

BANK OF ENGLAND

Staff Working Paper No. 946 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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Abstract

What shapes banks' response to capital requirement reforms? While pre-reform capitalisation is important in the short term, we posit that profitability is key in the medium term, as it underpins banks' capacity to build capital. We examine the impact of capital surcharges on systemically important banks. Through a novel application of textual analysis to identify when banks react, we show that less profitable banks contract when faced with higher requirements, especially if they are closer to the thresholds that determine their surcharges. Conversely, more profitable banks continue to expand, improving banking efficiency but raising concerns about concentration and exposure to tail risks.

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.

- (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⁾ Bank for International Settlements. Email: tirupam.goel@bis.org (corresponding author)

1 INTRODUCTION

Banking regulation relies on the principle that regulatory requirements can make banks internalise the negative externalities associated with excessive leverage and risk-taking. While capital requirements have traditionally focused on banks' idiosyncratic risks, the global financial crisis in 2008 led to a rethinking. Capital requirements have not only been raised since the crisis, their scope has also been broadened to address systemic risk. Yet what do we know about the impact of capital requirements on banks?

In the short run, an increase in capital requirements typically induces banks to shrink. As a large body of the literature has shown, the response generally involves less lending (e.g. Couaillier et al. 2024, Gropp et al. 2019, Imbierowicz, Kragh, and Rangvid 2018, Jimenéz et al. 2017, Aiyar, Calomiris, and Wieladek 2014, Berger et al. 2008). A key reason is that raising capital by retaining earnings is a gradual process that takes time, while banks raise capital externally only under exceptional circumstances.¹ Hence, they must reduce risky exposures to increase their capital ratio in the short run. Weakly capitalised banks are thus hit harder.

In the medium-term, however, the impact of higher capital requirements on banks is ambiguous because capital can adjust. Here, a bank's profitability is more important than its current capital ratio. More profitable banks can retain earnings more easily and thus have greater capacity to generate capital internally (e.g. Cohen and Scatigna 2016, Cohen 2013). As such, higher capital requirements constrain unprofitable banks more tightly than weakly capitalised yet more profitable peers in the medium-term. Assessing how profitability affects banks' responses is thus crucial for understanding how regulation works. Surprisingly, little is known about the role of profitability in this context. Instead, much more attention focuses on how regulation affects profitability (e.g. Ahmad et al. 2020).

To fill this gap, we examine how banks' profitability determines their responses to

a major reform in capital requirements. We assess a cornerstone of the too-big-to-fail reforms: the framework for Global Systemically Important Banks (G-SIBs). This framework imposes capital surcharges on some – but not all – large internationally active banks. These surcharges are based on banks' global market share across several core financial activities. The weighted average of these market shares yields the "G-SIB score" and represents the key regulatory measure of banks' systemic importance.² Since equity is costly to raise (Kashyap, Stein, and Hanson 2010), the framework creates incentives for G-SIBs, notably the less profitable ones, to reduce their systemic importance.³ Our analysis is based on publicly available data and comprises more than 80 of the largest banks from 21 countries, representing more than half of the global banking system's total assets.

To test for the potentially diverging responses by banks to an increase in capital requirements depending on their profitability, we adopt a difference-in-differences (DD) approach. Our main outcome variable is banks' G-SIB scores. To uphold the Stable Unit Treatment Value Assumption (SUTVA) within our DD approach, we adjust for the inherent relativity in the official scores by re-basing them to the sample's first year. We estimate panel DD regressions on less profitable banks, i.e. banks with pre-treatment return on assets (ROA) below the sample median, and a similar set of regressions on the more profitable banks. We complement this analysis by including profitability as a third interaction term in the DD approach.

Several features of the G-SIB framework help us identify a causal effect of regulatory changes on banks' responses. Foremost, the calibration of the capital surcharges is exogenous to the banks' pre-reform profitability, providing an ideal setup to evaluate the role of profitability. Second, we establish that G-SIBs and Non G-SIBs (i.e. banks not subject to the framework) evolved similarly before the reform was implemented. Finally, we exploit exogenous discontinuities in how the G-SIB scores translate into capital surcharges. To fortify our specification, we pursue tests to confirm the persistence of profitability as a structural characteristic, unrelated to G-SIB designation. In all our regressions, we control for various bank characteristics, notably bank capital buffers, as well as differences across countries and time. We also employ matching techniques to address variation in other bank characteristics potentially influencing their behaviour besides profitability.

One remaining challenge in our identification is that, like many major reforms, the G-SIB framework was gradually implemented over time. The framework was announced in 2011 while higher capital requirements were phased in from 2016 to 2018 (BCBS 2013). This approach allowed banks to time their adjustments and reduce transition costs (e.g. Dagher et al. 2020, Mendicino et al. 2020). Prior research often simplifies by assuming that banks respond either upon reform announcement or implementation. However, banks' long-term commitments and operational complexities can invalidate this assumption and make it challenging to pinpoint the timing of treatment in such cases.

We address this challenge by proposing a novel application of textual analysis by examining banks' annual reports. These reports, originating from decision-makers within banks, provide valuable insights into how regulatory reforms impact a bank's strategy. Despite these benefits, prior academic research on regulatory reforms has made little use of the text in annual reports. Our identification of the treatment date involves two steps. First, we count references to the framework in G-SIBs' annual reports and compare them with those of other major banks. Second, we assess the context of these references to precisely extract specific responses to the framework. We identify 2015 as the year when most G-SIBs began incorporating the framework into their strategic planning, one year ahead of the start of the regulatory phase-in period.⁴

We present several new findings. Foremost, we show that differences in banks' profitability prompt diverging responses to an increase in capital requirements. The framework caused less profitable G-SIBs to cut back their systemic importance compared to less profitable Non G-SIBs. By contrast, more profitable G-SIBs continued to raise their systemic importance in tandem with more profitable Non G-SIBs.

As activity shifted from less profitable G-SIBs to their more profitable counterparts, the systemic importance wedge between the two groups widened noticeably, as compared with the corresponding wedge between more and less profitable Non G-SIBs. In difference to prior research that documents a reduction in G-SIBs' lending activity – on average – after the introduction of the surcharges (e.g. Favara, Ivanov, and Rezende 2021, Degryse, Mariatahsan, and Tang 2023), this paper uncovers the framework's heterogeneous impact based on banks' profitability.

The empirical effects are economically significant. An Oaxaca-Blinder style decomposition suggests that the profitability advantage boosted the more profitable G-SIBs' average score by about 41 basis points (bps) post treatment, which corresponds to around 24% of these banks' average pre-treatment score. Our triple-difference specification affirms that, compared with the less profitable G-SIBs, the more profitable G-SIBs' average scores rose by around 30 to 40 basis points (bps). Overall, we estimate that the enhanced profitability of these banks contributed 4.6 percentage points to their global market share by the end of the observation period.

Several robustness checks confirm that bank profitability, rather than other factors such as banks' domicile or business model, is the main determinant of banks' mediumterm response to the framework. In particular, we confirm that profitability continues to be a significant driver of bank behaviour even in the presence of bank capitalisation as a competing driver. We also consider a variety of alternative measures of profitability and alternative estimation approaches. Our conclusions prove robust both quantitatively and in terms of statistical significance in all these inspections.

The unique design of the G-SIB capital surcharges allows us to further sharpen our our identification. Each G-SIB is assigned to a bucket based on its score, and surcharges rise in discrete steps between buckets. The bucket thresholds thus create a discontinuity: banks near the threshold should react more strongly to the framework. We exploit this exogenous variation in the regulatory treatment and confirm that less profitable banks near the thresholds significantly reduce their scores compared to other banks.

Our identification strategy offers a notable advantage by accommodating different treatment dates among banks. We allow for potentially staggered treatment across G-SIBs by leveraging recent estimation methods (e.g. Callaway and Sant'Anna 2021). Our findings affirm the qualitative and quantitative robustness of our main analysis.

What do these findings imply for policy? Clearly, the framework improves G-SIBs' resilience by raising banks' capital ratios. However, the broader policy implications hinge on the origin of profitability. If banks are more profitable due to efficiency, then the reallocation of banking activity towards more profitable banks is desirable. Yet, if profitability stems from greater risk-taking, the same reallocation could pose financial stability concerns (e.g. Martynova, Ratnovski, and Vlahu 2020). Using the COVID-19 crisis as an experiment, we find that more profitable G-SIBs experienced a larger increase in systemic risk during the pandemic. This suggests that higher profitability in good times at least partly reflected increased exposure to tail risks (e.g. Meiselman, Nagel, and Purnanandam 2023).

Literature review Our paper contributes to banking literature in three key ways. First, it advances the understanding of how banks respond to regulatory reforms, building on the existing research that predominantly focuses on the role of capital. For instance, studies by Gropp et al. (2019) and Berger et al. (2008) highlight that poorly capitalised banks react more promptly to tighter regulatory targets, favouring balance sheet adjustments over earning retention for capital. This aligns with Kashyap, Stein, and Hanson (2010) who emphasise the impact of external capital-raising frictions on banks' responses. Additionally, Jimenéz et al. (2017) assert that the impact of dynamic provisioning requirements depends on banks' capitalisation.

Our findings align with Cohen and Scatigna (2016) and Cohen (2013), reporting that more profitable banks increased lending amid rising regulatory requirements post the 2007–08 crisis. Fang et al. (2020) and De Jonghe, Dewachter, and Ongena (2020) find weaker banks contract credit supply more under higher capital requirements in emerging markets and Belgium, respectively. Our work is also linked to Peek and Rosengren (1995), establishing that banks facing binding regulatory requirements due to negative shocks to capital tend to shrink more.

Moreover, our paper contributes to the understanding of post-crisis reforms addressing the too-big-to-fail problem. While existing literature evaluated the impact of capital requirements on banks' balance sheets or risk-taking, less attention has been paid to the regulation's effect on banks' systemic importance. Violon, Durant, and Toader (2020) find G-SIBs cut back on asset growth and leverage following the G-SIB framework introduction. Goel, Lewrick, and Mathur (2019) highlight an acceleration in G-SIBs' balance sheet adjustments, while Degryse, Mariatahsan, and Tang (2023) observe an adverse effect on lending volumes. In contrast to existing literature, our analysis reveals the framework's diverse impact on G-SIBs based on profitability differences. Furthermore, we demonstrate how capital surcharges drive adjustments in G-SIB scores and reallocation of activity across banks more generally. Understanding this is essential for supervisors in evaluating banks' systemic importance.

Finally, we propose a new methodology for identifying regulatory treatments. Prior research has used announcement dates, e.g., release of the G-SIB assessment methodology (Violon, Durant, and Toader 2020). Yet, it remains unclear when banks integrate future requirements into capital planning. Our method utilises banks' annual reports, providing crucial insights into the timing and manner of banks' responses to regulatory reforms. Previous studies have also relied on annual reports of *non-financial* firms to

assess financial constraints (Hoberg and Maksimovic 2015), create measures of risk and ambiguity (Friberg and Seiler 2017), measure offshoring activities (Hoberg and Moon 2017), or gauge firms' exposure to political risk (Hassan et al. 2019). Our paper extends this research by employing a two-step approach: we perform a keyword search and then evaluate the context of the keyword occurrences to refine the interpretation of the search results.

This paper is structured as follows. In Section 2, we delineate the key aspects of the G-SIB framework, highlighting our use of textual analysis to identify regulatory treatment. Section 3 introduces the data, followed by our empirical methodology in Section 4. Section 5 discusses our primary empirical findings. Section 6 examines the robustness of our findings and explores financial stability implications. We conclude with Section 7. The online appendix offers additional background on the G-SIB framework and textual analysis, along with a stylized model for enhanced intuition on the underlying adjustment mechanisms, supplementary results, and robustness checks.

2 INSTITUTIONAL DETAILS AND IDENTIFY-ING TREATMENT DATE

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 framework seeks to induce large internationally active banks to internalise the negative externalities they impose on the global banking system (see BCBS 2021, chapter SCO40). To achieve this objective, it imposes capital requirements proportionate to banks' systemic importance, as indicated by banks' average market share in various

financial activities – the G-SIB *score* (see Annex A for additional details).

Banks with scores above a certain threshold are designated as *global systemically important banks* or "G-SIBs". These banks 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, Stein, and Hanson 2010).

We refer to all other banks in the sample of large internationally active banks assessed by the framework as "Non G-SIBs". The framework does not impose any additional requirements on Non G-SIBs.

Several features of the framework facilitate our empirical analysis. First, the regulatory treatment is not tied to banks' profitability, which supports identification. Second, the framework was uniformly phased in across jurisdictions, thus applying consistently to all assessed banks. Third, the relevant underlying data are publicly available. Finally, the rules-based framework simplifies the identification of the treated banks (G-SIBs) and control banks (Non G-SIBs), enabling us to draw conclusions in an international context and transparent manner.

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 framework was announced in 2011, long before its global implementation in 2016. Additionally, it was phased in gradually, from 2016 to 2018. Existing studies on regulatory reforms in general, or the G-SIB framework in particular, often use the announcement or implementation date as the *treatment* date,⁵ yet it remains unclear how much in advance banks begin to adjust (e.g. to overcome operational constraints or spread the adjustment costs over multiple years). We leverage banks' annual reports, a vital source of information on a bank's strategic response to new regulation, to identify the *de-facto* treatment date for the G-SIB framework. We first count occurrences of keywords related to the framework, e.g. "gsib" or "systemically relevant bank", in annual reports (see Online Appendix A.1 for the complete keyword list). Following Baker, Bloom, and Davis (2016), we then scale the keyword count by the total number of words in the report to adjust for variations in report length over time or across banks.

[Figure 1 about here.]

The evolution of scaled occurrences highlights a significant increase in frameworkrelated discussions by G-SIBs during 2014 and 2015 – in contrast to a decline observed for Non G-SIBs (see Figure 1, Panel A).⁶ Furthermore, the number of G-SIBs that mention the framework increased from two-thirds in 2011 to the full sample in 2015. G-SIBs began incorporating the new framework in their strategic considerations most actively during 2014 and 2015, suggesting these years as potential treatment dates.⁷

To pinpoint the precise treatment date, we evaluate the context of keywords in G-SIBs' annual reports. We extract sentences from the reports containing one or more keywords and categorise them on their relevance to banks' capital planning. Following the pattern in Panel A of Figure 1, we focus on reports from 2013 to 2015, totalling 1,255 sentences.

Next, each author of this paper independently classifies sentences into three categories. Sentences in the first category are *action-oriented* and discuss a bank's active responses 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).⁸ 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. 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 exceeding 0.85. We calculate the average number of sentences in each category across authors for each annual report to mitigate 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 and general discussion) across annual reports is also 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, Panel B).

This suggests that most G-SIBs took action to meet the G-SIB requirements in 2015, the year before the regulatory phase-in of the surcharges. 2015 thus serves as the treatment year for our main empirical analysis. Nevertheless, we can leverage the flexibility of our text analysis approach to assess the possibility of a staggered treatment across banks, which confirms the robustness of our main analysis (see Section 6.2).

3 DATA

Our primary data source is the Basel Committee on Banking Supervision's (BCBS) public bank-level dataset of the G-SIB framework. The main variable of interest is the G-SIB score, representing the average of banks' market share in various financial activities. The score is available annually since 2013 for 84 large global banks across 21 jurisdictions. These banks, with a collective total asset value of about \$82 trillion in 2018, constituted over half of the global banking system.⁹ Among them, 32 banks were designated as G-SIBs in at least one year. We exclude the two banks designated for the first time after 2015 (i.e. post-treatment) to ensure that banks' post-treatment behaviour does not influence their treatment status. Our final sample thus comprises 82 banks.

A major advantage of the dataset lies in the consistent computation of scores across

banks and time using a common template. In addition, the BCBS and the national supervisors ensure data consistency. The data are publicly available. These publicly available scores are computed for both G-SIBs and Non G-SIBs, ideal for our analysis.

We complement the G-SIB dataset with bank balance sheet items, income statements and regulatory information from Fitch, supplemented by hand-collected data from disclosures and supervisory notifications (see Table 1). Our primary measure for bank profitability is the return on assets (ROA), defined as the ratio of operating profit to total assets.¹⁰ For regulatory metrics, we consider various measures of bank capitalisation to reflect the tightness of regulation. Specifically, we calculate a *Common Equity* Tier-1 (CET1) capital ratio buffer as the difference between the ratio of CET1 capital to risk-weighted assets (RWA) and the sum of all CET1 minimum capital requirements, which includes any capital surcharges for systemically important banks. We factor in banks' leverage ratio buffer as the difference between the Basel III leverage ratio and the minimum leverage ratio requirement. Furthermore, we approximate banks' total lossabsorbing capacity (TLAC) based on the sum of total regulatory capital and long-term funding as a percentage share of RWA. Finally, we use national credit aggregates from the Bank for International Settlement's credit statistics in our analysis of staggered treatment effects (see Section 6.2) and changes in SRISK from the New York University's V-Lab to examine effects during the COVID-19 pandemic (see Section 6.4).

Throughout our analysis, we concentrate on the period from 2013 to 2018, covering the first year G-SIB scores are available to the completion of the framework's phase-in.

[Table 1 about here.]

Adjusting the G-SIB score Directly using the official G-SIB score poses challenges in studying the G-SIB framework's impact. First, the scores are an average of banks' market share in various financial activities, which means that they are *relative* in nature. As such, 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 is necessary for a causal difference-indifferences analysis. To overcome this limitation, we recalculate the scores as the weighted average of indicators normalised by their sum total across banks in 2013. This approach disentangles the evolution of banks' scores over time, ensuring that they are no longer dependent on the performance of other banks.

Second, exchange rate fluctuations may impact banks' scores which are based on indicator values in euro. For instance, an appreciation of the U.S. dollar vis-a-vis euro would inflate U.S. banks' scores beyond the actual evolution of their financial activities. To neutralise this effect, we convert the indicator values back into the banks' reporting currency and restate all indicators in euro based on the 2013 exchange rates.¹¹

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 disregard this cap to avoid obscuring actual score changes.

With these adjustments, we obtain an *adjusted* G-SIB score, our main dependent variable. Annex A details the adjustment methodology and illustrates the official versus adjusted scores. Table 1 presents the summary statistics for the official and adjusted G-SIB scores. We also note that the two scores have a high correlation of 0.98. Additionally, we compare the results obtained from using the official and adjusted scores and show that our conclusions are not driven by the score adjustments.

4 EMPIRICAL METHODOLOGY

Our goal is to assess how more and less profitable G-SIBs adjusted their systemic importance – measured by the G-SIB score – in response to the introduction of the capital surcharges. Since banks' capital requirements are determined on the basis of their G-SIB score, it is the main target of banks' response to the introduction of the framework.¹²

Baseline specification We employ a difference-in-differences framework. 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 binary variable that equals one in the post-treatment period (2015–18) and zero otherwise. G-SIB_i equals one (zero otherwise) for banks that have officially been designated a G-SIB before 2015, i.e. pre-treatment.

 $X_{i,t-1}$ includes lagged time-varying bank-specific characteristics: CET1 capital buffer, leverage ratio buffer, TLAC, density ratio, and ratios of cash to assets, deposits to liabilities and non-performing loans to total loans (defined in Table 1). The regulatory measures, in particular, account for the important effect of capitalisation on bank behaviour (e.g. Dagher et al. 2020, Gropp et al. 2019, Imbierowicz, Kragh, and Rangvid 2018). Throughout our analysis, we use the first lag of these variables to mitigate endogeneity concerns. α_i controls for unobserved time-invariant bank characteristics. $\delta_{c,t}$ considers time-varying attributes in country c where bank i is headquartered, such as macroeconomic or regulatory changes. $\varepsilon_{i,t}$ is the error term. We cluster standard errors at the bank level.

Equation (1) allows us to examine whether G-SIBs and Non G-SIBs, regardless of their profitability, reacted differently to the G-SIB framework. This establishes a baseline. If the capital surcharges incentivise G-SIBs to lower their systemic importance compared to Non G-SIBs, then $\hat{\gamma}$ should be negative and statistically significant.

We maintain a clear separation between the treatment and control groups by adopting

a time-invariant definition of G-SIB status. This prevents potential bias from banks switching between G-SIB and Non G-SIB status. Moreover, using the adjusted version of the official score avoids direct impacts on one bank's score from changes in another bank's activity. Finally, Figure 1 displays a notable decline in framework-related keyword occurrences for Non G-SIBs post-treatment, indicating the framework's limited relevance for these banks.

Our main identifying assumption in equation (1) is that G-SIBs' and Non G-SIBs' scores, while differing in level terms, followed parallel pre-treatment trends and would have continued these trends in the absence of the new framework. Note that this assumption does not require random designation of banks as G-SIBs and Non G-SIBs (e.g. Moon 2022). Visual inspection of the pre-treatment trends supports the parallel trends assumption (see Figure 2, Panel A). A formal test of the change in the difference between the average score of G-SIBs and Non G-SIBs from one year to another in the pre-treatment period confirms parallel evolution.¹³

We also confirm that the two groups of banks did not systematically differ in pretreatment characteristics influencing the evolution of the score. For most bank-level controls, we find no significant differences in pre-treatment means of G-SIBs and Non G-SIBs (see Table C.1 in Annex C). Finally, the inclusion of country-time fixed effects in all our regressions helps address concerns regarding potential coincidence of time-varying shocks and the G-SIB treatment.

[Figure 2 about here.]

Profitability as driver of adjustments A bank's response to higher capital requirements reflects a dynamic cost-benefit analysis. For instance, the bank may choose to generate capital internally by retaining earnings, or deleverage if retaining earnings is difficult and raising external capital is costly (Myers and Majluf 1984). We exploit the

fact that profitability lies at the heart of this choice. Indeed, retaining earnings is easier and less costly for the more profitable banks – they may thus prefer to build capital rather than deleverage. Conversely, less profitable banks might perceive deleveraging as the optimal response. As a result, the introduction of capital surcharges is likely to elicit *distinct* responses from less and more profitable banks.¹⁴

To formally assess the differential impact of the framework on more and less profitable banks, we independently apply equation (1) to sub-samples of banks with high and low return on assets (ROA) – our primary measure of profitability. We categorize banks as more profitable ("high ROA") or less profitable ("low ROA") based on whether their average ROA during the pre-treatment period exceeds or falls below the median value of the sample distribution. Our hypothesis posits that $\hat{\gamma}$ should be smaller (i.e. be negative and larger in absolute value) in the case of low ROA banks.

Triple interaction specification Our second main specification allows for a heterogeneous impact of the framework on more and less profitable banks within a single model:

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

Here, $Profitability_i$ is measured as the *level* of bank *i*'s average pre-treatment ROA. The full set of interaction terms (namely $Post_t$, $Post_t \times G$ - 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 in equation (1).

The triple interaction specification relies on the assumption that treatment assignment is unrelated to bank profitability. Notably, the G-SIB designation does not consider profitability as a criterion, reducing the likelihood of systematic differences. Nevertheless, G-SIBs might exhibit distinct profitability patterns due to various factors (e.g. potential economies of scale). To dispel this possibility, we confirm that there are no systematic differences in profitability distribution of G-SIBs and Non G-SIBs (Figure 2, Panel B). Relatedly, there is no material correlation between a bank's ROA and its G-SIB status.¹⁵

The use of pre-reform profitability also helps rule out concerns about reverse causality, which may arise if G-SIB score adjustments affect banks' profitability. To fortify our specification, we affirm that ROA reflects a persistent structural bank characteristic. For one, the correlation of ROA across years is high and statistically significant. This observation tallies with the stable evolution of average ROA across groups (refer to Table D.1 and Figure D.1 in Online Appendix D). All of this accords with the fact that less than 10% of the bank-year observations witness banks' ROA transitioning across the median threshold that determines the high and low ROA categories.¹⁶

Matching We employ matching to further address any differences between G-SIBs and Non G-SIBs. This involves fitting a propensity score model based on the bank's pre-treatment characteristics. We focus on those bank characteristics that we use as controls in our baseline regression. Each variable is standardised to adjust for difference in variances. Propensity scores are used as matching weights, potentially zero for control banks. We use these weights in a weighted regression of equation (2), employing kernel matching with a calliper of 0.05 and a common matching support to obtain close matches (refer to Annex C for the matched balance test). We also explore restricting matches within profitability categories, aligning high (low) ROA G-SIBs exclusively with high (low) ROA Non G-SIBs.

5 RESULTS

Average impact of the G-SIB framework We find that G-SIBs and Non G-SIBs did not evolve differently in response to the introduction of the framework. Column (1) of Table 2 is based on the simplest version of the specification in equation (1) without

any controls or fixed effects. It shows that G-SIBs decreased their average score by 13 basis points (bps) as compared to Non G-SIBs, albeit statistically insignificantly. Compared 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.¹⁷

We confirm that these results are not an artefact of our adjustments to the score (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.

[Table 2 about here.]

Differential impact on more and less profitable banks Our hypothesis posits that the insignificant impact of the framework on G-SIBs as a whole conceals a potentially heterogeneous effect within that group. As conjectured 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 supports our conjecture (Figure 3): only high ROA banks increased their scores on average (first two bars), while low ROA banks decreased theirs (last two bars). Among high ROA banks, G-SIBs increased their scores by *less* than Non G-SIBs. By comparison, among the low ROA banks, G-SIBs decreased their scores by *more* than Non G-SIBs. In the process, the more profitable G-SIBs collectively increased their global market share by 1.8 percentage points from 2014 to 2018, whereas the less profitable G-SIBs saw a decline of 4.9 percentage points.

[Figure 3 about here.]

We estimate equation (1) on separate sub-samples of more and less profitable banks to assess these observations formally (Table 3). We find that the less profitable G-SIBs significantly decreased their scores as compared to Non G-SIBs (Panel A). They have also lowered their scores compared to the less profitable Non G-SIBs (Panel B). The magnitude of the effect, between 16 to 27 bps, is economically meaningful considering that the official G-SIB buckets are 100 bps in size.

[Table 3 about here.]

The more profitable G-SIBs, by contrast, have not adapted their scores differently as compared with Non G-SIBs (Panel C) or the more profitable Non G-SIBs (Panel D). 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.¹⁸

To estimate the contribution of profitability to the scores of the more profitable G-SIBs, we perform an Oaxaca-Blinder style quantification. Specifically, we utilise the estimated coefficients for the low ROA banks in column (3) in Panel A of Table 3 and employ them to predict the scores for the more profitable G-SIBs. This provides the counterfactual scores if these banks had been less profitable, while keeping all other bank characteristics unchanged. We find that high ROA G-SIBs, on average, raised their scores by 19 bps from 2014 to 2018. However, had these banks been less profitable, their scores would have declined by 22 bps. The banks' enhanced profitability thus boosted their average score by around 41 bps, equivalent to about 24% of their score in 2014. Collectively, the enhanced profitability of these banks contributed 4.6 percentage points to their global market share during the observation period.

[Table 4 about here.]

We turn to equation (2) to further examine the differential impact on less and more profitable banks. 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 scores of Non G-SIBs.

The results in Table 4 support our hypothesis. The unsaturated specification in column (1) shows that, on average, more profitable G-SIBs increased their adjusted score by about 33 bps after treatment as compared to 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 banks 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)) confirms the heterogeneous treatment effect. Our findings are also robust to replacing ROA in levels by a dummy for high versus low ROA banks (column (4)).

Additional robustness checks A battery of additional robustness tests reinforce our findings. For one, in Table 5, matching treated and control banks (column (1)), and in particular, matching high (low) ROA G-SIBs exclusively with high (low) ROA Non G-SIBs (column (2)) leads to the same conclusion as before.

Our results are also robust to restricting the sample to banks with an average pretreatment score within 100 bps of the G-SIB score cutoff, i.e. banks that are most similar in terms of their systemic importance (column (3)).

[Table 5 about here.]

Next we address the fact that our pre-treatment period is short (which is because the G-SIB scores are available only as of 2013). We approximate the G-SIB score using banks' total assets, which are available for a longer pre-treatment period as well as at a higher frequency. While not perfect, bank size is an important input into the G-SIB score calculation, also reflecting banks' footprint in various activities.¹⁹ Using the approximated score as the left-hand side variable, we estimate the regression in equation (2) using quarterly observations for the period from 2010 to 2018. The regression confirms the finding that more profitable banks expand their footprint as compared to the control group (see column (4) in Table 5).

Another potential confounding factor is that reforms for *domestically* important banks (D-SIBs) could affect the requirements for some Non G-SIBs in the sample and bias our results towards finding no effect of the reform. While we already control for variation in the D-SIB surcharges through the CET1 capital buffer in our regressions (see Section 3) and include country-time fixed effects throughout, we further assess the robustness of our results by excluding all Non G-SIBs for which D-SIB surcharges are phased in or announced during the analysis period (column (5)). The main coefficient of interest tallies with our baseline result and remains statistically and economically significant under this alternative specification.²⁰

We then consider an alternative specification where the post-treatment period is set to begin in 2016 in column (6). This corresponds to the start of the phase-in of the capital surcharges and implicitly assumes that G-SIBs did not adjust ahead of the actual implementation. The resulting triple interaction coefficient remains statistically significant but declines in magnitude. This accords with the bulk of banks' adjustment happening in 2015, while also hinting at the persistence of the treatment effect as discussed below.²¹

Further checks strengthen our conclusion. In Section 6.3, we investigate whether profitability continues to be a material driver of bank behaviour once we consider capitalisation as a competing characteristic. Online Appendix E considers alternative measures of profitability, such as return-on-equity, cost-to-income ratio, and ROA based on a longer reference period from 2010 to 2014, results from which concur with our baseline. We also consider additional controls and alternative sample composition, accounting for banks' business models, and assessing the role of geographic factors. Finally, we study how the framework impacted banks' capital and assets as well as the various indicators that are used to compute the G-SIB scores in Online Appendices F and G, respectively.

Persistence of the treatment effect Finally, we assess persistence of the framework's impact by allowing the treatment effect in equation (2) to differ across years. Specifically, we replace the *Post* dummy with an indicator variable 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. In line with our previous results, 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.²²

Overall, our findings based on the triple interaction regressions are consistent with those based on sub-sample regressions (Table 3) and the unconditional observations in Figure 3. Together, these results underscore that the G-SIB framework has had a differential impact on more and less profitable G-SIBs and that this differential impact is both economically and statistically significant.

[Figure 4 about here.]

6 DISCUSSION

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

We further sharpen our analysis by using the unique design of the G-SIB capital surcharges. The bucket thresholds introduce a discontinuity in the capital requirements. Banks close to the thresholds have a stronger incentive to lower their score to either push themselves into a lower bucket or to avoid moving into a higher bucket. This discontinuity affects the less profitable banks more strongly, amplifying their incentive to shrink their score. The distance from the bucket thresholds thus represents an ideal source of exogenous variation in the regulatory treatment, allowing us to refine our examination of whether banks' score adjustments are due to the G-SIB framework.

We test the above predictions based on the following regression, which includes our previous set of bank-level controls $(X_{i,t-1})$ and fixed effects:

$$Score_{i,t} = \gamma \left[Close_{t-1} \times Profitability_i \right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}.$$
(3)

The indicator variable, $Close_{t-1}$, measures proximity to the bucket threshold. In the pre-treatment period, the indicator is equal to zero for all banks because proximity to the thresholds does not affect capital surcharges. In the post-treatment period, the indicator is equal to one (zero otherwise) if a G-SIB's or Non G-SIB's official score was within 20 bps of a bucket threshold, following the approach in Behn et al. (2022). As per this indicator, about one fifth of the bank-year observations are close to a threshold, with no systematic concentration among the less or more profitable banks. We interact the proximity indicator with banks' profitability, expecting that profitability dampens the effect of proximity to the threshold (i.e. $\hat{\gamma} > 0$).

[Table 6 about here.]

Banks close to the threshold reduce their scores as compared to the others (column (1) of Table 6). At 15 bps, the effect is stronger for less profitable banks (column (2)) than for the more profitable ones, for which the effect is insignificant (column (3)). Interacting closeness and pre-treatment profitability (in levels) reveals that higher profitability dampens the effect of being near a threshold (column (4)). Using the binary classification of banks into high and low ROA types suggests that high profitability fully offsets the effect of proximity to a threshold: at 0.76, the sum of the base effect of closeness (-14.87) and the interaction term (15.63) is close to zero and statistically insignificant (column (5)).

6.2 Could the treatment date vary across banks?

Our main analysis is based on a common timing of the regulatory treatment in the year 2015. However, a few G-SIBs may have already started to adjust in 2014. Our textual analysis approach helps us to identify G-SIBs for which this may have been the case. Indeed, Figure 1 shows that the word counts and number of action-oriented sentences among some banks increased in advance of others (see also Panel B of Figure B.1 in Annex B for bank-wise counts). For a few other G-SIBs, the measure picks up later in 2016 during the regulatory phase-in of the capital requirements.

[Figure 5 about here.]

Formally, we consider G-SIBs whose 2014 annual report contained a greater number of references to how they responded to the G-SIB framework than their 2015 report 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. Next, we conduct a staggered difference-in-differences analysis, taking into account this variation in treatment dates across banks. We use the estimator suggested by Callaway and Sant'Anna (2021), which amounts to estimating the average treatment effect for groups of G-SIBs based on equation (1), with each group representing the cohort of G-SIBs treated in a given year. The "never treated" Non G-SIBs form the control group.

Figure 5 reports the estimated group-weighted average treatment effects for the treated (ATT) for the case of bank-specific treatment dates. Panel A compares the low ROA G-SIBs to the low ROA Non G-SIBs, while Panel B compares the high ROA G-SIBs to the high ROA Non G-SIBs. The x-axis represents periods to treatment, with 0 representing the treatment year, which can be either 2014, 2015, or 2016.

Low ROA G-SIBs, as compared to their Non G-SIB peers, start shrinking their sys-

temic importance as of the treatment date. Overall, they reduce their score by about 25 bps.²³ By contrast, high ROA G-SIBs do not reduce their score as compared to high ROA Non G-SIBs. These results tally with the sub-sample difference-in-differences results in Table 3, consistent with 2015 representing the treatment year for most G-SIBs.

6.3 Is profitability more important than bank capitalisation?

We now directly assess whether bank profitability spurs banks' responses to regulatory changes above and beyond the role of bank capitalisation, which has been shown to be particularly relevant (e.g. Couaillier et al. 2024, Gropp et al. 2019). We undertake a horserace between profitability and capitalisation as competing drivers of banks' responses to the G-SIB framework's introduction. To do so, we introduce an additional term in equation (2): the triple interaction of the post-treatment period indicator ($Post_t$), the G-SIB indicator ($G-SIB_i$), and banks' pre-treatment capitalisation.

[Table 7 about here.]

We consider four capital metrics: CET1 capital and total (regulatory) capital as ratios of risk-weighted assets, and the respective buffers given by the difference with the corresponding minimum capital requirements.²⁴ The specifications with these metrics in the supplementary triple interaction are reported in columns (2) to (5) of Table 7, while column (1) reproduces the baseline regression (that is, column (3) of Table 4) for the ease of comparison. All other controls are kept the same as in the baseline regression.

Across the specifications, we affirm the robustness of the coefficient on the triple interaction term with profitability. At the same time, the capital buffer emerges as a complementary factor influencing bank behaviour alongside profitability.

6.4 Are there financial stability implications?

The reallocation of banking activity towards more profitable banks can enhance intermediation efficiency.²⁵ However, if higher profitability is driven by greater risk-taking and exposure to tail risks (e.g., Meiselman, Nagel, and Purnanandam 2023, Martynova, Ratnovski, and Vlahu 2020), the reallocation could also undermine the banking sector's resilience.

To explore this issue, 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, Engle, and Richardson 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. 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:

$$\Delta SRISK_i = \gamma \left[G\text{-}SIB_i \times Profitability_i \right] + \mu X_i + \varepsilon_i. \tag{4}$$

 $\Delta SRISK_i$ measures the change in bank *i*'s SRISK from its mean value in the three months preceding the market turmoil in March 2020 to its highest monthly value in 2020. *G-SIB_i* is the G-SIB identifier variable, whereas *Profitability_i* is a dummy that identifies the more and less profitable banks (as in Table 3). X_i comprises lagged (i.e. end-2019) bank-level controls. If higher profitability is fuelled by higher exposure to tail risk, more profitable G-SIBs' SRISK should exhibit a larger increase during the COVID-19 shock. The $\hat{\gamma}$ coefficient for high ROA G-SIBs should thus be larger than the corresponding coefficient for low ROA G-SIBs.

[Table 8 about here.]

Table 8 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 fourth row, we also report the difference between the $\hat{\gamma}$ for the more and less profitable G-SIBs to test our conjecture.

More profitable G-SIBs exhibited a significantly larger increase in SRISK than the less profitable ones, across various SRISK measures (Table 8). 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, rose about one percentage point more than for less profitable G-SIBs (columns (1) and (2)). The change in these banks' SRISK (column (3)) and their SRISK changes in terms of expected capital shortfalls (column (4) and, in log changes, column (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, Nagel, and Purnanandam (2023) for U.S. banks during earlier crises.

7 CONCLUSION

The stability of the global financial system rests on the resilience of banks. Capital regulation strives 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 only less profitable G-SIBs to lower their systemic importance. The more profitable G-SIBs, however, continue to expand despite the additional requirements. This finding accords with these banks' comparative ease of building capital internally through retaining earnings, which – in contrast to their less profitable competitors – alleviates the pressure to contract the balance sheet.

Our findings highlight that capital regulation affects the banking sector along multiple dimensions. It improves banks' resilience by raising their capital ratios, but also shifts banking activity to more profitable banks. This could bolster intermediation efficiency, but may also raise financial stability concerns. Indeed, using the COVID-19 crisis as an experiment, we show 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 mentions 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.

ANNEX

A G-SIB FRAMEWORK AND SCORE ADJUST-MENT

The primary goal of the G-SIB framework is to annually identify G-SIBs from an assessment sample of about 80 of the largest internationally active banks across 21 jurisdictions (BCBS 2013). The framework computes a score for each bank to gauge its systemic importance. The score, expressed in basis points (bps), represents an estimate of the bank's weighted average global market share in various financial activities. Banks with a score of at least 130 bps are designated as G-SIBs, with some room for supervisory override to this rule. G-SIBs are sorted into five buckets based on their scores. The first bucket spans 130 to 229 bps, the second one 230 to 329 bps, and so on. A 1% CET-1 capital ratio surcharge applies to G-SIBs in the first bucket. The surcharge increases by 0.5 percentage points per subsequent bucket until the fourth one. Beyond that, the surcharge rises by one percentage point. The G-SIB assessment methodology along with the initial list of G-SIBs was published in November 2011. The surcharges were disclosed in November 2012. They were phased in as of January 2016 over a three-year period and were applicable for the first time to G-SIBs identified as such in November 2014.

The G-SIB score is a weighted average of 12 indicator scores of financial activity across five categories. The indicator values are reported in euros. For banks outside the euro area, reporting currency figures are converted to euros (BCBS 2013).

For each bank *i*, each indicator *j*, and year *t*, an indicator score is computed as the ratio of the bank's indicator value, $value_{ij,t}$, and the sum of indicator values of all banks in the G-SIB assessment sample, the so called "sample-total". Then, the 'official' G-SIB score, ofcl-score_{*i*,*t*}, is computed as the weighted average of the 'official' indicator scores,

ofcl-ind-score_{ijt}, while applying a cap of 500 bps on the substitutability category score. See the formulae below, and Table G.1 in Online Appendix G for the weights w_i :

$$\frac{value_{ij,t}}{\sum_{i} value_{ij,t}} \times 10,000 = ofcl-ind-score_{ij,t}; \quad \sum_{j=1}^{12} w_j \times ofcl-ind-score_{ij,t} = ofcl-score_{i,t}.$$
(5)

By comparison, the 'adjusted' G-SIB score, $Score_{i,t}$, is obtained by first computing the 'adjusted' indicator scores, ind-score_{ij,t}, based on 2013 sample-totals and then applying the same weights as in equation (5) to calculate the weighted sum:

$$\frac{value_{ij,t}}{\sum_{i} value_{ij,2013}} \times 10,000 = ind\text{-}score_{ij,t}; \quad \sum_{j=1}^{12} w_j \times ind\text{-}score_{ij,t} = Score_{i,t}.$$
(6)

Since the 2013 sample-total is time-independent, this approach normalises indicator values and *preserves* the true evolution of each bank's financial activities over time. By contrast, the official G-SIB score provides a relative comparison across banks in each year. As part of the score adjustment, we also strip away the exchange rate effect by restating all indicators using the 2013-euro exchange rates. Finally, we undo the regulatory override on the substitutability score, which limits this category's score to 500 bps, to obtain an unbiased measure of banks' adjustments.

While these adjustments are important to ensure the robustness from a methodological perspective, their combined effect is limited. The pairwise correlation of the scores of the four groups of banks (by G-SIB status and profitability category) is above 95 percent and the adjusted scores closely track the official ones as shown in Figure A.1.

[Figure A.1 about here.]

B REFERENCES TO G-SIB FRAMEWORK

Panel A of Figure B.1 displays the 70 most frequent words mentioned in G-SIB-related sentences in G-SIBs' annual reports from 2013 to 2015. Panel B shows the share of action-oriented sentences in 2014 and 2015 for banks designated as G-SIBs before 2015 and with non-zero counts of action-oriented sentences in 2014 or 2015.

[Figure B.1 about here.]

C MATCHED BALANCE TEST

Table C.1 reports the pre-treatment means of the co-variates used in the matching exercise. The p-values of tests of differences in the means in the unmatched sample are reported in column (3) and those in the two matched samples are reported in columns (4) and (5). Matching helps reduce the difference between the control and treatment groups, most notably for the leverage ratio buffer and the density ratio.

[Tabel C.1 about here.]

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NOTES

- 1. The dilution of existing shareholders represents one important obstacle to the issuance of new capital (e.g. Myers and Majluf 1984).
- 2. Systemic importance is thus closely tied to the bank's size and estimates the impact its failure on the financial system (BCBS 2021).
- 3. Garcia, Lewrick, and Sečnik (2023) and Behn et al. (2022) provide evidence of such incentives, showing that G-SIBs window dress their balance sheet to lower their score ahead of year-end reporting dates.
- 4. This aligns with the fact that G-SIB designation before November 2014 had no impact on forthcoming capital surcharges, limiting regulatory incentives for banks to respond before that date. The observed adjustment duration also matches the twelve-month notice period given to banks for adapting their capital ratio to changes in the countercyclical capital buffer requirement.
- 5. Event studies, centred on crucial announcement dates like the release of the G-SIB methodology or the G-SIBs list, avoid these challenges as they aim to evaluate immediate market impact. However, these

studies do not address the framework's influence on banks' medium-term strategic adjustments, which is our study's focus.

- 6. The rise in the average scaled occurrences of G-SIBs from 2013 to 2015 is statistically significant at the 5% level. This is based on a regression of scaled word counts, incorporating bank, country, and year dummies. A similar pattern emerges when using a normalised version of the scaled word counts, as in Husted, Rogers, and Sun (2020). A word count analysis using banks' earnings call reports confirms this conclusion. However, due to data limitations, earnings call reports are available only for a small subset of banks and a limited number of years, making them unsuitable as a complementary basis for our analysis.
- 7. References to the G-SIB framework in banks' annual reports are unrelated to their pre-treatment capital buffer (see Online Appendix B). This alleviates endogeneity concerns that could have arisen if weakly capitalised banks had been more likely to mention the G-SIB framework in their annual reports because they are more constrained by the introduction of the capital surcharges.
- 8. Panel A of Figure B.1 in Annex B plots a word cloud of the 70 most frequent words, excluding articles and other basic words, in the action-oriented sentences. Online Appendix A.2 provides additional examples of action-oriented sentences. The majority of these sentences discuss plans initiated or completed by the bank in the previous year, rather than being of a forward-looking nature.
- 9. Banks' financial assets totalled nearly \$150 trillion globally in 2018 (FSB 2022).
- 10. An advantage of using ROA as opposed to, e.g. return on equity (ROE), is that ROA is leverageindependent. ROA is also less affected by differences in national tax regimes across our sample banks.
- 11. This aligns with the recommendations in Benoit, Hurlin, and Pérignon (2019) for improving the G-SIB methodology.
- 12. Our textual analysis confirms that banks actively target the G-SIB score and its components. For example, consider Citibank and JP Morgan respectively below (see Online Appendix A.2 for more examples):

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 (...) (Citibank 2015, p. 34).

In the last year, we took some dramatic actions to reduce our GSIB capital surcharge (...) These steps included reducing (...) level 3 assets (...) and notional derivatives amounts (...). We did this faster than we, or anyone, thought we could. (JPMorgan Chase 2015, p. 16).

- 13. The difference-in-differences coefficient is statistically insignificant, irrespective of whether we include bank fixed effects, suggesting that the parallel trends hypothesis cannot be rejected.
- 14. Differences in banks' adjustments could also stem from the higher opportunity cost of deleveraging in the case of more profitable banks. We illustrate this distinct but complementary channel using a stylized model in Online Appendix C. Another potential channel could be that the more profitable banks face a lower cost of raising capital externally (e.g. De Jonghe, Dewachter, and Ongena 2020).

- 15. Standard t-tests confirm that the average pre-treatment ROA of G-SIBs and Non G-SIBs is statistically indifferent (p-value = 0.24). The same conclusion holds when zooming into a sub-sample with only the more or less profitable banks (respective p-values equal 0.74 and 0.47). By contrast, t-tests do confirm that the more and less profitable banks materially differ in terms of their pre-treatment ROA (p-value = 0.00). Finally, 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).
- 16. We also pursue a t-test of the difference in the share of action-oriented sentences between more and less profitable G-SIBs. The difference in shares is insignificant, both during the pre-treatment period (2013-14) and in the treatment year (2015), with p-values of 0.18 and 0.36 respectively.
- 17. 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'.
- 18. Online Appendix F further shows that more profitable G-SIBs have significantly increased their capital as compared to the less profitable G-SIBs during the post-treatment period.
- 19. Analogous to the adjusted G-SIB score in the main analysis, the approximated score is based on calculating a bank's total assets as a percentage share of the sum of total assets of the sample banks in 2010 (i.e. the starting year of the quarterly data).
- 20. A potential related issue is the phase-in of the capital conservation buffer alongside that of the G-SIB surcharges. However, since this buffer applies to both G-SIBs and Non G-SIBs, it should not affect our identification strategy.
- 21. The specifications tested in columns (5) and (6) of Table 5 in the triple-difference setup are also examined using the sub-sample difference-in-differences setups considered in Table 3. These results, not reported for brevity, are also consistent with the baseline and are available upon request.
- 22. As noted in Section 2.2, some G-SIBs may have responded to the framework one year ahead of their peers, which is consistent with the (statistically insignificant) uptick in the coefficient estimate of the triple interaction term in 2014 in Figure 4. To accommodate any potential variation in treatment dates among banks, we employ a staggered difference-in-differences analysis in Section 6.2.
- 23. Several recent studies show that the standard two-way fixed-effects model may produce biased estimates if the treatment is staggered (e.g. Baker, Larcker, and Wang 2022). These results are robust to using alternate methods proposed by Sun and Abraham (2021) and De Chaisemartin and D'Haultfœuille (2020).
- 24. For each of these capital metrics, we test and affirm that there are no significant pre-reform differences between more and less profitable G-SIBs.
- 25. The average (score-weighted) ROA of the G-SIB assessment sample increased from 1.39% in 2013 to 1.50% in 2018. Keeping the scores fixed at their 2013 levels, the average ROA would have increased to only 1.44%. The reallocation of banking activity towards the more profitable banks thus contributed to more than half of the increase in the average (score-weighted) ROA.

TABLES

	Mean	Stdev	P10	P25	P50	P75	P90	Ν
Official GSIB score (basis points)	128.53	107.30	28.93	47.52	85.80	186.08	284.03	443
Adjusted GSIB score (basis points)	134.68	115.08	29.42	52.67	89.63	188.33	288.82	443
Close to bucket threshold (binary)	0.19	0.40	0.00	0.00	0.00	0.00	1.00	370
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	11.65	13.56	15.80	487
CET1 capital ratio buffer $(\%)$	4.16	2.92	1.47	2.18	3.54	5.44	7.86	487
Total capital ratio (%)	16.14	4.00	11.93	13.55	15.27	17.88	21.21	485
Total capital ratio buffer $(\%)$	4.68	3.90	1.01	2.15	3.62	6.18	9.81	485
Leverage ratio $(\%)$	5.44	1.35	3.87	4.47	5.26	6.30	7.17	450
Leverage ratio buffer $(\%)$	2.22	1.38	0.77	1.28	2.04	2.88	4.04	450
Total loss absorbing capacity $(\%)$	45.67	32.19	16.15	26.63	36.35	56.05	81.01	475
Density ratio (%)	47.13	17.53	26.15	33.10	43.82	61.25	70.66	486
Non-performing loans ratio $(\%)$	2.72	2.95	0.49	0.96	1.60	3.28	6.71	496
Cash to total assets $(\%)$	7.04	5.59	1.34	2.53	5.94	10.13	13.71	492
Deposit to total liabilities $(\%)$	56.41	17.91	30.34	41.73	59.01	70.21	79.24	486
Credit to GDP gap (percentage points)	-1.32	14.79	-17.93	-9.88	0.76	7.60	18.65	504
Δ SRISK% (percentage points)	0.63	1.48	0.02	0.08	0.19	0.58	1.00	70
Δ SRISK (US\$ billion)	21.34	23.59	4.96	8.90	14.05	22.40	52.20	70

Table 1.	Cummon	atatiatica	of main	rominh	
Table 1.	Summary	statistics	or main	vanat	nes

Note: The table presents summary statistics for the variables used in the analysis, derived from an unbalanced sample of 82 banks across 21 jurisdictions spanning 2013 to 2018. Units are displayed next to the variable names. Close to bucket threshold: a binary indicator variable equal to 1 if the official G-SIB score is within 20 bps of a bucket threshold. 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 (RWA). CET1 capital buffer: difference between the CET1 capital ratio and the sum of all fully-loaded CET1 minimum capital requirements, including the Basel III minimum capital requirement, capital conservation buffer, and G-SIB or D-SIB capital surcharges where applicable. Total capital ratio: Total regulatory capital over RWA. Total capital buffer: difference between the total capital ratio and the sum of all fully-loaded minimum total regulatory capital requirements. Leverage ratio: Basel III leverage ratio. Leverage ratio buffer: difference between the Basel III leverage ratio and the 3% minimum leverage ratio requirement. For U.S. G-SIBs, a 5% enhanced supplementary leverage ratio (eSLR) requirement is used. Total loss absorbing capacity (TLAC): approximated as ratio of total regulatory capital and long-term funding to RWA due to lack of bail-inable debt data. Density ratio: RWA 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. Credit-to-GDP gap: difference between the credit-to-GDP ratio and its long-term trend. Δ SRISK%: percentage point change in the banks' percent contribution to the financial system's total systemic risk (see Brownlees and Engle 2016 and Acharya, Engle, and Richardson 2012). Δ SRISK: change in the expected capital shortfall in a crisis in US\$ billions. For SRISK measures, changes are calculated by comparing the bank's maximum monthly value in 2020 and the corresponding three-month mean before the March 2020 turmoil.

	(1)	(2)	(3)	(4)
$Post \times G-SIB$	-12.77	-7.711	-11.14	-1.670
	(-1.49)	(-0.91)	(-1.52)	(-0.17)
Post	3.833	2.924	0.633	
	(1.40)	(1.06)	(0.24)	
G-SIB	188.1***	176.4^{***}		
	(8.32)	(8.93)		
CET1 capital ratio buffer			1.111	0.0987
			(0.81)	(0.04)
Leverage ratio buffer			5.692^{**}	-5.367
			(2.13)	(-1.35)
Total loss absorbing capacity			0.00715	0.0607
			(0.05)	(0.26)
Non-performing loans ratio			4.346^{**}	6.020^{*}
			(2.26)	(1.96)
Cash to total assets			-1.914^{**}	-3.385^{***}
			(-2.06)	(-3.15)
Deposit to total liabilities			-0.816	0.458
			(-1.56)	(0.56)
Density ratio			-0.629	-1.321^{**}
			(-1.17)	(-2.02)
Return on assets			-6.279	-6.721
			(-1.14)	(-0.87)
Ν	443	443	384	352
Adj. R2	0.592	0.619	0.978	0.980
Bank controls and FE	No	No	Yes	Yes
Country-time FE	No	No	No	Yes
G-SIB score	Adjusted	Official	Adjusted	Adjusted

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

Note: The table reports results of the regression in equation (1) using the entire 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 binary variable that takes value 1 in the post-treatment period (2015-18), and G-SIB is a binary 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.

		Panel A		Panel B			
	Low	ROA G-SI	Bs vs	Low ROA G-SIBs vs			
	A	ll Non G-SI	lBs	Low I	Low ROA Non G-S		
	(1)	(2)	(3)	(4)	(5)	(6)	
$Post \times G-SIB$	-22.39^{**}	-20.60^{**}	-23.67^{***}	-17.71^{*}	-16.31	-27.01^{**}	
	(-2.56)	(-2.16)	(-2.68)	(-1.90)	(-1.63)	(-2.28)	
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	282	218	218	153	
Adj. R2	0.681	0.674	0.985	0.602	0.595	0.976	
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 C	-		Panel D	-	
	High	ROA G-SI	Bs vs	High	ROA G-SI	Bs vs	
	A	ll Non G-SI	lBs	High R	COA Non (3-SIBs	
	(1)	(2)	(3)	(4)	(5)	(6)	
$Post \times G-SIB$	2.456	12.69	12.18	-1.357	9.192	15.13	
	(0.16)	(0.97)	(0.92)	(-0.09)	(0.68)	(1.04)	
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)		

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

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 binary variable that takes value 1 in the post-treatment period (2015-18), and G-SIB is a binary variable that takes value 1 for banks that have been designated as such at least once before 2015. Bank-level controls comprise the CET1capital buffer, the leverage ratio buffer, TLAC, 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.

329

0.665

 No

 No

Official

241

0.984

Yes

Yes

225

0.614

 No

 No

Adjusted Adjusted

225

0.659

No

No

Official

180

0.985

Yes

Yes

Adjusted

329

0.626

 No

No

Adjusted

Ν

Adj. R2

Score

Bank controls and FE

Country-time FE

	(1)	(2)	(3)	(4)
	G-SIB score	GSIB score	G-SIB score	G-SIB score
$Post \times G-SIB \times Profitability$	32.67**	43.69***	29.17***	35.47**
	(2.56)	(4.07)	(3.44)	(2.26)
Post \times G-SIB	-40.33^{***}	-45.04^{***}	-36.13^{***}	-20.55^{**}
	(-3.22)	(-3.51)	(-3.17)	(-2.07)
Post \times Profitability	7.639^{*}	7.475	18.80	-6.423
	(1.68)	(1.59)	(1.48)	(-0.55)
G-SIB \times 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	352	352
Adj. R2	0.594	0.626	0.984	0.982
Bank controls and FE	No	No	Yes	Yes
Country-time FE	No	No	Yes	Yes
Score	Adjusted	Official	Adjusted	Adjusted
ROA measure	Level	Level	Level	Binary

Table 4: Triple interaction regression results

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 binary variable that takes value 1 in the post-treatment period (2015-18), and G-SIB is a binary 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 (2013-14) ROA in levels, except in column (4) where a binary variable is used, which takes value 1 if the pre-treatment ROA is above the sample median. Bank-level controls comprise the CET1 capital buffer, the leverage ratio buffer, TLAC, 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	G-SIB score	G-SIB score	G-SIB score	G-SIB score	G-SIB score	G-SIB score
$Post \times G-SIB \times Profitability$	30.64***	36.80***	33.28***	40.45***	29.97**	21.15**
	(2.74)	(3.59)	(3.38)	(4.65)	(2.33)	(2.55)
$Post \times G-SIB$	-29.97^{*}	-43.48^{***}	-36.83^{**}	-22.72^{***}	-37.80^{*}	-23.73^{**}
	(-1.70)	(-3.97)	(-2.45)	(-2.69)	(-1.88)	(-2.37)
Post \times Profitability	14.91	-0.0411	17.13^{*}	2.059	12.67	8.536
	(0.78)	(-0.00)	(1.99)	(1.03)	(0.59)	(0.96)
Ν	256	229	244	2,207	231	352
Adj. R2	0.985	0.981	0.972	0.986	0.982	0.982
Score	Adjusted	Adjusted	Adjusted	Proxy	Adjusted	Adjusted
Matching	Yes	Yes (exact)	No	No	No	No
Banks close to G-SIB threshold	No	No	Yes	No	No	No
D-SIBs s.t. surcharges	In	In	In	In	Drop	In
Treatment year	2015	2015	2015	2015	2015	2016

Table 5: Triple interaction regression results: robustness checks

Note: The table reports results of the regression in equation (2). The dependent variable is the adjusted G-SIB score. Post is a binary variable that takes value 1 in the post-treatment period (2015-18), and G-SIB is a binary 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 (2013-14) ROA in levels. All regressions include country-year fixed effects, bank fixed effects and the following bank-level controls: CET1 capital buffer, the leverage ratio buffer, TLAC, 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 (1) and (2), we use a propensity score model based on matching the standardized value of all the bank-level controls, averaged over the pre-treatment period. A calliper 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 (2). In column (3), we restrict the regression sample to only those banks whose average official score in the pre-treatment period is within 100 bps of the 130 bps threshold that determines whether a bank is a G-SIB. In column (4), instead of the adjusted G-SIB score, we use a proxy that is constructed using the evolution of banks' asset-based market shares within the sample since 2010. Also, the regression in this column is based on quarterly data, thus making use of the higher frequency at which bank balance sheet data is available. In column (5), Non G-SIBs that are subject to D-SIB capital surcharges are dropped, while in column (6), the treatment year is set to 2016. 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.

	All banks	Low ROA banks	High ROA banks	All banks	All banks
	(1)	(2)	(3)	(4)	(5)
Close to bucket threshold	-6.645^{*}	-15.48^{**}	-2.244	-14.89^{**}	-14.87^{***}
	(-1.81)	(-2.17)	(-0.49)	(-2.35)	(-2.83)
Close to bucket threshold \times Profitability				7.894^{**}	15.63^{**}
				(2.05)	(2.61)
N	301	135	149	301	301
Adjusted R2	0.985	0.980	0.990	0.986	0.986
Profitability				Continuous	Binary

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

Note: The dependent variable is the adjusted G-SIB score. Close is an indicator variable (lagged by one year) that takes value 1 if the bank's official G-SIB score is within 20 bps of the closest bucket threshold. In column (4), the profitability measure is based on average pre-treatment (2013-14) ROA in levels. In column (5), it is defined as a binary variable that takes value 1 if the bank's pre-treatment ROA is above the sample median. The regressions in columns (1), (4) and (5) comprise all banks, those in column (2) (column (3)) include only banks with a pre-treatment ROA below (above) the sample median. All regressions include country-year fixed effects, bank fixed effects and the following bank-level controls: CET1 capital buffer, leverage ratio buffer, TLAC, 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.

		CET1 capital	CET1 capital	Total capital	Total capital
	Baseline	ratio	buffer	ratio	buffer
	(1)	(2)	(3)	(4)	(5)
$Post \times G-SIB \times Profitability$	29.17***	26.47^{**}	29.43***	24.84**	30.38***
	(3.44)	(2.37)	(2.78)	(2.21)	(3.05)
Post \times G-SIB \times Capital metric		5.727	10.73^{**}	5.713	8.464**
		(1.17)	(2.60)	(1.63)	(2.51)
N	352	352	352	352	352
Adj. R2	0.984	0.985	0.986	0.985	0.987

Table 7: Profitability versus bank capitalisation: a horse-race

Note: The table reports results of a regression in the style of equation (2) appended with a triple interaction of $Post \times$ G-SIB × Capital metric. The dependent variable is the adjusted G-SIB score. *Profitability* is measured based on the level of pre-treatment (2013-14) ROA. *Capital metric* is equal to the pre-treatment value of the metric reported in the top row of columns (2) to (5). All regressions include country-year fixed effects, bank fixed effects and the following bank-level controls: CET1 capital buffer, the leverage ratio buffer, TLAC, 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.

	Δ SRISK%	Δ SRISK%	Δ SRISK%	Δ SRISK	Δ SRISK
			relative changes	US\$ billion	log changes
	(1)	(2)	(3)	(4)	(5)
High ROA GSIB	1.63**	1.22***	0.41^{***}	34.38***	0.44^{***}
	(2.67)	(4.53)	(3.22)	(4.31)	(3.46)
Low ROA GSIB	0.38	0.27	0.08	12.29^{**}	0.06
	(1.08)	(0.81)	(0.60)	(2.11)	(0.37)
High ROA Non GSIB	0.19	-0.27	0.51	-5.13	0.36^{*}
	(1.34)	(-0.47)	(1.65)	(-0.54)	(1.85)
Difference High vs Low ROA GSIBs	1.26^{***}	0.95^{*}	0.33^{*}	22.10^{**}	0.39^{**}
	(8.88)	(3.61)	(3.87)	(4.40)	(5.08)
N	70	69	62	69	60
Adjusted R2	0.10	0.11	0.03	0.39	0.07
Bank controls	No	Yes	Yes	Yes	Yes

Table 8: Systemic risk during the pandemic

Note: The table reports regression results for equation (4). The dependent variable is the change in the bank's percentage of financial sector capital shortfall, SRISK% (columns (1) and (2)); the change in SRISK% as a share of its average value in the three months preceding March 2020, 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 2020 maximum monthly value and the three-month pre-March 2020 mean. Bank controls comprise the end-2019 values of the CET1 capital buffer, leverage ratio buffer, TLAC, the ratio of non-performing loans to total loans, deposits to total liabilities, and the density ratio. The fourth 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 fourth row) are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C.1: Mean difference of co-variates before and after matching.

	1	Means		s of the test of differ	ence in means
	G-SIBs	Non G-SIBs	Unmatched	Match Strategy 1	Match Strategy 2
	(1)	(2)	(3)	(4)	(5)
CET1 capital buffer (%)	3.14	3.43	0.55	0.43	0.22
Leverage ratio buffer (%)	1.09	1.85	0.00	0.99	0.55
Non-performing loans ratio (%)	3.22	2.77	0.51	0.24	0.66
Cash to total assets $(\%)$	6.89	6.27	0.61	0.59	0.98
Deposits to total liabilities $(\%)$	53.00	58.03	0.28	0.99	0.13
Density ratio (%)	43.83	51.36	0.04	0.58	0.49
TLAC (%)	38.28	44.77	0.26	0.40	0.93
Return on assets $(\%)$	0.88	1.05	0.23	0.54	0.81

FIGURES



Figure 1: Framework references in G-SIBs' annual reports

Note: Panel A plots the average occurrences of keywords (see Online Appendix A.1) for banks with G-SIB framework-related discussions in their annual reports, with 95% bootstrapped confidence intervals. The total keywords for each bank-year are scaled by the annual report's total length. The 12 largest Non G-SIBs are selected based on 2013 scores, excluding banks designated as G-SIBs in 2011 but removed from the list thereafter. Panel B illustrates the average and median share of action-oriented sentences between 2013 and 2015, with outliers excluded. The graph includes 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.

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



Note: A high (low) ROA bank has an above (below) median pre-treatment (2013-14) ROA. Panel A displays the adjusted G-SIB scores in basis points for a balanced sample. Panel B plots the adjusted G-SIB score in basis points versus ROA in % in the pooled sample of banks. Blue and red (grey) markers represent pre-treatment (post-treatment) observations.



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 basis points 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.



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

Note: Coefficient estimates in basis points on triple interaction terms in a version of the regression equation (2) where the treatment effect can differ across years, as compared to the starting year 2013. Bank-level controls comprise the CET1 capital buffer, leverage ratio buffer, TLAC, 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). The blue (grey) bars indicate the 90% (95%) confidence intervals based on robust standard errors, clustered at the bank level. The dashed vertical line marks the treatment year.



Figure 5: Impact of the G-SIB framework when considering 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: This table reports the average treatment effect on G-SIBs (ATT) based on the bias-corrected staggered treatment estimator (Callaway and Sant'Anna 2021). The dependent variable is the adjusted G-SIB score. Controls include bank and time fixed effects, the pre-treatment values of CET1 capital buffer, the leverage ratio buffer, TLAC, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, the density ratio, and the credit-to-GDP gap.



Figure A.1: Banks' official and adjusted G-SIB scores

Note: For each pair of lines that are coincident in the base year (2013), the thinner line shows the official G-SIB score while the thicker line shows the adjusted G-SIB score. The cap on the substitutability category for the official score is ignored to illustrate that the two scores coincide in the base year.



Figure B.1: References to the G-SIB framework in banks' annual reports

Note: Panel (A) 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. Panel (B) reports the share of action-oriented sentences as 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.

DOES REGULATION ONLY BITE THE LESS PROFITABLE? EVIDENCE FROM THE TOO-BIG-TO-FAIL REFORMS

ONLINE APPENDIX

A TEXTUAL ANALYSIS

A.1 Keywords

The keywords used to identify sentences that make reference to the G-SIB framework are listed below. Note that 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).

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).

A.2 Action-oriented sentences in annual reports

The list below provides examples of action-oriented sentences from G-SIBs' annual reports.

- 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 CAPITAL, PROFITABILITY AND FRAMEWORK MENTIONS

In this appendix, we fortify our main analysis in Section 5 by affirming that there is no systematic difference in the mentions of 'keywords' related to the G-SIB framework by banks with different capitalisation levels. This helps mitigate concerns that the measurement of the treatment date is flawed by differences in capitalisation.

An initial visual inspection confirms that there is no discernible relationship between G-SIBs' lagged CET1 capital ratio buffers and keyword mentions in their annual reports (Figure B.1).

This finding is reinforced by a regression of keyword mentions on lagged CET1 capital ratio buffers (Table B.1). We consider two measures of keyword mentions: (i) the number of keywords, and (ii) the share of keywords in the total number of words in the annual report. In all the regressions we control for the usual set of time-varying bank characteristics and fixed effects. We find that word counts and their shares are unrelated to differences in bank capital buffers (columns (1) and (3)) as well as differences in G-SIBs' profitability in the post-treatment period (columns (2) and (4)).

Figure B.1: G-SIB mentions in annual reports and lagged CET1 capital buffers



Note: The scatterplot displays G-SIB-related word counts (horizontal axis) and banks' lagged CET1 buffers (vertical axis). A similar pattern (not displayed) emerges from calculating word counts as shares of overall annual report length, or using the shares of action-oriented sentences.

C SIZE-CAPITAL TRADE-OFF AND PROFITABIL-ITY: A MODEL

This appendix discusses a distinct but complementary channel that may also play a role in bank's dynamic cost-benefit trade-off when responding to higher capital requirements: the opportunity cost of shrinking. We consider an economy with one representative bank and no aggregate uncertainty. The bank starts with capital k, chooses the level of deposits d to raise subject to a capital ratio requirement χ , and selects the amount of assets to

	Word counts		Word cou	int shares
	(1)	(2)	(3)	(4)
CET1 capital buffer	0.059	-0.460	-0.532	-0.433
	(0.03)	(-0.30)	(-0.76)	(-0.73)
Post \times Profitability		4.380		1.500
		(0.69)		(0.61)
N	142	142	142	142
Adj. R2	0.764	0.760	0.873	0.874
Bank controls and FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes

Table B.1: G-SIB mentions, CET1 capital buffers, and pre-treatment profitability

Note: The table reports results of a regression of G-SIB related word counts on lagged CET1 capital buffers. In columns (3) and (4), the coefficient estimates have been multiplied by 1,000 to improve readability. The dependent variable is the number of G-SIB-related keywords in G-SIBs' annual reports in columns (1) and (2), and the share of keywords in columns (3) and (4). Post equals one for the post-treatment years (2015-18), and Profitability denotes a bank's average pre-treatment ROA. All regressions include bank and country-year fixed effects, and the following bank-level controls: the leverage ratio buffer, TLAC, 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.

invest in: a = k + d. Assets have a constant return to scale and yield R per unit of asset. The deposit interest rate is r < R. The bank's objective is to maximise its cash flow, Ra-rd, which is also its capital position in the next period, k_{+1} . Due to constant returns to scale, the regulatory constraint always binds so that $a = k/\chi$ and $d = k(1/\chi - 1)$. In the next period, the bank has capital k_{+1} , chooses assets $a_{+1} = k_{+1}/\chi$ and deposits $d_{+1} = k_{+1}/(1/\chi - 1)$. This process repeats itself each period.

We introduce an unexpected regulatory shock as follows. On date t, the regulatory requirement is raised from χ to $\chi + \epsilon a$. This new capital ratio requirement reflects the incentive scheme of the G-SIB framework: a bank that maintains 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 balance sheet or by raising capital externally. We note that banks typically avoid raising capital externally (e.g. Myers and Majluf (1984)), unless there is a convincing 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 δ externally entails a cost that varies as a quadratic function of the amount of capital raised: $\lambda \delta^2$, with $\lambda > 0$.

In response to the regulatory shock, the bank solves the following problem, where β is the discount factor:

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

We focus on an interior solution where $\delta > 0$. The first order conditions are derived as follows:

$$\max_{\delta,a} \quad \beta \Big((R-r)a + r(k+\delta) \Big) - \lambda \delta^2 \quad s.t. \quad \delta = \chi a + \epsilon a^2 - k.$$
$$\implies [a]: \quad \beta (R-r) - \theta (\chi + 2\epsilon a) = 0; \qquad [\delta]: \quad \beta r - 2\lambda \delta + \theta = 0.$$

 $\theta > 0$ 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 then eliminate δ to focus on the balance sheet size a that the bank chooses:

$$\beta(R-r) = (2\lambda\delta - \beta r)(\chi + 2\epsilon a); \qquad \delta = \chi a + \epsilon a^2 - k$$
$$\implies \beta(R-r) = \left(2\lambda(\chi a + \epsilon a^2 - k) - \beta r\right)(\chi + 2\epsilon a).$$

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 – which relates to the value of R – differ in terms of their response to higher capital requirements. The total derivative of equation (1) w.r.t. R yields the following, where $\dot{a} = \frac{da}{dR}$:

$$\beta = 2\epsilon \dot{a} \left(2\lambda(\chi a + \epsilon a^2 - k) - \beta r \right) + \left(2\lambda(\chi \dot{a} + 2\epsilon a\dot{a}) \right) (\chi + 2\epsilon a)$$
$$\implies \beta = \dot{a} \left(2\epsilon \underbrace{\left(2\lambda(\chi a + \epsilon a^2 - k) - \beta r \right)}_{A>0} + 2\lambda \underbrace{\left(\chi + 2\epsilon a\right)^2}_{B>0} \right).$$

The coefficient on \dot{a} is positive since (i) $\epsilon > 0$; (ii) expression A, which also appears in equation (1), must be positive as otherwise we arrive at a contradiction in equation (1) given that R - r > 0, $\chi > 0$, $\epsilon > 0$ and a > 0; (iii) $\lambda > 0$; and (iv) expression B is positive. This implies that in response to tighter regulation, a bank that is more profitable but otherwise identical to a less profitable bank, will choose a comparatively larger balance sheet. To be able to do this, a more profitable bank raises more capital: $\delta = \chi a + \epsilon a^2 - k \implies \dot{\delta} = (\chi + \epsilon 2a)\dot{a} > 0.$

Intuitively, the opportunity cost of choosing a smaller balance sheet is higher for a more profitable bank. It thus prefers a larger balance sheet. This does not necessarily mean that a more profitable bank 'expands by more' – it may also 'shrink by less' as compared to a less profitable bank. Ultimately, the direction of change depends on the cost of raising capital and the magnitude of increase in the capital requirement.

D EVOLUTION OF BANK PROFITABILITY OVER TIME

Table D.1: 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: All coefficients are statistically significant at the 1% level.





Note: Banks are grouped based on G-SIB status and whether their pre-treatment ROA is above the median. The difference between the average ROA of high ROA and low ROA banks is statistically significant in each year.

E ADDITIONAL ROBUSTNESS TESTS

E.1 Alternative profitability measures, controls, and sampling

We consider several alternative measures of profitability to further assess the robustness of our findings based on the specification in equation (2). Summary statistics of these variables is provided in Table E.1, while the regression results are reported in Table E.2.

In column (1), we substitute our baseline measure of profitability, namely the average ROA in the pre-treatment period, with the ROA in 2014, i.e. the most recent observation before treatment. In column (2), we instead consider the average ROA during an extended

	Mean	Stdev	P10	P25	P50	P75	P90	Ν
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
CAPM Beta	1.19	0.38	0.74	0.96	1.19	1.39	1.67	391

Table E.1: Summary statistics of additional variables

Note: The table shows summary statistics for the additional variables used in the Online Appendix E. Statistics are based on 2013 to 2018 data on an unbalanced sample of 82 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. 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.

reference period, namely 2010-2014. We use the average pre-treatment return on equity as the dependent variable in column (3), the cost-to-income ratio – a measure of banks' efficiency – in column (4), the return on risk-weighted assets in column (5), the riskadjusted return on assets in column (6), and the Z-score in column (7). In each case, the coefficient of interest – the one on the triple interaction term reported in the first row – remains positive and highly significant as in our baseline results (recall Table 4). These findings underscore our main conclusion regarding the pivotal role of profitability, both in terms of statistical and economic significance.

	ROA	ROA	Return on	Cost-to-income	Return on	Risk-adjusted	
	(2014)	(2010-14)	equity	efficiency	RWA	ROA	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post \times G-SIB \times Profitability	29.15^{***}	36.96***	2.444^{***}	1.481^{***}	23.95^{***}	4.620^{***}	1.069^{***}
	(2.82)	(4.36)	(2.97)	(3.58)	(3.17)	(4.11)	(3.00)
Post \times G-SIB	-35.26^{***}	-42.33^{***}	-43.24^{***}	-68.90^{***}	-55.18^{***}	-34.13^{***}	-45.87^{***}
	(-2.66)	(-3.62)	(-3.04)	(-3.27)	(-2.85)	(-3.18)	(-2.89)
Post \times Profitability	10.03	11.91	0.876	-0.176	10.71^{**}	1.931^{**}	0.231
	(0.67)	(0.90)	(1.45)	(-0.32)	(2.15)	(2.15)	(1.38)
N	352	336	352	352	352	352	352
Adj. R2	0.983	0.983	0.983	0.983	0.985	0.985	0.984
Bank controls and FE	Yes						
Country-time FE	Yes						

Table E.2: Alternative profitability and efficiency metrics

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); average ROA during 2010 to 2014 in column (2); the average pre-treatment (2013–14) return on equity in column (3); the average pre-treatment cost-to-income efficiency in column (4); the return on risk-weighted assets (RWA) in column (5); the risk-adjusted ROA in column (6); and the Z-score in column (7). See Table 1 for the definition and summary statistics of these measures. Bank-level controls comprise the CET1 capital buffer, the leverage ratio buffer, TLAC, 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.

Next, we restrict the sample to those banks for which we have data in *each* year

from 2013 to 2018. This reduces the number of banks from 82 to 65. Our findings are robust to this change, both in terms of economic and statistical significance as reported in Table E.3 (column (1)).

	Balanced	G-SIB as	Control for
	sample	designated	CAPM beta
	(1)	(2)	(3)
$Post \times G-SIB \times Profitability$	28.69***	25.63***	25.49^{**}
	(3.39)	(2.96)	(2.48)
$Post \times G-SIB$	-35.66^{***}	-31.73^{***}	-32.61^{**}
	(-3.16)	(-2.82)	(-2.63)
Post \times Profitability	20.33	20.37	19.44
	(1.50)	(1.64)	(1.36)
N	323	352	304
Adj. R2	0.983	0.984	0.983
Bank controls and FE	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes
G-SIB score	Adjusted	Adjusted	Adjusted
Post dummy	2015	2015	2015
G-SIB dummy	Baseline	Official	Baseline

Table E.3: Alternative specifications and sample composition

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 approach influences our results, we run our analysis using the official G-SIB designation which can vary across time. In this specification, the G-SIB binary variable, 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 E.3, 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.

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

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) we include 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 buffer, the leverage ratio buffer, TLAC, 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.

benchmark indices (see Table E.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 (3) of Table E.3. This lends support to the interpretation that for more profitable G-SIBs the cost of downsizing outweighs the benefits of reducing their systemic importance.

E.2 Controlling for banks' business model

In this section, we study the potential impact 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 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, wholesalefunded, trading, or universal – based on their average balance sheet characteristics, as shown in the Table E.4.

	Retail-oriented	Trading	Wholesale	Universal
	(Obs = 179)	(Obs = 138)	(Obs = 75)	(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]

Table E.4: Table: Summary statistics by business model clusters

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.

	Business models					
	(1)	(2)	(3)			
$Post \times G-SIB \times Profitability$	28.59***	28.37***	28.67***			
	(3.29)	(3.35)	(3.49)			
Post \times G-SIB	-35.95^{***}	-35.63^{***}	-35.71^{***}			
	(-3.21)	(-3.29)	(-3.29)			
Post \times Profitability	19.45	19.59	19.32			
	(1.52)	(1.53)	(1.54)			
Ν	352	352	352			
Adj. R2	0.984	0.984	0.984			
Lagged bank controls and FE	Yes	Yes	Yes			
Country-time FE	Yes	Yes	Yes			
No. of business model clusters	4	3	2			

Table E.5: Controlling for differences in business models

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 buffer, the leverage ratio buffer, TLAC, 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.

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 E.5 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.

E.3 Assessing the role of geographical factors

One potential concern is that geographical factors could be affecting our findings, such as national regulatory reforms or different macroeconomic developments in banks' home jurisdictions. The use of country-year fixed effects throughout our analysis alleviates this concern to a large extent. Three additional tests, as detailed below, reinforce that our results are not driven by geographical factors.

First, we exclude U.S. banks to assess if deviations from the BCBS's methodology impact our results. U.S. regulators employ an additional albeit closely related method for calibrating G-SIB capital surcharges. U.S. G-SIBs face the higher of the surcharges, usually from the U.S. method. This suggests weaker incentives for U.S. banks to comply with the BCBS G-SIB framework. In line with this, excluding U.S. banks reinforces our findings of a notable difference in the response of more and less profitable G-SIBs, as indicated in column (1) of Table E.6.

	Exclude U.S. banks	Only EME	U.S. dummy	EU dummy	Asia-Pac dummy	EME dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Post \times G-SIB \times Profitability	39.35***	91.09***				
	(4.92)	(3.12)				
Post \times US=1 \times Profitability			-17.95			
			(-0.75)			
Post \times EU=1 \times Profitability				24.26		
				(1.07)	1405	
$Post \times Asia-Pac=1 \times Profitability$					14.97	
Post v FMF-1 v Profitability					(0.60)	5 590
$FOST \times EME = 1 \times FTOILTADILITY$						(0.18)
$Post \times G-SIB$	-46.22^{***}	-147.9^{**}				(0.10)
	(-4.19)	(-2.52)				
Post \times Profitability	27.92***	4.698	41.33^{***}	25.77	29.64^{**}	31.66^{**}
	(3.55)	(0.35)	(3.41)	(1.62)	(2.02)	(2.22)
Ν	293	100	352	352	352	352
Adj. R2	0.984	0.981	0.982	0.982	0.982	0.982
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table E.6: Geographical factors

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 buffer, the leverage ratio buffer, TLAC, 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.

Second, we replicate our analysis by considering only banks from emerging market economies (EME). This accounts for disparities in financial development compared to more advanced economies. It also addresses potential concerns related to Total Loss-Absorbing Capital (TLAC) requirements for G-SIBs in advanced economies, even though we include a proxy of banks' TLAC in our regressions. TLAC requirements could impact G-SIBs' scores by altering banks' funding composition. However, these requirements became effective only in 2019 for advanced economies, making it unlikely to influence our results. In emerging market economies, TLAC requirements will not be in effect until the beginning of 2025. As demonstrated in column (2) of Table E.6, our findings remain robust even with the exclusion of advanced economy banks.

Third, we replace the G-SIB binary variable with a *country-group* dummy indicating banks from a particular region or emerging market. This is done to evaluate the influence of the banks' origin on score adjustments. The placebo tests indicate that profitable banks from specific regions have not changed their scores compared to their peers in a statistically significant manner, as shown in columns (3) to (6) of Table E.6. This accords with the G-SIB framework being the primary driver of banks' adjustments.

F TESTING THE IMPACT ON CAPITAL AND ASSETS

The theoretical model in Online Appendix C predicts that more profitable G-SIBs respond to the framework by increasing their capital and assets by more than less profitable G-SIBs. We test this additional prediction based on the following regression, run on the sub-sample of G-SIBs:

$$Capital_{i,t} \text{ or } Assets_{i,t} = \gamma \left[Post_t \times Profitability_i \right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$$
(1)

Capital_{i,t} is G-SIB *i*'s log capital at time *t*, Asset_{i,t} is G-SIB *i*'s log assets at time *t*, Post_t denotes the post-treatment period as in equation (1) and Profitability_i is the bank's pre-treatment ROA. In contrast to the baseline regression that uses annual data from 2013 to 2018, here we use quarterly observations from 2010 to 2018 to take full advantage of the available data on capital and assets. $X_{i,t-1}$ represents lagged bank controls as detailed in Table F.1. 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.

In Table F.2 (columns (1) and (2)), as anticipated by the theoretical model, more profitable G-SIBs show a significant increase in capital compared to less profitable G-SIBs

	Mean	Stdev	P10	P25	P50	P75	P90	Ν
Capital (log)	4.38	0.85	3.05	3.80	4.43	5.23	5.43	491
Assets (log)	7.06	0.72	5.89	6.71	7.20	7.67	7.85	491
CET1 capital ratio buffer $(\%)$	7.82	2.62	5.13	6.00	7.21	8.81	11.81	491
Leverage ratio buffer $(\%)$	3.37	1.72	1.43	2.02	3.21	4.70	5.87	491
Non-performing loans ratio $(\%)$	2.27	1.95	0.29	0.64	1.59	3.53	4.87	491
Cash to total assets $(\%)$	4.61	4.55	0.89	1.32	2.57	6.56	12.00	491
Deposit to total liabilities $(\%)$	56.64	18.24	29.46	46.57	58.13	73.74	79.03	491
Density ratio (%)	45.56	14.68	29.74	33.72	43.62	57.80	63.84	491
Total loss absorbing capacity $(\%)$	40.64	20.26	18.47	28.89	34.25	50.58	65.11	491

Table F.1: Summary statistics of the quarterly dataset

Note: Quarterly data from 2010 to 2018 on an unbalanced sample of 25 G-SIBs from 8 jurisdictions. Capital: log of total regulatory capital in US\$ billions. Assets: log of total assets in US\$ billions. CET1 capital buffer: percentage difference between Common Equity Tier 1 (CET1) capital to risk-weighted asset (RWA) ratio and the sum of CET1 minimum capital requirement and capital conservation buffer. Leverage ratio buffer: due to limited data for computing the Basel III leverage ratio over the entire period, we calculate it as the percentage difference between the ratio of total regulatory capital to total assets (in %) and the 3% minimum leverage ratio requirement. For U.S. G-SIBs, we assume a 5% requirement consistent with the enhanced supplementary leverage ratio (eSLR) for these banks. Non-performing loan ratio: 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. Density ratio: ratio of RWA to total assets. Total loss-absorbing capacity: total regulatory capital and long-term funding as a share of RWA.

Table F.2: Differential evolution of capital and assets of low and high profitability G-SIBs

	Capital	Capital	Assets	Assets
	(1)	(2)	(3)	(4)
$Post \times Profitability$	0.128^{***}	0.108^{***}	0.182^{***}	0.114^{***}
	(4.63)	(3.25)	(5.50)	(3.17)
Ν	491	491	491	491
Adj. R2	0.995	0.995	0.990	0.993
Profitability	Continuous	Continuous	Continuous	Continuous
Controls	No	Yes	No	Yes

Note: This table presents estimates of the interaction term in the specified model: $y_{i,t} = \gamma [Post_t \times Profitability_i] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$. The dependent variable is log capital (columns (1) and (2)) and log assets (columns (3) and (4)), respectively. Post is a binary variable taking value 1 in the post-treatment period (2015-18). Profitability is measured by the average pre-treatment (2013-14) ROA in levels. This table is based on quarterly data from 2010 to 2018 for the G-SIB sample. Bank-level controls include the CET1 capital buffer, leverage ratio buffer, TLAC, non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio (all lagged by one period). Refer to Table F.1 for variable definitions and summary statistics. Each specification includes bank fixed effects and country-year fixed effects. Robust standard errors cluster at the bank level, and t-statistics are reported in parentheses. *** p < 0.01,** p < 0.05,* p < 0.1.

during the post-treatment period (i.e., $\hat{\gamma} > 0$). Substituting log capital for log assets further confirms that more profitable G-SIBs have also significantly increased their assets compared to their less profitable peers (columns (3) and (4)).

	Weight	Mean	Stdev	P10	P25	P50	P75	P90	Ν
CATEGORY SCORES									
1. Size	20%	136.84	101.53	46.22	63.01	101.39	183.87	307.36	443
2. Interconnectedness	20%	134.56	85.01	40.78	66.15	115.55	195.01	244.31	443
3. Substitutability	20%	146.15	209.19	14.49	34.05	68.97	177.98	350.00	443
4. Complexity	20%	114.71	134.66	10.54	29.77	55.81	157.92	297.51	443
5. Cross-jurisdictional Activity	20%	141.13	160.89	4.13	29.03	84.69	191.45	363.70	443
INDICATOR SCORES									
2a. Intra-financial system assets	6.6%	123.94	93.83	27.04	44.41	98.58	185.20	264.22	443
2b. Intra-financial system liabilities	6.6%	135.37	102.40	19.36	54.21	111.37	201.01	266.62	443
2c. Securities outstanding	6.6%	144.39	94.66	39.54	63.91	131.34	199.03	268.00	443
3a. Payments activity	6.6%	138.68	202.76	12.84	35.36	66.31	153.78	308.55	443
3b. Assets under custody	6.6%	151.81	342.74	2.67	11.69	39.73	110.10	289.29	443
3c. Underwritten transactions	6.6%	147.96	196.50	2.18	24.86	66.57	161.82	463.31	443
4a. Notional amount of OTC derivatives	6.6%	109.97	174.53	1.35	4.22	28.28	112.68	391.15	443
4b. Trading and AFS securities	6.6%	121.94	138.12	11.42	30.52	66.34	178.28	310.56	443
4c. Level 3 assets	6.6%	112.21	140.90	0.95	15.97	52.40	154.38	308.43	443
5a. Cross-jurisdictional claims	10%	142.06	164.27	3.44	25.29	82.32	214.99	353.12	443
5b. Cross-jurisdictional liabilities	10%	140.19	160.35	4.72	23.56	84.94	199.31	368.31	443

Table G.1: Summary statistics

Note: The table shows summary statistics for the adjusted G-SIB categories and indicators. It also reports the regulatory weights (see BCBS (2013)) used for the calculation of the G-SIB score. Category weights sum to 100%. Indicator weights sum to the weight of the corresponding category (e.g. weight 2a +weight 2b +weight 2c =weight 2). OTC = over the counter. AFS = available for sale.

G BANKS' ADJUSTMENT MARGINS

In this appendix, we zoom into the different categories and indicators that constitute the overall G-SIB score to assess banks' adjustment margins. We run the regression specified in equation (2) with the adjusted category and indicator scores as the dependent variable. Table G.1 shows summary statistics of the dependent variables, while Table G.2 presents coefficient estimates of the triple interaction term.

More profitable G-SIBs increased their scores as compared to the less profitable G-SIBs in four of the five categories, notably in *Size* and *Substitutability*. Further analysis reveals that in addition to size, the rise in the average score of more profitable G-SIBs is driven by a significantly higher footprint along the following G-SIB indicators: *underwriting activities, notional amount of OTC derivatives, and cross-jurisdictional liabilities.*

	\times Profitability	P-value	Adj. R2	Ν
CATEGORY SCORES				
1. Size	32.20***	(4.52)	0.989	352
2. Inter-connectedness	16.49	(1.21)	0.931	352
3. Substitutability	49.64***	(2.75)	0.986	352
4. Complexity	21.67	(1.06)	0.925	352
5. Cross-jurisdictional activity	25.84^{*}	(1.91)	0.984	352
INDICATOR SCORES				
2a. Intra-financial system assets	12.40	(0.57)	0.882	352
2b. Intra-financial system liabilities	11.39	(0.46)	0.871	352
2c. Securities outstanding	25.68	(1.61)	0.953	352
3a. Payments activity	21.70	(0.56)	0.945	352
3b. Assets under custody	7.889	(0.51)	0.992	352
3c. Underwritten transactions	119.3***	(4.43)	0.950	352
4a. Notional amount of OTC derivatives	61.39^{***}	(2.99)	0.961	352
4b. Trading and AFS securities	20.64	(0.73)	0.858	352
4c. Level 3 assets	-17.01	(-0.37)	0.794	352
5a. Cross-jurisdictional claims	24.76	(1.60)	0.982	352
5b. Cross-jurisdictional liabilities	26.93*	(1.93)	0.978	352

Table G.2: Regressions based on category and indicator scores

Note: The dependent variables are the corresponding adjusted scores at the category and indicator levels (first column). Indicators are numbered according to their category. The table presents coefficient estimates of the triple interaction term ($Post_t \times G-SIB_i \times Profitability_i$) based on equation (2), with t-statistics reported in parentheses. Post is a binary variable (1 in the post-treatment period (2015-18)), and G-SIB is a binary variable (1 for banks designated as such at least once before 2015). Profitability is measured by the average pre-treatment (2013-14) ROA in levels. Bank-level controls include CET1 capital buffer, leverage ratio buffer, TLAC, ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and density ratio (all lagged by one year). Each specification includes bank fixed effects and country-year fixed effects. Robust standard errors are clustered at the bank level. ***p < 0.01,** p < 0.05,* p < 0.1.

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