with banks' total assets cast in terms of 2013 exchange rates as the dependent variable, and the *post* dummy replaced by quarterly dummies. We find that the difference in the evolution of the dependent variable in case of G-SIBs and Non G-SIBs is insignificant at the 5% level.

Figure 2: Banks' G-SIB scores and return on assets



(A) Evolution of average G-SIB scores

(B) G-SIB scores versus ROA

Note: A high (low) ROA bank is one whose average pre-treatment (2013-14) ROA is above (below) the median. Based on a balanced sample of banks, for which scores are available in each year from 2013 to 2018. The left-hand panel shows the evolution of adjusted scores (in bps) for more and less profitable G-SIBs and Non G-SIBs. The right-hand panel plots the adjusted G-SIB score (in bps) versus ROA (in %) in the pooled sample of banks.

having a direct impact on another bank's score (recall Section 3). Finally, recall from Figure 1 that occurrences of framework-related keywords declined notably for Non G-SIBs post-treatment, suggesting that the framework was of little relevance to these banks.

We first use equation (1) to assess if G-SIBs and Non G-SIBs – irrespective of their profitability – reacted differently to the G-SIB framework. This serves as a baseline. If the framework and attendant capital surcharges incentivise G-SIBs to lower their systemic importance (or shrink their market share) as compared to Non G-SIBs, then $\hat{\gamma}$ should be negative and statistically significant.

Then, to assess the differential impact of the framework on the more and less profitable banks, we run equation (1) separately on the sub-samples of banks with high and low return on assets (ROA) – our main measure of profitability. We classify banks into more profitable (High ROA) and less profitable (Low ROA) ones based on whether their average pre-treatment (2013–14) ROA is above or below the median value of the sample distribution. Using pre-treatment ROA addresses endogeneity concerns that could arise from any impact of the G-SIB framework on bank profitability.

Our conjecture is that $\hat{\gamma}$ should be lower (i.e. negative and with a larger absolute value) in the case of low ROA banks. This is because a bank's optimal response to the framework reflects a dynamic cost-benefit analysis. For a high ROA bank, the opportunity cost of shrinking is larger – as a result, a high ROA bank may prefer to shrink by less and instead raise more capital to meet the higher requirement. Building capital (either externally or via retaining earnings) may also be easier for a high ROA bank. By contrast, for a low ROA bank, shrinking may be the optimal response. We formally explore these mechanisms in Section 6 below.

Profitability and the triple-interaction specification Our second main specification allows us to estimate the heterogeneous impact of the framework on more and less profitable banks within a single model:

$$Score_{i,t} = \gamma \left[Post_t \times G\text{-}SIB_i \times Profitability_i \right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}. \tag{2}$$

Here, $Profitability_i$ is measured as the *level* of bank i's average pre-treatment ROA. The full set of interaction terms (namely $Post_t$, $Post_t \times G\text{-}SIB_i$, and $Post_t \times Profitability_i$) are included in the estimations but are not explicitly stated in equation (2) for the sake of brevity. The rest of the setup is as before. Two comments about this specification are in order.

First, to ensure that this specification is not biased, we check whether being a G-SIB is related to being more profitable. We note from Figure 2 (right-hand panel) that banks in our sample vary widely in terms of their ROA. The inter-quartile range of ROA is 0.5% to 1.3% in the pooled sample (see also Table 1). G-SIBs are neither significantly more nor less profitable than Non G-SIBs and there is no apparent correlation between a bank's ROA and its score.[12] That profitability is unrelated to being a G-SIB makes it a suitable basis for assessing the differential impact of the framework.

Second, the use of pre-reform profitability helps rule out concerns about reverse causality, which may arise if adjustments to the framework also affect banks' profitability. Relatedly, we assess whether ROA reflects a relatively stable structural characteristic of a bank that underpins its response to the G-SIB framework, or whether ROA varies significantly. To this end, we explore how banks' ROA evolved over time. The correlation of ROA across years is high and statistically significant, indicating that profitability is highly persistent in the cross-section (see Appendix D.1). Moreover, banks switch between the more and less profitable category, based on the median pre-treatment ROA dummy, in less than 10% of the observations.

As a robustness check, we also match G-SIBs and Non G-SIBs. This offers an alternative way to address any potential systematic differences in how treated and control banks evolved in the pre-treatment period. Specifically, we fit a propensity score model based on the pre-treatment observations of those bank-level attributes that we use as controls in our baseline analysis. We standardise each variable to account for differences in the variance across variables. The propensity scores form the basis of the match weights (which can be zero for control banks). We use these weights to run a weighted regression of equation (2). We pursue kernel matching while imposing a caliper of 0.05 and a common matching support (see Appendix D.2 for the match balance test). We also consider restricting the matches to within profitability categories.

[12] Standard t-tests cannot reject the hypothesis that the average pre-treatment ROA of G-SIBs is equal to that of Non G-SIBs (p-value = 0.24). Likewise, t-tests do not reject equality of the mean pre-treatment ROA of more (less) profitable G-SIBs and more (less) profitable Non G-SIBs. t-tests do reject equality when comparing the means of more and less profitable G-SIBs (or Non G-SIBs). Moreover, the year-wise correlation between ROA and the adjusted G-SIB score is always insignificant, except in 2014 when it is significant at the 10% level (p-value = 0.06).

5 Results

Baseline impact of the G-SIB framework The average score of G-SIBs did not evolve differently as compared to that of Non G-SIBs in response to the introduction of the framework. Column (1) of Table 2 presents the results of the simplest version of the specification in equation (1) without any controls or fixed effects. The negative coefficient on the interaction term implies that G-SIBs decreased their average score by 13 basis points (bps) relative to Non G-SIBs, albeit statistically insignificantly. Relative to their own pre-treatment level, G-SIBs reduced their average score by an insignificant 9 bps, whereas Non G-SIBs increased the same by around 4 bps.[13]

We confirm that these results are not an artefact of our adjustments to the score, discussed in Section 3: running the same regression on the official G-SIB score in column (2) has little effect on the coefficient estimates. Saturating the regression by controlling for bank fixed effects as well as time-varying bank characteristics (column (3)) or adding country-year fixed effects (column (4)) has no material effect on our takeaways.

Impact on more and less profitable banks Our hypothesis is that the insignificant average impact of the framework on the G-SIBs as a whole masks a heterogeneous effect within that group. Indeed, as we conjecture in Section 4, a bank's optimal response to the framework depends on its profitability. We test this empirically, by first studying the unconditional evolution of G-SIBs' scores. The pre- versus post-treatment change in the average score of more and less profitable G-SIBs and Non G-SIBs in Figure 3 supports our hypotheses. As expected, only the high ROA banks are able to increase their scores (first two bars) while the low ROA banks decrease the same (last two bars). Within the high ROA banks, G-SIBs increased their scores by less than Non G-SIBs. Among the low ROA banks, G-SIBs decreased their scores by more than Non G-SIBs.

[13]The former change is computed by adding the coefficients on the 'Post' and 'Post $\times$ G-SIB' terms. The latter change is given by the coefficient on 'Post'.

Table 2: Baseline differences-in-difference (DD) results

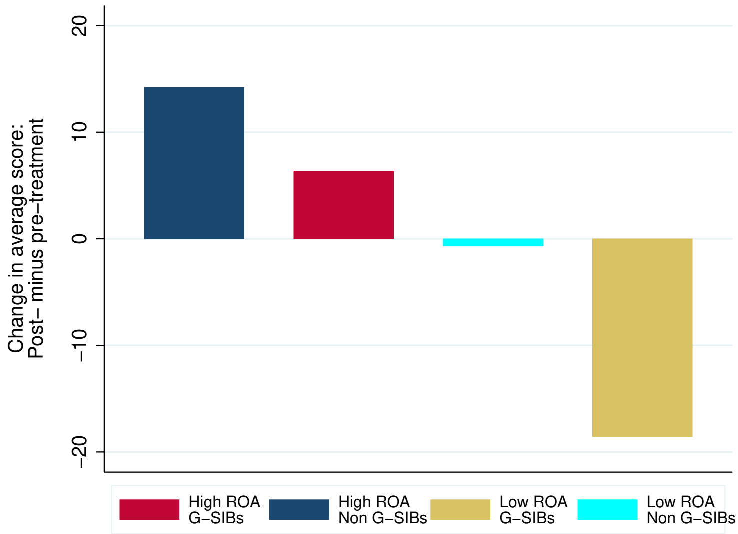
	(1)	(2)	(3)	(4)
Post × G-SIB	-12.77	–7.711	–7.244	–0.512
	(–1.49)	(–0.91)	(–0.89)	(–0.05)
Post	3.833	2.924	3.077	
	(1.40)	(1.06)	(1.32)	
G-SIB	188.1***	176.4***		
	(8.32)	(8.93)		
CET1 ratio			3.024**	0.628
			(2.23)	(0.30)
Non-performing loans ratio			3.662**	6.067*
			(2.19)	(1.97)
Cash to assets			–1.097	–2.818***
			(–1.28)	(–3.30)
Deposits to total liabilities			–1.144**	0.311
			(–2.48)	(0.41)
Density ratio			0.132	–1.470**
			(0.27)	(–2.22)
Return on assets			–5.844	–5.800
			(–1.08)	(–0.83)
N	443	443	408	373
R2	0.595	0.622	0.982	0.989
Bank controls and FE	No	No	Yes	Yes
Country-time FE	No	No	No	Yes
G-SIB score	Adjusted	Official	Adjusted	Adjusted

Note: The table reports results of the regression in equation (1). The dependent variable is the adjusted G-SIB score, except in column (2) where it is the official G-SIB score. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. Bank-level controls are lagged by one year. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

To assess these observations formally, we estimate equation (1) on separate sub-samples of more and less profitable banks (Table 3). We find that the less profitable G-SIBs significantly decreased their scores relative to Non G-SIBs (columns (1) to (3), Panel A). They have also lowered their scores relative to the less profitable Non G-SIBs (columns (4) to (6), Panel A). The magnitude of the effect, between 16 to 22 bps, is economically meaningful considering that the official G-SIB buckets are 100 bps in size. By contrast, the more profitable G-SIBs have not adapted their scores differently if compared with Non G-SIBs (columns (1) to (3), Panel B) or the more profitable Non G-SIBs (columns (4) to (6)). The findings suggest that the G-SIB framework had a bite only on the less profitable banks, but no material impact on the more profitable ones.

While the results based on sub-sample regressions are intuitive, they are silent on

Figure 3: Evolution of adjusted G-SIB scores



Note: A high (low) ROA bank is one whose average pre-treatment (2013-14) ROA is above (below) the median. Based on a balanced sample of banks, for which scores are available in each year from 2013 to 2018. The graph shows the change in average adjusted G-SIB score (in bps) for each category. The changes in case of high ROA Non G-SIBs (first bar) and low ROA G-SIBs (fourth bar) are statistically significant; the others are insignificant.

whether the differential impact on less and more profitable banks is material. For this, we turn to equation (2). Our hypothesis is that $\hat{\gamma}$, the coefficient on the triple interaction term, is positive. This would imply that more profitable G-SIBs increased by more (or reduced by less) their score after treatment compared to the change in score of the less profitable G-SIBs, after controlling for trends in the score of Non G-SIBs.

The regression results in Table 4 support our hypothesis. The unsaturated specification in column (1) without fixed effects shows that, on average, more profitable G-SIBs increased their adjusted score by about 33 bps after treatment relative to trends in the control group. Column (2) reports the corresponding results based on using the official G-SIB score. As expected, the coefficient is biased upwards given that an increase in the score of the more profitable G-SIBs implies, all else equal, a decline in the scores of the less profitable ones. Accounting for bank controls, bank fixed effects, and country-year fixed effects (column (3)) leads to a similar conclusion. Our findings are also robust

Table 3: Sub-sample difference-in-differences on high ROA and low ROA G-SIBs

Panel A

	Low ROA G-SIBs vs All Non G-SIBs			Low ROA G-SIBs vs Low ROA Non G-SIBs		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB	–22.39**	–20.60**	–20.95**	–17.71*	–16.31	–20.80*
	(–2.56)	(–2.16)	(–2.35)	(–1.90)	(–1.63)	(–1.83)
Post	3.833	2.924		–0.848	–1.367	
	(1.39)	(1.06)		(–0.21)	(–0.34)	
G-SIB	174.1***	167.9***		164.8***	159.3***	
	(8.04)	(8.02)		(7.35)	(7.34)	
N	371	371	309	218	218	166
R2	0.683	0.677	0.992	0.607	0.600	0.990
Bank controls and FE	No	No	Yes	No	No	Yes
Country-time FE	No	No	Yes	No	No	Yes
Score	Adjusted	Official	Adjusted	Adjusted	Official	Adjusted

Panel B

	High ROA G-SIBs vs All Non G-SIBs			High ROA G-SIBs vs High ROA Non G-SIBs		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB	2.456	12.69	14.05	–1.357	9.192	18.39
	(0.16)	(0.97)	(1.02)	(–0.09)	(0.68)	(1.25)
Post	3.833	2.924		7.646**	6.423*	
	(1.39)	(1.05)		(2.22)	(1.79)	
G-SIB	210.2***	189.8***		217.0***	196.2***	
	(4.54)	(4.99)		(4.66)	(5.11)	
N	329	329	253	225	225	186
R2	0.629	0.669	0.991	0.619	0.664	0.991
Bank controls and FE	No	No	Yes	No	No	Yes
Country-time FE	No	No	Yes	No	No	Yes
Score	Adjusted	Official	Adjusted	Adjusted	Official	Adjusted

Note: The table reports results of the regression in equation (1), for the sub-samples indicated in the column headings. Banks are classified as high (low) ROA based on whether their average pre-treatment (2013-14) ROA is above (below) the median. The dependent variable is either the adjusted or official G-SIB score, as indicated in the last row of the table. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

to replacing ROA in levels by a profitability dummy that equals 1 (0 otherwise) if the average pre-treatment ROA of the bank is above (below) the sample median (as in the sub-sample regressions) (column (4)).[14]

A battery of robustness tests reinforces our findings. For one, matching treated and

[14] To provide additional evidence that our findings are driven by differences in bank profitability and not by other balance sheet characteristics, we sequentially interact each of the bank-level controls comprised in $X_{i,t-1}$ with the post-treatment and G-SIB designation dummies. Our findings remain consistent with the ones presented above.

Table 4: Triple interaction regression results

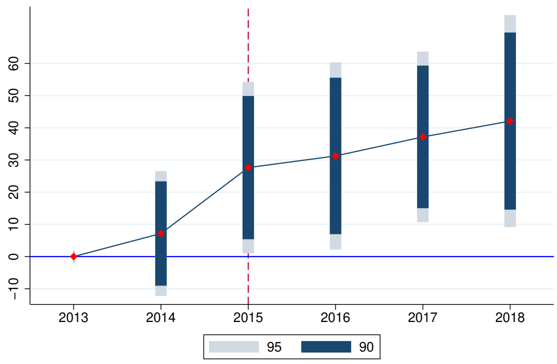
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB × Profitability	32.67**	43.69***	30.66***	34.20**	30.35***	32.92**
	(2.56)	(4.07)	(3.33)	(2.05)	(3.19)	(2.53)
Post × G-SIB	–40.33***	–45.04***	–35.87***	–17.80*	–33.11**	–41.81***
	(–3.22)	(–3.51)	(–2.92)	(–1.74)	(–2.60)	(–2.84)
Post × Profitability	7.639*	7.475	15.89	–5.647	12.65	14.26
	(1.68)	(1.59)	(1.49)	(–0.52)	(1.07)	(0.58)
G-SIB × Profitability	–5.653	–7.635				
	(–0.18)	(–0.30)				
Post	–4.249	–4.994				
	(–0.86)	(–0.99)				
G-SIB	191.0***	181.1***				
	(5.98)	(6.08)				
Profitability	–10.88*	–10.40*				
	(–1.73)	(–1.77)				
N	443	443	373	373	373	261
R2	0.600	0.632	0.991	0.990	0.990	0.990
Bank controls and FE	No	No	Yes	Yes	Yes	Yes
Country-time FE	No	No	Yes	Yes	Yes	Yes
Score	Adjusted	Official	Adjusted	Adjusted	Adjusted	Adjusted
ROA measure	Level	Level	Level	Dummy	Level	Level
Matching	No	No	No	No	Yes	Yes
Exact matching within ROA category	No	No	No	No	No	Yes

Note: The table reports results of the regression in equation (2) for the full sample. The dependent variable is the adjusted G-SIB score, except in column (2) where it is the official G-SIB score. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. The profitability measure is always based on average pre-treatment (i.e. 2013-14) ROA in levels, except in column (4) where a dummy based on whether the pre-treatment ROA is above the sample median is used. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio (all lagged by one year). To match treated (G-SIBs) with control banks (Non G-SIBs) in columns (5) and (6), we use a propensity score model based on matching the standardized value of the banks' pre-treatment (2013–14) CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposits to liabilities. A caliper of 0.05 and common support are imposed on the propensity score based kernel matching, which we use to obtain the weights to perform a weighted regression of equation (2). Furthermore, exact matching within ROA categories (i.e. high or low) is imposed as an additional requirement for the regression in column (6). Robust standard errors are clustered at the bank level and *t*-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

control banks (Table 4, column (5)), and in particular, matching high (low) ROA G-SIBs exclusively with high (low) ROA Non G-SIBs (column (6)) leads to the same conclusion that more profitable G-SIBs increased their scores relative to the others. Likewise, considering alternative controls or sample composition (Appendix D.3), alternative measures of profitability such as banks' return-on-equity, cost-to-income ratio, or risk-adjusted return on assets (Appendix D.4), or accounting for banks' business models (Appendix D.5) confirms the robustness of our findings.

Zooming in on individual banking activities, we find that the increase in the average

Figure 4: Assessing the evolution of the impact of the framework over the years



Note: Coefficient estimates in basis points on the triple interaction terms in a version of the regression equation (2) where the treatment effect can differ across years, relative to the starting year 2013. The blue (grey) bars indicate the 90% (95%) confidence intervals based on robust standard errors, clustered at the bank level. The dashed vertical red line indicates the treatment year.

score of more profitable G-SIBs is driven by a significantly higher footprint along several G-SIB indicators. In addition to expanding the overall size of their on- and off-balance sheet exposures relative to their peers, more profitable G-SIBs have increased their underwriting activities, their OTC derivative books, and their cross-border funding (see Appendix C for a discussion of G-SIBs margins of adjustment).

Finally, we assess the persistence of the impact of the framework by allowing the treatment effect in equation (2) to differ across years. Specifically, we replace the *post* dummy by a dummy for all except the first period in our sample and assess the significance of the interaction coefficient. Figure 4 plots the coefficients on the triple interaction term for each year. We observe a significant shift in the score of more profitable G-SIBs in the treatment year, which persists in the years following the treatment.

Overall, our findings based on the triple-interaction regressions are consistent with the findings based on sub-sample regressions (Table 3) and the unconditional observations in Figure 3. The differential effect of the G-SIB framework on more and less profitable G-SIBs that we uncovered using the sub-sample regressions is both economically and statistically significant.

6 Size-capital trade-off and profitability: a model

Why do more profitable G-SIBs raise their scores relative to their peers? To understand the underlying mechanism behind our empirical results, we provide a stylized model of how banks respond to higher capital requirements and assess why pre-treatment differences in profitability shape banks' differential responses to higher capital requirements.

We consider an economy with one representative bank and no aggregate uncertainty. Each period, the bank starts with capital k, based on which it chooses the level of deposits to raise, d, and the amount of assets to invest in, a. The balance sheet identity implies that $a = k + d$. Assets have a constant return to scale and pay R per unit of asset. The deposit rate is $r < R$.

The bank's objective is to maximise its cash flow, $Ra - rd$, which becomes its new capital, k_{+1}, in the next period. In doing so, the bank is subject to a capital ratio requirement that imposes a minimum, χ, on the ratio of the banks' capital to assets. Because of constant returns to scale on assets, the regulatory constraint always binds, such that $a = k/\chi$ and $d = k(1/\chi - 1)$. In the next period, the bank uses k_{+1} and chooses its assets $a_{+1} = k_{+1}/\chi$ and deposits as $d_{+1} = k_{+1}/(1/\chi - 1)$. This decision process repeats itself each period.

We introduce an unexpected regulatory shock as follows. As of time t, the regulatory requirement is raised from χ to $\chi + \epsilon a$, with $\epsilon > 0$. This new capital ratio requirement reflects the incentive scheme of the G-SIB framework: a bank that runs a larger balance sheet has to meet a higher capital requirement.

The bank faces a size-capital trade-off. It can meet the new requirement by either shrinking its size (i.e. balance sheet) or by raising capital externally. We note – as laid out in the seminal work by by Myers and Majluf (1984) – that banks typically avoid raising capital externally, unless there is a credible and justifiable reason from an investor perspective, such as a business expansion, a capital shortfall, or heightened regulatory requirements. In line with this reasoning, we assume that raising capital externally entails a preference cost such that the marginal cost is increasing in the amount to be raised. For simplicity of exposition, we assume a quadratic cost, $\lambda\delta^2$, of raising additional capital, δ.

To maximise its cash flow in the next period, the bank must decide – in addition to selecting the amount of assets and deposits – how much additional capital to raise on date t:

$$\max_{\delta,a,d} \quad \beta(Ra - rd) - \lambda\delta^2 \quad s.t. \quad a = k + d + \delta; \quad (k+\delta)/a = \chi + \epsilon a,$$

with β representing the discount factor.

To solve the problem, we focus on an interior solution where $\delta > 0$, eliminate d using the balance sheet identity, and derive the first order conditions as follows:

$$\max_{\delta,a} \quad \beta\Big((R-r)a + r(k+\delta)\Big) - \lambda\delta^2 \quad s.t. \quad \delta = w\chi a + \epsilon a^2 - k.$$

$$\implies [a]: \quad \beta(R-r) - \theta(w\chi + 2\epsilon a) = 0; \qquad [\delta]: \quad \beta r - 2\lambda\delta + \theta = 0.$$

$\theta > 0$ is the Lagrange multiplier on the regulatory constraint. Eliminating θ gives two equations in two unknowns (a, δ) that characterise the solution to the bank's problem. We eliminate δ to focus on the amount of assets, a, the bank chooses, or equivalently the size of its balance sheet:

$$\begin{aligned} \beta(R-r) = &\quad (2\lambda\delta - \beta r)(w\chi + 2\epsilon a); \qquad \delta = w\chi a + \epsilon a^2 - k \\ \implies \quad \beta(R-r) = &\quad \Big(2\lambda(w\chi a + \epsilon a^2 - k) - \beta r\Big)(w\chi + 2\epsilon a). \end{aligned}$$

An explicit solution for a is not generally available. However, an application of the Implicit Function Theorem sheds light on how more versus less profitable banks – based on the value of R – differ in terms of their response to higher capital requirements. The total derivative of equation (3) w.r.t. R yields the following, where $\dot{a} = \frac{da}{dR}$:

$$\begin{aligned} \beta = \;& 2\epsilon\dot{a}\Big(2\lambda(w\chi a + \epsilon a^2 - k) - \beta r\Big) + \Big(2\lambda(w\chi\dot{a} + 2\epsilon a\dot{a})\Big)(w\chi + 2\epsilon a) \\ \implies \quad \beta = \;& \dot{a}\Big(2\epsilon\underbrace{\big(2\lambda(w\chi a + \epsilon a^2 - k) - \beta r\big)}_{A>0} + 2\lambda\underbrace{(w\chi + 2\epsilon a)^2}_{B>0}\Big). \end{aligned}$$

It follows that the coefficient on $\dot{a}$ is positive:[15] in response to tighter regulation, a bank that is more profitable, but otherwise identical to a less profitable bank, will choose a larger balance sheet.

Intuitively, the opportunity cost of choosing a smaller balance sheet is greater for a more profitable bank. The increase in capital requirements thus makes the more profitable bank raise more capital, δ, to support a relatively larger balance sheet (as opposed to raising less capital and running a smaller balance sheet).[16] This does not necessarily imply that a more profitable bank expands its balance sheet. The change in the size of the bank can be positive or negative, depending on the cost of raising capital and the magnitude of increase in the capital requirement. In response to tighter regulation, a more profitable bank may either *shrink its assets by less* or *grow them by more* as compared to a less profitable bank of the same ex-ante size.

Another reason for why profitability can matter for how banks respond to higher capital requirements is that profitability relates to a bank's ability to organically generate capital in the future via retained earnings. While we do not incorporate this channel explicitly, our model provides the intuition for what the impact could be. A more profitable bank – on the back of higher return on its assets – would end up with more capital k_{+1} on date $t + 1$ as compared to a less profitable one. This would then support a larger

[15] This is because (i) $\epsilon > 0$; (ii) expression A, which also appears in equation (3), must be positive as otherwise we arrive at a contradiction in equation (3) given that $R - r > 0$, $\chi > 0$, $\epsilon > 0$ and $a > 0$; (iii) $\lambda > 0$; and (iv) expression B is positive.

[16] More profitable banks may also face a lower cost of raising capital (e.g. De Jonghe *et al.* (2020)), which would reinforce the mechanism in the model.

Table 5: Differential evolution of capital, assets, and capital ratio of low and high profitability G-SIBs

	(1) Capital	(2) Capital	(3) Capital	(4) Assets	(5) Capital ratio
Post × Profitability	0.11***	0.08***	0.10***	0.15***	–0.59***
	(5.14)	(3.19)	(3.05)	(5.60)	(–2.79)
N	681	681	681	681	681
R2	0.996	0.997	0.997	0.995	0.977
Clustering	Bank	Bank	Bank	Bank	Bank
Bank FE	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes
Profitability	Continuous	Continuous	Dummy	Continuous	Continuous
Controls	No	Yes	Yes	Yes	Yes

Note: This table provides estimates of the interaction term in the following specification: $y_{i,t} = \gamma\,[Post_t \times Profitability_i] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$. The dependent variable is log capital (columns (1) to (3)), log assets (column (4)), and the capital ratio (column (5)), respectively. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18]. The profitability measure is always based on average pre-treatment (i.e. 2013-14) ROA in levels, except in column (3) where a dummy based on whether the pre-treatment ROA is above the sample median is used. This table is based on quarterly data from 2010 to 2018, and is based on the sample of G-SIBs. Bank-level controls comprise of the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities (all lagged by one period). See Appendix D.6 for the definitions and summary statistics of all variables. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

balance sheet and enable a more profitable bank to more easily meet a phased-in increase in capital requirements, as in case of the G-SIB framework.

The prediction of the model is consistent with our main empirical finding in Section 5 that more profitable banks increase their G-SIB scores – of which size is a core component – relative to their peers. Moreover, it highlights the varying strength of the incentives that more and less profitable banks have in terms of raising capital versus shrinking their balance sheet in response to higher capital requirements. This rationalises why a more profitable bank responds differently to more stringent regulation.

Our model also predicts that more profitable G-SIBs raise more capital than less profitable ones in response to the introduction of the G-SIB capital surcharges. We test this additional prediction based on the following regression, run on the sub-sample of G-SIBs:

$$Capital_{i,t} = \gamma\,[Post_t \times Profitability_i] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}. \tag{3}$$

$Capital_{i,t}$ represents G-SIB i's log capital at time t, whereas $Post_t$ indicates the post-treatment period as in equation (1) and $Profitability_i$ is the bank's pre-treatment ROA, as before. In contrast to our regressions based on G-SIB scores, we use quarterly observations for the period from 2010 to 2018 to take full advantage of the available data on capital. $X_{i,t-1}$ represents lagged bank controls as detailed in Appendix D.6. We saturate the regression with bank fixed effects, α_i, and country-quarter fixed effects, $\delta_{c,t}$. $\varepsilon_{i,t}$ is the error term.

Table 5 highlights that, as predicted by the model, more profitable G-SIBs have significantly increased their capital relative to less profitable G-SIBs during the post treatment period (i.e., $\hat{\gamma} > 0$). This finding is robust to different specifications, such as replacing profitability by a binary variable that distinguishes high and low ROA G-SIBs based on the pre-treatment sample median (column (3)).

Substituting log capital for log assets confirms that more profitable G-SIBs have also significantly increased their assets relative to their less profitable peers (column (4)). Their capital ratio, by contrast, declined modestly relative to that of low ROA G-SIBs (column (5)). While all G-SIBs had to raise their capital ratio in response to higher requirements, the emphasis by the more profitable banks was on increasing their balance sheet size.

7 Discussion

7.1 Are the adjustments driven by the G-SIB framework?

One potential concern is that, despite the conservative specification we use throughout the paper, we may nevertheless be capturing adjustments by banks that are not due to the G-SIB framework.

The unique design of the G-SIB capital surcharges allows us to further sharpen our analysis and address this concern. The bucket thresholds introduce a discontinuity in the capital requirements absent any confounding economic rationale that should make banks behave differently if their score is close to the threshold. These banks have a stronger incentive to lower their score to either push themselves into a lower bucket or to avoid moving into a higher bucket. The distance from the bucket thresholds thus represents an ideal source of exogenous variation in the regulatory treatment that allows us to test whether banks' score adjustments are due to the G-SIB framework.

We test whether banks that are close to the threshold have reduced their scores relatively more than other banks based on the following regression:

$$Score_{i,t} = \gamma\left[Close_{t-1} \times G\text{-}SIB_i\right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}, \tag{4}$$

Following Behn *et al.* (2019), we measure *closeness* by defining an indicator variable, $Close_{t-1}$, that is equal to one (zero otherwise) if a bank's official G-SIB score was within 20 bps of a bucket threshold in the previous year. About one fifth of the bank-year observations are close to the threshold as per this definition, with no systematic concentration among the less or more profitable banks. Table 6 depicts the estimates for this indicator based on assessing the less profitable G-SIBs and the more profitable ones, respectively.

We observe that less profitable G-SIBs which are close to the threshold reduce their scores by even more than those that are not (columns (1) and (2)). This is consistent with these banks' stronger incentives to reduce their systemic importance. Closeness, however, does not appear to influence the more profitable G-SIBs' adjustment (columns (3) and (4)). The framework thus appears to exert a strong effect on only the less profitable G-SIBs, corroborating our main findings in Section 5 and also in line with the mechanism outlined in our theoretical framework in Section 6.

Another potential concern is that geographical factors could be affecting our findings, such as national regulatory reforms or different macroeconomic developments in banks'

Table 6: Assessing the role of proximity to G-SIB bucket thresholds

	Low ROA G-SIBs vs		High ROA G-SIBs vs	
	All Non G-SIBs	Low ROA Non G-SIBs	All Non G-SIBs	High ROA Non G-SIBs
	(1)	(2)	(3)	(4)
Close to bucket threshold	–12.14***	–15.49***	–1.023	–1.753
	(–3.03)	(–3.55)	(–0.20)	(–0.34)
Post × G-SIB	–12.76*	–10.95	2.453	2.581
	(–1.85)	(–1.58)	(0.15)	(0.18)
Post × Profitability	6.372*		7.729**	
	(1.80)		(2.14)	
Post	–1.847	–1.804	–4.922	0.222
	(–0.63)	(–0.59)	(–1.54)	(0.08)
N	294	171	255	177
R2	0.989	0.988	0.989	0.990
Bank controls and FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes

Note: The dependent variable is the adjusted G-SIB score. *Close to bucket threshold* is a dummy variable that equals one if the bank's official G-SIB score in the previous year is within 20 bps of the closest bucket threshold. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18]. *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. The profitability measure is based on average pre-treatment (i.e. 2013-14) ROA in levels. Bank-level controls include the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

home jurisdictions. We note that the use of country-year fixed effects throughout our main analysis already mitigates this concern to a large extent. Several additional tests, such as running placebo tests on banks' origin (rather than their G-SIB status), further confirms that geographical factors do not drive our results (see Appendix D.7).[17]

7.2 Could the treatment date vary across banks?

One advantage of identifying the treatment date based on textual analysis is that we can identify G-SIBs for which the timing of the treatment may have differed. Our main analysis is based on a common timing of the regulatory treatment in the year 2015.

[17] A related question is whether reforms for *domestically* important banks (D-SIBs) could bias our results towards finding no effect of the G-SIB framework. However, almost all banks in our sample, including all G-SIBs, are D-SIBs, suggesting that D-SIB requirements apply to most banks in our sample, and not just Non G-SIBs. The only exception is Chinese banks for which the finalisation of a D-SIB assessment methodology was still ongoing as of 2018. Another question is whether the phase-in of the capital conservation buffer alongside the G-SIB surcharges could influence our results. However, since this buffer is applied to both G-SIBs and Non G-SIBs, it should not affect our identification strategy.

However, a few G-SIBs may have already started to adjust in 2014 since their number of action-oriented sentences starts to rise ahead of those of the other banks (recall the left-hand panel of Figure 1 and see also Appendix B.4). For a few other G-SIBs, the measure picks up only at the regulatory phase-in of the capital requirements in 2016.

We conduct a staggered difference-in-differences analysis to account for the possibility that the treatment date could vary across banks. We estimate the average treatment effect following the estimator suggested by Callaway and Sant'Anna (2021).[18] G-SIBs whose 2014 annual report contains a greater number of references to how they responded to the G-SIB framework than their 2015 report are considered to have been treated in 2014. For G-SIBs without any such discussion in either their 2014 or 2015 reports, the treatment date is considered to be 2016, the year when the phase-in of the framework begins.

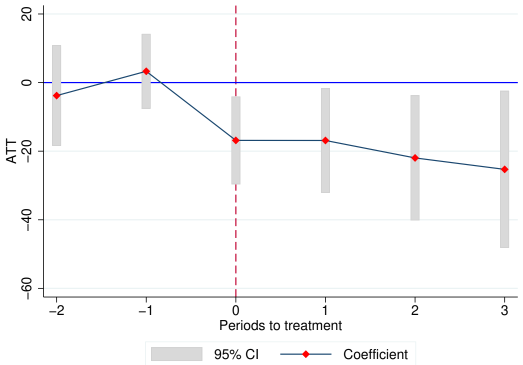
The Callaway and Sant'Anna (2021) estimator uses equation 1 to calculate the average treatment effect for each group of G-SIBs, with the groups g identified by the year in which the G-SIBs are treated. The "never treated" Non G-SIBs are the control group throughout. The specification accounts for bank and time fixed effects. Covariates, such as bank controls and country controls (credit-to-GDP gap and debt-service ratio gap) are included, and their value is fixed at as of the last period before treatment for each group.

Figure 5 reports the estimated treatment effect for the case of bank-specific treatment dates. The left-panel compares the low ROA G-SIBs to the low ROA Non G-SIBs, while the right-panel compares the high ROA G-SIBs to the high ROA Non G-SIBs. The group-weighted average treatment effects for the treated (ATT) are reported with their 95% confidence intervals. The x-axis represents periods to treatment, with 0 representing the treatment year, which can be either 2014, 2015, or 2016.

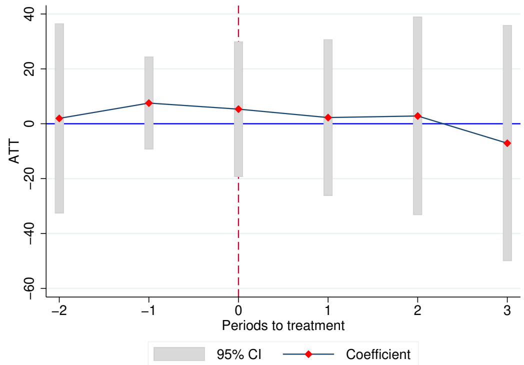
[18] Several recent studies show that the standard two-way fixed-effects model may produce biased estimates if the treatment is staggered (e.g. Baker *et al.*, 2022; Callaway and Sant'Anna, 2021; De Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). The results reported in this subsection are robust to using alternate methods proposed by Sun and Abraham (2021) and De Chaisemartin and D'Haultfœuille (2020).

Low ROA G-SIBs, relative to their Non G-SIB peers, start to shrink their systemic importance from treatment date. Overall, they reduce their score by about 25 bps. By contrast, high ROA G-SIBs do not reduce their score relative to high ROA Non G-SIBs. These results tally with the sub-sample results in Table 2 and are consistent with the large number of G-SIBs for which 2015 stands out as the treatment year.

Figure 5: Robustness of results to bank-specific treatment dates



(A) Low ROA G-SIBs vs. low ROA Non G-SIBs



(B) High ROA G-SIBs vs. high ROA Non G-SIBs

Note: The table reports results of an event study regression for two sub-samples low ROA G-SIBs to low ROA Non G-SIBs (left-hand panel) and high ROA G-SIBs to high ROA Non G-SIBs (right-hand panel). The dependent variable is the adjusted G-SIB score (bps). This table uses bank-specific treatment dates and the bias-corrected estimator from Callaway and Sant'Anna (2021). Bank-level controls comprise of the pre-treatment values of CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio. Country controls (credit-to-GDP gap and debt-service ratio gap) are also included. Robust standard errors are clustered at the bank level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

7.3 Are there financial stability implications?

What are the financial stability implications of more profitable G-SIBs increasing their systemic importance? Clearly, the reallocation of banking activity towards more profitable banks could enhance intermediation efficiency.[19] However, if higher profitability is driven by more aggressive risk-taking and exposure to tail risks (e.g., Meiselman *et al.*,

[19] The average score-weighted ROA increased from 1.39% in 2013 to 1.50% in 2018. Keeping the scores fixed at their 2013 levels, the score-weighted ROA would have increased to only 1.44% in 2018. The reallocation in market shares towards more profitable banks thus contributed to more than half of the total increase in the average score-weighted ROA.

2020, Martynova *et al.*, 2020), the reallocation could also undermine the banking sector's resilience.

To address this concern, we assess changes in banks' systemic risk contribution during a tail risk event. We measure these changes based on the banks' SRISK (see Brownlees and Engle, 2016 and Acharya *et al.*, 2012). In contrast to the G-SIB score, which banks actively manage in response to regulatory incentives, SRISK is a widely used market-based measure.[20] Changes in SRISK during episodes of stress thus reflect investors' reassessment of banks' exposure to tail risks, and are therefore outside the bank's direct control. This makes SRISK an ideal measure to evaluate how investors perceive the riskiness of banks. Using the outbreak of the COVID-19 pandemic in early 2020 as a global exogenous shock and a tail risk event, we run the following cross-sectional regression:

$$\Delta SRISK_i = \gamma \left[\textit{G-SIB}_i \times Profitability_i \right] + \mu X_i + \varepsilon_i. \tag{5}$$

$\Delta SRISK_i$ measures the change in bank i's SRISK from its mean value in the three months preceding the March 2020 market turmoil to its highest monthly value in 2020. $\textit{G-SIB}_i$ is the G-SIB identifier variable, whereas $Profitability_i$ distinguishes high from low ROA banks based on their pre-treatment ROA (i.e. 2013–14). The more and less profitable G-SIBs thus correspond exactly to those banks used throughout our analysis (e.g. Tables 2 and 3). X_i comprises lagged (i.e. end-2019) bank-level controls. If higher profitability is fueled by higher exposure to tail risk, more profitable G-SIBs' SRISK should exhibit a larger increase during the COVID-19 shock. The estimated γ coefficient for high ROA G-SIBs should thus be larger than the corresponding coefficient for low ROA G-SIBs.

Table 7 depicts the estimated impact of the shock for the different types of banks, using the less profitable Non G-SIBs as the base case. In the first row, we also report

[20]SRISK is available for 70 of our sample banks. We report summary statistics in Table 1.

the difference between the γ estimates for the more and less profitable G-SIBs to test our conjecture.

Table 7: Systemic risk during the pandemic

	ΔSRISK%	ΔSRISK%	ΔSRISK% relative changes	ΔSRISK US$ billion	ΔSRISK log changes
	(1)	(2)	(3)	(4)	(5)
Difference High vs Low ROA GSIBs	1.26***	1.06***	0.31**	23.83***	0.37**
	(8.88)	(8.60)	(5.27)	(9.53)	(5.71)
High ROA GSIB	1.63**	1.36***	0.38**	36.33***	0.40**
	(2.67)	(4.58)	(2.85)	(6.38)	(2.66)
Low ROA GSIB	0.38	0.30	0.07	12.50**	0.03
	(1.08)	(0.99)	(0.60)	(2.63)	(0.20)
High ROA Non GSIB	0.19	–0.29	0.53*	–3.98	0.34*
	(1.34)	(–0.52)	(1.81)	(–0.41)	(1.79)
N	70	69	62	69	60
R2	0.14	0.16	0.18	0.41	0.16
Bank controls	No	Yes	Yes	Yes	Yes

Note: The table reports results of the regression in equation (5). The dependent variable is the change in the bank's percentage of financial sector capital shortfall (SRISK%) from NYU V-Lab (columns (1) and (2)); the relative change in SRISK%, winsorized at 95% to account for outliers (column (3)); the change in the expected capital shortfall in a crisis (SRISK) in US$ billions (column (4)); and the log change in SRISK (column (5)). Changes are measured by the difference between the bank's maximum monthly value in 2020 and the corresponding mean value for the three months preceding the March 2020 turmoil. Bank controls comprise the end-2019 values of the CET1 capital ratio, the ratio of non-performing loans to total loans, deposits to total liabilities, and the density ratio. The first row reports the difference between the coefficient estimate for the more profitable G-SIBs and the corresponding estimate for the less profitable ones. Robust standard errors are clustered at the country level and t-statistics (F-statistics for the differences depicted in the first row) are reported in parentheses. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

The more profitable G-SIBs exhibited a significantly larger increase in SRISK than the less profitable ones. This result holds for a range of SRISK measures (Table 7). For one, more profitable G-SIBs' systemic risk contribution (i.e. the percentage of financial sector capital shortfall that would be experienced by a bank in the event of a crisis), averaging less than 5% before the shock, increased by about one percentage point more than the corresponding measure of less profitable G-SIBs (columns (1) and (2)). The relative change in these banks' SRISK (column (3)) and their SRISK changes in terms of expected capital shortfalls (column (4) and, in logs, (5)) also exceeded those of their less profitable peers. These results suggest that their higher profitability was at least partly due to greater exposure to tail risks, which tallies with the findings in (Meiselman *et al.*, 2020) for U.S. banks during earlier crises.

8 Conclusion

The stability of the global financial system rests on the resilience of systemically important banks. Regulation relies on capital requirements to bolster banks' resilience and mitigate systemic risks. While prior research has studied how banks adjust to changes in capital requirements, little is known about how differences in profitability shape banks' responses. However, this is key to understanding how capital regulation works and for the success of regulatory reforms.

In this paper, we show that the capital surcharges imposed by the G-SIB framework, a cornerstone of the too-big-to-fail reforms, induce less profitable G-SIBs to lower their systemic importance. The more profitable G-SIBs, however, continue to expand despite the additional requirements. Our theoretical framework rationalises this finding by showing that the higher opportunity cost of shrinking motivates more profitable banks to respond to tighter regulation by raising more capital in order to support their balance sheet as opposed to shrinking in size.

Our findings highlight that capital requirements affect the banking sector along multiple dimensions. In addition to supporting banks' resilience by raising their capital ratios, capital requirements also shift banking activity to more profitable banks, which could bolster intermediation efficiency. However, it may also raise financial stability concerns. Indeed, we show using the COVID-19 crisis as an experiment that higher profitability can be associated with greater exposure to tail risks. Moreover, rising concentration of systemic importance at a small number of global banks could add to the systemic risks posed by the banking sector. More research is thus needed on how to optimally design and calibrate capital requirements from a systemic risk perspective. This would ideally take into account interactions with complementary policies, such as enhanced supervision and resolution regimes.

Our paper also underscores the value of textual information for policy analysis. As with most major policy reforms, the identification of banks' responses is blurred by the gradual implementation of new rules. Our findings imply that a systematic evaluation of discussion related to the policy change in banks' annual reports or other forms of official communication can help identify when banks begin to incorporate the new rules. This provides a promising avenue for future research to sharpen policy analysis.

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Online Appendix – Background and Results

A G-SIB framework: institutional background

The G-SIB framework follows a rules-based approach to assign each bank in the assessment sample (roughly 80 internationally-active large banks) a score that reflects its systemic importance on an annual basis.

The score encompasses twelve indicators of a bank's systemic importance, grouped into five categories: cross-jurisdictional activity, complexity, interconnectedness, size, and substitutability (see Table A2 for the full list of indicators and the corresponding summary statistics). For each indicator, a score is computed for each bank that equals the bank's indicator value divided by the sum of indicator values of all banks in the assessment sample. The indicator scores thus reflect the bank's global market share in the underlying activity. The overall score – referred to as the "G-SIB score" – equals a weighted average across the bank's twelve indicator scores (see BCBS (2013) for details, such as the indicator weights). The scores are measured in basis points (bps), and banks with a G-SIB score of at least 130 bps are designated as G-SIBs based on an annual assessment. Supervisors can apply judgement and override this rule by designating a bank as a G-SIBs even though its score is below the threshold. However, this option has only been used a few times in the past.

G-SIBs are allocated into five different buckets depending on their scores. Each bucket covers a range of 100 bps. A G-SIB with, for example, a score between 130 to 229 bps is allocated to the first bucket.

G-SIBs with a higher score are subject to higher capital requirements. Starting from a level of 1% of Common Equity Tier-1 capital to risk weighted assets for G-SIBs in the first bucket, the surcharges increase by 0.5 percentage points per bucket up to 2.5% in the fourth bucket. From that point on, the surcharge increases by one percentage point per bucket to provide an even greater incentive against further increases in systemic importance (BCBS (2013)).

This paper focuses on the impact of the capital surcharges. G-SIBs are also subject to other regulatory requirements, such as more intense supervision as well as recovery and resolution planning. However, the surcharges create incentives for G-SIBs to reduce their systemic importance, while the other requirements, that apply to all G-SIBs irrespective of their score, do not. That is unless the bank could lower the score below the threshold that determines G-SIB designation.

The G-SIB assessment methodology was first published in November 2011, alongside an initial list of G-SIBs which has been updated annually since then. The Financial Stability Board disclosed the attendant capital surcharges for the first time in November 2012, although these were phased in only as of January 2016 over a three-year period (BCBS (2013)). As such, the surcharges were initially applicable to banks designated as G-SIBs in November 2014.

B Textual analysis

B.1 List of keywords

Table A1: List of keywords used in the word count analysis and to identify sentences that make reference to the G-SIB framework.

Keywords
global systemically important bank(s)
global systemically important financial institution(s)
global systemically important institution(s)
globally systemic international bank(s)
globally systemically important bank(s)
systemically important bank(s)
systemically important banking institution(s)
systemically important financial institution(s)
systemically important institution(s)
systemically relevant bank(s)
systemically significant financial institution(s)
gsib(s), g-sib(s), gsifi(s), g-sifi(s), gsii(s), g-sii(s), sifi(s), sii(s)

Note: All words in the annual reports are converted to lower case to ensure that all keywords are captured regardless of how they are capitalised (e.g. G-SIB or G-Sib).

B.2 Examples of action-oriented sentences in annual reports

- In the last year, we took some dramatic actions to reduce our GSIB capital surcharge, which we now have successfully reduced from 4.5% to an estimate of 3.5%. (JP Morgan, 2015)
- This is one reason why we worked so hard to reduce the GSIB capital surcharge - we do not want to be an outlier in the long run because of it. (JP Morgan, 2015)
- The Bank formulated the Administrative Measures of ICBC for Global Systemically Important Banks and proactively carried forward the implementation of advanced capital management approaches. (Industrial and Commercial Bank of China, 2014)
- Additionally, GSIB buffers will be included in the hurdle rate. (Royal Bank of Scotland, 2015)
- G-SIB Rule may limit or otherwise restrict how we utilize our capital, including common stock dividends and stock repurchases, and may require us to increase or alter the mix of our outstanding regulatory capital instruments. (Bank of New York Mellon, 2014)
- Economic capital is set at a level that will cover adverse events with a probability of 99.93% (confidence interval), while regulatory capital is quantified on the basis of a CET1 target ratio in line with that of major international banking groups and taking into account the impacts of the supervisory regulations in force or that will be adopted (CRR, Global Systemically Important Financial Institutions (G-SIFIs), etc.). (UniCredit, 2014)
- Our long-term targeted capital structure also considers capital levels sufficient to exceed Basel III capital requirements including the G-SIB surcharge. (Wells Fargo, 2015)
- Accordingly, we believe we will be able to sufficiently meet the new capital regulations including the framework to identify G-SIFIs. (Mizuho, 2014)
- However, Citi's ongoing efforts during 2015 in managing balance sheet efficiency has resulted in lower scores for substantially all of the quantitative measures of systemic importance, and consequently has reduced Citi's estimated GSIB surcharge to 3%, also derived under method 2, which would become effective January 1, 2017. (Citibank, 2015)

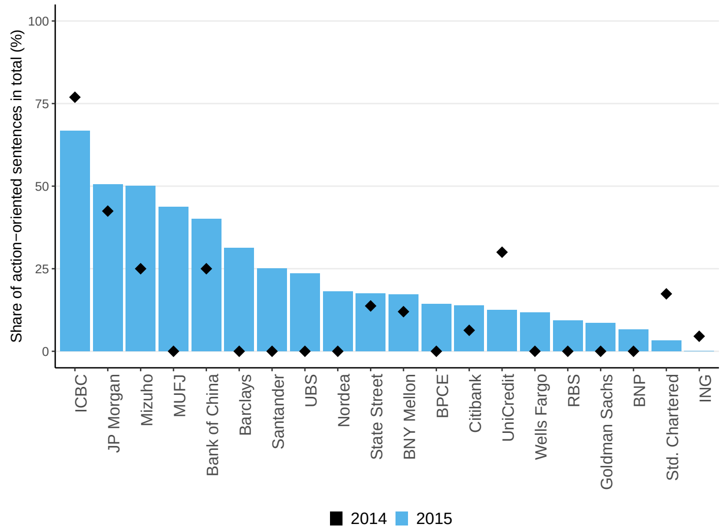
B.3 Most frequent words in relevant sentences

Figure A1: Word cloud of G-SIB related sentences

Note: The graph plots the 70 most frequent words mentioned in G-SIB related sentences. The sample consists of the annual reports of 31 G-SIBs in 2013, 2014, and 2015.

B.4 Bank-specific share of relevant sentences

Figure A2: Share of action-oriented sentences by bank in 2014 and 2015



Note: Share of action-oriented sentences: bars for 2015 and diamonds for 2014. Banks with non-zero counts of action-oriented sentences in 2015 (except ING) are shown. The sample is restricted to G-SIBs designated as such before 2015.

C Banks' adjustment margins

In this appendix, we zoom into the different categories and indicators that constitute the overall G-SIB score to assess banks' margins of adjustment. We run the regression specified in equation (2) with the adjusted category and indicator scores as the dependent variable. Table A2 shows the summary statistics of the dependent variables while Table A3 presents the coefficient estimates of the triple interaction term.

Table A2: Summary statistics

	Mean	Stdev	P10	P25	P50	P75	P90	N
CATEGORY SCORES								
1. Size	136.84	101.53	46.22	63.01	101.39	183.87	307.36	443
2. Interconnectedness	134.56	85.01	40.78	66.15	115.55	195.01	244.31	443
3. Substitutability	146.15	209.19	14.49	34.05	68.97	177.98	350.00	443
4. Complexity	114.71	134.66	10.54	29.77	55.81	157.92	297.51	443
5. Cross-jurisdictional Activity	141.13	160.89	4.13	29.03	84.69	191.45	363.70	443
INDICATOR SCORES								
2a. Intra-financial system assets	123.94	93.83	27.04	44.41	98.58	185.20	264.22	443
2b. Intra-financial system liabilities	135.37	102.40	19.36	54.21	111.37	201.01	266.62	443
2c. Securities outstanding	144.39	94.66	39.54	63.91	131.34	199.03	268.00	443
3a. Payments activity	138.68	202.76	12.84	35.36	66.31	153.78	308.55	443
3b. Assets under custody	151.81	342.74	2.67	11.69	39.73	110.10	289.29	443
3c. Underwritten transactions	147.96	196.50	2.18	24.86	66.57	161.82	463.31	443
4a. Notional amount of OTC derivatives	109.97	174.53	1.35	4.22	28.28	112.68	391.15	443
4b. Trading and AFS securities	121.94	138.12	11.42	30.52	66.34	178.28	310.56	443
4c. Level 3 assets	112.21	140.90	0.95	15.97	52.40	154.38	308.43	443
5a. Cross-jurisdictional claims	142.06	164.27	3.44	25.29	82.32	214.99	353.12	443
5b. Cross-jurisdictional liabilities	140.19	160.35	4.72	23.56	84.94	199.31	368.31	443

Note: The table shows summary statistics for the adjusted G-SIB indicators and categories. OTC = over the counter. AFS = available for sale.

More profitable G-SIBs raised their scores relative to the less profitable G-SIBs along four out of the five categories, and most significantly so in the case of *Size* and *Substitutability*. Zooming in even further, we find that the increase in the average score of more profitable G-SIBs is driven by a significantly higher footprint along the following G-SIB indicators: *size* (which is also a category in itself), *underwriting activities*, *notional amount of OTC derivatives*, and *cross-jurisdictional liabilities*.

While an in-depth analysis of the causal link between these indicators and bank profitability is beyond the scope of this paper, we can link our findings to related results in the literature. There are various reasons why *size* and profitability may be positively related, which can help explain the result that more profitable G-SIBs continued to increase their size score after treatment. Regehr and Sengupta (2016), for instance, document a positive correlation between size and profitability in the United States. The authors argue

Table A3: Regressions based on category and indicator scores

	Coefficient on Post × G-SIB × Profitability		R-squared
CATEGORIES			
1. Size	27.04***	(3.48)	0.993
2. Inter-connectedness	11.28	(0.83)	0.962
3. Substitutability	55.54***	(2.99)	0.992
4. Complexity	31.91*	(1.75)	0.960
5. Cross-jurisdictional activity	27.54*	(1.93)	0.991
INDICATORS			
2a. Intra-financial system assets	5.301	(0.29)	0.937
2b. Intra-financial system liabilities	4.877	(0.19)	0.928
2c. Securities outstanding	23.65	(1.34)	0.975
3a. Payments activity	23.73	(0.54)	0.969
3b. Assets under custody	11.96	(0.75)	0.995
3c. Underwritten transactions	130.9***	(5.94)	0.973
4a. Notional amount of OTC derivatives	63.40***	(2.81)	0.978
4b. Trading and AFS securities	12.38	(0.45)	0.919
4c. Level 3 assets	19.95	(0.51)	0.894
5a. Cross-jurisdictional claims	28.00	(1.65)	0.990
5b. Cross-jurisdictional liabilities	27.09*	(1.93)	0.986

Note: The dependent variables are the respective adjusted scores at the category and indicator levels (first column). The indicators are numbered based on the category they belong to. The table reports the coefficient estimates of the triple interaction term ($Post_t \times G\text{-}SIB_i \times Profitability_i$) based on equation (2), with t-statistics reported in parentheses. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. The profitability measure is based on average pre-treatment (i.e. 2013-14) ROA in levels. Bank-level controls include the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio (all lagged by one year). Each specification also includes bank fixed effects and country-year fixed effects. The number of observations is 373 in each regression. Robust standard errors are clustered at the bank level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

that increasing size can increase profitability by allowing banks to economise on fixed costs. Greater size may also pose diversification benefits, as discussed in Mester (2010), for instance.

Our result on *underwriting transactions* is consistent with prior research suggesting that financial firms with higher market share and reputation account for a larger share of underwriting business (see, for example, Santiago *et al.* (2020), Krigman *et al.* (2001)). The positive coefficient suggests that as the more profitable G-SIBs expanded their market share relative to the less profitable ones, they were able to attract a higher share of the global underwriting business as well. Likewise, we observe a significant wedge opening up in G-SIBs' *notional amount of OTC derivatives*. Consistent with the high fixed costs associated with OTC trading (e.g. Faruqui *et al.* (2018)), the more profitable G-SIBs appear to have adjusted more easily to rising capital charges on non-cleared derivatives (e.g. CGFS (2018)) and have expanded their OTC derivative portfolios relative to the less profitable G-SIBs.

We note that several categories and indicators do not exhibit a significant increase in the scores of more profitable G-SIBs. Our finding on interconnectedness, for instance, accords with previous research that implies no material change in G-SIBs' financial interlinkages since the financial crisis of 2007–08 (e.g. McNelis and Yetman (2020) and Malik and Xu (2017)).

D Additional results and robustness tests

D.1 Evolution of bank profitability over time

Table A4: Correlation of banks' ROA from one year to the next

	2013	2014	2015	2016	2017	2018
2013	1					
2014	0.94	1				
2015	0.86	0.84	1			
2016	0.85	0.84	0.88	1		
2017	0.81	0.79	0.80	0.92	1	
2018	0.75	0.73	0.74	0.87	0.95	1

Note: Pearson's correlation coefficients of banks' ROA from one year to the next. All coefficients are statistically significant at the 1% level.

D.2 Matched balance test

Table A5 reports the mean values of the covariates that underpin the matching regressions presented in columns (5) and (6) of Table 4 for Non G-SIBs (control group) and G-SIBs (treatment group), respectively. We also report the p-values of tests of differences in the means for the original sample (i.e. unmatched, column (3)) and for each matched sample (columns (4) and (5)) based on the two matching approaches presented in Table 4. As shown, the matching approaches further reduce differences in the means of the control and treatment group, most notably for the CET1 ratio and the density ratio.

Table A5: Mean difference of co-variates before and after matching.

Variable	Non G-SIBs	G-SIBs	p-val (unmatch)	p-val (1)	p-val (2)
	(1)	(2)	(3)	(4)	(5)
CET1 ratio	10.96	11.66	0.07	0.94	0.26
Density ratio	51.06	44.08	0.01	0.56	0.22
Non-performing loan ratio	2.83	3.40	0.26	0.76	0.32
Cash to total assets	6.27	6.89	0.47	0.20	0.81
Deposits to total liabilities	58.03	53.00	0.12	0.75	0.46

Note: Based on pre-treatment (2013-14) bank characteristics. Columns (1) and (2) denote the average value of the covariates for Non G-SIBs and G-SIBs, respectively. Column (3) denotes the p-value of the test of mean difference in the unmatched sample. Columns (4) and (5) denote the corresponding value based on the matched samples used in the regressions of columns (5) and (6) of Table 4, respectively.

D.3 Alternative specifications and control variables

In this appendix, we show that the results are robust to restricting the composition of the sample, alternative choices of the G-SIB identifier, and the inclusion of alternative control variables. Table A6 reports the summary statistics for the additional bank-level variables used in the robustness checks.

Table A6: Summary statistics of additional variables

	Mean	Stdev	P10	P25	P50	P75	P90	N
Return on equity (%)	14.41	7.49	5.57	9.66	13.75	18.59	24.38	492
Return on risk-weighted assets (%)	1.99	0.88	0.81	1.44	2.01	2.53	3.11	485
Risk-adjusted return on assets (%)	5.62	4.67	1.34	2.42	4.23	7.45	12.21	492
Z-score (ratio)	43.40	27.03	17.03	27.50	36.61	50.58	81.57	492
Cost to income (%)	55.72	16.18	30.46	44.96	58.14	66.94	74.58	492
Capital buffer (%)	4.64	3.03	1.65	2.54	3.94	6.08	8.74	486
CAPM Beta	1.19	0.38	0.74	0.96	1.19	1.39	1.67	391

Note: The table shows summary statistics for the additional variables used in the appendix. Statistics are based on 2013 to 2018 data on an unbalanced sample of 84 banks from 21 jurisdictions. The units are displayed alongside the name of the variables. Risk-adjusted return on assets is equal to ROA divided by its standard deviation during 2010 and 2014. Z-score equals the sum of ROA and equity capital to assets ratio divided by the standard deviation of ROA during 2010 to 2014. Cost to income is the ratio of non-interest expenses to the sum of non-interest income and net-interest income. Capital buffer is defined as 7% + G-SIB surcharge – CET1 ratio. CAPM Beta measures a bank's average annual systematic risk, based on regressing weekly excess equity returns on the market excess return of the bank's domestic benchmark index using 10-year government bonds as risk-free rates and 50-week rolling windows.

We start by restricting the sample to those banks for which we have data in *each* year from 2013 to 2018. This reduces the number of banks from 84 to 65. Our findings are robust to this change, both in terms of economic and statistical significance as reported in Table A7 (column (1)).

In our main analysis, we categorise all banks as G-SIBs that have been designated as such at least once before 2015. In doing so, we control for any confounding effects resulting from banks switching between the treatment and control group. To assess whether this

Table A7: Alternative specifications and sample composition

	Balanced sample	G-SIB as designated	Control for Capital-buffer	Control for CAPM beta
	(1)	(2)	(3)	(4)
Post × G-SIB × Profitability	28.84***	27.23***	33.05***	27.10**
	(3.19)	(2.84)	(3.36)	(2.36)
Post × G-SIB	–34.31***	–31.66**	–34.81***	–31.90**
	(–2.92)	(–2.62)	(–2.82)	(–2.35)
Post × Profitability	21.46	17.25	14.63	17.93
	(1.53)	(1.65)	(1.43)	(1.40)
N	330	373	373	313
R2	0.990	0.991	0.991	0.990
Bank controls and FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes
G-SIB score	Adjusted	Adjusted	Adjusted	Adjusted
Post dummy	2015	2015	2015	2015
G-SIB dummy	Baseline	Official	Baseline	Baseline

Note: The table reports robustness checks on the baseline results in Table 4 using equation (2). The dependent variable is the adjusted G-SIB score. The balanced sample in column (1) comprises only those banks that have been included in the G-SIB assessment sample in each year. Column (2) uses the official designation year for the G-SIB dummy. In columns (3) and (4), we also include respectively the capital buffer and the CAPM Beta as controls. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. *Profitability* is the level of average pre-treatment (2013-14) ROA. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposits to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

definition influences our results, we run our analysis using the official G-SIB designation, which can vary across time. In this specification, the G-SIB dummy, as defined in equation (2), equals 1 (zero otherwise) only in those years when the bank is actually designated a G-SIB. As shown in Table A7, column (2), the alternative definition has little impact on our results. This result reflects the fact that only a few banks transition into or out of being a G-SIB.

Next, we assess whether differences in the size of the banks' capital buffers shaped the response to the framework. In our main analysis, we control for differences in the CET1 capital ratio across banks. However, the G-SIB surcharges imply that capital buffers – as measured by the difference between the CET1 ratio and the sum of minimum capital requirements and the fully-loaded surcharge – can differ across banks even if they have the same CET1 capital ratio. We thus replace the CET1 capital ratio with the capital buffer in our main regressions. Our findings do not change as a result of this inclusion (Table A7, column (3)).

Finally, we gauge whether the more profitable G-SIBs' adjustment is driven by a higher opportunity cost of reducing their scores or whether it reflects a lower cost of issuing capital to meet higher capital requirements. To disentangle these effects, we control for differences in banks' cost of equity as inferred from their systematic risk

("Beta"). We estimate the latter based on a standard Capital Asset Pricing Model using 50-week rolling regressions of banks' weekly excess returns on the excess return of their domestic benchmark indices (see Table 1 for the summary statistics of the Betas). We find that accounting for variation in banks' Betas has no meaningful impact on the coefficients of interest as shown in column (4) of Table A7. This lends support to the interpretation that for more profitable G-SIBs, the cost of downsizing outweighs the benefits of reducing their systemic importance.

D.4 Alternative profitability measures

We consider alternative measures of profitability to further assess the robustness of our findings based on the specification in equation (2).

Table A8 reports the results based on substituting the average ROA in the pre-treatment period (our baseline measure) with the ROA in 2014, i.e. the most recent observation before treatment (column (1)). We also consider the average pre-treatment return on equity (column (2)). In addition, we inspect an estimate of the banks' efficiency, measured as one minus the bank's cost-to-income ratio (column (3)). We also test regressions based on using the return on risk-weighted assets (column (4)), the risk-adjusted return on assets (column (5)) and the Z-score (column (6)) (see Table 1 for the variable definitions).

For each of these measures the coefficient of interest – the one on the triple interaction term reported in the first row – remains positive and highly significant as in our previous results (recall Table 4). The findings thus underscore our main conclusion regarding the pivotal role of profitability, both in terms of statistical and economic significance.

D.5 Controlling for business model

We study the impact on our main results of differences in banks' business model. These differences could bias our results if the business model affects pre-treatment profitability, the G-SIB score, or how banks respond to the framework in general. To assess this possibility, we allocate banks to different business models based on various balance sheet characteristics using cluster analysis. We then control for differences in banks' business models in our regressions to test the robustness of our main findings.

The cluster analysis relies on three asset side variables (loans, securities, and cash), two funding variables (deposits and wholesale funding), and one income variable (non-interest income). All variables are scaled by total assets (TA). We use hierarchical agglomerative

Table A8: Alternative profitability and efficiency metrics

	ROA (2014) (1)	Return on equity (2)	Cost-to-income efficiency (3)	Return on RWA (4)	Risk-adjusted ROA (5)	Z-score (6)
Post × G-SIB × Profitability	30.64***	2.824***	1.541***	21.78***	4.323***	1.013***
	(2.79)	(3.97)	(3.99)	(2.74)	(3.67)	(2.89)
Post × G-SIB	–35.15**	–46.64***	–69.88***	–50.12**	–32.98***	–45.24**
	(–2.45)	(–3.16)	(–3.47)	(–2.45)	(–2.87)	(–2.63)
Post × Profitability	8.715	0.976*	–0.146	10.57**	1.953**	0.236
	(0.77)	(1.71)	(–0.30)	(2.31)	(2.12)	(1.43)
N	373	373	373	373	373	373
R2	0.990	0.991	0.991	0.991	0.991	0.991
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports results of the regression in equation (2) using alternative measures of profitability. The dependent variable is the adjusted G-SIB score. *Profitability* is measured based on ROA in 2014 in column (1); the average pre-treatment (2013–14) return on equity in column (2); the average pre-treatment cost-to-income efficiency in column (3); the return on risk-weighted assets (RWA) in column (4); the risk-adjusted ROA in column (5); and the Z-score in column (6). See Table 1 for the definition and summary statistics of these measures. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposits to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

clustering methods to classify each bank-year observation into a pre-defined number of clusters. The algorithm starts by treating each observation as an independent cluster. It then proceeds to merge observations that are more similar to one another in terms of their input variables (based on minimizing the sum of squared Euclidean distances). At the highest level of aggregation, there is only one cluster. Similar to Roengpitya *et al.* (2017), the clusters are interpreted as one of four business models – retail-funded, wholesale-funded, trading, or universal – based on their average balance sheet characteristics, as shown in the Table A9.

Table A9: Table: Summary statistics by business model clusters

	Retail-oriented (Obs = 179)	Trading (Obs = 138)	Wholesale (Obs = 75)	Universal (Obs = 94)
Loans/TA	**0.63**	**0.42**	0.28	**0.53**
	[0.51, 0.74]	[0.17, 0.55]	[0.09, 0.37]	[0.44, 0.62]
Securities/TA	**0.18**	**0.28**	0.25	**0.18**
	[0.10, 0.27]	[0.16, 0.41]	[0.17, 0.36]	[0.09, 0.28]
Cash/TA	0.06	0.11	0.06	0.05
	[0.01, 0.14]	[0.01, 0.19]	[0.01, 0.13]	[0.01, 0.10]
Deposits/TA	**0.63**	0.60	**0.29**	**0.38**
	[0.51, 0.76]	[0.52, 0.70]	[0.16, 0.41]	[0.27, 0.47]
Wholesale funding/TA	**0.20**	0.27	**0.39**	**0.40**
	[0.12, 0.32]	[0.16, 0.38]	[0.23, 0.50]	[0.27, 0.52]
Non-interest income/TA	0.01	0.01	0.02	0.01
	[0.00, 0.02]	[0.01, 0.02]	[0.01, 0.03]	[0.00, 0.02]

Note: The table shows summary statistics for the four business model clusters, calculated based on input variables in the first column. Based on these summary statistics, business models have been interpreted as one of retail, trading, wholesale, and universal. The first row for each variable is the mean for the observations classified as that cluster, while the values in the square brackets are the $10^{th} - 90^{th}$ percentiles.

The cluster analysis yields a time-varying business model allocation for each bank, which we include as an additional regressor in equation (2). The results in Table A10 show that regardless of the number of clusters, which vary from 4 clusters in column (1) to 2 clusters in column (3), controlling for differences in business models has little impact on the interaction terms of interest.

Table A10: Controlling for differences in business models

	Business models		
	(1)	(2)	(3)
Post × G-SIB × Profitability	30.87***	30.90***	30.83***
	(3.37)	(3.41)	(3.50)
Post × G-SIB	–36.49***	–36.52***	–36.50***
	(–3.14)	(–3.17)	(–3.18)
Post × Profitability	15.61	15.59	15.64
	(1.46)	(1.46)	(1.48)
N	373	373	373
R2	0.991	0.991	0.991
Bank controls and FE	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes
No. of business model clusters	4	3	2

Note: The table reports results of the regression in equation (2) with the inclusion of business model clusters as additional regressors. There are three variations depending on the number of clusters. The dependent variable is the adjusted G-SIB score. All other variables are as defined in Table 4. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposits to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

D.6 Quarterly dataset

Table A11 reports the summary statistics of the quarterly data used in the regressions in Table 5.

Table A11: Summary statistics of the quarterly dataset

	Mean	Stdev	P10	P25	P50	P75	P90	N
Capital (log)	4.54	0.80	3.35	4.06	4.63	5.21	5.46	681
Assets (log)	7.26	0.70	6.41	6.86	7.46	7.75	7.96	681
Capital ratio (%)	7.26	0.70	4.62	5.27	6.47	8.55	9.79	681
Non-performing loan ratio (%)	2.25	1.93	0.39	0.75	1.51	3.46	5.17	681
Cash to total assets (%)	6.54	6.44	0.95	1.44	4.63	9.30	16.96	681
Deposits to total liabilities (%)	57.99	18.60	30.83	46.29	60.37	74.36	80.50	681

Note: Statistics are based on quarterly data from 2010 to 2018 data on an unbalanced sample of 27 G-SIBs from 8 jurisdictions. The units are displayed alongside the name of the variables. All dependent variables are based on Q1 2010 exchange rates. Capital: log of total regulatory capital in US$ billions. Assets: log of total assets in US$ billions. Capital ratio: total regulatory capital divided by risk-weighted assets. Non-performing loan ratio: the ratio of non-performing loans to total loans. Cash to total assets: total cash holdings as a share of total assets. Deposits to total liabilities: total deposits as a share of total liabilities.

D.7 Assessing the role of geographical factors

We assess whether geographical factors, such as national regulatory reforms or different macroeconomic developments in banks' home jurisdiction, affect our findings. The use of country-year fixed effects throughout our main analysis generally controls for such effects. Three additional tests confirm that geographical factors do not drive our results.

First, we exclude U.S. banks to test whether deviations from the BCBS's methodology in the U.S. regulation of G-SIBs affect our results. U.S. regulators apply an additional, although closely related, method for the calibration of the G-SIB capital surcharges. U.S. G-SIBs are subject to the higher of the capital surcharge that result from this method and the BCBS methodology, with the former typically resulting in higher surcharges. This implies that U.S. banks may have weaker incentives to respond to the BCBS G-SIB framework. In line with this, we find that the exclusion of U.S. banks reinforces our results of a significant difference in the response of more and less profitable G-SIBs as shown in column (1) of Table A12.

Second, we repeat our analysis based on including only banks from emerging market economies (EME). This takes account of differences in the degree of financial development relative to more advanced economies. In addition, it enables us to address any potential concern that could be linked to the introduction of Total Loss-Absorbing Cap-

Table A12: Geographical factors

	Sub-samples		Country-group dummies			
	Exclude U.S. banks	Only EME banks	U.S.	EU	Asia-Pacific	EME
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB × Profitability	42.86***	62.99**				
	(6.00)	(2.70)				
Post × US × Profitability			–10.45			
			(–0.43)			
Post × EU × Profitability				29.29		
				(1.31)		
Post × Asia-Pacific × Profitability					17.07	
					(0.89)	
Post × EME × Profitability						–11.72
						(–0.53)
Post × G-SIB	–44.77***	–83.90*				
	(–3.99)	(–1.81)				
Post × Profitability	18.25**	–0.475	31.63***	20.76	23.74*	31.19**
	(2.65)	(–0.06)	(2.93)	(1.61)	(1.83)	(2.13)
N	313	109	373	373	373	373
R2	0.992	0.989	0.990	0.990	0.990	0.990
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports results of the regression in equation (2) for different sub-samples indicated in the column headings. The dependent variable is the adjusted G-SIB score. European Union (EU), column (4), comprises the United Kingdom during the period of observation. Asia-Pacific, column (5), comprises banks from Japan, China, India, Australia, Singapore, Korea, and Russia. All other variables are as defined in Table 4. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposits to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

ital (TLAC) requirements for G-SIBs in advanced economies. TLAC requirements could have potentially affected G-SIBs' scores by inducing changes in the composition of banks' funding. However, these requirements have become effective only as of 2019 in advanced economies and are thus unlikely to affect our results. In emerging market economies, TLAC requirements will not take effect before the start of 2025. As shown in column (2) of Table A12, our findings prove robust to the exclusion of advanced economy banks.

Third, we replace the G-SIB dummy by a *country-group* dummy that identifies banks from a specific region or from emerging markets to assess the impact of the banks' origin on score adjustments. These placebo tests show that profitable banks from specific regions have not changed their scores relative to their peers in a statistically significant manner as shown in columns (3) to (6) of Table A12. This accords with the G-SIB framework being the primary driver of banks' adjustments.

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