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Abstract

Profitability underpins the opportunity cost of shrinking assets and the ability to generate capital. It thus shapes banks' responses to higher capital requirements. We present a stylised model to formalise this insight and test our theoretical predictions on a cornerstone of the too-big-to-fail reforms. Leveraging textual analysis to identify the treatment date, we show that less profitable banks reduced their systemic importance as intended by regulation. Those close to the regulatory thresholds that determine bank-specific capital surcharges – a source of exogenous variation in the regulatory treatment – shrunk by even more. In contrast, more profitable banks continued to expand.

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

JEL classification: G21, G28, L51.

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1 Introduction

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

In this paper, we examine how profitability, after controlling for capitalisation, determines banks' adjustments to greater capital requirements. Profitability matters for the dynamic trade-off banks face when reacting to tighter regulation. It not only determines the opportunity cost of shrinking, but also underpins the ability to raise capital organically by retaining profits. We develop a stylized model to formalise this insight, and to guide our empirical analysis. The model predicts that in response to higher capital requirements a more profitable bank would shrink by less (or grow by more) as compared to a less profitable bank. Indeed, the more profitable bank responds to tighter regulation by building up more capital.

To test the predictions of the model, we turn to a cornerstone of the too-big-to-fail reforms: the framework for Global Systemically Important Banks (G-SIBs). It imposes additional capital surcharges on some – but not all – large internationally active banks, and therefore incentivises these banks to reduce their systemic importance.[1] Importantly, the framework is exogenous to the banks' pre-reform profitability. It thus provides a useful setup to evaluate the role of bank profitability in an international context using publicly available data.

[1]The G-SIB framework defines the systemic importance of a bank, broadly, as the weighted average of its market share in various financial activities. It is thus an estimate of the impact a bank's failure would have on the financial system, i.e. the systemic loss-given-default (BCBS, 2021).

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

The finding that differences in profitability drive banks' adjustment patterns confirms the predictions of the model. It underscores that banks weigh their response to regulation dynamically rather than solely based on their current capitalisation. Moreover, the results underscore that neglecting differences in profitability across banks can mislead reform evaluations. Specifically, it would lead to the erroneous conclusion that the framework had no impact on G-SIBs.

Several robustness checks confirm that bank profitability, rather than other factors such as risk-taking, the business model, or domicile, is the main determinant of the banks' response to the framework. We also consider alternative measures of profitability (including risk-adjusted ones), treatment dates, and results based on sub-sample regressions (e.g. by geography). Furthermore, we consider alternative estimation approaches by matching G-SIBs with comparable Non G-SIBs, including matching banks exactly on the basis of their profitability. Our conclusions prove robust both quantitatively and in terms of statistical significance in all these experiments.

The limited regulatory traction on the more profitable banks raises questions about financial stability concerns. To shed some light on this question, we investigate two metrics of financial stability – concentration and banks' systemic risks.[2] We show that while both these indicators have declined on average for banks in our sample, the systemic risk posed by more profitable G-SIBs has increased modestly.

An innovative aspect of our analysis is that we develop a methodology to identify regulatory treatments based on textual analysis. Identification of the treatment date is challenging since major reforms are generally announced long before their implementation, and are phased-in over multiple years. The G-SIB framework is no exception: it was announced in 2011, while the implementation of higher capital requirements was phased in from 2016 to end-2018 (BCBS, 2013). We analyse annual reports by applying a combination of word count and keyword-in-context approaches and identify 2015 as the year when banks started incorporating the framework into their strategic planning. Annual reports originate from decision makers within banks, and contain valuable information around how regulatory reforms affect a bank's strategy. Despite these benefits, academic research has thus far made little use of the text contained in annual reports to assess the effects of regulatory reforms.

2 Related literature

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. For instance, Berger *et al.* (2008) and Gropp *et al.* (2019)

[2]We consider systemic risk – which is distinct from the concept of systemic importance – to be the expected system-wide loss caused by the failure or distress of an individual bank. We measure it as the product of the bank's systemic importance and its market-implied default risk. Alternatively, we also look at one popular proxy of banks' systemic risk, SRISK (Acharya *et al.*, 2012; Brownlees and Engle, 2016). We note that our measure of systemic importance explains close to half of the variation in SRISK.

show that poorly capitalised banks respond more quickly and strongly than their peers to tighter regulatory targets, and typically pursue balance sheet adjustments rather than raising capital via retaining earnings. This conclusion accords with Kashyap *et al.* (2010), who underscore that frictions in raising capital externally have a material impact on banks' response to higher requirements. In a similar vein, Jimenéz *et al.* (2017) conclude that the impact of dynamic provisioning requirements depends on banks' capitalisation. Complementing this line of research, our paper shows that even after controlling for capitalisation levels, pre-treatment profitability, i.e. the ability to generate capital in the future, proves to be a key driver of banks' responses to changes in capital requirements.

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

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

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

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

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

3 Responding to regulation: the role of profitability

This section presents a simple model to guide our empirical analysis. We assess how a bank, conditional on its profitability, adjusts to higher capital requirements.

We consider an economy with one bank and no aggregate uncertainty. The bank is on a steady-state growth path. Each period, it starts with capital k, based on which it chooses the level of deposits to raise, d, and the amount of assets to invest in, a. Assets have constant returns to scale and pay R per unit of asset, while deposits cost $r < R$. The bank is subject to the balance sheet constraint, $a = k + d$, and a minimum capital ratio requirement, χ. Because of constant returns to scale on assets, the regulatory constraint must bind, and the bank chooses assets, $a = k/\chi$, and deposits, $d = k(1/\chi - 1)$. In the following period, the bank's cash-flow is $Ra - rd$, which is the new capital k_{+1} of the bank. Using the new capital, the bank chooses its assets for the next period as $a_{+1} = k_{+1}/\chi$ and deposits as $d_{+1} = k_{+1}/(1/\chi - 1)$, and this decision process continues.

Next, we introduce an unexpected regulatory shock as follows. Until time $t - 1$, the regulatory requirement is χ, but from t onward (inclusive), the requirement is set to $\chi + \epsilon a$. The new capital ratio requirement captures the spirit of the G-SIB framework: a bank that chooses a larger balance sheet has to meet higher capital requirements.

We assume that when hit by the shock, the bank can meet the new requirement by either shrinking its balance sheet or raising capital externally. We note that – as laid out in the seminal work by by Myers and Majluf (1984) – banks typically avoid raising capital externally, unless there is a credible and justifiable reason from an investor perspective, such as a business expansion, a capital shortfall, or heightened regulatory requirements. In line with this reasoning, we assume that raising capital externally entails a preference cost such that the marginal cost is increasing in the amount to be raised.

This specification leads to the following problem of the bank that has to decide how much additional capital, δ, to raise on date t.

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

where β is the discount factor. For simplicity of exposition, we assume a quadratic cost of raising capital, and also abstract from multi-period considerations by assuming that the bank maximises the next period's cash-flow. To solve the problem, we eliminate d and derive the first order conditions. We focus on an interior solution where $\delta > 0$.

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

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

where $\theta > 0$ is the Lagrange multiplier on the regulatory constraint. Eliminating θ gives two equations in two unknowns (a, δ) that characterise the solution to the bank's problem. Finally, we eliminate δ to focus on a:

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

$$\implies \beta(R-r) = \Big(2\lambda(\chi a + \epsilon a^2 - k) - \beta r\Big)(\chi + 2\epsilon a). \tag{1}$$

An explicit solution for a is not generally available. However, an application of the Implicit Function Theorem sheds light on how more versus less profitable banks – ie high R versus low R – differ in terms of their response to higher capital requirements. The total derivative of Equation (1) w.r.t. R yields the following, where $\dot{a} = \frac{da}{dR}$:

$$\beta = 2\epsilon\dot{a}\Big(2\lambda(\chi a + \epsilon a^2 - k) - \beta r\Big) + \Big(2\lambda(\chi\dot{a} + 2\epsilon a\dot{a})\Big)(\chi + 2\epsilon a)$$

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

It follows that the coefficient on $\dot{a}$ is positive.[5] This means that in response to tighter regulation, a more profitable bank chooses a larger balance sheet.

The previous result *implies* that the change in size of the *treated* bank relative to that of a *control* bank (one that is not subject to the higher requirement) – given by the expression below – is larger when the treated bank's profitability is higher.

$$\underbrace{\left(\frac{k+\delta}{\chi+\epsilon a} - \frac{k_{-1}}{\chi}\right)}_{\phi} - \left(\frac{k}{\chi} - \frac{k_{-1}}{\chi}\right). \tag{2}$$

Here k_{-1} is the capital the bank had on date $t-1$.

Intuitively, the *opportunity cost* of choosing a smaller balance sheet is greater for a more profitable bank. As such the bank raises more capital, δ, in response to higher capital requirements to support a relatively larger balance sheet.

Another reason why profitability can matter for how banks respond to higher capital requirements is that it relates to the ability to organically generate capital in the future by retaining earnings. While we do not model this channel explicitly, we note that a more profitable bank – on the back of higher return on its assets – would end up with more capital k_{+1} on date $t+1$ as compared to a less profitable one.

The above results do not imply that a more profitable bank would necessarily expand. In Equation (2), ϕ, which denotes the change in size of a *treated* bank, can be positive or negative, depending on the cost of raising capital and the increase in capital requirements. In response to tighter regulation, a more profitable bank could thus 'shrink by less' or 'grow by more' as compared to a less profitable bank.

[5]This is because (i) $\epsilon > 0$; (ii) expression A, which also appears in equation (1), must be positive as otherwise we arrive at a contradiction in equation (1) given that $R - r > 0$, $\chi > 0$, $\epsilon > 0$ and $a > 0$; (iii) $\lambda > 0$; and (iv) expression B is positive.

To summarise, the stylized model provides intuition for why a more profitable bank would respond differently to an increase in (potentially size-dependent) capital requirements – such as the G-SIB framework which we discuss in the next section.

4 Applying text analysis to the G-SIB framework

We use the implementation of the G-SIB framework, a cornerstone of the too-big-to-fail reforms, to test whether regulation bites harder the less profitable banks as compared to their more profitable peers.

The G-SIB framework assesses large internationally active banks and imposes higher capital requirements on those with greater systemic importance. It intends to make these banks internalise the negative externalities they impose on the global banking system (see Chapter SCO40 in BCBS (2021)). It uses a weighted average of banks' market share in twelve different financial activities (so-called indicators, grouped into five categories) as a measure of systemic importance – the "G-SIB score". Banks with scores above a certain threshold are designated *global systemically important banks* or G-SIBs. We refer to all other banks in the assessment sample as Non G-SIBs. G-SIBs are grouped into different "buckets" such that those with higher scores have to meet higher capital requirements (see appendix A for more details on the framework). Depending on how much costlier capital is relative to debt (Kashyap *et al.*, 2010), the framework creates incentives for G-SIBs to reduce their systemic importance. Therefore, the design of the framework is well suited to test the differential impact of capital requirements on banks.

Several other features of the framework also support our analysis. The rules-based designation of G-SIBs makes the identification of the treated and control banks straightforward. It also implies that the regulatory treatment is not directly related to the banks' pre-reform profitability, which we exploit in our empirical analysis. Furthermore, the framework applies across jurisdictions on a consistent basis and uses publicly available data, allowing us to draw conclusions in an international context and in a fully transparent manner.

4.1 Identifying the regulatory treatment date

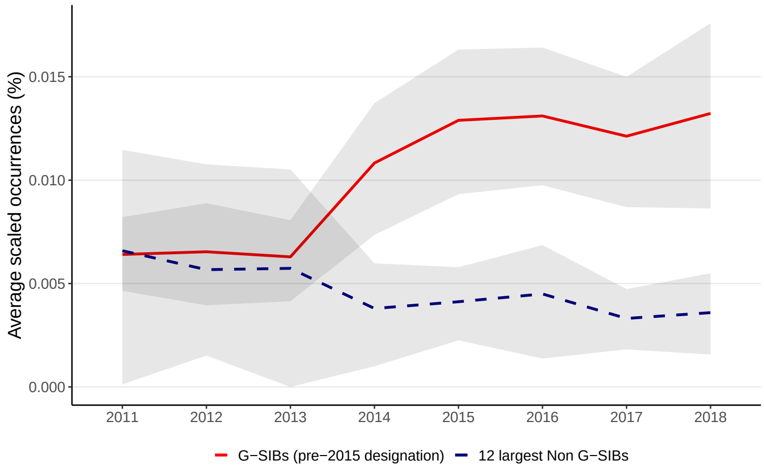
Identifying precisely when banks start to incorporate regulatory reforms into their behaviour is challenging for several reasons. Major reforms are typically announced long before their implementation, with the implementation then being phased-in gradually. Existing studies on the evaluation of reforms typically use the announcement or implementation date as *treatment* dates, but it is not obvious as to how much in advance, and to what extent, banks adjust. These challenges also apply in the case of the G-SIB framework.[6]

We leverage banks' annual reports – a pivotal source of information about a bank's strategic response to new regulation – to identify the true treatment date for the G-SIB framework. To this end, we first count the number of times keywords related to the G-SIB framework (e.g. "gsib" or "systemically relevant bank") appear in the annual reports (see Appendix B for the full list of keywords). Following Baker *et al.* (2016), we then scale the keyword count by the total number of words in the corresponding annual report to adjust for changes in the length of the report over time. The evolution of scaled occurrences highlights a significant increase in framework-related discussions by G-SIBs during 2014 and 2015 – in contrast to a decline observed for Non G-SIBs (see Figure 1).[7]

[6]Event studies around key announcement dates, such as the publication of the G-SIB methodology or the G-SIB lists, offer one alternative 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 in the medium-term.

[7]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.

Figure 1: Framework references in annual reports: G-SIBs vs. the 12 largest Non G-SIBs



Note: The graph plots the average occurrences of relevant keywords for banks that have G-SIB framework-related discussions in their annual reports, with 95% bootstrapped confidence intervals. The total G-SIB-related keywords (see Appendix B) for each bank-year are scaled by the total length of the annual report. The sample includes 31 G-SIBs based on pre-2015 designation and the 12 largest Non G-SIBs based on 2013 scores. We exclude from the control sample those banks that were designated as G-SIBs in 2011 but dropped from the G-SIB list thereafter.

The pattern suggests that G-SIBs started to incorporate the framework in their strategic considerations from 2014 onwards.[8] This observation accords with the fact that G-SIB designations before 2014 had no impact on banks' capital requirements. Furthermore, the number of G-SIBs mentioning the framework increases from two-thirds in 2011 to the full sample in 2015.

Basic keyword counts can be agnostic to the context of their occurrence. We address this issue by extracting sentences in G-SIBs' annual reports that contain a keyword and then categorise them in their order of relevance to banks' capital planning. Guided by the pattern in Figure 1, we focus on the years 2013 to 2015, which yields 1255 sentences in total. Next, each author independently tags the sentences based on the four categories set out in Table 1, while discarding sentences that are irrelevant or out of context. Sentences in categories 1 and 2 comprise *general discussions* of the framework, while those

[8] 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.

Table 1: Categories used to tag sentences with examples

Category	Example
4: Discussion of active response (e.g. capital planning, dividend payouts) to the framework.	*In the last year, we took some dramatic actions to reduce our G-SIB capital surcharge ... (JP Morgan, 2015)*
3: Acknowledgement that G-SIB capital surcharges are (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)*
2: Acknowledgement that G-SIB capital surcharges apply to the bank.	*RBS has been provisionally allocated a G-SII buffer of 1.5%. (RBS, 2014)*
1: General description of the framework.	*The requirements, initially for those banks identified in November 2014 as G-SIBs, are being phased in from 1 January 2016, becoming fully effective on 1 January 2019. (HSBC, 2015)*

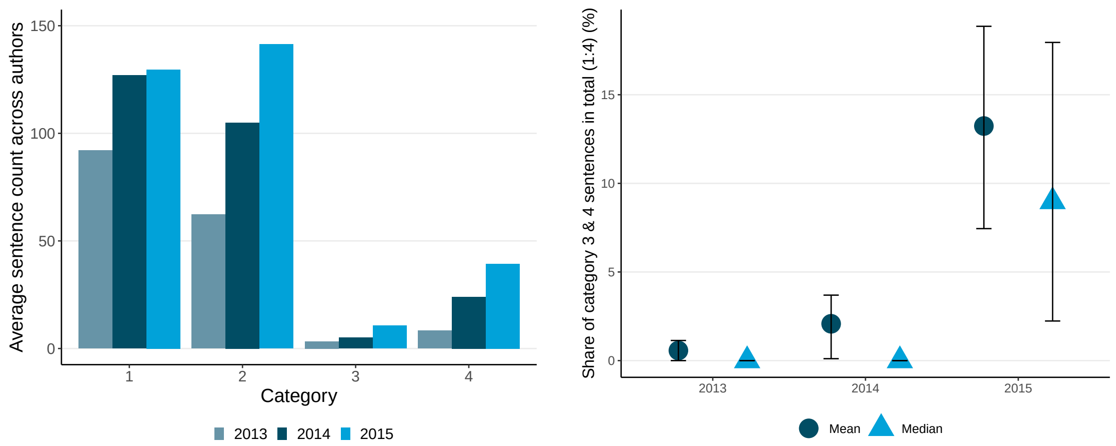
in categories 3 and 4 are *action-oriented* and discuss active responses by the bank to the G-SIB framework.[9]

The authors' tags are highly correlated, with disagreement in less than 8% of the sentences and pair-wise correlation coefficients of more than 0.9. In what follows, we take the average count across authors for each sentence category to mitigate any potential biases.

We find that not only the number but also the share of action-oriented sentences is the highest in 2015 (see Figure 2). Moreover, the median (mean) share is (close to) zero in 2013 and 2014, whereas it is significantly higher in 2015. The increase occurs not just along the intensive margin, but also along the extensive margin. The number of annual reports containing such sentences doubles from 10 in 2013 and 2014 to 19 in 2015 (see Appendix E).

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

Figure 2: 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 1 to 4. The *right-hand panel* plots the average and median share of action-oriented category 3 and 4 sentences for each year, calculated after exclusion of outliers. The graph further shows the 95% bootstrapped confidence intervals for the mean and median. Non-overlapping intervals indicate significant differences across years at the 5% level. Outliers are defined as observations 1.5 times the distribution's inter-quartile range below (above) the first (third) quartile. The sample is restricted to G-SIBs based on pre-2015 designation.

Representation across countries also increases. In 2014, US G-SIBs account for the majority of category 3 and 4 sentences; while in 2015, we also identify such sentences in the reports of banks from five European countries and Japan.

Overall, these findings suggest 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 tallies with the regulatory phase-in of the G-SIB capital surcharges as of the beginning of 2016.

5 Empirical analysis

5.1 Data

Our goal is to identify shifts in the systemic importance of G-SIBs relative to that of Non G-SIBs as a result of the G-SIB framework. The G-SIB score – as a measure of systemic importance – is an ideal *starting* point for this assessment for several reasons. For one, the BCBS collects annually the inputs for the score, i.e. the *indicators* of a bank's market share in twelve financial activities, based on a common template and on a consistent basis across banks and over time. The BCBS and national supervisors also review these data for consistency, and make them available publicly. In addition, the indicators are available for both G-SIBs (ie treated banks) and Non G-SIBs (ie control banks) – 84 large global banks from 21 jurisdictions in total – which is ideal for our DD analysis.

Despite being an ideal starting point, some features of the official score render it inappropriate for our analysis. First, the scores are relative. Thus, a ceteris paribus increase in, for example, the score of one G-SIB mechanically leads to a decline in that of all other banks, including the control banks. This violates a main assumption of the DD analysis. To make the score non-relative, we recompute the score as the weighted average of market shares relative to 2013. We thus decouple the evolution of banks' scores over time.

Second, since the indicator values are denominated in euro, exchange rate fluctuations can affect banks' scores over time. The appreciation of the U.S. dollar against the euro in 2014, for example, is likely to have increased U.S. banks' scores above and beyond the actual evolution of their balance sheets. To get around this issue, we purge the indicators of exchange rate effects by converting the indicator values back into the banks' reporting currency and restate all indicators in euro based on the 2013 exchange rates.[10]

Third, the official scores are subject to a regulatory override wherein a bank's value for the *Substitutability* category is capped at 500 bps to limit the impact of this relatively skewed category on a bank's overall score. We abstract away from this cap to avoid masking any changes in banks' systemic importance.

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

Table 2: Summary statistics

	Mean	Stdev	P10	P25	P50	P75	P90	N
GSIB SCORES								
GSIB Score (official)	128.53	107.30	28.93	47.52	85.80	186.08	284.03	443
GSIB Score (adjusted)	134.68	115.08	29.42	52.67	89.63	188.33	288.82	443
CATEGORY SCORES								
1. Size	136.84	101.53	46.22	63.01	101.39	183.87	307.36	443
2. Interconnectedness	134.56	85.01	40.78	66.15	115.55	195.01	244.31	443
3. Substitutability	146.15	209.19	14.49	34.05	68.97	177.98	350.00	443
4. Complexity	114.71	134.66	10.54	29.77	55.81	157.92	297.51	443
5. Cross-jurisdictional Activity	141.13	160.89	4.13	29.03	84.69	191.45	363.70	443
INDICATOR SCORES								
2a. Intra-financial system assets	123.94	93.83	27.04	44.41	98.58	185.20	264.22	443
2b. Intra-financial system liabilities	135.37	102.40	19.36	54.21	111.37	201.01	266.62	443
2c. Securities outstanding	144.39	94.66	39.54	63.91	131.34	199.03	268.00	443
3a. Payments activity	138.68	202.76	12.84	35.36	66.31	153.78	308.55	443
3b. Assets under custody	151.81	342.74	2.67	11.69	39.73	110.10	289.29	443
3c. Underwritten transactions	147.96	196.50	2.18	24.86	66.57	161.82	463.31	443
4a. Notional amount of OTC derivatives	109.97	174.53	1.35	4.22	28.28	112.68	391.15	443
4b. Trading and AFS securities	121.94	138.12	11.42	30.52	66.34	178.28	310.56	443
4c. Level 3 assets	112.21	140.90	0.95	15.97	52.40	154.38	308.43	443
5a. Cross-jurisdictional claims	142.06	164.27	3.44	25.29	82.32	214.99	353.12	443
5b. Cross-jurisdictional liabilities	140.19	160.35	4.72	23.56	84.94	199.31	368.31	443
BANK CHARACTERISTICS								
Return on assets (%)	0.95	0.58	0.31	0.51	0.89	1.31	1.69	492
Return on equity (%)	14.41	7.49	5.57	9.66	13.75	18.59	24.38	492
Return on risk-weighted assets (%)	1.99	0.88	0.81	1.44	2.01	2.53	3.11	485
Risk-adjusted return on assets (%)	5.62	4.67	1.34	2.42	4.23	7.45	12.21	492
Z-score (ratio)	43.40	27.03	17.03	27.50	36.61	50.58	81.57	492
CET1 capital ratio (%)	12.12	2.99	8.78	10.16	11.64	13.56	15.80	486
Density ratio (%)	47.12	17.54	26.15	33.10	43.79	61.25	70.66	485
Cost to income (%)	55.72	16.18	30.46	44.96	58.14	66.94	74.58	492
Non-performing loan ratio (%)	2.77	2.99	0.52	0.94	1.64	3.35	7.04	478
Cash to assets (%)	7.04	5.59	1.34	2.53	5.94	10.13	13.71	492
Deposit to total liabilities (%)	56.41	17.91	30.34	41.73	59.01	70.21	79.24	486
Capital buffer	4.64	3.03	1.65	2.54	3.94	6.08	8.74	486
Close to bucket threshold	0.18	0.38	0.00	0.00	0.00	0.00	1.00	504
1-year EDF (%)	0.72	1.15	0.23	0.32	0.50	0.82	1.30	429
1-year PD (%)	0.25	0.27	0.01	0.05	0.16	0.36	0.62	470
SRISK (%)	2.76	2.93	0.18	0.82	1.56	3.63	7.29	417
CAPM Beta	1.19	0.38	0.74	0.96	1.19	1.39	1.67	391

Note: The table shows summary statistics for the 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 surcharge – 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 20 bps 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.

With these modifications, we obtain an *adjusted* G-SIB score, which serves as our main outcome variable of interest. To show that our conclusions are not driven by these adjustments, we compare the results obtained from using the official and adjusted scores in the main tables. Table 2 presents summary statistics for the official and adjusted G-SIB scores, which have a correlation of 0.98.

We complement the BCBS data on G-SIB indicators with bank controls – especially profitability – from Fitch (see Table 2). Finally, to study the policy implications of our findings, we collect market-based measures of banks' implied probability of default based on credit default swap (CDS) spreads and expected default frequency (EDF), and obtain SRISK – a widely used systemic risk measure (see Brownlees and Engle, 2016 and Acharya *et al.*, 2012) – as one measure of banks' systemic risk from New York University VLAB.

Throughout our analysis, we focus on the time period from 2013 to 2018, i.e. from the first year for which G-SIB scores are available up to the completion of the phase-in of the framework.

5.2 Baseline analysis of the impact of the framework

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

$$Score_{i,t} = \gamma \left[Post_t \times \textit{G-SIB}_i \right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}, \tag{3}$$

where $Score_{i,t}$ represents either the adjusted or official 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 $\textit{G-SIB}_i$ equals 1 (zero otherwise) for banks that have been designated a G-SIB before 2015, i.e. pre-treatment.[11] $X_{i,t-1}$ ac-

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

counts for time-varying bank-specific characteristics: the CET1 capital ratio, the density ratio as well as the ratios of cash to assets, deposits to liabilities and non-performing loans to total loans (see Table 2 for the variable definitions). Throughout our analysis, we use the first lag of these variables to address any potential endogeneity concerns. α_i controls for a bank's unobserved time-invariant characteristics. $\delta_{c,t}$, in turn, accounts for time-varying characteristics of country c where bank i is headquartered, such as changes to the macroeconomic environment or regulation. $\varepsilon_{i,t}$ is the error term. We 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 $\hat{\gamma} < 0$.

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 first 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 – i.e. equation (3) – by replacing the *Post* dummy with a *year* dummy. The coefficient for the $G\text{-}SIB_i \times 2014$ interaction term is statistically insignificant in both the unsaturated and saturated (i.e. 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 G-SIBs' adjusted scores also supports the parallel trend assumption (see Figure 4, left-hand panel, in Section 5.3 below).

We note that the comparatively small 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

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

terms of their total assets – one of the key inputs to computing the score – G-SIBs and Non G-SIBs evolved in parallel before treatment, i.e. from 2010 to 2014.[12]

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 5.1). 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 6. 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.

Turning to the regression analysis, we note that 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 13 bps 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 about 9 bps, whereas Non G-SIBs increased the same by around 4 bps.[13] Both these changes are small and statistically insignificant. We confirm that these results are not an artefact of our adjustments to the score, discussed in Section 5.1: running the same regression on the official G-SIB score in column (2) has little effect on the coefficient estimates.

[12]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, i.e. Q1 2010, the change in the difference of the average scores of G-SIBs' and Non G-SIBs' is insignificant at the 5% level in each quarter of the pre-treatment period, i.e. 2010-2014. Thereafter, the change in the score difference is typically significant at the 5% level.

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

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

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

Note: The table reports results of the regression in equation 3. The dependent variable is the adjusted G-SIB score (columns (1), (3) and (4)) and the official G-SIB score (column (2)), respectively. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. Bank-level controls are lagged by one year. Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

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 framework. However, we note that virtually all banks in our sample, including all G-SIBs, are D-SIBs suggesting that D-SIB requirements should not affect our findings.[14]

To control for any remaining differences in regulatory reforms that may have affected the banks, we include country-year fixed effects throughout our analysis and perform a variety of checks to confirm the robustness of our results in Section 6.

Saturating the regression by controlling for bank fixed effects as well as time-varying

[14] 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.

bank characteristics (column (3)) or adding country-year fixed effects (column (4)) shows that the change in the scores of G-SIBs remains insignificant and, if anything, becomes even smaller in absolute value.

5.3 Exploring the differential impact across banks

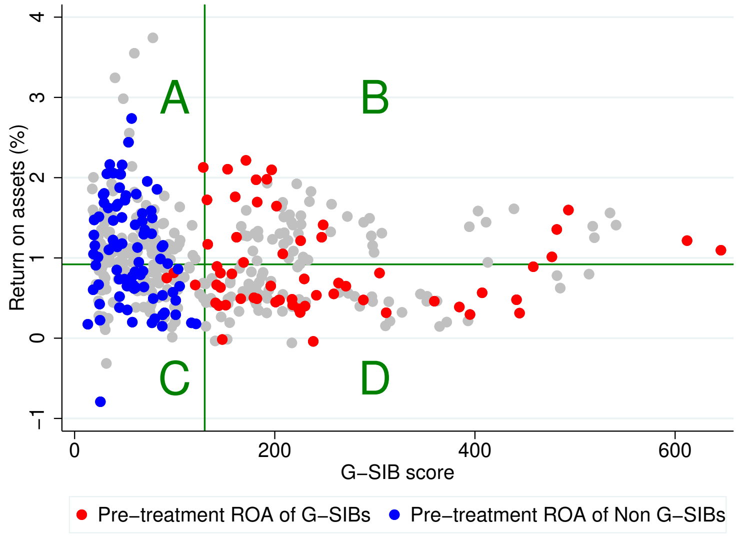
The insignificant response by G-SIBs as a group could mask a differential effect on a subgroup of banks. As suggested by the model in Section 3, the bank's optimal response to the framework reflects a dynamic cost-benefit analysis: the regulatory capital relief following a reduction in systemic importance needs to be compared with the attendant loss in future revenue due to a smaller market presence. Profitability plays a central role in this optimisation as we show below.

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 (see also 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 3).[15] Profitability is an attribute that is unrelated to treatment, and is thus a suitable basis for assessing the differential impact of the framework on banks.

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 6.3).

[15] Standard t-tests cannot reject the hypothesis that the average pre-treatment ROA of G-SIBs is equal to that of Non G-SIBs (p-value = 0.24). Likewise, t-tests do not reject equality of the mean pre-treatment ROA of more (less) profitable G-SIBs and more (less) profitable Non G-SIBs, 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 3: Adjusted G-SIB scores versus return on assets



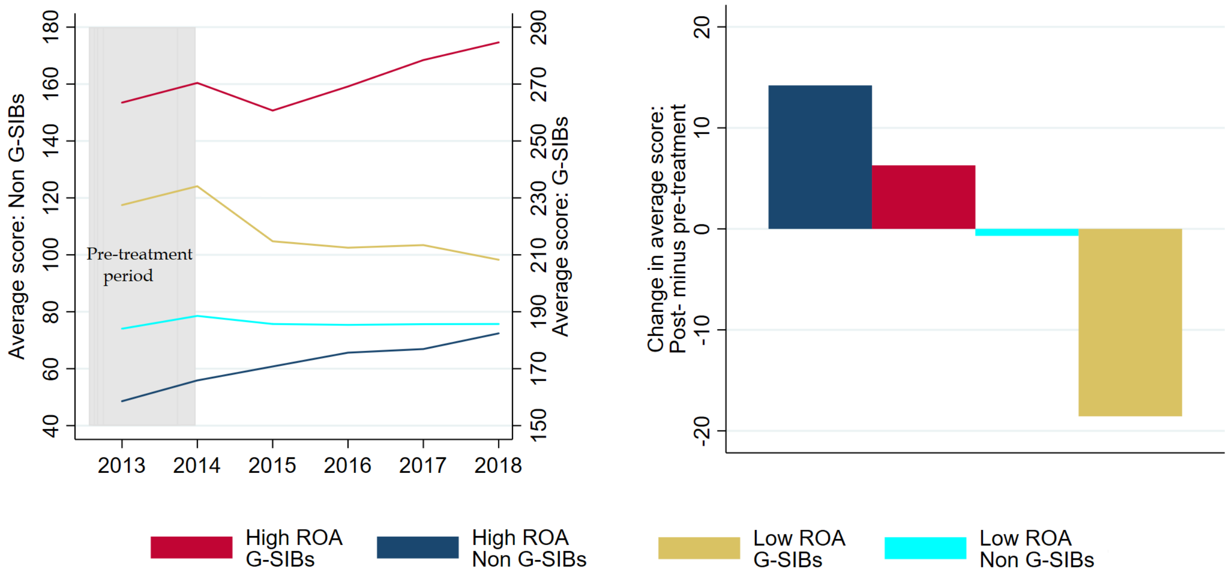
Note: The table plots the adjusted G-SIB score versus ROA in the pooled sample of banks. Region A shows high ROA Non G-SIBs (N=168); region B shows high ROA G-SIBs (N=84); region C plots low ROA Non G-SIBs (N=138); and region D demonstrates low ROA G-SIBs (N=114).

The evolution of the average score of more and less profitable G-SIBs and Non G-SIBs points to materially different trends post treatment (Figure 4). While all four *types* of banks increased their scores in parallel pre-treatment (i.e. 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 banks' responses to the G-SIB framework.

To assess these observations formally, we consider separate sub-sample regressions on more and less profitable banks (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

it is significant at the 10% level (p-value = 0.06).

Figure 4: 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.

(columns (1) to (3), Panel A) or relative to only the more profitable Non G-SIBs (columns (4) to (6), Panel A). In sharp contrast, less profitable G-SIBs significantly decreased their scores relative to Non G-SIBs (columns (1) to (3), Panel B). They have also lowered their scores relative to the less profitable Non G-SIBs (columns (4) to (6), Panel B). The magnitude of the effect, between 16 to 22 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 4.

To assess the differential impact on the more and less profitable G-SIBs and Non G-SIBs within a unified model, we adopt the following *triple interaction* specification:

$$Score_{i,t} = \gamma \left[Post_t \times G\text{-}SIB_i \times Profitability_i\right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}. \qquad (4)$$

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

	Panel A					
	High ROA G-SIBs vs All Non G-SIBs			High ROA G-SIBs vs High ROA Non G-SIBs		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB	2.456	12.69	14.05	-1.357	9.192	18.39
	(0.16)	(0.97)	(1.02)	(-0.09)	(0.68)	(1.25)
Post	3.833	2.924		7.646**	6.423*	
	(1.39)	(1.05)		(2.22)	(1.79)	
G-SIB	210.2***	189.8***		217.0***	196.2***	
	(4.54)	(4.99)		(4.66)	(5.11)	
N	329	329	253	225	225	186
R2	0.629	0.669	0.991	0.619	0.664	0.991
Lagged bank controls and FE	No	No	Yes	No	No	Yes
Country-time FE	No	No	Yes	No	No	Yes
Score	Adjusted	Official	Adjusted	Adjusted	Official	Adjusted
	Panel B					
	Low ROA G-SIBs vs All Non G-SIBs			Low ROA G-SIBs vs Low ROA Non G-SIBs		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × G-SIB	-22.39**	-20.60**	-20.95**	-17.71*	-16.31	-20.80*
	(-2.56)	(-2.16)	(-2.35)	(-1.90)	(-1.63)	(-1.83)
Post	3.833	2.924		-0.848	-1.367	
	(1.39)	(1.06)		(-0.21)	(-0.34)	
G-SIB	174.1***	167.9***		164.8***	159.3***	
	(8.04)	(8.02)		(7.35)	(7.34)	
N	371	371	309	218	218	166
R2	0.683	0.677	0.992	0.607	0.600	0.990
Bank controls and FE	No	No	Yes	No	No	Yes
Country-time FE	No	No	Yes	No	No	Yes
Score	Adjusted	Official	Adjusted	Adjusted	Official	Adjusted

Note: The table reports results of the regression in equation 3, for the sub-samples indicated in the column headings. The dependent variable is either the adjusted or official G-SIB score, as indicated in the last row of the table. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Here, $Profitability_i$ is measured as the *level* of bank i's average pre-treatment ROA. A major advantage of this approach is that it helps avoid taking a stance on the threshold that distinguishes the more from the less profitable banks. We always include the full set of interaction terms (e.g. $Post_t$, $Post_t \times G\text{-}SIB_i$) in the regressions (depending on the fixed effects), although they are not explicitly stated in equation (4) for the sake of brevity. The rest of the setup is as before.

Table 5: Triple interaction regression results

	(1)	(2)	(3)	(4)
Post × G-SIB × Profitability	32.67**	43.69***	30.66***	34.20**
	(2.56)	(4.07)	(3.33)	(2.05)
Post × G-SIB	–40.33***	–45.04***	–35.87***	–17.80*
	(–3.22)	(–3.51)	(–2.92)	(–1.74)
Post × Profitability	7.639*	7.475	15.89	–5.647
	(1.68)	(1.59)	(1.49)	(–0.52)
G-SIB × Profitability	–5.653	–7.635		
	(–0.18)	(–0.30)		
Post	–4.249	–4.994		
	(–0.86)	(–0.99)		
G-SIB	191.0***	181.1***		
	(5.98)	(6.08)		
Profitability	–10.88*	–10.40*		
	(–1.73)	(–1.77)		
N	443	443	373	373
R2	0.600	0.632	0.991	0.990
Bank controls and FE	No	No	Yes	Yes
Country-time FE	No	No	Yes	Yes
G-SIB score	Adjusted	Official	Adjusted	Adjusted
ROA measure	Level	Level	Level	Dummy

Note: The table reports results of the regression in equation 4 for the full sample. The dependent variable is the adjusted G-SIB score (columns (1), (3) and (4)) and the official G-SIB score (column (2)), respectively. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. The profitability measure is always based on average pre-treatment (i.e. 2013-14) ROA data, either in levels (columns (1) to (3)), or as an above median dummy in column (4). Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposit to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

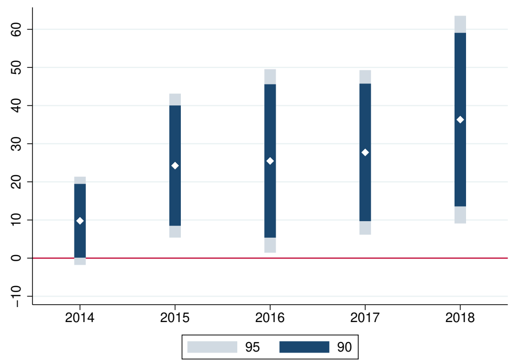
Our hypothesis is that $\hat{\gamma}$, the coefficient on the triple interaction term, is positive. This would imply that more profitable G-SIBs increased by more (or reduced by less) their score after treatment compared to the change in score of the less profitable G-SIBs, after controlling for trends in the score of Non G-SIBs.

The regression results in Table 5 support our hypothesis. The unsaturated specification in column (1) without fixed effects shows that, on average, more profitable G-SIBs increased their adjusted score by about 33 bps after treatment relative to trends in the control group. Column (2) reports the corresponding results based on using the official G-SIB score. As expected, the coefficient is biased upwards given that an increase in the score of the more profitable G-SIBs implies, all else equal, a decline in the scores of the less profitable ones.

Accounting for bank controls and fixed effects as well as country-year fixed effects (column (3)) leads to a similar conclusion regarding the relative change in the scores of the two types of G-SIBs. These findings are consistent with the observations based on Figure 4 and Table 4.

For robustness, we also consider a specification in which we define profitability as the ROA *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. With the dummy-based measure of profitability too, we find that the coefficient on the triple interaction terms remains statistically significant (column (4)). Overall, these results reinforce the differential effect of the G-SIB framework we uncovered using the subsample DDs.[16]

Figure 5: Assessing the evolution of the impact of the framework over the years



Note: Coefficient estimates in basis points on the triple interaction terms in a version of the regression equation (4) where the treatment effect can differ across years, relative to the starting year 2013.

Finally, we assess the persistence of the impact of the framework. To this end, we loosen the constraint on regression equation (4) by allowing the treatment effect to differ across years, relative to the starting year, 2013.[17] As shown in Figure 5, we find a

[16]To provide additional evidence that our findings are driven by differences in bank profitability and not by other balance sheet characteristics, we interact each of the balance sheet variables comprised in $X_{i,t-1}$ (see also Table 3) with the post-treatment and G-SIB designation dummies, and we sequentially include these triple interaction terms in addition to the baseline triple interaction involving profitability. Our findings remain consistent with the ones presented in our main analysis.

[17]Specifically, we estimate $Score_{i,t} = \sum_t \gamma_t \left[\mathbb{1}_t \times G\text{-}SIB_i \times Profitability_i\right] + \mu X_{i,t-1} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$,

significant difference at the 5% level in the impact on more and less profitable G-SIBs (relative to Non G-SIBs) in each post-treatment year, but not in the pre-treatment year.

5.4 Proximity to bucket thresholds

This section inspects the behaviour of banks that are close to their G-SIB bucket thresholds to reinforce the causal interpretation of our results. The thresholds introduce a discontinuity in the capital requirements absent any confounding economic rationale for why banks should behave differently if their score is close to the threshold. The distance from the bucket thresholds thus represents an ideal source of exogenous variation in the regulatory treatment.

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

	High ROA G-SIBs vs All Non G-SIBs	High ROA G-SIBs vs High ROA Non G-SIBs	Low ROA G-SIBs vs All Non G-SIBs	Low ROA G-SIBs vs Low ROA Non G-SIBs	All Banks
	(1)	(2)	(3)	(4)	(5)
Close to bucket threshold	–1.023	–1.753	–12.14***	–15.49***	
	(–0.20)	(–0.34)	(–3.03)	(–3.55)	
Low ROA bank close to threshold					–9.611*
					(–1.96)
High ROA bank close to threshold					–2.138
					(–0.40)
Post × G-SIB × Profitability					26.80*
					(1.82)
Post × G-SIB	2.453	2.581	–12.76*	–10.95	–14.98**
	(0.15)	(0.18)	(–1.85)	(–1.58)	(–2.06)
Post × Profitability	7.729**		6.372*		–6.573
	(2.14)		(1.80)		(–0.74)
Post	–4.922	0.222	–1.847	–1.804	
	(–1.54)	(0.08)	(–0.63)	(–0.59)	
N	255	177	294	171	319
R2	0.989	0.990	0.989	0.988	0.993
Bank controls and FE	Yes	Yes	Yes	Yes	Yes
Country-time FE	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 in the previous year is within 20 bps of the closest bucket threshold. *Low (high) ROA bank close to threshold* equals one if a low (high) ROA bank's official G-SIB score in the previous year is within 20 bps of the closest bucket threshold. *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18]. *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. *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, 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. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

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

with $\mathbb{1}_t$ representing an indicator variable for each year, and assess the significance of the γ_t coefficients.

by defining an indicator variable that is equal to one (zero otherwise) if a bank's official G-SIB score is within 20 bps of the bucket threshold. About one fifth of the bank-year observations are close to the threshold as per this definition, with no systematic concentration among the less or more profitable banks. Table 6 depicts the estimates for this indicator based on assessing the more profitable G-SIBs (columns (1) and (2)), the less profitable ones (columns (3) and (4)), or all the banks together (column (5)).

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 importance (columns (3) to (5)). Closeness, however, does not appear to influence the more profitable G-SIBs' adjustment (columns (1), (2) and (5)).

5.5 Banks' adjustment margins

We zoom into the different categories and indicators that constitute the overall G-SIB score to assess banks' margins of adjustment. We run specification (4) with the adjusted *category* scores as the dependent variable. Table 7 presents the coefficient estimates of the triple interaction term for each category. More profitable G-SIBs raised their scores relative to the less profitable G-SIBs along four out of the five categories, and most significantly so in the case of *Size* and *Substitutability*.

Zooming in even further, we find that the increase in the average score of more profitable G-SIBs is driven by a significantly higher footprint along the following G-SIB *indicators*: *size* (which is also a category in itself), *underwriting activities*, *notional amount of OTC derivatives*, and *cross-jurisdictional liabilities*.

While an in-depth analysis of the causal link between these indicators and bank profitability is beyond the scope of this paper, we can link our findings to related results in the literature. There are various reasons why *size* and profitability may be positively related,

Table 7: Regressions based on category and indicator scores

	Post × G-SIB × Profitability		R2
CATEGORIES			
1. Size	27.04***	(3.48)	0.993
2. Inter-connectedness	11.28	(0.83)	0.962
3. Substitutability	55.54***	(2.99)	0.992
4. Complexity	31.91*	(1.75)	0.960
5. Cross-jurisdictional activity	27.54*	(1.93)	0.991
INDICATORS			
2a. Intra-financial system assets	5.301	(0.29)	0.937
2b. Intra-financial system liabilities	4.877	(0.19)	0.928
2c. Securities outstanding	23.65	(1.34)	0.975
3a. Payments activity	23.73	(0.54)	0.969
3b. Assets under custody	11.96	(0.75)	0.995
3c. Underwritten transactions	130.9***	(5.94)	0.973
4a. Notional amount of OTC derivatives	63.40***	(2.81)	0.978
4b. Trading and AFS securities	12.38	(0.45)	0.919
4c. Level 3 assets	19.95	(0.51)	0.894
5a. Cross-jurisdictional claims	28.00	(1.65)	0.990
5b. Cross-jurisdictional liabilities	27.09*	(1.93)	0.986

Note: The dependent variables are the respective adjusted scores at the category and indicator level. The table reports the coefficient estimates of the triple interaction term ($Post_t \times G\text{-}SIB_i \times Profitability_i$) based on equation (4), with t-statistics reported in parentheses. Each specification includes the full set of bank fixed effects and controls, as well as country-year fixed effects as detailed in Table 5. The number of observations is 373 in each regression. The indicators are numbered based on the category they belong to. Robust standard errors are clustered at the bank level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

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, Krigman *et al.*, 2001; Santiago *et al.*, 2020). The positive coefficient suggests that as the more profitable G-SIBs expanded their market share relative to the less profitable ones, they were able to attract a higher share of the global underwriting business as well. Likewise, we observe a significant wedge opening up in G-SIBs' *notional amount of OTC derivatives*. Consistent with the high fixed costs associated with OTC trading (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 (e.g. McNelis and Yetman, 2020 and Malik and Xu, 2017).

6 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.

6.1 Alternative specifications and sample composition

We start by restricting the sample to those banks for which we have data in *each* year from 2013 to 2018. This reduces the number of banks from 84 to 65. Our findings are robust to this change, both in terms of economic and statistical significance as reported in Table 8 (column (1)).

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

Table 8: Balanced sample and alternative G-SIB and treatment dummies

	Balanced sample (1)	G-SIB as designated (2)	Bank-specific treatment (3)	Control for capital buffer (4)	Control for CAPM beta (5)	Exclude U.S. banks (6)	Only EME (7)
Post × G-SIB × Profitability	28.84***	27.23***	28.10***	33.05***	27.10**	42.86***	62.99**
	(3.19)	(2.84)	(2.97)	(3.36)	(2.36)	(6.00)	(2.70)
Post × G-SIB	–34.31***	–31.66**	–31.70**	–34.81***	–31.90**	–44.77***	–83.90*
	(–2.92)	(–2.62)	(–2.56)	(–2.82)	(–2.35)	(–3.99)	(–1.81)
Post × Profitability	21.46	17.25	6.345	14.63	17.93	18.25**	–0.475
	(1.53)	(1.65)	(0.66)	(1.43)	(1.40)	(2.65)	(–0.06)
N	330	373	373	373	313	313	109
R2	0.990	0.991	0.990	0.991	0.990	0.992	0.989
Bank controls and FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post dummy	2015	2015	Bank-specific	2015	2015	2015	2015
G-SIB dummy	Baseline	Official	Baseline	Baseline	Baseline	Baseline	Baseline

Note: The table reports robustness checks on the baseline results in Table 5 using equation 4. The dependent variable is the adjusted G-SIB score. The balanced sample in column (1) comprises only those banks that have been included in the G-SIB assessment sample in each year. Column (2) uses the official designation year for the G-SIB dummy. Column (3) uses bank-specific treatment years based on the text analysis in Section 4.1. In columns (4) and (5), we also include respectively the capital buffer and the CAPM Beta as controls. Column (6) excludes U.S. banks and column (7) includes only banks from emerging market economies (EME). *Post* is a dummy variable that takes value 1 in the post-treatment period [2015-18], and *G-SIB* is a dummy variable that takes value 1 for banks that have been designated as such at least once before 2015. *Profitability* is the level of average pre-treatment (2013-14) ROA. Bank-level controls comprise the CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposits to total liabilities, and the density ratio (all lagged by one year). Robust standard errors are clustered at the bank level and t-statistics are reported in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

definition influences our results, we run our analysis using the official G-SIB designation, which can potentially vary across time. That is, the dummy equals 1 only in those years when the bank is actually designated a G-SIB. As shown in Table 8, column (2), the alternative definition has little impact on our results. This result reflects the fact that only a few banks transition into or out of being a G-SIB.

Next, we consider bank-specific treatment dates. In our baseline analysis, we made the conservative assumption that all G-SIBs are treated at the same time, i.e. in 2015. This is the year that emerged as the most likely treatment date for G-SIBs. Yet, our identification strategy enables us to identify banks that may have adjusted before or after 2015. For instance, one could consider G-SIBs whose 2014 annual report contains a greater number of references to how they responded to the G-SIB framework (as compared to the 2015 report) to have been treated in 2014. For G-SIBs without any such discussion in either their 2014 or 2015 reports, the treatment date could be considered to be 2016, the year when the G-SIB capital surcharges take effect. We test the implications of using these alternative, bank-specific treatment dates and find that our results are robust (see column (3) of Table 8). The result is consistent with the large number of G-SIBs for which 2015 stands out as the treatment year.

We assess whether differences in the size of the banks' capital buffers shaped the response to the framework. In our main analysis, we control for differences in the CET1 capital ratio across banks. However, the G-SIB surcharges imply that capital buffers – as measured by the difference between the CET1 ratio and the sum of minimum capital requirements and the fully-loaded surcharge – can differ across banks even if they have the same CET1 capital ratio. We thus replace the CET1 capital ratio with the capital buffer in our main regressions. Our findings do not change as a result of this inclusion (Table 8, column (4)).

We also gauge whether the more profitable G-SIBs' adjustment is driven by a higher opportunity cost of reducing their scores or whether it reflects a lower cost of issuing capital to meet higher capital requirements. To disentangle these effects, we control for differences in banks' cost of equity as inferred from their systematic risk ("Beta"). We estimate the latter based on a standard Capital Asset Pricing Model using 50-week rolling regressions of banks' weekly excess returns on the excess return of their domestic benchmark indices (see Table 2 for the summary statistics of the Betas). We find that accounting for variation in banks' Betas has no meaningful impact on the coefficients of interest as shown in column (5) of Table 8. This lends support to the interpretation that for more profitable G-SIBs, the cost of downsizing outweighs the benefits of reducing their systemic importance.

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. The use of country-year fixed effects throughout our main analysis already mitigates this concern to a large extent. To further examine the role of geographical factors, we pursue several additional investigations.

First, we exclude U.S. banks to test whether deviations from the BCBS's methodology in the U.S. regulation of G-SIBs affect our results. U.S. regulators apply an additional, although closely related, method for the calibration of the G-SIB capital surcharges. U.S. G-SIBs are subject to the higher of the capital surcharge that result from this method and the BCBS methodology, with the former typically resulting in higher surcharges. This implies that U.S. banks may have weaker incentives to respond to the BCBS G-SIB framework. In line with this, we find that the exclusion of U.S. banks reinforces our results of a significant difference in the response of more and less profitable G-SIBs as shown in column (6) of Table 8.

Second, we repeat our analysis based on including only banks from emerging market economies (EME). This takes account of differences in the degree of financial development relative to more advanced economies. In addition, it enables us to address any potential concern that could be linked to the introduction of Total Loss-Absorbing Capital (TLAC) requirements for G-SIBs in advanced economies.[18] As shown in column (7) of Table 8, our findings prove robust to the exclusion of advanced economy banks.

Finally, 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. We find that 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 9. This accords with the G-SIB framework being the primary driver of banks' adjustments.

[18]TLAC requirements could have potentially affected G-SIBs' scores by inducing changes in the composition of banks' funding. However, these requirements have become effective only as of 2019 in advanced economies and are thus unlikely to affect our results. In emerging market economies, TLAC requirements will not take effect before the start of 2025.

Table 9: Replacing G-SIB dummy with a country group dummy

	US	EU	Asia-Pacific	EME
	(1)	(2)	(3)	(4)
Post × Group × Profitability	–4.501	39.18	8.418	–17.92
	(–0.22)	(1.42)	(0.46)	(–0.94)
Post × Profitability	33.81***	23.56**	30.28**	36.78***
	(2.67)	(2.11)	(2.56)	(3.02)
N	404	404	404	404
R2	0.988	0.989	0.988	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 4 for different sub-samples indicated in column headings. The dependent variable is the adjusted G-SIB score. European Union (EU) comprises the United Kingdom during the period of observation. The 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. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

6.2 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 (4).

Table 10 reports the results based on substituting the average ROA in the pre-treatment period (our baseline measure) with the ROA in 2014, i.e. the most recent observation before treatment (column (1)). In addition, we consider the average pre-treatment return on equity (column (2)) and an estimate of the banks' efficiency, measured as one minus the bank's cost-to-income ratio (column (3)).[19] The findings underscore our main conclusion regarding the pivotal role of profitability, both in terms of statistical and economic significance.

We also assess whether risk-adjusted measures of profitability support our previous findings. Higher profitability could reflect higher risk tolerance (e.g. Martynova *et al.*, 2020) or even risk-taking (Meiselman *et al.*, 2020). By controlling for risk-taking in our profitability measure, we shed light on whether the observed shift in systemic importance towards more profitable G-SIBs implies a build-up in risk-taking rather than a reallocation

[19] 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 10: Robustness based on alternative profitability and efficiency metrics

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

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

in favour of more efficient and better-run banks (Peni and Vähämaa, 2012).

Table 10 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 (recall Table 5). This implies that fundamental differences in profitability are a key determinant of the differential impact of the framework on G-SIBs.

6.3 Endogenous profitability and business model

Our focus is on the role of pre-reform profitability in shaping banks' response to the G-SIB framework. The use of pre-reform profitability helps rule out concerns around reverse causality, which may arise from the fact that adjustments to the framework could also affect banks' profitability. In this subsection, we provide additional evidence 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 (see Appendix F). More profitable banks, based on the median ROA dummy in the pre-treatment period, become less profitable banks in the post-treatment period (or vice-versa) in less than 10 percent of the observations. Profitability thus provides a reliable measure of the structural characteristics of banks that underpin their response to the G-SIB framework during the period under study.

Table 11: Robustness: Control for business models

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

Note: The table reports results of the regression in equation 4 with the inclusion of business model clusters as additional regressors (details in Appendix G). There are three variations with four, three, and two clusters, shown in each column. 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. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

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 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 G). 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 11 show that controlling for differences in business models has little impact on the coefficient of interest.

6.4 Alternative estimation strategies

We further assess the robustness of our main findings by considering alternative estimation strategies based on matching banks. To match the treated with the control banks, we fit a propensity score model based on the pre-treatment observations of the core bank-level attributes that we used as controls in our baseline analysis (see Table 12). We standardise each variable to control for differences in the variance across variables. We then pursue kernel matching, while imposing a caliper of 0.05 and common support of the propensity score for treated and control banks.

We also consider restricting the matches to within a profitability category, i.e. matching high (low) ROA G-SIBs exclusively with high (low) ROA Non G-SIBs. For robustness, we also match on an expanded set of attributes that include loans, securities, wholesale funding and non-interest income (all scaled by total assets), as also used for the cluster analysis in Section 6.3 (see Appendix H for matching statistics and efficiency).

Table 12: Assessing robustness based on matching

	Matching		
	(1)	(2)	(3)
Post × G-SIB × Profitability	30.90***	24.13*	35.88***
	(3.10)	(1.95)	(5.00)
Post × G-SIB	–32.33**	–29.42**	–32.92***
	(–2.49)	(–2.21)	(–3.37)
Post × Profitability	10.45	7.498	31.92*
	(1.05)	(0.70)	(1.93)
N	373	339	200
R2	0.990	0.990	0.993
Bank controls and FE	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes
Matching variables	Core	Core	Expanded
Matching only within ROA types	No	Yes	No

Notes: To match treated with control banks (i.e. G-SIBs with Non G-SIBs), we use a propensity score model based on matching the following *core* bank attributes: the standardized value of the banks' pre-treatment (2013–14) CET1 capital ratio, the ratio of non-performing loans to total loans, cash to assets, deposits to assets and the density ratio in columns (1) and (2). In column (3), we expand the attributes and add the standardized value of pre-treatment loans, securities, wholesale liabilities, and non-interest income (all scaled by total assets). A caliper of 0.05 and common support are imposed on the propensity score based kernel matching. Exact matching on the profitability dummy is imposed in column (2).

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. The estimates suggest a significant rise in more profitable G-SIBs' scores, in a range of about 24 to 36 bps relative to the matched Non G-SIBs, which tallies with the findings in Section 5.3.

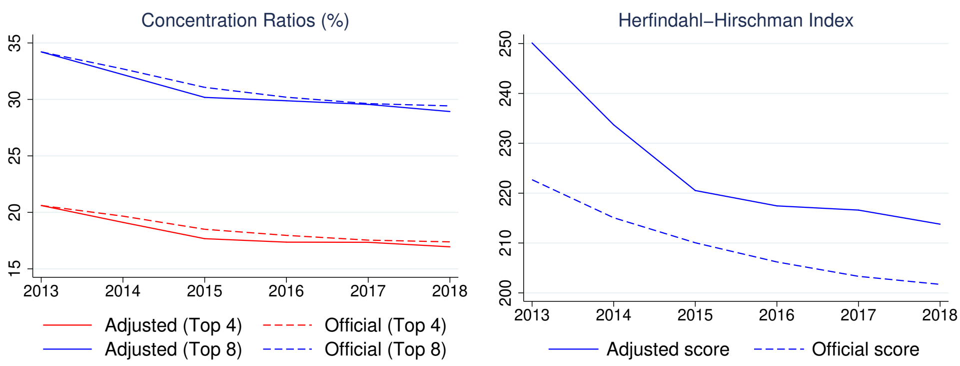
7 Should regulators be concerned?

We have shown that less profitable G-SIBs have decreased their average systemic importance 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). The adjustment by these banks raises the question of how concentration and systemic risks have evolved in the global banking sector.

7.1 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 6 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 4).

Figure 6: Concentration ratios and Herfindahl-Hirschman Index



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

7.2 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, i.e. 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. 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 13 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.

Table 13: 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	–0.032	–11.382*	–0.075	–25.805**	–0.487
	(–1.57)	(–1.90)	(–1.41)	(–2.00)	(–1.36)
Less profitable G-SIBs	–0.055	–19.672**	–0.122**	–47.035***	–0.505
	(–1.88)	(–2.23)	(–2.13)	(–3.05)	(–1.47)
More profitable G-SIBs	0.009	2.938	0.006	10.865	–0.458
	(0.74)	(0.96)	(0.06)	(0.58)	(–0.60)

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 (3) (first set of row) or (4) (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. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

For G-SIBs as a group, we note that default risk measures (Table 13, columns (1) and (3), top row) have not declined materially, despite a notable increase in banks' capital ratios and greater reliance on more stable sources of funding (Goel *et al.* (2019)). At the same time, systemic importance has also not decreased significantly post treatment (recall Section 5.2). Taken together, however, these two forces have led to a reduction in the systemic risk contribution of G-SIBs (columns (2) and (4), top row). SRISK has also declined for G-SIBs, although the change is statistically insignificant (column (5), top row). Closer inspection reveals that the systemic risk contribution has declined in particular for the less profitable G-SIBs (columns (2) and (4), second row). By contrast, for the more profitable G-SIBs, systemic risk contribution has increased, although insignificantly so (columns (2) and (4), last row).

8 Conclusion

In this paper, we assess how profitability shapes banks' adjustment to higher capital requirements. First, we show theoretically that a more profitable bank would choose to raise more capital and shrink by less – or grow by more – as compared to a less profitable bank. This is because profitability underpins both the opportunity cost of shrinking, as well as the ability to generate capital organically. We test the predictions of our model by assessing the G-SIB framework, a cornerstone of the too-big-to-fail reforms. The framework imposes additional capital surcharges on some, but not all, large internationally active banks. We find that the less profitable G-SIBs have reduced their systemic importance as intended by the framework. This is in stark contrast to the more profitable G-SIBs, which have continued to grow despite the additional constraints.

Our findings underscore that considering differences in profitability can help better understand bank behavior and thus guide policy design. For instance, to the extent that the G-SIB framework seeks to equalise the systemic risk contribution across banks (i.e. PD $\times$ Score, see e.g. BCBS (2013)), the rising systemic importance of some banks warrants monitoring of whether there has been a commensurate decline in their default risks.

Relatedly, while a more demanding capital surcharge schedule could bolster G-SIBs' resilience, our findings imply that this could accelerate the reduction in the scores of the less profitable G-SIBs and widen the wedge viz-a-viz 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 – i.e. 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 therefore offers exciting avenues for future research.

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Appendices

A Institutional details of the G-SIB framework

The G-SIB framework follows a rules-based approach to, on an annual basis, assign each bank in the assessment sample (roughly 80 internationally-active large banks) a score that reflects its systemic importance. The score encompasses twelve indicators of a bank's systemic importance (see Table 2 for the full list of indicators), grouped into five categories: cross-jurisdictional activity, complexity, interconnectedness, size, and substitutability . For each indicator, a score is computed for each bank that equals the bank's indicator value divided by the sum of indicator values of all banks in the assessment sample. The indicator scores thus reflect the bank's global market share in the underlying activity. The overall score – referred to as the "G-SIB score" – equals a weighted average across the bank's twelve indicator scores. The scores are measured in basis points (bps), and banks with a G-SIB score of at least 130 bps are designated as G-SIBs based on an annual assessment. Supervisors can apply judgement and override this rule by designating a bank as a G-SIBs even though its score is below the threshold. However, this option has only been used a few times in the past.

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

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

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

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

B List of keywords

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

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

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

C Action-oriented sentences in annual reports

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

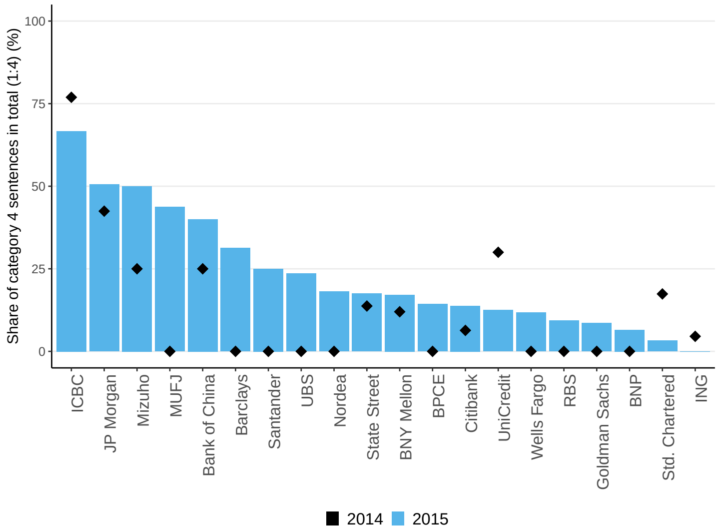
D Most frequent words in relevant sentences

Figure: Word cloud of G-SIB related sentences

Note: The graph plots the 70 most frequent words mentioned in G-SIB related sentences in categories 1 to 4 as per Table 1. The sample consists of the annual reports of 31 G-SIBs in 2013, 2014, and 2015.

E Bank-specific share of relevant sentences

Figure: Share of category 3 and 4 sentences by bank, for 2014 and 2015



Note: Banks with non-zero counts of category 3 & 4 sentences in 2015 (except ING) are shown with bars, with their respective 2014 shares as diamonds. The sample is restricted to G-SIBs designated as such before 2015.

F Bank profitability over time

Table: Pearson's correlation coefficients of ROA

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

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

G 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 6.3 and reported in Table 11 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 the table below. We also reduce the number of clusters allowed to two and three as robustness checks and note that the results remain consistent.

Table: Summary statistics by business model clusters

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

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

H Matching quality

Table: Test of difference in average value of co-variates before and after matching.

Variable	Non G-SIBs	G-SIBs	p-val (unmatch)	p-val (1)	p-val (2)	p-val (3)
Cash to assets	0.062	0.068	0.456	0.191	0.748	0.272
Density ratio	0.51	0.44	0.012	0.750	0.429	0.920
CET1 ratio	0.11	0.12	0.073	0.885	0.888	0.511
NPL to loans	0.028	0.034	0.256	0.472	0.843	0.270
Deposits to assets	0.53	0.49	0.086	0.791	0.702	0.073
Return on assets	1.04	0.88	0.106	0.259	0.864	0.851
Loan to assets	0.54	0.38	0	NA	NA	0.206
Securities to assets	0.19	0.25	0	NA	NA	0.372
Wholesale liabilities to assets	0.30	0.28	0.364	NA	NA	0.074
Non-interest income to assets	0.009	0.014	0	NA	NA	0.652

Note: Based on pre-treatment (2013-14) bank characteristics. Columns 2 and 3 denote the average value of the covariates for the two groups of banks. Column 4 denotes the p-value of the test of difference in the unmatched sample. Columns 5 through 7 denote the test of difference under the respective matching strategies discussed in Table 12.