BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 922

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January 2021

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This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

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

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Abstract

Regulatory reforms following the financial crisis of 2007–08 created incentives for large global banks to lower their systemic importance. We establish that differences in profitability shape banks' response to these reforms. Indeed, profitability is key because it underpins banks' ability to generate capital and drives the opportunity cost of shrinking. Our analysis shows that only the less profitable banks lowered their systemic footprint relative to their equally unprofitable peers that were unaffected by the regulatory treatment. The more profitable banks, by contrast, continued to raise their systemic importance in sync with their untreated peers.

JEL Codes: G21, G28, L51
Keywords: global systemically important bank (G-SIB); textual analysis; capital regulation; systemic risk; bank profitability; difference-in-differences (DD).

*The views expressed in this paper are those of the authors and not necessarily of the Bank for International Settlements. For their helpful comments, we thank Stijn Claessens, Ben Cohen, Cathérine Koch, Damien Lynch, Aniruddha Rajan, Christian Schmieder, Hyun Song Shin, Előd Takáts, Nikola Tarashev, Kostas Tsatsaronis, Christian Upper, Quynh-Anh Vo, as well as seminar participants at the Bank of England and the Bank for International Settlements. We also thank Jhuvesh Sobrun and Alan Villegas for assistance with the dataset.

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1 Introduction

Banking regulation builds on the premise that capital requirements can make banks internalise the negative externalities they impose on the financial system. The case for regulation is particularly strong for large global banks. As the financial crisis of 2007–08 highlighted, the size, complexity and interconnectedness of these banks implies that their failure risks undermining financial stability.

The crisis experience has sparked a stream of research on too-big-to-fail concerns in banking, giving rise to new measures of systemic risks and deepening our understanding of their origin (e.g., Acharya *et al.* (2012), Adrian and Brunnermeier (2016), Brownlees and Engle (2016), Acharya *et al.* (2017)). However, much less is known about the effectiveness of policy reforms to mitigate such risks. A case in point is the framework for global systemically important banks (G-SIBs), which is one element of the broader post-crisis agenda to address too-big-to-fail concerns. By applying higher capital surcharges to banks that are more systemically important, the G-SIB framework intends to bolster their resilience. At the same time, it creates incentives for these banks to lower their systemic footprint in order to benefit from capital relief.

In this paper, we assess whether the introduction of the framework – the regulatory treatment – has led G-SIBs to reduce their systemic importance. Our focus is on exploring the framework's differential impact on banks given that the strength of regulatory incentives can vary. Incentives to lower their systemic importance are likely to be particularly strong for banks that face high costs of raising capital. Yet banks that stand to sacrifice a lot of revenue by downsizing may have few incentives to reduce their systemic footprint.

Our main finding is that profitability plays a determining – but typically overlooked – role in shaping banks' response to the framework. The framework caused the less profitable G-SIBs, measured in terms of their pre-treatment return on assets (ROA), to cut back their systemic importance relative to the less profitable Non G-SIBs (the untreated peers). The contraction was even stronger for those G-SIBs that were close to the regulatory thresholds that determine their capital surcharges. By contrast, the more profitable G-SIBs have continued to raise their systemic footprint in sync with the more profitable Non G-SIBs. The wedge in the footprint of the more and less profitable G-SIBs has thus widened substantially post treatment. Nevertheless, the concentration of systemic importance within our global sample of banks has declined somewhat during the period of observation. The contraction by the less profitable G-SIBs has thus more than compensated for the increase in systemic importance of the more profitable banks.

Moreover, we assess jointly the changes in banks' systemic importance and their market-implied default risks to approximate the evolution of the banks' systemic risk contribution. This assessment points to a significant decline in the less profitable G-SIBs' systemic risk contribution, and a small but insignificant increase in case of the more profitable G-SIBs.[1]

Our findings are based on a difference-in-differences (DD) specification, which allows us to benchmark G-SIBs' responses to the framework against those of Non G-SIBs. The DD approach lays the ground for our main analysis based on a triple interaction of G-SIB designation, profitability, and the regulatory treatment. Throughout our analysis, we control for fixed and time-varying bank characteristics, as well as for differences in the economic or regulatory developments across jurisdictions over time.

We conduct several robustness checks to confirm that bank profitability, rather than other factors such as the banks' business model or domicile, is the main determinant of the banks' response to the framework. We consider several alternative measures of profitability, treatment dates, and results based on sub-sample regressions (e.g. by geography).

[1]Complementary regulatory reforms, such as enhancing supervision or improving banks' resolvability are likely to have contributed to reducing banks' systemic risk contribution (Financial Stability Board (2020)). An assessment of these reforms is beyond the scope of this paper.

We also explore different estimation approaches, including matching more (less) profitable G-SIBs with comparable Non G-SIBs. Our conclusions prove robust both quantitatively and in terms of statistical significance.

Our paper makes three contributions to the banking literature. First, it complements a growing literature on the determinants of how banks adjust to regulatory reforms. Most of the literature has focused on the role of capital, i.e. the banks' present ability to meet capital requirements, while this paper underscores the role of profitability, i.e. the banks' ability to generate capital in the future. For instance, Berger *et al.* (2008) and relatedly Gropp *et al.* (2019) show that poorly capitalised banks respond more quickly and strongly than their peers to tighter regulatory targets, and typically pursue balance sheet adjustments rather than raising capital via retaining earnings. This conclusion accords with Kashyap *et al.* (2010), who underscore that frictions in raising capital externally have a material impact on banks' response to higher requirements. In a similar vein, Jimenéz *et al.* (2017) conclude that the impact of dynamic provisioning requirements depends on banks' capitalisation. Complementing this line of research, our paper shows that even after controlling for capitalisation levels, pre-treatment profitability proves to be a key driver of banks' responses to the G-SIB framework.[2] Our finding relates to that of Cohen and Scatigna (2016), who report that the more profitable banks expanded lending by more amid rising regulatory requirements after the 2007—08 crisis, and to Fang *et al.* (2020), who document that weak banks react more to changes in capital requirements. Theoretical support for our findings can be found in Goel *et al.* (2020), who show that banks' internal reallocation of capital in response to regulatory changes depends on the relative profitability of their business units.

Second, this paper furthers our understanding of the effectiveness of post crisis reforms aimed at addressing the too-big-to-fail problem. While an established literature assesses

[2] A large literature assesses the reverse effect – i.e. how regulation affects bank profitability. See Ahmad *et al.* (2020) for a survey of that literature.

the effects of capital requirements on banks' individual risk-taking (see Adrian *et al.* (2018) for a discussion), less is known about the effect of regulation on the systemic footprint of banks in the medium term, which is our pursuit in this paper.[3,4] Indeed, existing studies have typically assessed the impact of regulation on banks' individual balance sheet measures. Violon *et al.* (2020), for instance, find that relative to other banks, G-SIBs cut back on asset growth and leverage, whereas other measures, such as ROA, were little affected. Goel *et al.* (2019) point to an acceleration of G-SIBs' balance sheet adjustments after the G-SIB framework was introduced. Behn and Schramm (2020) assess the effect of G-SIB designation on syndicated lending. While they find no effect on lending volumes, Degryse *et al.* (2020) point to an adverse effect. By contrast, our focus is on the framework's impact on the overall systemic footprint of G-SIBs. To this end, we exploit the rich information contained in the newly available Basel Committee on Banking Supervision (BCBS) dataset on 12 supervisory indicators of systemic importance. The indicators span several key dimensions of banks' systemic importance (e.g., complexity and interconnectedness), with a bank's indicator score representing its global market share in the corresponding business activity (e.g, underwriting in debt and equity markets). Using the regulatory weights, we calculate a weighted average of the indicator scores to measure the banks' systemic importance.[5] In this regard, our analysis complements the ongoing evaluation of the too-big-to-fail reforms undertaken by the public sector (Financial Stability Board (2020)), which focuses on the progress made in enhancing banks' resilience and resolvability as well as the associated changes in market perceptions.

[3] Few papers assess size-dependent bank regulation quantitatively, including Passmore and von Hafften (2019), Goel (2016), and Corbae and D'Erasmo (2020).

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

[5] Our measure is closely related to the calculation of the official G-SIB score, but controls for the mechanical impact of changes in a bank's score on the scores of other banks, and of variation in exchange rates.

Finally, we contribute to the literature by proposing a new methodology to identify the regulatory treatment. Identification is a key challenge in measuring the effects of regulation. Major reforms are not quasi-natural experiments. They are generally announced long before their implementation, which in turn is typically phased-in over multiple years. The G-SIB framework is no exception. Its assessment methodology was first published by the BCBS in 2011, whereas the capital surcharges were phased in during the period from 2016 to 2019 (BCBS, 2013). Previous research has relied on announcement dates, such as the publication of the assessment methodology or banks' initial G-SIB designation.[6] It is, however, far from obvious when a bank would start to incorporate future requirements into its capital planning and how strong the effect of the initial announcement would be.

To overcome this challenge, we apply textual analysis to banks' annual reports. We evaluate references to the G-SIB framework in banks' annual reports to identify when the banks incorporated the framework into their strategic capital planning. Similar to earnings conference calls, as used, for example, by Hassan *et al.* (2019) to measure firm-level political risk, an important advantage of the reports is that they originate from decision makers within banks rather than reflecting analysts' or journalists' views. For regulated entities, such as banks, the discussion of how the regulatory framework and upcoming reforms affect the bank's strategy assumes an important part in the annual report. Yet, academic research has made little use of the text contained in annual reports to assess the effects of regulatory reforms.[7]

Our assessment of large banks' annual reports from 2011 to 2018 points to a significant increase in the number of references to the framework by G-SIBs – in contrast to Non

[6]See, for example, see Financial Stability Board (2020) or Violon *et al.* (2020).

[7]Use of annual reports as a general source of information about public firms is more common. For instance, keyword searches, similar to our approach, on 10-K filings of US non-financial firms have been used by Hoberg and Maksimovic (2015) and Bodnaruk *et al.* (2015) to assess financial constraints, Friberg and Seiler (2017) to construct measures of risk and ambiguity, Loughran and McDonald (2011) to measure tone and link it to excess returns, and Hoberg and Moon (2017, 2018) for measuring offshoring activities.

G-SIBs – in the lead up to the phase-in of the capital surcharges in 2016. A context-based analysis of these references – which helps distinguish between general discussions of the framework and specific actions taken by the bank in response to the framework – points to the year 2015 as the treatment date. JP Morgan, for instance, notes in its 2015 report that *"... we took some dramatic actions to reduce our G-SIB capital surcharge ..."* (JPMorgan Chase (2015), p 16). Our identification strategy thus provides a more informed view on the timing of the regulatory treatment if compared with previous studies that rely on announcement dates.

We organise the remainder of this paper as follows. Section 2 sketches the main elements of the G-SIB framework and develops the identification strategy to determine the regulatory treatment. Section 3 presents the data and our main empirical findings, with robustness checks provided in Section 4. We discuss policy implications in Section 5 and conclude with Section 6.

2 The G-SIB framework

2.1 Institutional background

The G-SIB framework has two main building blocks. First is an assessment methodology that assigns scores to banks and designates all banks whose score is above a certain threshold as G-SIBs. Second is a schedule that defines the capital surcharges that apply to G-SIBs depending on their score.[8]

The G-SIB assessment methodology follows a rule-based approach. It encompasses twelve indicators of a bank's systemic importance (eg holdings of level-3 assets, notional

[8] G-SIB designation also implies other regulatory requirements for the bank, such as more intense supervision as well as recovery and resolution planning. Yet, in contrast to the capital surcharges, these requirements apply to all G-SIBs irrespective of their score. As such, they do not provide incentives to reduce the score, unless the bank could lower the score below the threshold that determines G-SIB designation.

amounts of over-the-counter (OTC) derivatives), organised into five categories: cross-jurisdictional activity, complexity, interconnectedness, size, and substitutability.[9] For each indicator, a score is computed for each bank that equals the bank's indicator value divided by the sum of indicator values of all banks in the assessment sample (roughly 80 internationally-active large banks). The indicator scores thus reflect the bank's global market share in the underlying activity. The overall score – referred to as the "G-SIB score" – equals a weighted average across the bank's twelve indicator scores. The scores are measured in basis points (bps), and banks with a G-SIB score of at least 130 bps are designated as G-SIBs.[10] The assessment is conducted once a year based on annual data from the previous year.

Capital surcharges increase with the G-SIB score, and as a result seek to encourage G-SIBs to reduce their scores. G-SIBs are allocated into five different buckets depending on their scores.[11] The bucket allotment determines the capital surcharge (so-called higher loss absorbency requirement). Starting from a level of 1% of Common Equity Tier-1 capital to risk weighted assets (CET1 capital ratio) for G-SIBs in the first bucket, the surcharges increase by 0.5 percentage points per bucket up to 2.5% in the fourth bucket. From that point on, the surcharge increases by one percentage point per bucket to provide an even greater incentive against further increases in systemic importance (BCBS, 2013).

The empirical question that follows is whether the framework's incentives are sufficiently strong to initiate a reduction in G-SIBs' systemic importance or at least prevent any increase.

[9] A revised methodology, comprising the volume of banks' trading activities as an additional indicator, will take effect in the year 2021 (BCBS, 2018).

[10] Supervisors can apply judgement and override this rule by designating a bank as a G-SIBs even though its score is below the threshold. This option has only been used a few times in the past.

[11] Each bucket covers a range of 100 bps. A G-SIB with, for example, a score of 130 to 229 bps is allocated to the first bucket.

2.2 Identifying the regulatory treatment date

We pinpoint the regulatory treatment date in this subsection by identifying when the framework started affecting banks' behaviour. The G-SIB assessment methodology was first published in November 2011, alongside an initial list of G-SIBs. The Financial Stability Board disclosed the attendant capital surcharges for the first time in November 2012 and has since then published an updated list of G-SIBs every year in November. The capital surcharges were phased in as of January 2016 over a three-year period (BCBS (2013)). As such, they were initially applicable to banks designated as G-SIBs in November 2014.

The gradual implementation of the framework makes the identification of the regulatory treatment challenging. Event studies around key announcement dates, such as the publication of the G-SIB methodology or the G-SIB lists, offer one approach to overcoming this challenge. While such studies provide insights into the immediate market impact, they cannot account for the impact of the framework on banks' strategic balance sheet or business model adjustments.[12] These adjustments are costly (eg given long-term financial commitments) and are likely to play out only in the medium-term.

Studies that estimate the medium-term impact have typically focused on the initial publication date of the G-SIB assessment methodology in 2011 or the disclosure of the capital surcharges in 2012 as possible treatment dates. These studies implicitly assume that banks respond immediately to future regulatory requirements. Yet it remains unclear how much in advance, and to what extent, the adjustment would occur, especially when the time between the announcement and the eventual phase-in spans several years as in the case of the G-SIB framework.

We leverage a pivotal source of information to identify the treatment date more accurately: the bank's annual reports. These reports provide a key channel through which

[12] Initial market reactions reflect an often noisy signal of how shareholders and creditors perceive the impact. Importantly, their views may differ from those of bank management, particularly regarding how the bank should respond.

the bank's management communicates its strategic decisions to stakeholders.

We extract the relevant information from the annual reports using a three-step approach. First we establish a list of all keywords (including abbreviations) that banks use to refer to the G-SIB framework (eg "global systemically important bank"), including terminology introduced by national supervisory authorities (eg "systemically relevant bank"). Table A.1 presents the full list of keywords.

Second, we count keyword occurrences in the annual reports of the 33 banks that were designated as a G-SIB at least once between 2013 and 2018, and of the 12 Non G-SIBs with the highest G-SIB scores in 2013. Following Baker *et al.* (2016), we scale the raw keyword count for each bank-year in our sample by the total number of words in the corresponding annual report. This accounts for the fact that the average length of the reports has increased over time. Finally, we average the scaled occurrences across banks for each year.

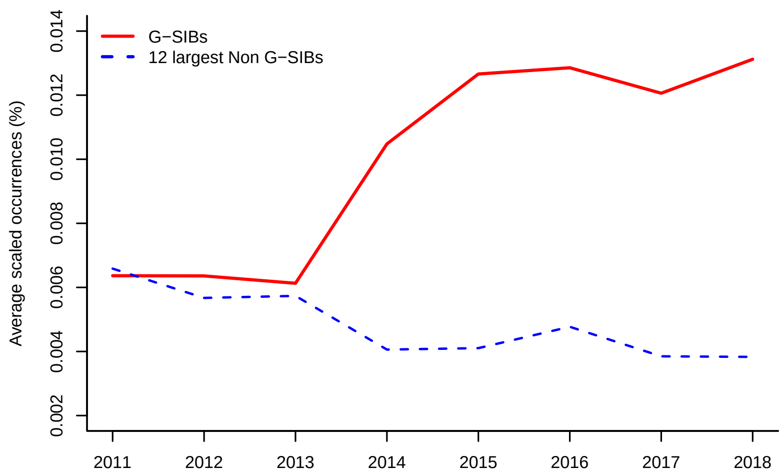
The evolution of average scaled occurrences, shown in Figure 1, points to a notable increase in framework-related discussions by G-SIBs in 2014.[13] By contrast, corresponding occurrences in the case of Non G-SIBs declined, creating a distinct wedge between the two groups, which widened further in 2015.[14] The observed pattern suggests that G-SIBs started to incorporate the framework in their strategic considerations from 2014 onwards. This accords with G-SIB designations before November 2014 having no impact on banks' capital requirements. Furthermore, the number of G-SIBs mentioning the framework increases from two-thirds to the full sample from 2011 to 2015.

Our third and final step combines the previous steps with a keyword-in-context anal-

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

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

Figure 1: Scaled occurrences of relevant keywords for G-SIBs and 12 largest Non G-SIBs



Note: The graph plots the occurrences of G-SIB-related keywords, averaged across banks, as a percentage share of the total number of words of each bank's annual report. The solid line represents the 33 G-SIBs in the sample, while the dashed line represents the twelve largest Non G-SIBs based on the 2013 scores. In decreasing order of 2013 scores, these include: Nomura, Danske Bank, Norinchukin, Bank of Nova Scotia, National Australia Bank, Intesa, Rabobank, ANZ, BoComm, Commonwealth, Bank of Montreal, and Industrial Bank. We exclude from the control sample those banks that were designated as G-SIBs in 2011 but dropped from the G-SIB list thereafter: Dexia, Lloyds and Commerzbank. However, including these as Non G-SIBs does not alter any of our conclusions.

ysis. The main concern with basic keyword counts is that they can be agnostic to the context of the occurrence. We address this issue by manually categorising each sentence in the G-SIBs' annual reports that contains a keyword. This allows us to wean out irrelevant and out of context sentences, and distinguish a general discussion of the framework from a reference to how the bank is actively responding to the G-SIB framework. Specifically, we consider 6 sentence categories as shown in Table 1. The categories are ordered in terms of providing increasingly relevant insights into the timing of the regulatory treatment from the perspective of the bank.

Guided by the pattern in Figure 1, we focus on G-SIBs' annual reports between 2013 and 2015 for the keyword-in-context analysis. We proceed in two steps. First, we extract all 1341 keyword-related sentences from the annual reports. The evolution of these sentence counts corroborates with our findings from the raw word counts.

Next, each author independently reads and tags each sentence based on the six cat-

Table 1: Categories used to tag sentences

Category	Definition	Example
5: Active response	Discussion of capital planning or other actions taken by the bank in response to the G-SIB capital surcharges.	*UniCredit's capital position remains above the minimum SREP requirement, including the phase-in G-SIB buffer, thanks to the ongoing and continued commitment to further internal capital generation as envisaged in UniCredit's Strategic Plan published on November 11, 2015 (UniCredit, 2015).*
4: Surcharges satisfied	Acknowledgement that G-SIB capital surcharges are satisfied or close to being satisfied.	*In addition, we continued to strengthen our capital position and reported a fully-applied Swiss systemically relevant bank (SRB) common equity tier 1 capital ratio of 14.5% and a Swiss SRB leverage ratio of 5.3% at year end, leaving us well-positioned to deal with both challenging market conditions and the future requirements of the revised Swiss too big to fail (TBTF) framework (UBS, 2015).*
3: Surcharges apply	Acknowledgement that G-SIB capital surcharges are applicable to the bank.	*RBS has been provisionally allocated a G-SII buffer of 1.5% (RBS, 2014).*
2: General description	General description of the G-SIB capital surcharges (either mentioned explicitly or implicitly as part of G-SIB requirements), or what it means for banks.	*In November 2015, the FSB and BCBS published an updated list of G-SIBs (RBC, 2015).*
1: Out of context	A valid occurrence of the keyword, but not in the context of the G-SIB capital surcharges (eg discussions around TLAC, resolution, SLR, or the D-SIB framework)	*At the international level, the Financial Stability Board (FSB) has proposed to set a common standard on Total Loss Absorbing Capacity (TLAC) for global systemically important banks (G-SIBs) (BPCE, 2014).*
0: Irrelevant	An irrelevant occurrence of the keyword, such as in a table or a glossary, or with an unintended meaning.	*Global Systemically Important Banks: Banks recognized as key players in the financial market with global features as announced by the Financial Stability Board (Agricultural Bank of China, 2014).*

egories, 0 through 5. The authors' tags are highly correlated, with disagreement in less than 8% of the sentences.[15] The high correlation reflects the relative ease with which the sentences can be categorised. In what follows, we focus on the *relevant* categories, namely 2 to 5, given that category 0 and 1 sentences are either irrelevant or out of context.

[15] The pair-wise correlation coefficients of the three authors' tags are equal to 0.92, 0.94 and 0.94, respectively, and are all highly statistically significant.

Figure 2: Word cloud of G-SIB related sentences

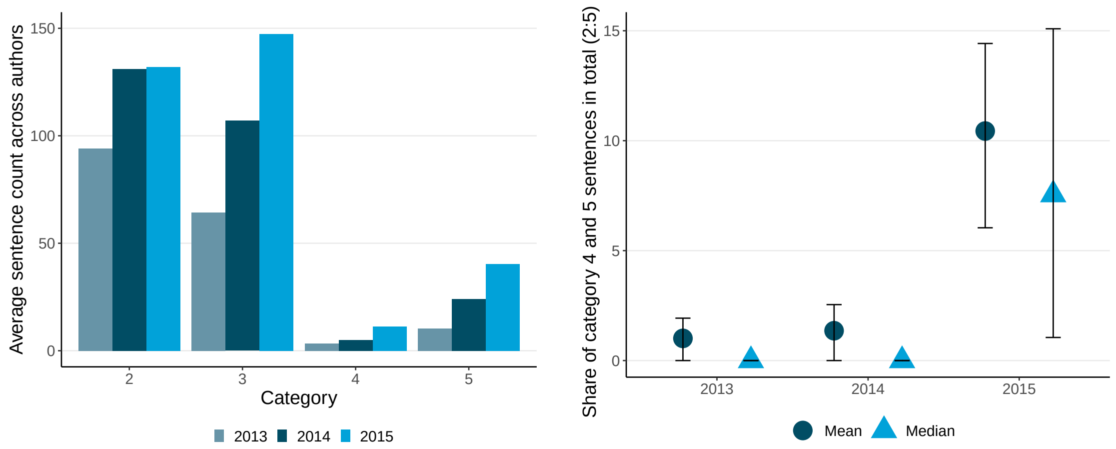
Note: The graph plots the 70 most frequent words mentioned in G-SIB related sentences in categories 2 to 5. The sample consists of the annual reports of the 33 G-SIBs in 2013, 2014, and 2015.

Figure 2 plots a word cloud of the 40 most frequent words (after excluding articles and other basic words) in sentences that have been allocated to the relevant categories by at least one author. It provides a high-level sense of the nature of references banks make to the G-SIB framework. For the remainder of our analysis, we take the average count across authors for each sentence category to mitigate any biases. Other approaches, such as using the median or minimum tags across authors does not affect our conclusions.

Among the sentences in categories 2 to 5, those in categories 2 and 3 comprise general discussions of the framework. By contrast, those in categories 4 and 5 are *action-oriented* ie they closely track active responses by the bank to the G-SIB framework.[16] We find

[16]Appendix B lists several examples of such action-oriented sentences. We note that majority of these sentences are backward-looking, i.e. they represent plans initiated and actions already started or completed by the bank in the previous year.

Figure 3: Distribution of sentences by categories, and share of action-oriented sentences



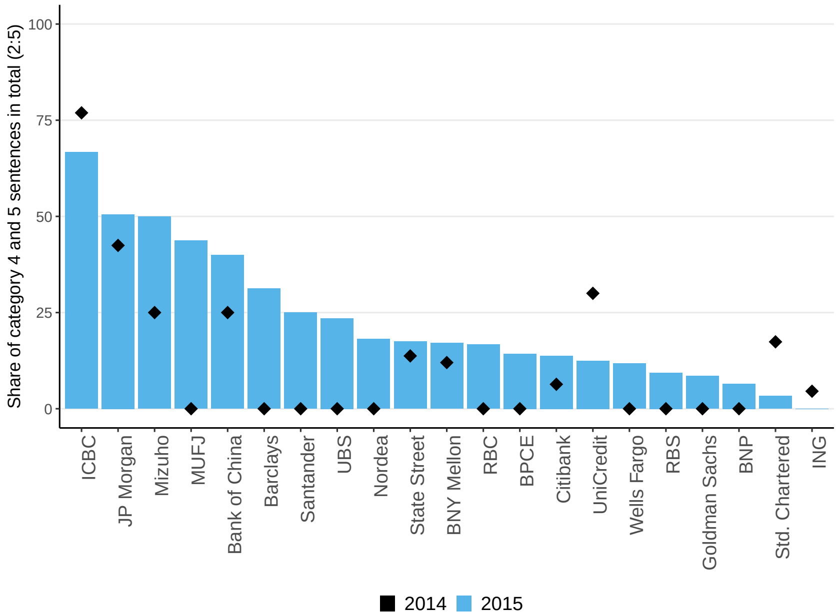
Note: The *left-hand panel* shows the average (across authors) number of sentences in categories 2 to 5. The *right-hand panel* plots the average and median share of action-oriented category 4 and 5 sentences for each year, calculated after exclusion of outliers. The graph further shows the 95% confidence intervals for the mean and median each year using bootstrapping. Non-overlapping intervals indicate significant differences across years at the 5% level. Outliers are defined as observations 1.5 times the distributions inter-quartile range below (above) the first (third) quartile. This drops six observations each in 2013 and 2014, and three observations in 2015.

that not only the number but also the share of category 4 and 5 sentences is the highest in 2015 (see Figure 3). Crucially, the median share is zero in 2013 and 2014, but statistically significantly higher in 2015. Similarly, the mean share of category 4 and 5 sentences also rises significantly and sharply in 2015 as compared to the previous two years.

The increase in the share of action-oriented sentences in 2015 occurs not just along the intensive margin, but also along the extensive margin in two dimensions: banks as well as countries. That is, the number of G-SIBs with annual reports containing category 4 and 5 sentences, doubles from 10 in 2013 and 2014 to 20 in 2015 (see Figure 4). Representation across countries also increases. In 2014, US G-SIBs account for the majority of category 4 and 5 sentences; however, in 2015, we also identify such sentences in the reports of banks from five European countries, Japan, and Canada.

Overall, these findings reveal that 2015 is the treatment year. This is the year when most G-SIBs begin to communicate strategic actions in response to the G-SIB framework. This contrasts with existing studies that rely the announcements in 2011 or 2012 as the

Figure 4: Share of category 4 and 5 sentences by bank, for 2014 and 2015



Note: Banks with non-zero counts of category 4 & 5 sentences in 2015 (except ING) are shown with bars, with their respective 2014 shares as diamonds.

treatment dates. Our result tallies with the regulatory phase-in of the G-SIB capital surcharges as of the beginning of 2016.

3 Empirical analysis

3.1 Data and G-SIB score adjustment

Our primary dataset is the BCBS' compilation of banks' disclosures of the 12 G-SIB indicators. These form the basis for computing the official G-SIB score, the regulatory approximation of a bank's systemic importance. BCBS data are available from 2013 to 2018, and comprise an unbalanced sample of 84 banks from 21 jurisdictions.[17]

Our goal is to identify potential shifts in the systemic importance of G-SIBs relative

[17]The list of banks and the corresponding data are available from the BCBS website at www.bis.org.

to that of Non G-SIBs because of the G-SIB framework. The G-SIB score is an ideal starting point to underpin such an assessment for several reasons. For one, the underlying indicators provide a comprehensive overview of the banks' systemic footprint along a wide range of financial activities. Furthermore, the BCBS collects the indicators based on a common template and on a consistent basis across banks and over time. In addition, the BCBS and national supervisors review them for consistency. Finally, the indicators are available for both G-SIBs and Non G-SIBs which is crucial for a comparative analysis of the framework's impact on G-SIBs.

Some design features, however, suggest that an adjustment of the official G-SIB scores is needed to assess banks' responses. First, the scores are based on a relative comparison of banks' indicators. An increase in, for example, the average score of all G-SIBs would thus mechanically lead to a decline in the average score of all Non G-SIBs. Furthermore, a doubling of all banks' indicator values would not affect the individual scores at all. Second, since the indicator values are denominated in euro, exchange-rate fluctuations can have a material impact on banks' scores over time. The appreciation of the US dollar against the euro in 2014, for example, is likely to have increased US banks' scores given their larger share of dollar denominated assets and liabilities. Third, the official scores are subject to a regulatory override. Specifically, the score in the Substitutability category is capped at 500 basis points to limit the impact of this category on a bank's overall score.

To address these issues, we adapt the official G-SIB score to obtain an *adjusted* G-SIB score, which serves as our measure of systemic importance. First, we *re-base* the official score using the indicator denominator in 2013. Rather than dividing each bank's indicator value by the sum of indicator values of all banks (ie the denominator) in the corresponding year, we divide by the sum of indicator values in 2013, the first year of observation. With this adjustment, we decouple the evolution of scores of G-SIBs and Non G-SIBs over time. This ensures that we can causally interpret our estimates from the difference-in-

Table 2: Summary statistics

	Mean	Stdev	P10	P25	P50	P75	P90	N
GSIB SCORES								
GSIB Score (official)	128.36	105.93	29.16	48.07	87.52	182.44	283.43	455
GSIB Score (adjusted)	134.61	113.62	29.56	54.63	91.04	184.56	288.56	455
CATEGORY SCORES								
1. Size	136.44	100.24	46.51	63.80	103.26	178.51	307.20	455
2. Interconnectedness	134.00	84.03	40.97	67.37	115.37	189.89	243.15	455
3. Substitutability	146.49	206.83	14.86	35.58	72.54	183.12	347.27	455
4. Complexity	114.03	132.96	11.14	30.00	57.00	156.87	294.84	455
5. Cross-jurisdictional Activity	142.08	159.04	4.28	29.78	91.11	196.95	359.69	455
INDICATOR SCORES								
2a. Intra-financial system assets	122.95	92.83	27.31	45.59	98.10	182.17	260.79	455
2b. Intra-financial system liabilities	133.74	101.71	19.92	53.79	110.55	198.70	265.43	455
2c. Securities outstanding	145.30	93.68	40.23	65.74	135.95	199.49	267.45	455
3a. Payments activity	137.88	200.17	13.44	35.84	70.39	150.88	305.67	455
3b. Assets under custody	151.36	338.67	2.94	12.27	39.73	110.74	283.33	455
3c. Underwritten transactions	150.22	195.28	2.50	25.47	67.66	174.10	458.64	455
4a. Notional amount of OTC derivatives	109.81	172.31	1.37	4.31	34.96	113.83	384.39	455
4b. Trading and AFS securities	121.81	136.44	11.57	32.11	68.85	173.80	305.23	455
4c. Level 3 assets	110.47	139.46	1.10	16.29	50.78	147.79	308.39	455
5a. Cross-jurisdictional claims	143.37	162.44	3.47	25.93	87.41	217.19	344.49	455
5b. Cross-jurisdictional liabilities	140.79	158.49	4.84	24.10	86.42	200.08	366.25	455
BANK CHARACTERISTICS								
Return on assets (%)	0.96	0.57	0.31	0.52	0.92	1.30	1.69	504
Return on equity (%)	14.55	7.46	5.93	9.82	14.02	18.76	24.37	504
Return on risk-weighted assets (%)	2.02	0.88	0.82	1.46	2.04	2.60	3.14	491
Risk-adjusted return on assets (%)	5.74	4.67	1.36	2.45	4.35	7.77	12.31	504
Z-score (ratio)	43.91	26.99	17.07	27.89	36.89	51.04	81.35	504
CET1 capital ratio (%)	12.19	2.99	8.92	10.21	11.67	13.57	15.86	449
Density ratio (%)	46.61	17.38	26.33	33.10	43.17	60.41	70.49	491
Cost to income (%)	55.78	15.99	30.60	45.16	58.12	66.71	74.53	504
Non-performing loan ratio (%)	2.73	2.98	0.50	0.91	1.61	3.31	6.91	489
Cash to assets (%)	6.90	5.60	1.31	2.41	5.82	9.97	13.56	504
Deposit to total liabilities (%)	56.52	17.73	30.93	42.48	59.15	69.87	79.21	498
Capital buffer (%)	4.70	3.04	1.73	2.65	3.94	6.05	8.74	449
Close to bucket threshold	0.19	0.40	0.00	0.00	0.00	0.00	1.00	504
1-year EDF (%)	0.71	1.13	0.21	0.31	0.49	0.81	1.29	441
1-year PD (%)	0.24	0.27	0.01	0.04	0.15	0.35	0.62	482
SRISK (%)	2.75	2.90	0.18	0.82	1.62	3.49	7.24	429
CAPM Beta	1.18	0.38	0.73	0.95	1.18	1.38	1.66	403

Note: The table shows summary statistics for the variables used in the analysis. Statistics are based on 2013 to 2018 data on an (unbalanced) sample of 84 banks from 21 jurisdictions. For the scores, the units are basis points (bps). For the bank characteristics, the units are displayed alongside the name of the variables. In the case of the G-SIB indicators and categories, the table reports the statistics for the adjusted scores. OTC = over the counter. AFS = available for sale. Risk-adjusted return on assets is equal to return on assets (ROA) divided by the standard deviation of ROA 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. CET1 capital ratio is equal to Common Equity Tier-1 (CET1) capital over risk-weighted assets. Density ratio equals risk-weighted assets over assets. Cost to income is the ratio of non-interest expenses to the sum of non-interest income and net-interest income. Capital Buffer is defined as 7% + G-SIB surchage – CET1 ratio. Closeness to bucket threshold is a binary indicator variable equal to 1 if the official G-SIB score is in a range of 20bps from one of the bucket thresholds. EDF is the 1-year Expected Default Frequency from Moodys. PD is probability of default implied by CDS spreads from Bloomberg. SRISK is the percent contribution of a bank to total systemic risk of the financial system. 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.

differences analysis pursued in the following sections. Second, we purge the indicators of exchange rate effects by converting the indicator values back into the banks' reporting currency and restating all indicators in euro based on the 2013 exchange rates.[18] Third, deviating from the regulatory approach, we do not apply any cap on banks' score in the Substitutability category. This avoids masking any adjustment by banks that benefit from the cap given particularly large scores in this category.[19]

Table 2 presents summary statistics for the official and adjusted G-SIB scores, and the adjusted category and indicator scores. We note that the official and adjusted scores are highly correlated, with a statistically significant pairwise correlation coefficient of 0.988.

We complement the BCBS data with financial data from Fitch Connect as listed in Table 2 to underpin our regression analysis in the following sections. This allows us to control for bank-level attributes and to examine any differential regulatory impact on banks depending on their pre-treatment characteristics. We gather several measures of profitability, notably return on assets (ROA), defined as the ratio of operating profit to total assets. We also collect data on banks' Common Equity Tier-1 (CET1) capital ratio to assess how tightly banks are constrained by the G-SIB capital surcharges, which is calibrated in CET1 terms. We use several other balance sheet and P&L metrics to assess similarities between banks' business models, and as co-variates for our matching analysis.

Finally, we collect market-based measures of banks' implied probability of default based on credit default swap (CDS) spreads and expected default frequency (EDF). We also gather data on the New York University VLAB's SRISK (see Brownlees and Engle, 2016 and Acharya *et al.*, 2012) as a baseline measure of banks' systemic risk to assess policy implications in Section 5.

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

[19] The BCBS is considering options to remove the cap in its regular review of the methodology (BCBS, 2018).

3.2 Baseline analysis of the impact of the framework

We formally assess how the systemic importance of G-SIBs evolved relative to Non G-SIBs by applying a difference-in-differences (DD) approach. Specifically, we estimate:

$$score_{i,t} = \beta\, [post_t \times gsib_i] + \gamma X_{i,t} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}, \tag{1}$$

where $score_{i,t}$ represents the adjusted G-SIB score of bank i in year t. $post_t$ is a dummy variable that equals 1 in the post-treatment period (2015–18) and 0 during the pre-treatment period (2013–14), whereas $gsib_i$ equals 1 (zero otherwise) for banks that have been designated a G-SIB at least once since 2013. $X_{i,t}$ accounts for time-varying bank-specific characteristics: the CET1 capital ratio, the density ratio as well as the ratios of cash to asset, deposits to liabilities, non-performing loans to total loans, and cost to income (see Table 2 for the variable definitions). α_i controls for a bank's unobserved time-invariant characteristics. $\delta_{c,t}$, in turn, accounts for time-varying characteristics of country c where bank i is headquartered, such as changes to the macroeconomic environment or regulation.[20] $\varepsilon_{i,t}$ is the error term. We always cluster the standard errors at the bank-level. To assess whether the framework has led G-SIBs to reduce their scores relative to Non G-SIBs, we test whether $\hat{\beta} < 0$.[21]

Our identifying assumptions are that G-SIBs and Non G-SIBs followed parallel trends before the treatment, and that only G-SIBs were affected by the treatment.

We test the validity of the parallel trend assumption by examining whether the difference in the score of G-SIBs and Non G-SIBs in 2014 is significantly different from that in 2013. To this end, we run the DD specification – ie equation (1) – by replacing

[20] Note that when fixed-effects are not included, the *post* and *gsib* dummies are included as separate regressors.

[21] In the absence of any controls, $\hat{\beta}$ denotes the estimated change in the difference between the average score ($\overline{score}$) of G-SIBs and Non G-SIBs from pre- to post-treatment: $\hat{\beta} = \left(\overline{score}_{\text{G-SIB, post}} - \overline{score}_{\text{G-SIB, pre}}\right) - \left(\overline{score}_{\text{Non-G-SIB, post}} - \overline{score}_{\text{Non-G-SIB, pre}}\right)$.

the *post* dummy with a *year* dummy. The coefficient for the $gsib \times 2014$ interaction term is statistically insignificant in both the unsaturated and saturated (ie including fixed-effects) versions of the regression, with p-values equal to 0.55 and 0.89, respectively. Thus the parallel trends hypothesis cannot be rejected. A visual inspection of the pre-treatment trends in G-SIBs and Non GSIBs adjusted scores also supports the parallel trend assumption (see Figure 6, left-hand panel, in Section 3.3 below).

We note that the limited number of pre-treatment observations might limit the ability to test for parallel trends. We cannot overcome this limitation directly because G-SIB scores prior to 2013 are not available, and comprehensive proxies at a higher frequency cannot be computed as banks typically do not report the indicators that are needed to calculate the G-SIB score at a higher frequency. Yet, we find that in terms of their total assets – one of the key inputs to computing the G-SIB score – G-SIBs and Non G-SIBs evolved in parallel before treatment, ie from 2010 to 2014.[22]

Several design choices help to ensure the validity of the second assumption that Non G-SIBs were not treated. First, we avoid that changes in one bank's activity has a direct impact on another bank's score by adjusting the calculation of the scores accordingly (recall Section 3.1). Second, we keep the treatment and control groups clearly separated based on a time-invariant definition of G-SIB status. We consider variations of these choices to assess the robustness of our findings in Section 4. We also recall from Figure 1 that occurrences of framework-related keywords declined notably for Non G-SIBs post-treatment, suggesting that the framework was of little relevance to these banks. One potential concern is that the introduction of regulatory requirements for *domestically* important banks (D-SIBs) could bias our results towards finding no effect of the G-SIB

[22] Specifically, we run a DD specification on banks' total assets cast in terms of 2013 exchange rates as the dependent variable at a quarterly frequency from 2010 to 2018. We include quarterly dummies to test for any potential violation of the parallel trends assumption. We find that relative to the reference quarter, ie Q1 2010, the change in the difference of the average scores of G-SIBs' and Non G-SIBs' is insignificant at the 5% level (ie p-value > 0.05) in each quarter of the pre-treatment period, ie 2010-2014. Thereafter, the change in the score difference is typically significant at the 5% level (p-value < 0.05).

Table 3: Baseline differences-in-difference (DD) results

	(1)	(2)	(3)
Post × G-SIB	−9.931	−8.692	−1.450
	(−1.19)	(−1.28)	(−0.17)
Post	3.833	3.228	
	(1.40)	(1.17)	
G-SIB	179.7***		
	(8.15)		
CET1 capital ratio		2.075	−0.433
		(1.46)	(−0.18)
Return on assets		−15.66*	−6.813
		(−1.86)	(−0.73)
Non-performing loan ratio		3.551	5.741
		(1.46)	(1.14)
Cost to income		−0.199	0.125
		(−0.71)	(0.56)
Cash to assets		−2.050***	−2.264***
		(−2.78)	(−3.12)
Deposit to total liabilities		−0.398	0.334
		(−0.73)	(0.62)
Density ratio		−1.026*	−1.705**
		(−1.73)	(−2.47)
N	455	397	363
R2	0.572	0.982	0.990
Bank controls and FE	No	Yes	Yes
Country-time FE	No	No	Yes

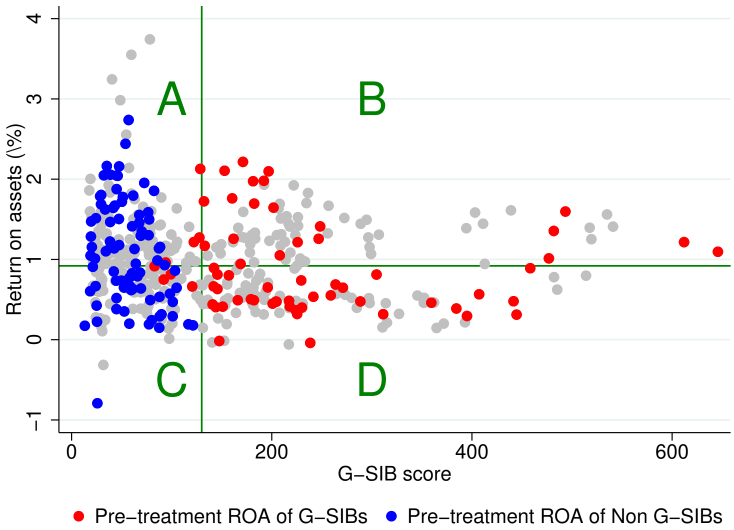
Note: The table reports results of the regression in equation 1. The dependent variable is the adjusted G-SIB score. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once since 2013. Bank-level controls include the CET1 capital ratio, return on assets, the ratio of non-performing loans to total loans, cost to income ratio, cash to assets, deposits to total liabilities, and the density ratio. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

framework. However, we note that virtually all banks in our sample, including all G-SIBs, are D-SIBs and thus subject to such requirements.[23] To control for any remaining differences in regulatory reforms that may have affected the banks, we include country-year fixed effects throughout our analysis.[24]

[23] All banks in our sample were designated as D-SIBs by their national supervisory authorities in 2018, with the exception of Chinese banks, for which the finalisation of a D-SIB assessment methodology was still ongoing. Relatedly, the capital conservation buffer was phased in alongside the G-SIB surcharges in January 2016. However, this buffer is applied to both G-SIBs and Non G-SIBs and should thus not affect our identification strategy.

[24] One potential concern is that the introduction of Total Loss-Absorbing Capital (TLAC) requirements for G-SIBs could have affected G-SIBs' scores by inducing changes in the composition of banks' funding. However, these requirements have become effective only as of 2019 in advanced economies. Furthermore, as shown in Table 10 (column (4)) in Section 4.2, our results prove robust to including only banks from emerging market economies, where TLAC requirements will not take effect before the start of 2025.

Figure 5: Adjusted G-SIB scores versus return on assets



Note: The table plots the adjusted G-SIB score versus ROA in the pooled sample of banks. Region A shows high ROA Non G-SIBs (N=168); region B shows high ROA G-SIBs (N=84); region C plots low ROA Non G-SIBs (N=138); and region D demonstrates low ROA G-SIBs (N=114).

The DD model suggests that the change in the average score of G-SIBs, relative to their pre-treatment level as well as relative to Non G-SIBs, is insignificant. Column (1) of Table 3 presents the results of the simplest version of the baseline specification without any controls or fixed-effects. The negative coefficient on the interaction term implies that G-SIBs decreased their average score by a statistically insignificant 9.9 basis points relative to Non G-SIBs in response to the regulatory treatment. Relative to their own pre-treatment level, G-SIBs reduced their average score by 6.1 basis points whereas Non G-SIBs increased the same by 3.8 points.[25] Both these changes are small and statistically insignificant. Saturating the regression by controlling for bank fixed effects as well as time-varying bank characteristics (column (2)) or also adding country-year fixed effects

[25]The former change is computed by adding the coefficients on the 'Post' and 'Post × G-SIB' terms. The latter change is given by the coefficient on 'Post'.

(column (3)) shows that the change in the scores of G-SIBs remains insignificant and, if anything, becomes even smaller in absolute value.

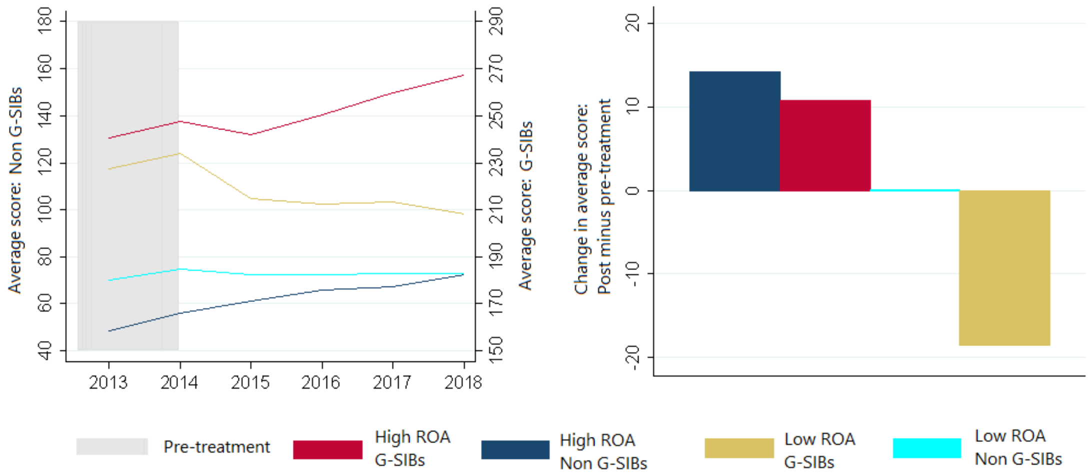
3.3 Exploring the differential impact across banks

The insignificant response by G-SIBs as a group could mask a differential effect on individual banks. Indeed, while the G-SIB framework provides *incentives* for banks to adjust their systemic footprint downwards – it does not impose any limits on banking activity. As such, the response to the framework reflects a cost-benefit analysis by the bank: the regulatory capital relief (surcharge) needs to be compared with the loss (gain) in revenue that stems from reducing (expanding) its market presence in specific financial activities, which entails a decrease (increase) in its G-SIB score. Profitability plays a crucial role in this cost-benefit analysis and is thus likely to determine the bank's optimal response.

Banks in the G-SIB assessment sample vary widely in terms of their profitability. Return on assets (ROA) – our core measure of profitability – has an inter-quartile range of 0.5% to 1.3% in the pooled sample (recall Table 2). Importantly, G-SIBs are neither significantly more nor less profitable than Non G-SIBs and there is no apparent correlation between a bank's ROA and score (Figure 5).[26] In the following, we categorise banks as more (high ROA) and less profitable (low ROA) based on whether their average pre-treatment ROA (2013–14) is above or below the median value of the sample distribution. Using pre-treatment ROA addresses endogeneity concerns that could arise from any impact of the G-SIB framework on bank profitability (see also Section 4.3). We note that, consistent with our observations above, neither G-SIBs nor Non G-SIBs are clustered in any one category (Figure 5).

[26] Standard t-tests cannot reject the hypothesis that the average pre-treatment ROA of G-SIBs is equal to that of Non G-SIBs (p-value = 0.25). Likewise, t-tests do not reject equality of the mean pre-treatment ROA of more (less) profitable G-SIBs and more (less) profitable Non G-SIBs, whereas they do reject equality for comparing the means of more and less profitable G-SIBs (Non G-SIBs). Moreover, the correlation between ROA and the adjusted G-SIB score is always insignificant, except in 2014 when

Figure 6: 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 *left-hand panel* shows the evolution of adjusted scores for more and less profitable G-SIBs and Non G-SIBs. The *right-hand panel* shows the change in adjusted average score for each category. The changes for high ROA Non G-SIBs (first bar) and low ROA G-SIBs (fourth bar) are significant; the others are insignificant.

The evolution of average score of more and less profitable G-SIBs and Non G-SIBs points to materially different trends post treatment (Figure 6). While all four *types* of banks increased their scores in parallel pre-treatment (ie between 2013 and 2014), less profitable G-SIBs decreased their scores substantially in the post-treatment period. More profitable banks, by contrast, continued to increase their scores. Compared to the finding that G-SIBs as a group only marginally lowered their average score post treatment, these observations uncover substantial heterogeneity in the potential effects of the G-SIB framework.

We consider several sub-sample regressions to assess how bank profitability shapes the impact of the framework on G-SIBs (Table 4). We find that the more profitable G-SIBs have not lowered their scores in a statistically significant manner relative to Non G-SIBs (columns (1) to (3), upper part of the table) or relative to only the more profitable Non G-SIBs (columns (4) to (6)). In sharp contrast, less profitable G-SIBs significantly

it is significant at the 10% level (p-value = 0.055).

Table 4: Sub-sample difference-in-differences on high ROA and low ROA G-SIBs

High ROA G-SIBs vs	All Non G-SIBs			High ROA Non G-SIBs		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB	2.371	5.816	14.39	–3.396	3.177	16.58
	(0.17)	(0.55)	(1.39)	(–0.24)	(0.34)	(1.50)
Post	8.438***	3.697		14.21***	2.504	
	(3.29)	(1.26)		(4.60)	(0.68)	
G-SIB	183.5***			191.8***		
	(4.29)			(4.45)		
N	288	253	214	204	186	172
R2	0.555	0.985	0.992	0.530	0.986	0.993
Bank controls and FE	No	Yes	Yes	No	Yes	Yes
Country-year FE	No	No	Yes	No	No	Yes
Low ROA G-SIBs vs	All Non G-SIBs			Low ROA Non G-SIBs		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB	–26.99***	–24.16***	–22.81**	–18.76**	–22.67**	–24.71**
	(–3.10)	(–3.56)	(–2.66)	(–2.07)	(–2.74)	(–2.45)
Post	8.438***	6.393**		0.200	1.995	
	(3.30)	(2.60)		(0.06)	(0.35)	
G-SIB	170.3***			158.4***		
	(7.80)			(6.94)		
N	318	279	252	198	172	154
R2	0.661	0.983	0.991	0.564	0.978	0.989
Bank controls and FE	No	Yes	Yes	No	Yes	Yes
Country-year FE	No	No	Yes	No	No	Yes

Note: The table reports results of the regression in equation 1, for various sub-samples indicated in column headings. The dependent variable is the adjusted G-SIB score. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once since 2013. Bank-level controls include the CET1 capital ratio, return on assets, the ratio of non-performing loans to total loans, cost to income ratio, cash to assets, deposit to total liabilities, and the density ratio. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$.

decreased their scores relative to Non G-SIBs (columns (1) to (3), lower part of the table). They have also lowered their scores relative to the less profitable Non G-SIBs (columns (4) to (6)). The magnitude of the effect, between 19 to 27 bps, is economically meaningful considering that the official buckets are 100 bps in size. This shows that G-SIB designation played a key role in driving the reduction in the scores even after accounting for any general pressure on chronically unprofitable banks to restructure their balance sheets. The regression results thus reinforce the (unconditional) visuals shown in Figure 6.

To *jointly* assess the differential trends among more and less profitable G-SIBs and Non G-SIBs, we adopt the following *triple-interaction* specification:

$$score_{i,t} = \beta\,[post_t \times gsib_i \times profitability_i] + \gamma X_{i,t} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}. \tag{2}$$

Here $profitability_i$ is measured as the *level* of bank i's average pre-treatment ROA. This definition avoids taking a stance on the threshold that distinguishes the more from the less profitable banks. For robustness, we also define profitability as a *dummy* that equals 1 (0 otherwise) if the average pre-treatment ROA of the bank is above the sample median, as in the subsample DDs. We always include the full set of interaction terms (eg $post_t$, $post_t \times gsib_i$) in the regressions (depending on the fixed effects), although they are not explicitly stated in equation (2) for the sake of brevity.

Our main hypothesis is that $\hat{\beta}$, the coefficient on the triple interaction term, is positive. This would imply that more-profitable G-SIBs increased by more (or reduced by less) their score after treatment compared to the change in score of the less profitable G-SIBs, after controlling for trends in the score of Non G-SIBs. Specifically, with the median profitability dummy and no fixed effects or controls in specification (2), $\hat{\beta}$ equals:

$$\hat{\beta} = \Big[\Big(\overline{score}_{\text{More profitable G-SIB, post}} - \overline{score}_{\text{More profitable G-SIB, pre}}\Big) - \Big(\overline{score}_{\text{Less profitable G-SIB, post}} - \overline{score}_{\text{Less profitable G-SIB, pre}}\Big)\Big] - \Big[\Big(\overline{score}_{\text{More profitable Non-G-SIB, post}} - \overline{score}_{\text{More profitable Non-G-SIB, pre}}\Big) - \Big(\overline{score}_{\text{Less profitable Non-G-SIB, post}} - \overline{score}_{\text{Less profitable Non-G-SIB, pre}}\Big)\Big]$$

where $\overline{score}$ represents the average score.

The regression results in Table 5 support our hypothesis. The unsaturated specification in column (1) without fixed effects and measuring profitability in levels shows that,

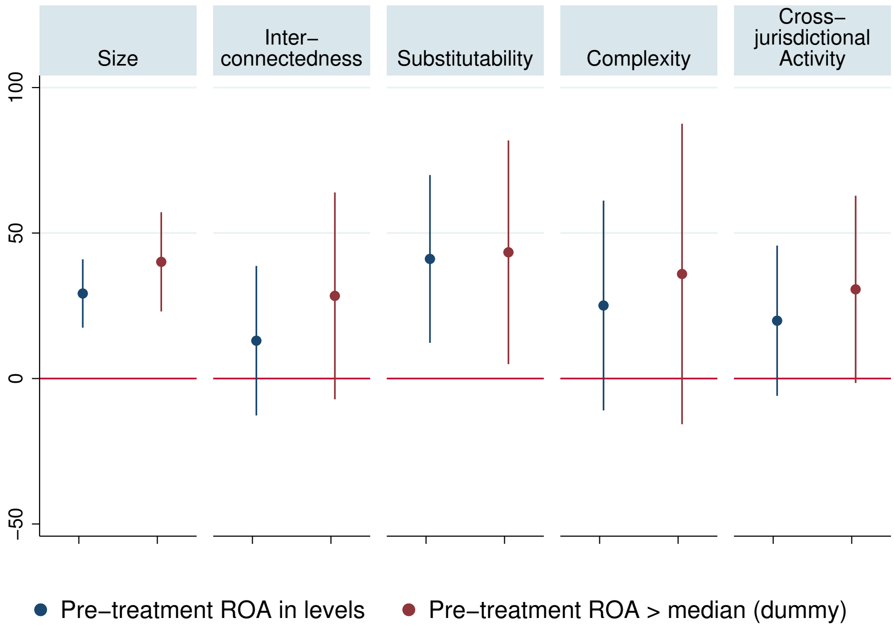
Table 5: Triple-interaction regression results

Profitability measure:	Pre-treatment ROA in levels			Pre-treatment ROA > median (dummy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB × Profitability	33.87***	31.03***	25.66***	20.87	25.23*	35.70**
	(2.72)	(2.74)	(2.70)	(1.24)	(1.75)	(2.57)
Post × G-SIB	–39.08***	–37.39***	–29.53**	–17.71*	–19.16**	–21.86**
	(–3.15)	(–3.30)	(–2.53)	(–1.91)	(–2.30)	(–2.39)
Post × Profitability	7.639*	7.675	12.45	8.493	6.220	–5.329
	(1.68)	(1.65)	(1.40)	(1.60)	(1.13)	(–0.41)
G-SIB × Profitability	–10.36			29.39		
	(–0.35)			(0.61)		
Post	–4.249	–4.215		–0.848	–0.317	
	(–0.86)	(–0.72)		(–0.21)	(–0.07)	
G-SIB	187.0***			164.8***		
	(5.97)			(7.39)		
Profitability	–10.88*			–16.15**		
	(–1.73)			(–2.14)		
N	455	397	363	455	397	363
R2	0.577	0.984	0.991	0.584	0.983	0.991
Bank controls and FE	No	Yes	Yes	No	Yes	Yes
Country-time FE	No	No	Yes	No	No	Yes

Note: The table reports results of the regression in equation 2 for the full sample. The dependent variable is the adjusted G-SIB score. *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 since 2013. The profitability measure is always based on average pre-treatment (i.e. 2013-14) ROA data, either in levels in columns 1-3, or as an above median dummy in columns 4-6. Bank-level controls include the CET1 capital ratio, the ratio of non-performing loans to total loans, cost to income ratio, cash to assets, deposit to total liabilities, and the density ratio. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

on average, more profitable G-SIBs increased their score by about 34 bps after treatment relative to trends in the control group. Accounting for bank controls and fixed effects (column (2)) and country-year fixed effects (column (3)) leads to a similar conclusion, even though the economic significance, as measured by the magnitude of the coefficient, declines somewhat to 26 bps. These findings are consistent with the observations based on Figure 6 and Table 4. With the above-median dummy as the measure of profitability, we find that the coefficient on the triple interaction terms remains statistically significant once we include the various controls (columns (5) and (6)). Overall, these results reinforce the differential effect of the G-SIB framework we uncovered using the subsample DDs.

Figure 7: Coefficients from category score regressions

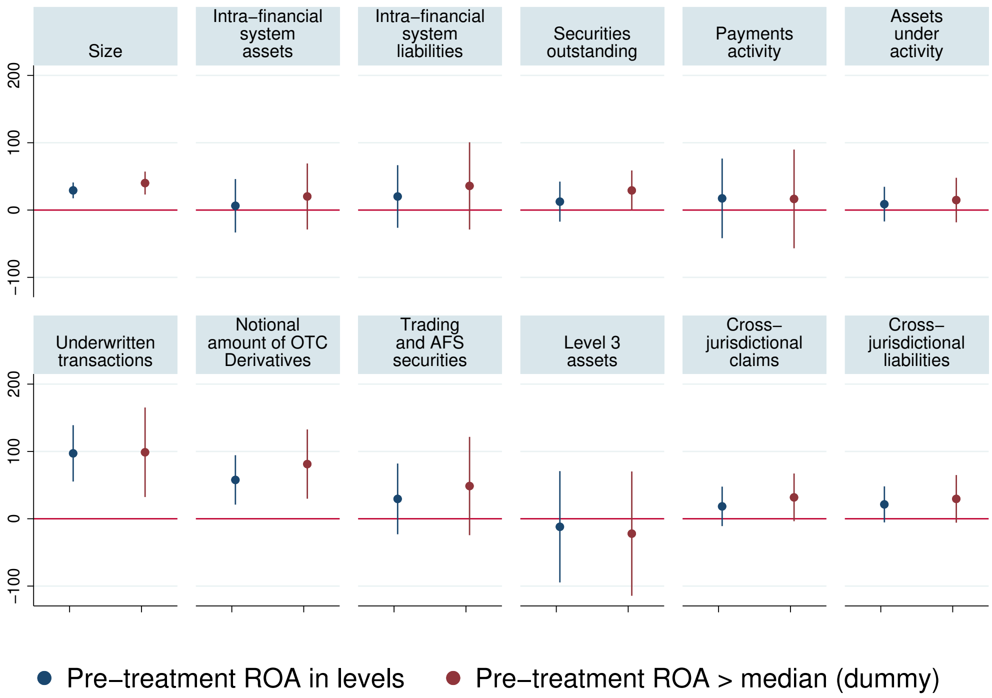


Note: The figure shows results based on the specification in equation (2). The dependent variables are the respective category scores, and the specification includes a full set of bank fixed effects and controls, as well as country-year fixed effects. The results are in Table C.1. The coefficients on the triple interaction of $Post \times G-SIB \times Profitability$ are shown here as circles, for the two measures of profitability: average pre-treatment (2013-14) ROA in levels on the left, and as an above-median dummy on the right, in each sub-panel. 90% confidence intervals are indicated based on robust standard errors clustered at bank level.

3.4 Banks' adjustment margins

We zoom into the five categories that constitute the overall G-SIB score to assess banks' margins of adjustment. We run specification (2) with the adjusted *category* scores as the dependent variable. Figure 7 plots the coefficient estimates of the triple interaction term for each category, with the detailed results presented in Table C.1 in the appendix. More profitable G-SIBs – be it in terms of pre-treatment ROA levels (blue dots) or the corresponding above-median ROA dummy (red dots) – raised their scores relative to the less profitable G-SIBs along all categories, and significantly so in the case of Size and Substitutability.

Figure 8: Coefficients from indicator score regressions



Note: The figure shows results based on the specification in equation (2). The dependent variables are the respective indicator scores, and the specification includes a full set of bank fixed effects and controls, as well as country-year fixed effects. The results are in Tables C.2 and C.3. The coefficients on the triple interaction of $Post \times G-SIB \times Profitability$ are shown here as circles, for the two measures of profitability: average pre-treatment (2013-14) ROA in levels on the left, and as an above-median dummy on the right, in each sub-panel. 90% confidence intervals are indicated based on robust standard errors clustered at bank level.

Zooming in even further, we find that the increase in the average score of more profitable G-SIBs is driven by a significantly higher footprint along a few of the G-SIB *indicators*. Running specification (2) on the adjusted *indicator* scores reveals that, in addition to size (the only single-indicator category), key margins of adjustment are underwriting activities and OTC derivatives (see Figure 8 and Tables C.2 and C.3 in the appendix).

While an in-depth analysis of the causal link between these indicators and bank profitability is beyond the scope of this paper, we can link our findings to related results in the literature. There are various reasons why *size* and profitability may be positively related, which can help explain the result that more profitable G-SIBs continued to increase their size score after treatment. Regehr and Sengupta (2016), for instance, document a positive correlation between size and profitability in the United States. The authors argue that increasing size can increase profitability by allowing banks to economise on fixed costs. Greater size may also pose diversification benefits, as discussed in Mester (2010), for instance.

Our result on *underwriting transactions* is consistent with prior research suggesting that financial firms with higher market-share and reputation account for a larger share of underwriting business (see, for example, Carter *et al.*, 1998; Krigman *et al.*, 2001; Santiago *et al.*, 2020; William and Weiss, 1991). The positive coefficient suggests that as the more profitable G-SIBs expanded their market-share relative to the less profitable ones, they were able to attract a higher share of the global underwriting business as well. Likewise, we observe a significant wedge opening up in G-SIBs' *notional amounts of OTC derivatives*. Consistent with the high fixed costs associated with OTC trading (Faruqui *et al.*, 2018), the more profitable G-SIBs appear to have adjusted more easily to rising capital charges on non-cleared derivatives (CGFS, 2018) and have expanded their OTC derivative portfolios relative to the less profitable G-SIBs.

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

3.5 Proximity to bucket thresholds

This section concludes by inspecting the behaviour of banks that are close to their G-SIB bucket thresholds. Distance from bucket thresholds represent an ideal source of exogenous variation in the regulatory treatment. The thresholds introduce a discontinuity in the

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

	High ROA G-SIBs vs		Low ROA G-SIBs vs		All banks	
	High ROA Non G-SIBs (1)	All Non G-SIBs (2)	Low ROA Non G-SIBs (3)	All Non G-SIBs (4)	(5)	(6)
Post × G-SIB × Profitability					25.60***	26.31***
					(2.66)	(2.85)
Post × G-SIB	16.60	14.25	–25.10**	–23.11**	–29.29**	–30.42***
	(1.52)	(1.38)	(–2.40)	(–2.62)	(–2.51)	(–2.74)
Post × Profitability					12.69	12.77
					(1.42)	(1.46)
Close to bucket threshold	2.242	1.930	–12.85*	–7.669	–3.546	
	(0.30)	(0.25)	(–1.97)	(–1.13)	(–0.56)	
High ROA bank close to threshold						5.078
						(0.60)
Low ROA bank close to threshold						–15.94**
						(–2.41)
N	189	245	164	283	363	363
R2	0.993	0.993	0.991	0.992	0.991	0.991
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes

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

capital requirements absent any confounding economic rationale for why banks with a score close to the threshold should behave differently than banks with a similar score yet somewhat more distant from the threshold.

We test whether banks that are close to the threshold have reduced their scores relatively more than other banks. Following Behn *et al.* (2019), we measure closeness by defining an indicator variable that is equal to one (zero otherwise) if a bank's official G-SIB score is within 20 basis points of the bucket threshold. This is the case for about one fifth of the bank-year observations, with no notable differences between the more and less profitable banks. Table 6 depicts the estimates for this indicator based on assessing individually the more profitable G-SIBs (columns (1) and (2)), the less profitable ones

((3) and (4)), and for regressions based on the entire sample ((5) and (6)).

We observe that less profitable G-SIBs which are close to the threshold reduce their scores by even more than those that are not, consistent with these banks' stronger incentives to reduce their systemic footprint. Indeed, the additional contraction amounts to nearly half the one observed for less profitable G-SIBs on average in two of our specifications (columns (3) and (6)). Closeness, however, does not appear to influence the more profitable G-SIBs' adjustment, with none of the specifications pointing to any notable difference in the banks' pattern of adjustment.

4 Robustness

We conduct a range of robustness checks to confirm that bank profitability, rather than other factors such as the banks' business model or domicile, is the main determinant of the banks' response to the framework. We start by restricting the sample to those banks for which we have data in each year from 2013 to 2018. This reduces the number of banks from 84 to 67. Our findings are robust to this change, both in terms of economic and statistical significance as reported in Table 7 (column (1)).

We adjusted the official G-SIB score, as discussed in Section 3.1, to allow for a causal interpretation of our results. To ensure that this adjustment did not yield a pattern of score changes that is fundamentally different from the official ones, we use the official score as the dependent variable in specification (2). The result tallies with the baseline findings in terms of the sign and statistical significance of the triple interaction term (Table 7, column (2)). As expected, the coefficient is biased upwards in this regression. Given the relative setup of the official scores, an increase in the more profitable G-SIBs' scores, all else equal, mechanically leads to a decline in the scores of the less profitable ones.

Table 7: Balanced sample and alternative G-SIB and treatment dummies

	Balanced sample	Official G-SIB score	Official G-SIB dummy	Pre-treatment G-SIB dummy	Bank-specific treatment	Control for Capital-buffer	Control for CAPM Beta
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × G-SIB × Profitability	25.23**	34.33***	22.02**	23.05**	26.37**	23.98**	26.23**
	(2.60)	(4.21)	(2.36)	(2.48)	(2.49)	(2.51)	(2.47)
Post × G-SIB	-28.99**	-36.47***	-29.10**	-27.97**	-31.40**	-26.87**	-32.95***
	(-2.47)	(-3.23)	(-2.63)	(-2.48)	(-2.54)	(-2.26)	(-2.83)
Post × Profitability	13.43	4.494	14.41	15.58	-0.387	13.88	5.343
	(1.38)	(0.63)	(1.66)	(1.65)	(-0.04)	(1.56)	(0.65)
N	332	363	363	352	363	363	317
R2	0.990	0.992	0.991	0.991	0.991	0.991	0.991
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
G-SIB score	Adjusted	Official	Adjusted	Adjusted	Adjusted	Adjusted	Adjusted
Post dummy	2015	2015	2015	2015	Bank-specific	2015	2015
G-SIB dummy	Baseline	Baseline	Official	Pre-treatment	Baseline	Baseline	Baseline

Note: The table reports robustness checks on the baseline results in Table 5 using equation 2. Balanced sample in column (1) includes only those banks in the sample which have always been in the G-SIB assessment sample. Column (2) uses the official G-SIB score instead of the adjusted one, while in column (3) the G-SIB dummy is determined by the official designation year. In column (4), all banks who become G-SIBs after treatment are considered as Non G-SIBs. Column (5) allows for bank-specific treatment years based on the text analysis in section 2.2. Finally, in columns (6) and (7), we also include respectively the capital buffer and the CAPM Beta as controls. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once since 2013. *Profitability* is the level of average pre-treatment (2013-14) ROA. Bank-level controls include the CET1 capital ratio, the ratio of non-performing loans to total loans, cost to income ratio, cash to assets, deposits to total liabilities, and the density ratio. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

In our main analysis, we categorise all banks as G-SIBs that have been designated as such at least once since 2013. In doing so, we control for any confounding effects resulting from banks switching the treatment and control group. To assess whether this definition influences our results, we construct an alternative G-SIB indicator based on the official year-wise G-SIB designation. That is, the dummy equals 1 only in those years when the bank is designated a G-SIB. As shown in Table 7, column (3), our results are little affected by this alternative definition. Similarly, categorising all banks as Non G-SIBs that are designated as G-SIBs only after 2015 (the treatment year) has no notable impact on our results (column (4)). These results tally with the fact that only a few banks transition into or out of being a G-SIB.

Next, we consider a bank-specific treatment date depending on when the text analysis of a bank's annual report shows the most discussion of its response to the G-SIB framework. For instance, a bank whose 2014 annual report contains a greater number of framework related keywords in categories 4 and 5 is considered to be treated in 2014 instead of 2015 (recall Figure 4). For banks without any such discussion in their reports in either 2014 or 2015, we set the treatment date to 2016, the year when the G-SIB capital surcharges take effect. Our findings are robust to this variation as presented in column (5) of Table 7.

We also assess whether differences in the size of the banks' capital buffers shaped the response to the framework. In our main analysis, we control for differences in the CET1 capital ratio across banks. However, the G-SIB surcharges imply that capital buffers – as measured by the difference between the CET1 ratio and the sum of minimum capital requirements and the fully-loaded surcharge – can differ across banks even if they have the same CET1 capital ratio. We thus replace the CET1 capital ratio with the capital buffer in our main regressions. Our findings do not change as a result of this inclusion (Table 7, column (6)).

Finally, we gauge whether the more profitable G-SIBs' adjustment is driven by a higher opportunity cost of reducing their scores or whether it reflects a lower cost of issuing capital to meet higher capital requirements. To disentangle these effects, we control for differences in banks' cost of equity as inferred from their systematic risk ("Beta"). We estimate the latter based on a standard Capital Asset Pricing Model using 50-week rolling regressions of banks' weekly excess returns on the excess return of their domestic benchmark indices (see also Table 2). We find that accounting for variation in banks' Betas has no meaningful impact on the coefficients of interest as shown in column (7) of Table 7. This lends support to the interpretation that for more profitable G-SIBs, higher opportunity costs of downsizing rather than the cost of capital are keeping them from reducing their systemic footprint.

Table 8: Robustness based on alternative profitability and efficiency metrics

	Return on assets (2014)		Return on equity		Cost-to-income efficiency	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB × Profitability	25.57**	37.54**	2.453***	37.88***	1.123***	29.20*
	(2.38)	(2.56)	(3.58)	(2.81)	(2.83)	(1.73)
Post × G-SIB	–29.77**	–23.54**	–42.69***	–20.12**	–49.65**	–14.30
	(–2.20)	(–2.35)	(–3.36)	(–2.08)	(–2.42)	(–1.37)
Post × Profitability	9.383	–15.94	0.319	–24.38	0.126	–16.14
	(0.87)	(–0.84)	(0.58)	(–1.33)	(0.22)	(–1.33)
N	363	363	363	363	363	363
R2	0.991	0.990	0.991	0.990	0.991	0.990
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Profitability	Level	Dummy	Level	Dummy	Level	Dummy

Note: The table reports results of the regression in equation 2 using alternate measures of profitability. The dependent variable is the adjusted G-SIB score. In columns (1) and (2), *profitability* is based on ROA in 2014 only; in columns (3) and (4), *profitability* is based on the average pre-treatment (2013-2014) return on equity, and in columns (5) and (6), it is based on average pre-treatment cost-to-income efficiency. All other variables are as defined in Table 5. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

4.1 Alternative profitability measures, and risk-adjustment

We consider alternative measures of profitability to further assess the robustness of our findings based on the specification in (2). For each measure, we consider both its level as well as a dummy that distinguishes the more from the less profitable banks based on the median value of the respective measure.

Table 8 reports the results based on substituting the average ROA in the pre-treatment period (our baseline measure) with the ROA in 2014, i.e. the most recent observation before the treatment. In addition, we consider the average pre-treatment return on equity and an estimate of the banks' efficiency, measured as one minus the bank's cost-to-income ratio.[27] The findings are consistent with our main conclusions both in terms of statistical and economic significance.

We also assess whether risk-adjusted measures of profitability support our previous findings. The motivation is that higher profitability could reflect higher risk tolerance (eg Martynova *et al.*, 2020), suggesting that the observed shift in systemic importance

[27] While return on equity is widely used by equity analysts, an important drawback is that differences in national tax regimes could blur its comparison across banks in our global sample.

Table 9: Robustness with risk-adjusted profitability measures

	Return on risk-weighted assets		Risk-adjusted return on assets		Z-score	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB × Profitability	24.30***	42.95***	4.495***	32.29**	0.796**	31.19**
	(4.67)	(3.43)	(4.32)	(2.08)	(2.59)	(2.31)
Post × G-SIB	–58.27***	–27.48***	–34.86***	–19.61	–37.91**	–20.98*
	(–4.41)	(–3.06)	(–3.57)	(–1.58)	(–2.62)	(–1.98)
Post × Profitability	7.130*	0.795	1.476**	–7.268	0.254	6.354
	(1.70)	(0.07)	(2.06)	(–0.45)	(1.34)	(0.73)
N	363	363	363	363	363	363
R2	0.992	0.992	0.992	0.990	0.991	0.991
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Profitability	Level	Dummy	Level	Dummy	Level	Dummy

Note: The table reports results of the regression in equation 2 using risk-adjusted measures of profitability. The dependent variable is the adjusted G-SIB score. In columns (1) and (2), $profitability$ is based on return on risk-weighted assets; in columns (3) and (4), it is based on risk-adjusted return on assets, and in columns (5) and (6), it is based on the Z-score. All other variables are as defined in Table 5. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

towards more profitable G-SIBs implies a build-up in risk-taking rather than a reallocation in favour of more efficient and better-run banks (Peni and Vähämaa, 2012).

Table 9 depicts the estimates for three alternative measures of profitability that account for underlying risks: the return on risk-weighted assets (RORWA), the risk-adjusted return on assets (RAROA) and the Z-score. For each of these measures the coefficient of interest – the one on the triple interaction term – remains comparable to our baseline result, not only in terms of statistical but also economic significance. This implies that fundamental differences in profitability, rather than risk-seeking, explain the differential impact of the framework on G-SIBs.

4.2 Geographical factors

One potential concern is that geographical factors may be driving our findings, such as national regulatory reforms or different macroeconomic developments in banks' home jurisdiction. We include country-year fixed effects throughout our main analysis to address this concern. However, to further examine this issue, we pursue two sets of additional

Table 10: Sub-sample regressions based on country groups

	Exclude US	Only Europe	Only Asia-Pacific	Only EMEs
	(1)	(2)	(3)	(4)
Post × G-SIB × Profitability	37.39***	72.56*	28.21***	96.80***
	(4.48)	(1.72)	(3.08)	(2.94)
Post × G-SIB	–37.38***	–52.46***	–28.48*	–153.2**
	(–3.31)	(–3.22)	(–1.75)	(–2.41)
Post × Profitability	15.58*	10.99	24.89**	3.409
	(1.73)	(0.68)	(2.47)	(0.43)
N	307	137	136	95
R2	0.990	0.990	0.989	0.988
Bank controls and FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes

Note: The table reports results of the regression in equation 2 for different sub-samples indicated in column headings. The dependent variable is the adjusted G-SIB score. Asia-Pacific sub-sample in column (3) comprises banks from Japan, China, India, Australia, Singapore, Korea, and Russia. All other variables are as defined in Table 5. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

investigations.

First, we consider sub-sample regressions that focus on major country groups based on geographical regions or level of economic development. This provides further insights into whether our findings are also valid *within* these groups. We find that excluding US banks, which are subject to a more stringent national G-SIB requirement, or focusing only on European or Asia-Pacific banks leads to similar findings (Table 10).[28] Likewise, restricting the sample to banks from emerging market economies (EMEs) also implies that profitable G-SIBs increased their systemic footprint significantly.

Second, we assess whether the banks' origin, rather than the G-SIB designation, is driving our conclusions. We replace the G-SIB dummy by a country-group dummy that identifies banks *from* a specific region. However, profitable banks from specific regions have not changed their scores relative to their peers in a statistically significant manner as shown in the top row of Table 11.

[28] Given the limited number of observations in the BCBS dataset, not all sub-sample regressions are feasible. For instance, focusing exclusively on US banks leaves only 56 observations, of which merely 15 relate to Non G-SIBs.

Table 11: Replacing G-SIB dummy with a country group dummy

	US	Europe	Asia-Pacific	EME
	(1)	(2)	(3)	(4)
Post × Group × Profitability	–16.79	17.85	22.41	9.064
	(–0.88)	(0.68)	(0.98)	(0.38)
Post × Profitability	34.07**	21.59**	21.81**	24.11**
	(2.48)	(2.04)	(2.28)	(2.49)
N	363	363	363	363
R2	0.990	0.990	0.990	0.990
Bank controls and FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes

Note: The table reports results of the regression in equation 2 for different sub-samples indicated in column headings. The dependent variable is the adjusted G-SIB score. Asia-Pacific sub-sample in column (3) comprises banks from Japan, China, India, Australia, Singapore, Korea, and Russia. All other variables are as defined in Table 5. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

4.3 Endogenous profitability and business model

We have assessed the role of profitability in shaping banks' response to the G-SIB framework. However, the framework could also affect banks' profitability. This suggests to account for the possibility of reverse causality. While our choice of pre-treatment profitability as an indicator of fundamental bank characteristics should address this issue, we pursue additional checks in this section to alleviate any remaining concerns.

First, we assess how banks' ROA has evolved over time. The correlation is high and statistically significant, indicating that differences in profitability across banks are highly persistent (Table 12). Only in less than 10 percent of the observations does a more profitable bank, based on the median profitability dummy in the pre-treatment period, drop below the median threshold in the post-treatment period (or vice-versa). Profitability is thus a relatively stable characteristic of banks during the period under study. As such, it provides a reliable measure of the structural features of banks that underpin their response to the G-SIB framework.

Second, we control for differences in banks' business models. The business model might be considered an omitted variable that might not be fully accounted for in the bank controls already incorporated in our main regressions. This could bias our results

Table 12: Pearson's correlation coefficients of ROA

	2013	2014	2015	2016	2017	2018
2013	1					
2014	0.93	1				
2015	0.85	0.85	1			
2016	0.79	0.85	0.70	1		
2017	0.78	0.76	0.63	0.88	1	
2018	0.71	0.69	0.60	0.80	0.94	1

Note: The table reports the correlations in banks' yearly ROAs. All correlations are statistically significant at the 1% level.

Table 13: Robustness: Control for business models

	Level			Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB × Profitability	28.24***	27.93***	27.60***	38.96***	39.04***	38.78***
	(3.18)	(3.11)	(3.10)	(2.94)	(2.91)	(2.90)
Post × G-SIB	–31.30***	–30.85***	–30.64***	–23.15**	–23.06**	–23.08**
	(–2.80)	(–2.70)	(–2.68)	(–2.60)	(–2.52)	(–2.53)
Post × Profitability	12.88	13.55	13.86	–3.726	–4.085	–3.946
	(1.49)	(1.56)	(1.62)	(–0.28)	(–0.31)	(–0.30)
N	368	368	368	368	368	368
R2	0.991	0.991	0.991	0.990	0.990	0.990
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of business model clusters	4	3	2	4	3	2

Note: The table reports results of the regression in equation 2 with the inclusion of business model clusters as additional regressors (details in Appendix D). There are three variations with four, three, and two clusters. The dependent variable is the adjusted G-SIB score. All other variables are as defined in Table 5. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

if the business model affects both pre-treatment profitability as well as the G-SIB score. We allocate banks to different business models based on an additional set of balance sheet characteristics using cluster analysis (discussed in detail in Appendix D). This yields a time-varying business model allocation for each bank, which we include as an additional regressor in our baseline specification. The results in Table 13 show that controlling for the difference in business models leaves the coefficient of interest little changed.

4.4 Alternative estimation strategies

We further assess the robustness of our main findings by considering alternative estimation strategies based on matching banks. Specifically, we estimate the average treatment effect on profitable G-SIBs and less profitable ones relative to Non G-SIBs. While our main empirical approach is based on using the level of the banks' scores, we now define our dependent variable as the difference in each bank's average post-treatment score (2015–18) and the corresponding average pre-treatment score (2013–14). We include only banks for which scores are available in each year to ensure that the measure is comparable across banks. This results in 59 observations in total.

To match the banks, we start from the full set of balance sheet and income variables (scaled by the bank's total assets and transformed into z-scores to account for differences in the variance across variables) that underpin the cluster analysis of bank business models (see Section 4.3 above). We add to these the pre-treatment ROA and CET1 ratio of the banks. The underlying assumption is that by controlling for the banks' business model characteristics any remaining influences on the treatment are not related to the potential outcome. We then compare the covariate distributions for the treatment and control group and drop those covariates for which marked differences between G-SIBs and Non G-SIBs lead to a poor overlap, i.e. non-interest income and securities holdings, respectively. Matching is thus based on six variables in total.[29]

The results from the matching approach accord with our main finding of a heterogeneous impact of the framework on G-SIBs depending on the banks' profitability and, accordingly, the tightness of the regulatory constraint. Column (1) of Table 14 presents the average treatment effect for the less profitable G-SIBs – i.e., those with a pre-treatment ROA below the median of banks – and the corresponding estimate for the profitable ones

[29]The selection of variables differs from the time-varying bank controls used in our main analysis to make the robustness check more demanding.

Table 14: Assessing robustness based on matching

Average treatment effect on:	(1)	(2)	(3)	(4)
Less profitable G-SIBs	–27.84***	–35.43***	–24.87***	–35.65***
	(–3.06)	(–4.11)	(–3.30)	(–3.23)
More profitable G-SIBs	3.01	0.10	–4.20	20.05
	(–0.23)	(–0.01)	(–0.38)	(–0.74)
More vs less profitable G-SIBs	30.85***	35.53***	20.67*	55.71**
	(–2.75)	(–2.63)	(–1.89)	(–2.21)
N	59	59	59	59
Covariates	Balanced	All	Balanced	Balanced
Matching	Propensity score	Propensity score	Nearest neighbour	Inverse prob. weighting

Notes: The dependent variable is the difference in average post-treatment (2015–18) and pre-treatment (2013–14) score, based on a balanced sample of 59 banks, and z-values are indicated in parentheses. Covariates: *balanced* = z-score of pre-treatment: returns, loans, cash, deposits, wholesale funding (all as a share of total assets) and CET1 capital ratio; *all* = same as *balanced* but also adding the z-score of pre-treatment securities and non-interest income (as a share of total assets). Nearest neighbour matching is based on using 4 neighbours and imposing that G-SIBs with pre-treatment ROA above (below) the corresponding median are only matched with Non G-SIBs that fall into the same ROA category. The level of pre-treatment ROA is excluded from the list of covariates in this regression.

for matching based on propensity scores. Column (2) reports the corresponding results based on the full, i.e. less balanced, set of covariates for comparison. In column (3) we report the estimated effect based on matching each G-SIB with its four nearest Non G-SIB neighbours, where we impose the additional restriction that (less) profitable G-SIBs are always matched with (less) profitable Non G-SIBs. In column (4), we consider the case of a multi-valued treatment, assuming a priori that the treatment differs for profitable and less profitable G-SIBs. We fit a multinomial logistic regression to estimate the probability of treatment. We then use the inverse-probability weights in a weighted regression model of the outcome for each treatment level.

Overall, the estimates suggest a decline in less profitable G-SIBs' scores, in a range of about 25 to 35 basis points relative to the matched Non G-SIBs. By contrast, we find no significant impact on the profitable G-SIBs relative to Non G-SIBs. Accordingly, our estimates tally with our earlier finding in Section 3.3 of a large and statistically significant difference in the effect of the G-SIB framework on the two groups of G-SIBs.

5 Should regulators be concerned?

We have shown that less profitable G-SIBs have decreased their average systemic footprint after treatment. The more profitable G-SIBs, however, have increased the same, and significantly so in relative terms i.e. in comparison to their less profitable peers. And although high ROA G-SIBs appear to outperform their peers even after accounting for risks, as discussed in Section 4.1, the adjustment by these banks raises the question of how systemic risks have evolved in the global banking sector.

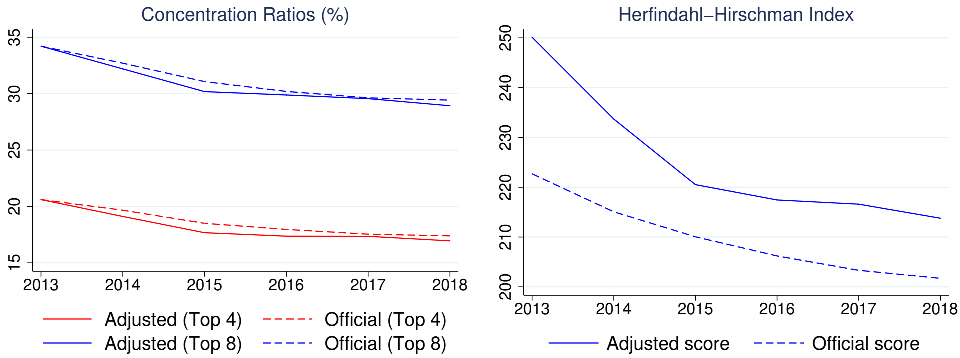
5.1 Systemic concentration

One dimension to consider is how the reallocation among G-SIBs has affected the concentration of systemic importance. To assess the underlying trends, we calculate two concentration ratios, based on the market share of the top–4 and the top–8 banks with the highest G-SIB scores. We also consider the commonly used Herfindahl-Hirschman Index. Figure 9 plots the results for the adjusted scores (solid lines) and for comparison, those based on the official scores (dashed lines). We note that concentration within the global sample of banks has decreased somewhat, irrespective of whether we consider the official or the adjusted scores. This suggests that the decline in the scores of less profitable G-SIBs has more than compensated for the increase in the scores of profitable G-SIBs and Non G-SIBs (recall Figure 6).

5.2 Systemic risk contribution

The systemic risk contribution of a bank depends on two factors. The first one is the impact its failure would have on the financial system, ie its systemic importance or systemic loss-given-default. The second factor is the bank's probability of default. Thus far, we have focused on the adjusted scores as a proxy for banks' systemic importance.

Figure 9: Concentration ratios and Herfindahl-Hirschman Index



Note: The *left-hand panel* shows the evolution of the concentration ratios (ie the combined market share of the 4 and respectively 8 banks with the highest score). The *right-hand panel* shows the Herfindahl-Hirschman Index.

We now turn to assessing trends in G-SIBs' probability of default to shed further light on the evolution of G-SIBs' systemic risk contribution since the framework's introduction.

We rely on market-based measures of default risk to approximate banks' systemic risk contribution. Specifically, we consider the 1-year probability of default (PD) implied by CDS spreads and the expected default frequency (EDF) over the same horizon. Multiplying measured default risk with the adjusted G-SIB score yields an estimate of the expected impact of failure, an approximation of the banks' systemic risk contribution. Table 15 reports the change in each of these measures based on the difference in the pre- and the post-treatment mean, while also reporting the statistical significance of these changes. For comparison, we also show the corresponding values for SRISK.[30]

For G-SIBs as a group neither the default risk measures (Table 15, columns (1) and (3)) nor the systemic importance (recall Section 3.2) have decreased significantly post treatment. Taken together, however, these reductions have led to a (weakly significant) reduction in the systemic risk contribution (columns (2) and (4)). SRISK, in turn, has

[30]Several measures of systemic risk have been proposed in the literature, each covering different dimensions of systemic risks, but no single measure comprises all dimensions. We consider SRISK, which has been widely used in academic research, alongside a combination of default risk and the G-SIB score in our assessment.

Table 15: Changes in risk-measures from pre- to post-treatment

	(1) PD	(2) PD x Score	(3) EDF	(4) EDF x Score	(5) SRISK
G-SIBs	–.029	–10.598*	–.069	–23.643*	–.378
	(–1.55)	(–1.87)	(–1.37)	(–1.94)	(–1.1)
Less profitable G-SIBs	–.055*	–19.672**	–.122**	–47.035***	–.505
	(–1.88)	(–2.23)	(–2.13)	(–3.05)	(–1.47)
More profitable G-SIBs	.009	2.666	.009	10.546	–.204
	(.8)	(1.03)	(.11)	(.66)	(–.31)

Note: The table shows changes from pre- to post-treatment. The numbers in brackets show the z-scores. Estimates are obtained by adding all the coefficients with a 'post' dummy in specification (1) (first set of row) or (2) (second and third sets of rows). *PD* is the 1-year CDS-implied probability of default. *EDF* is the 1-year expected default frequency. *Score* is the G-SIB score. *SRISK* is a measure of systemic risk from NYU Vlab.

also declined for G-SIBs, although the change is small and statistically insignificant.

Closer inspection reveals that default risks have declined for the less profitable G-SIBs, resulting in a significant decline in their systemic risk contribution – in line with the regulatory objective of the G-SIB framework. However, for the more profitable G-SIBs market perceptions of the banks' default risks have not declined in the post-treatment years despite a notable increase in the banks' capital ratios and greater reliance on more stable sources of funding (Goel *et al.* (2019)). Combined with the increase in the systemic importance of these banks, we observe a small, but insignificant increase in their systemic risk contribution. This accords with an equally insignificant change in SRISK.

6 Conclusion

In this paper, we assess whether the global regulatory framework for large global banks has encouraged these banks to lower their systemic footprint. Our analysis paints a mixed picture of the effect of the framework. The less profitable G-SIBs reduced their scores in response to the treatment. This stands in contrast to the more profitable ones. They have continued to increase their systemic footprint, with key margins of adjustments being the banks' size as well as their underwriting and OTC derivatives business.

Banks' strategic responses to the framework invite the question of whether the outcome is consistent with regulatory objectives. To the extent that regulation seeks to equalise the systemic risk contribution across banks, the rising systemic importance of some banks warrants monitoring of whether there has been a commensurate decline in the banks' default risks. In this context, higher capital surcharges as suggested by Passmore and von Hafften (2019), or a steeper surcharge schedule could bolster G-SIBs' resilience. However, our findings imply that higher surcharges could accelerate the reduction in the scores of the less profitable G-SIBs, thus widening the wedge between these banks and their more profitable competitors. This could lead to greater concentration of systemic importance in the global banking sector and revive too-big-to-fail concerns. Moreover, this could expose the limits of capital requirements in offsetting the risks implied by an increasingly concentrated banking sector. More research is thus needed to inform regulators on how to optimally design and calibrate the capital surcharges. This would ideally take into account interactions with complementary G-SIB policies, such as enhanced supervision and resolution regimes, which are beyond the scope of this paper.

Our proposed methodological approach underscores the value of text – ie non-numeric information – for policy evaluation. The systematic evaluation of G-SIB-related keywords in banks' annual reports allows us to identify when G-SIBs started incorporating the framework into their capital planning and business considerations. The methodology proposed in this paper offers a tool for policy analysis, when – as with most major reforms – the identification of banks' responses is blurred by the gradual implementation of new rules. Exploiting the rich information contained in banks' annual reports and related communications offers exciting avenues for future research.

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Appendices

A List of keywords

Table A.1: List of keywords used in the word count analysis and to identify sentences that make reference to the G-SIB framework.

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

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

B Examples of action-oriented sentences in bank annual reports

- In the last year, we took some dramatic actions to reduce our GSIB capital surcharge, which we now have successfully reduced from 4.5% to an estimate of 3.5%. (JPMorgan Chase, 2015)

- This is one reason why we worked so hard to reduce the GSIB capital surcharge - we do not want to be an outlier in the long run because of it. (JPMorgan Chase, 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)

C Category and indicator score regressions

In all the tables in this appendix, the dependent variable is the adjusted G-SIB score; standard errors are clustered at the bank level; all bank controls, and bank and country-year fixed effects are included; and profitability is given as the level of average pre-treatment ROA. The bank-level time varying controls include CET1 to risk-weighted assets, cash to assets, density ratio, non-performing loans to total loans, deposit to total liabilities, and cost to income ratio.

Table C.1: Regressions with category scores

	Size	Inter-connectedness	Substitutability	Complexity	Cross-jurisdictional Activity
	(1)	(2)	(3)	(4)	(5)
Post × G-SIB × Profitability	40.10***	28.41	43.39*	35.93	30.65
	(3.92)	(1.33)	(1.88)	(1.16)	(1.59)
Post × G-SIB	-23.00***	-20.88	-11.23	-52.08**	-2.109
	(-3.48)	(-1.13)	(-0.73)	(-2.46)	(-0.12)
Post × Profitability	-10.23	-26.53	-25.21	22.63	12.70
	(-1.00)	(-1.28)	(-1.16)	(0.86)	(0.66)
N	363	363	363	363	363
R2	0.993	0.959	0.991	0.963	0.990

Note: The dependent variables are the respective category scores, and the specification includes a full set of bank fixed effects and controls, as well as country-year fixed effects. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table C.2: Regressions with indicator scores: Interconnectedness and Substitutability

	Intra-financial system assets	Intra-financial system liabilities	Securities outstanding	Payments activity	Assets under custody	Underwritten transactions
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB × Profitability	20.18	35.89	29.16	16.51	14.87	98.78**
	(0.69)	(0.92)	(1.64)	(0.38)	(0.75)	(2.48)
Post × G-SIB	-27.45	-32.74	-2.455	-36.08	12.68	-10.29
	(-1.37)	(-0.92)	(-0.32)	(-1.02)	(0.84)	(-0.38)
Post × Profitability	-32.94	-43.55	-3.120	-11.77	9.395	-73.26
	(-1.02)	(-1.18)	(-0.18)	(-0.28)	(0.32)	(-1.33)
N	363	363	363	363	363	363
R2	0.928	0.925	0.973	0.966	0.995	0.968

Note: The dependent variables are the indicator scores for interconnectedness and substitutability, and the specification includes a full set of bank fixed effects and controls, as well as country-year fixed effects. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table C.3: Regressions with indicator scores: Complexity and Cross-jurisdictional Activity

	Notional amount of OTC derivatives	Trading and AFS securities	Level 3 assets	Cross-jurisdictional claims	Cross-jurisdictional liabilities
	(1)	(2)	(3)	(4)	(5)
Post × G-SIB × Profitability	81.24**	48.62	-22.07	31.77	29.54
	(2.63)	(1.11)	(-0.40)	(1.49)	(1.39)
Post × G-SIB	-94.84***	-35.58	-25.81	3.500	-7.717
	(-3.65)	(-0.78)	(-1.08)	(0.20)	(-0.39)
Post × Profitability	10.34	23.27	34.28	18.61	6.790
	(0.34)	(0.56)	(0.74)	(0.64)	(0.39)
N	363	363	363	363	363
R2	0.978	0.923	0.890	0.989	0.985

Note: The dependent variables are the indicator scores for complexity and cross-jurisdictional activity, and the specification includes a full set of bank fixed effects and controls, as well as country-year fixed effects. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$.

D Bank business models using cluster analysis

In this appendix, we outline the cluster analysis that we use to classify banks according to their business model. We note that the coefficient of interest as discussed in Section 4.3 and reported in Table 13 is unaffected by the inclusion of the resulting business model variables.

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 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, wholesale-funded, trading, or universal – based on their average balance sheet characteristics, as shown in table D.1. We also reduce the number of clusters allowed to two and three as robustness checks and note that the results remain consistent.

Table D.1: Summary statistics by business model clusters

	Retail-oriented (Obs = 301)	Trading (Obs = 22)	Wholesale (Obs = 37)	Universal (Obs = 138)
Loans/TA	**0.56**	**0.18**	0.24	**0.47**
	[0.42, 0.72]	[0.07, 0.34]	[0.05, 0.36]	[0.32, 0.59]
Securities/TA	**0.21**	**0.47**	0.30	**0.19**
	[0.10, 0.30]	[0.33, 0.66]	[0.21, 0.38]	[0.09, 0.27]
Cash/TA	0.08	0.07	0.04	0.06
	[0.01, 0.14]	[0.01, 0.22]	[0.01, 0.08]	[0/02, 0.11]
Deposits/TA	**0.62**	0.64	**0.21**	**0.38**
	[0.52, 0.73]	[0.48, 0.77]	[0.12, 0.26]	[0.29, 0.47]
Wholesale/TA	**0.23**	0.23	**0.48**	**0.36**
	[0.13, 0.35]	[0.08, 0.44]	[0.40, 0.58]	[0.24, 0.51]
NII/TA	0.01	0.02	0.02	0.01
	[0.00, 0.02]	[0.00, 0.04]	[0.00, 0.04]	[0.00, 0.02]

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

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