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Do G-SIBs engage in window-dressing behavior? An empirical analysis*

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Abstract

This paper examines whether global systemically important banks (G-SIBs) engage in window-dressing behavior to circumvent or reduce regulatory requirements, increasing vulnerability to economic shocks. Using a comprehensive global bank sample, we uncover evidence of such practices: G-SIBs reduce year-end exposures used for G-SIB capital buffer calculations, by roughly twice the magnitude of non-G-SIBs, and reverse these cuts early the next year. This pattern is strongest among G-SIBs that are near bucket thresholds or subject to high G-SIB capital surcharges.

Keywords: Capital Requirements, G-SIB Framework, Systemic Risk, Window Dressing

JEL classification: G21, G38

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1 Introduction

During the global financial crisis of 2007-09, numerous large and globally active banks either failed or were on the verge of failing. Particularly due to the size and the interconnected nature of those banks, this resulted in high stress in the financial system, which, in turn, also propagated through the real economy (e.g., [Ivashina and Scharfstein, 2010](#)). As a response, some banks deemed to be too-big-to-fail received government support and the wider impact that the stress of large and globally active banks could have become very clear. Consequently, the Financial Stability Board (FSB) proposed a framework aimed at mitigating the moral hazard associated with too-big-to-fail banks, thereby seeking to prevent future government bailouts ([Financial Stability Board, 2010](#)).

The Basel Committee on Banking Supervision (BCBS) introduced the global systemically important bank (G-SIB) framework in 2011, which primarily imposes an additional capital buffer requirement on G-SIBs ([Basel Committee on Banking Supervision, 2011](#)). This framework aims at protecting the financial system and the real economy from negative externalities and spillover risks posed by them by reducing the probability and severity of issues emanating from the failure of such banks. Moreover, the G-SIB framework is also supposed to contribute to a level-playing field by reducing the too-big-to-fail competitive advantages of large and globally active banks in funding markets arising from assumed government support (e.g., [Berndt et al., 2025](#)).

However, despite these desired positive effects, the design of the G-SIB framework was also viewed critically. The main reason for criticism is that “the calculation of G-SIB surcharges could also incentivize period-end window-dressing” ([Financial Stability Board, 2021](#)). Window dressing refers to banks’ behavior to influence relevant positions that are used as inputs to determine regulatory capital requirements with the aim of appearing less risky and circumventing or reducing those requirements and, eventually, being undercapitalized and more prone to shocks (e.g., [Allen and Saunders, 1992](#); [Basel Committee on Banking Supervision, 2018a](#)). Although the FSB expects the effects from potential window dressing to be small compared to

the framework's benefits, it admits that the framework design may allow and thus incentivize G-SIBs to lower their additional capital buffer requirement by, for instance, reducing participation in foreign exchange and short-term funding markets. Such behavior could impair financial markets' functioning and monetary policy implementation, as periodic adjustments amplify volatility and introduce temporary distortions (e.g., [Basel Committee on Banking Supervision, 2018a](#); [Financial Stability Board, 2021](#)). Window-dressing behavior is generally known to be value-destroying and associated with lower future performance ([Agarwal et al., 2014](#)). Furthermore, discussions about the effectiveness of the G-SIB framework have intensified following the acquisition of the distressed Credit Suisse by UBS in 2023. This takeover was facilitated by liquidity support from the Swiss National Bank (SNB) for UBS, raising concerns about the continued reliance on public support for G-SIBs.

Against this background, our paper examines whether G-SIBs engage in window-dressing behavior. Given the potential negative effects from window dressing explained above and the relevance of a sound capital base for banks' loss absorbing capacity, its detection and scale is of considerable public policy interest (e.g., [Allen and Saunders, 1992](#)).

Based on a comprehensive global bank sample, we provide empirical evidence supporting the existence of window-dressing behavior among banks. At the end of the year, G-SIBs reduce certain exposures more strongly than other banks. This reduction is economically meaningful in magnitude and approximately twice as large as that observed for other banks. The balance sheet positions analyzed include total assets, debt issued, derivatives, level 3 assets, as well as trading and available-for-sale securities, which are all relevant for calculating the G-SIB score and determining the additional capital buffer requirement. Moreover, these declines in exposures do not appear to be risk reductions of a strategic and longer-term nature because G-SIBs increase them again more strongly than other banks at the beginning of the subsequent year. This indicates a "V-shape" relationship and points to window-dressing behavior. The observed behavior is particularly pronounced for G-SIBs whose scores are close to a bucket threshold and for G-SIBs with high surcharges. In both cases, a reduction in the G-SIB score would be particularly valuable as it could be accompanied by a lower additional capital buffer

requirement.

With these results, our paper contributes to the multifaceted literature on regulatory arbitrage. More specifically, we enhance the literature on banks' window-dressing behavior within the G-SIB framework. While prior studies have predominately examined window-dressing behavior within specific geographic contexts (e.g., [Behn et al., 2022b](#); [Garcia et al., 2023](#); [Berry et al., 2024](#)), our analysis employs a comprehensive global bank sample, offering a broader perspective. An exception is [Naylor et al. \(2024\)](#), who also cover a global bank sample. Moreover, we contribute to the existing studies by not only concentrating on potential reductions in exposures at year-end, but also examining possible increases at the beginning of the next year (e.g., [Behn et al., 2022b](#); [Garcia et al., 2023](#); [Naylor et al., 2024](#)). This is highly relevant for underpinning empirical evidence of window-dressing behavior. Moreover, unlike, for example, [Behn et al. \(2022b\)](#) and [Garcia et al. \(2023\)](#), our analysis is not potentially affected by the denominator effect of G-SIB scores. The denominator effect refers to potential distortions if the denominator of G-SIB scores is not recalculated for intra-year points in time. Since G-SIB scores can be interpreted as a market share of a bank and thus depend on the indicators of other banks, the denominator should be recalculated in each period. By using the quarterly changes of indicators and recalculating the denominator in each quarter, our approach prevents the denominator effect.

We organize the remainder of this paper as follows. In Section 2, we provide details on the G-SIB framework. Section 3 reviews the literature and develops our hypotheses. In Section 4, we present the data sources and sample selection procedure used in our empirical analysis. Section 5 introduces our identification strategy and Section 6 summarizes our findings. In Section 7, we perform several robustness checks. Section 8 concludes.

2 The G-SIB framework

The G-SIB framework is designed to mitigate both the likelihood of a failure of a G-SIB and its potential systemic consequences for financial stability and the real economy. We outline

below the framework's conceptual foundations and assessment methodology ([Basel Committee on Banking Supervision, 2018b,0](#)). In general, the G-SIB framework follows an indicator-based measurement approach to derive a bank's G-SIB score, which, in turn, determines the additional loss absorbency requirement for G-SIBs.

The *G-SIB score* reflects the systemic risk that a bank poses to the wider system and aggregates information from five categories.¹ These categories encompass the (1) size of banks, (2) their interconnectedness, (3) the lack of readily available substitutes of financial infrastructure or services they provide, (4) their cross-jurisdictional activity, and (5) their complexity. Except from the bank size category, the BCBS has further split the remaining four categories into multiple *indicators* (see Table [A.1](#) in the Online Appendix). The advantage of this approach considering many different indicators is that it captures many different dimensions of what creates negative externalities and renders a bank critical for the stability of the financial system.

The indicators used in the G-SIB framework need to be reported by banks exceeding a Basel III leverage ratio exposure of EUR 200 billion at financial year-end (including exposures from insurance subsidiaries), as well as by banks designated as G-SIBs in the previous year. For each bank in this so-called G-SIB assessment sample, the market share for a specific indicator is determined by dividing the individual bank amount by the aggregate amount for this indicator summed across all banks in the sample. This result is multiplied by 10,000 to convert the indicator market share into basis points (bps). The overall G-SIB score, taking into account all indicators, is equal to the weighted average of the indicator market shares, with most of the indicators equally weighted within their category and also with each category equally weighted

¹ In the literature, different measures of systemic risk, such as the conditional value at risk and the systemic expected shortfall, have been proposed (e.g., [Adrian and Brunnermeier, 2016](#); [Acharya et al., 2017](#)).

within the G-SIB score. The G-SIB score calculation can be summarized as follows:²

$$G-SIB \text{ score}_i \text{ (in bps)} = \sum_{j=1}^{13} w_j \cdot \frac{Bank \text{ indicator}_{i,j}}{\sum_{i=1}^I Bank \text{ indicator}_{i,j,t}} \cdot 10,000, \quad (1)$$

where i indexes banks, j indexes indicators with a total of 13 indicators defined in the framework, and w is the weight assigned to each of the indicators. The weights are summarized in Table A.1 in the Online Appendix.

Banks with a G-SIB score that exceeds a certain cutoff level, currently set at 130 bps by the BCBS, will be classified as G-SIBs. Depending on their score, those banks are then allocated into five buckets that determine the additional capital buffer requirement that currently ranges from 1.0% to 3.5%.³ If a bank's score exceeds the top threshold of the fourth bucket, a new bucket will be added in order to maintain banks' incentives to avoid becoming more systemically important. The additional capital buffer requirement needs to be met with Common Equity Tier 1 (CET 1) capital only.

The G-SIB assessment exercise is conducted annually mostly using banks' financial year-end data and banks are reallocated to a new bucket, if necessary, based on their newly calculated score. This quantitative indicator-based measurement approach may also be supplemented with additional qualitative and further quantitative information from supervisory judgment.⁴ However, results of the indicator-based measurement approach shall only be overwritten in exceptional cases. This is expected to be rare and, for the sake of consistency, also subject to peer review.

With regard to the timeline of the framework, the additional capital buffer requirement for G-SIBs was phased in together with the capital conservation and countercyclical buffers, that

² For illustrative purposes and based on hypothetical data, [Basel Committee on Banking Supervision \(2014\)](#) provides an example for calculating the G-SIB score. The maximum score, that is, the score for a bank that would be the only bank in the assessment sample, is 10,000 basis points (i.e., 100%). The score of the substitutability category is capped at 500 bps.

³ The allocation of banks that participated in the G-SIB assessment exercise into these buckets is published on the FSB website ([Financial Stability Board, 2024](#)).

⁴ For example, supervisory judgment may be used to add banks to the G-SIB assessment sample, although they do not meet the criteria explained above, as well as to designate banks with scores below the cutoff level as G-SIBs.

is, between 2016 and 2018, and became fully effective on 1 January 2019 ([Basel Committee on Banking Supervision, 2011,0](#)). To enhance the methodology and address several identified shortcomings, the BCBS last revised the G-SIB framework in 2018, which applied from 2021 ([Basel Committee on Banking Supervision, 2018b](#)).⁵ [Libertucci et al. \(2024\)](#) assess the G-SIB framework ten years after its introduction. They find that G-SIBs' average score decreased since then, mainly due to reductions in complexity and interconnectedness, while non-G-SIBs' score on average increased.

3 Literature review and hypotheses development

3.1 Literature review

Our paper contributes to the literature on regulatory arbitrage, mostly understood as “*opportunities for banks to reduce substantially their regulatory capital requirements with little or no corresponding reduction in their overall economic risks*” ([Jones, 2000](#)). Lowering equity capital without limiting economic risks is problematic from a financial stability perspective because equity capital is necessary to absorb unexpected losses and ensure bank resilience, particularly during periods of stress (e.g., [Demirguc-Kunt et al., 2013](#)). In the literature, several opportunities for banks to engage in regulatory arbitrage have been identified.

One important literature strand is concerned with risk-weighted assets (RWA) heterogeneity after banks' adoption of internal risk models to determine their minimum capital requirements. [Mariathan and Merrouche \(2014\)](#) find that the ratio of RWA to total assets, usually referred to as RWA density, declines after banks received the regulatory approval to apply internal risk models. Because this finding is particularly pronounced among weakly capitalized banks, they conclude that the observed decline results from banks' strategic risk modelling. In various settings, several studies confirm the underreporting of banks' self-estimated risk parameters for the reason of saving equity capital (e.g., [Begley et al., 2017](#); [Berg and Koziol, 2017](#); [Plosser and](#)

⁵ Most notably, the trading volume indicator has been introduced and the scope of consolidation includes insurance subsidiaries.

[Santos, 2018](#); [Behn et al., 2022a](#)).

Another major strand of literature, to which our study contributes primarily, deals with banks' window-dressing behavior. Window dressing does not only appear as a response to banking regulation. Early research on this topic concentrated mainly on fund managers. Results indicate that fund managers seem to strategically rebalance certain portfolio positions to appear particularly safe or well-performing to investors at disclosure dates (e.g., [Lakonishok et al., 1991](#); [Musto, 1999](#); [Ng and Wang, 2004](#); [Agarwal et al., 2014](#)).

In the context of banking, [Allen and Saunders \(1992\)](#) were the first to examine window dressing. Based on call reports submitted to the regulatory authorities and closely monitored by both regulators and investors, their findings suggest that banks systematically window dress balance sheet positions at the quarter-end reporting dates. Later papers provide also evidence for window dressing of regulatory ratios. Most prominently, several studies exploit the different implementation of the leverage ratio in different countries, either calculated as a point-in-time measure based on the last day of the quarter only or using more frequent data, such as monthly or daily averaging. Consistently, results indicate that the calculation methodology based on quarter-end values or less frequent averaging leads to a decline in banks' repo market activity on certain days as an attempt to temporarily improve the leverage ratio (e.g., [Grill et al., 2017](#); [Anbil and Senyuz, 2018](#); [Kotidis and van Horen, 2018](#)).

Our analysis focuses on banks' window-dressing behavior within the G-SIB framework (see Section 2 for details). Most closely related to our study are four recent papers, most of which focus on a specific geographical region. [Behn et al. \(2022b\)](#), using data from banks headquartered in the European Banking Union, show that G-SIBs reduce activities affecting the G-SIB score at the end of the year. This finding is more pronounced for banks with G-SIB scores particularly close to a threshold between two buckets and for banks more active in repo markets. Based on a more comprehensive sample of banks from the European Union and a longer observation period, [Garcia et al. \(2023\)](#) confirm the observed reductions in G-SIB scores due to window dressing. Beyond that, they add that window dressing may undermine the identification of G-SIBs and indeed reduces capital surcharges for some banks. Furthermore,

they find that window dressing tends to be stronger for banks with tighter capital constraints. [Berry et al. \(2024\)](#) study U.S. banks and show that they primarily lower the notional amount of over-the-counter derivatives to reduce the additional capital requirement imposed by the G-SIB framework. [Naylor et al. \(2024\)](#) employ a difference-in-differences strategy and, in line with previous studies, find causal evidence that the G-SIB framework contributes to window-dressing behavior.

Apart from window dressing, there are further studies analyzing the G-SIB framework and its impact on banks and the real economy. [Benoit et al. \(2019\)](#) and [Passmore and von Hafften \(2019\)](#) identify several shortcomings in the assessment methodology, such as a bias in G-SIB scores towards the most volatile categories and an underestimation of the probability of bank failures. [Moenninghoff et al. \(2015\)](#) observe that the framework negatively affects the market value of G-SIBs, although the official designation of banks as G-SIBs itself partially offsets this effect. [Schich and Toader \(2017\)](#) find that G-SIBs benefit more from implicit guarantees than other banks, which suggests that the too-big-to-fail problem still persists. [Behn and Schramm \(2021\)](#) and [Favara et al. \(2021\)](#) examine the impact of the G-SIB framework on lending and consistently find no effect on overall credit supply, whereas [Degryse et al. \(2023\)](#) observe that a bank's designation as G-SIB reduces its syndicated loans supply to risky corporate borrowers. More broadly, [Violon et al. \(2020\)](#) investigate the impact of the G-SIB framework on banks' overall business model.

3.2 Hypotheses development

The G-SIB framework intends to incentivize banks to reduce their systemic importance by imposing an additional capital buffer requirement. More specifically, banks are expected to hold an additional capital buffer that aims at reducing the expected impact of a G-SIB's failure so that it equals the expected impact of a non-G-SIB's failure. Banks' G-SIB status and the required capital surcharge are determined based on an annual review of the calculated G-SIB score. Thus, the number of G-SIBs and their bucket allocation is not fixed over time, allowing banks to benefit from reducing or even preventing the additional buffer requirement by adjusting

their risk profile and business model in a sense that limits systemic spillover effects ([Basel Committee on Banking Supervision, 2018b](#)).

Importantly, although the G-SIB scores are periodically recalculated, they mostly rely on financial year-end data, which are point-in-time measures. To be more precise, with the exception of payments activity, underwritten transactions in debt and equity markets, as well as trading volume, the remaining ten indicators refer to banks' financial year-end. Those ten indicators weight almost 87% of a bank's G-SIB score ([Basel Committee on Banking Supervision, 2022a](#); [Garcia et al., 2023](#)). This methodological design provides banks with the opportunity to adjust relevant positions at the end of the year to reduce their systemic importance and thus to potentially save equity capital. If these reductions in positions are of a strategic and longer term nature, lower regulatory capital requirements are reasonable, whereas window dressing those positions at each end of the year do not justify lower requirements.

Comparing the additional G-SIB buffer requirement, currently ranging from 1% to 3.5%, to the capital conservation buffer requirement, amounting to 2.5%, the G-SIB surcharge appears to be a sizeable capital add-on. This is particularly notable given that the minimum CET 1 capital ratio stands at 4.5%. On top of that, from 2023, G-SIBs have to fulfil a higher leverage ratio requirement, that is, the leverage ratio buffer is set at 50% of a G-SIB's additional loss absorbency requirement ([Basel Committee on Banking Supervision, 2022b](#)). As a result, losing the G-SIB status or migrating to a lower bucket leads to substantial reductions in required equity capital for banks ([Benoit et al., 2019](#)). As outlined in Section 3.1, several studies suggest that saving equity capital is a key motive for banks' behavior, especially for those banks with tighter capital constraints (e.g., [Plosser and Santos, 2018](#); [Behn et al., 2022a](#)).

Against this background and in line with previous studies, we expect that banks indeed engage in window dressing to limit or prevent the additional capital requirement, specifically by reducing those activities at year-end that affect the G-SIB score. The incentive to lower these activities could be further reinforced by the fact that, by construction, a bank's G-SIB score and thus potentially the additional capital buffer requirement increase if other banks in the assessment sample reduce their indicator values by engaging in window dressing ([Garcia](#)

et al., 2023). We also expect that banks that reduce certain activities at the end of the year to subsequently increase them again at the beginning of the following year, which would further underpin window-dressing behavior.

4 Data sources and sample selection

For our empirical analysis, we collect balance sheet and income statement data on a consolidated level from Standard & Poor’s Global Market Intelligence for the period from 2011 until 2018 and for banks with total assets exceeding EUR 200 billion. This amount corresponds to the disclosure threshold defined in the G-SIB framework, meaning that banks with a leverage ratio exposure measure above this threshold at the financial year-end need to make publicly available the 13 indicators defined in the G-SIB assessment methodology (Basel Committee on Banking Supervision, 2018b).⁶

Similar to Berry et al. (2024), we limit this initial sample from Standard & Poor’s Global Market Intelligence to banks that have been at least once part of the G-SIB assessment sample between 2011 and 2018. This step is important for our identification strategy because those banks are most similar to G-SIBs, thus representing the best available control group (see details on our empirical model in Section 5.1).⁷ Moreover, we need to drop banks that only provide annual data to Standard & Poor’s Global Market Intelligence. Using quarterly and thus higher frequency data than the publicly available annual G-SIB data is necessary to reveal whether banks window dress certain activities at year-end. Finally, we exclude three banks from our sample that do not pursue a typical bank business, such as development banks, and drop observations where total assets are missing. Information on total assets is necessary to calculate our dependent variables (see Section 5.2 for more details).

Our final sample consists of 69 banks, of which approximately half have been designated as

⁶ The EUR 200 billion threshold has been set by the BCBS with the aim of ensuring that at least the 75 largest banks worldwide are subject to the disclosure requirements because those banks are per se part of the G-SIB assessment sample (see Section 2).

⁷ For readability purposes, we simply refer to non-G-SIBs in the following, although we mean non-G-SIBs that have been at least once part of the G-SIB assessment sample between 2011 and 2018.

G-SIBs at least once between 2011 and 2018. The banks in our sample exhibit on average total assets of EUR 883 billion, a return on equity of 2.6%, and are headquartered in 19 different countries. Examining banks' window-dressing behavior in the context of the G-SIB framework based on a worldwide sample is unique so far because the most closely related studies either focus on Europe or the U.S. (Behn et al., 2022b; Garcia et al., 2023; Berry et al., 2024). Only Naylor et al. (2024) apply a global sample as well. Moreover, with eight years from 2011 until 2018, our analysis covers one of the longest observation periods.

Eventually, we complement our bank balance sheet data with macroeconomic information at the country level from Refinitiv EIKON/Datastream. Publicly available data on the G-SIB framework are collected from the BCBS website, such as banks' G-SIB scores and surcharges.

5 Identification strategy

5.1 Empirical model

In our empirical strategy, we aim at identifying whether banks window dress certain positions at year-end that affect the G-SIB score in order to appear less systemically important. In this context, banks with the highest incentives for window dressing are G-SIBs because they already need to fulfill an additional capital buffer requirement and thus would benefit from reducing their G-SIB score and potentially saving equity capital.⁸ In contrast, non-G-SIBs are not subject to the additional G-SIB buffer requirement, which implies that a reduction in the G-SIB score does not result in any capital savings. In our sample, we limit the group of non-G-SIBs to banks that have been at least once part of the G-SIB assessment sample because those banks are most similar to G-SIBs in their size and other characteristics (see Section 6.1 for more details).

Thus, in our identification strategy, we primarily compare the behavior of G-SIBs, the treated group, with the behavior of non-G-SIBs in the assessment sample, the control group.

⁸ If banks migrate to the lower bucket or avoid the designation as G-SIB at all, their CET 1 capital relief amounts to either 0.5% or 1.0% of risk-weighted assets (Basel Committee on Banking Supervision, 2018b).

For that purpose, we estimate the following baseline model:

$$\begin{aligned} \Delta Y_{i,t} = & \alpha_0 + \alpha_i + \alpha_t + \beta_1 \cdot [Q1_t \text{ or } Q4_t] \cdot GSIB_i + \beta_2 \cdot [Q1_t \text{ or } Q4_t] \\ & + \sum_{j=1}^J \gamma_j \cdot B_{j,i,t-1} + \sum_{m=1}^M \delta_m \cdot C_{m,i,t-1} + \epsilon_{i,t}, \end{aligned} \quad (2)$$

where $\Delta Y_{i,t}$ is the quarterly change between $t-1$ and t in the specific indicator used to calculate the G-SIB score for bank i (see Section 5.2 for more details). α_0 is a constant, α_i are bank- and α_t are time-fixed effects to account for heterogeneity across banks and quarters.⁹ $Q1_t$ and $Q4_t$ are indicator variables either equal to one for the first or fourth quarter in each year, and zero otherwise. $GSIB_i$ is an indicator variable equal to one if bank i is designated as a G-SIB at least once between 2011 and 2018, and zero otherwise. $B_{j,i,t-1}$ are bank-specific and $C_{m,i,t-1}$ are country-specific control variables, all lagged by one time period to reduce endogeneity concerns (see Section 5.3 for more details). $\epsilon_{i,t}$ is the error term. Consistent with other studies, we cluster the standard errors at the bank level (e.g., Behn et al., 2022b; Garcia et al., 2023).

Our main coefficient of interest is β_1 , which measures the difference in the quarterly change in the specific G-SIB indicator change, $\Delta Y_{i,t}$, between G-SIBs and non-G-SIBs in the first or fourth quarter of each year. Since we, in line with other studies, also include time fixed effects in our model, the difference measured by β_1 refers to the effect, which is common to all first or fourth quarters during our observation period (e.g., Behn et al., 2022b; Garcia et al., 2023). As outlined in Section 3.2, we presume that β_1 is significantly negative in the fourth quarter, implying that G-SIBs reduce their indicator values at year-end more than non-G-SIBs. In the first quarter, we expect significantly positive coefficients, meaning that G-SIBs increase their indicator values at the beginning of the year more than non-G-SIBs. This would underpin that changes in certain positions by G-SIBs at year-end are not driven by strategic, more sustainable balance sheet adjustments, but rather by short-term window-dressing behavior.

In addition to our baseline model and to improve our identification strategy, we, first, identify banks that are close to bucket thresholds and, second, distinguish between banks that receive

⁹ The dummy variable, $GSIB_i$, is absorbed by the bank-fixed effects because it is time-invariant for bank i .

a low or a high G-SIB surcharge. These analyses aim to identify banks that have particularly high incentives to window dress and we thus expect to find stronger results.

5.2 Dependent variables

As elaborated in Section 5.1, we utilize the change in the indicators stipulated in the G-SIB framework and necessary for computing the G-SIB score as dependent variables. These indicators, primarily representing stock sizes as of the financial year-end, are particularly susceptible to banks' window-dressing behavior. A summary of these indicators is provided in Table A.1 in the Online Appendix. We replicate these indicators as accurately as possible and define the resulting proxies alongside all other variables in Table 1. Additionally, Table 2 provides descriptive statistics for the G-SIB indicator proxies and all other variables explained in this section.

In total, we are able to replicate five different indicators spanning three different categories. For the size category, we use banks' total assets (*TAssets*). In the interconnectedness category, we adopt banks' debt issued (*DebtIssued*) that comprises subordinated and senior debt. This measure aligns closely with the securities outstanding indicator of the G-SIB framework, capturing interconnectedness among financial corporations. The complexity category is represented by three different measures. First, we approximate the notional amount of OTC derivatives using the broader notional amount of derivatives (*Derivatives*). Second, we employ level 3 assets (*L3Assets*), which corresponds directly to the level 3 assets indicator in the G-SIB framework. Third, we combine trading account securities with available-for-sale securities (*Trading*) to reflect the trading and available-for-sale securities indicator. Although data for cross-jurisdictional activities are available, their coverage is limited and biased towards U.S. banks. Moreover, three of the four indicators in the substitutability category are based on annual business volumes, which makes them unsuitable for studying window dressing behavior. Consequently, we exclude the cross-jurisdictional activity and substitutability categories from our analysis.

Following the G-SIB framework outlined in Section 2, we divide for each individual bank

Table 1: Variable definitions.

Variable	Definition	Data source
<i>G-SIB indicators:</i>		
$\Delta TAssets$	Difference between banks' total assets, divided by the aggregate amount for this indicator summed across all banks in the sample, in t and $t - 1$ (in basis points).	Standard & Poor's Global Market Intelligence
$\Delta DebtIssued$	Difference between banks' debt issued, divided by the aggregate amount for this indicator summed across all banks in the sample, in t and $t - 1$ (in basis points).	Standard & Poor's Global Market Intelligence
$\Delta Derivatives$	Difference between banks' notional amount of derivatives, divided by the aggregate amount for this indicator summed across all banks in the sample, in t and $t - 1$ (in basis points).	Standard & Poor's Global Market Intelligence
$\Delta L3Assets$	Difference between banks' level 3 assets, divided by the aggregate amount for this indicator summed across all banks in the sample, in t and $t - 1$ (in basis points).	Standard & Poor's Global Market Intelligence
$\Delta Trading$	Difference between banks' trading account securities and available-for-sale securities, divided by the aggregate amount for this indicator summed across all banks in the sample, in t and $t - 1$ (in basis points).	Standard & Poor's Global Market Intelligence
<i>Main explanatory variables:</i>		
$GSIB$	Indicator variable equal to one if a bank has been designated as a G-SIB at least once between 2011 and 2018, and zero otherwise.	Financial Stability Board
$Q1$	Indicator variable equal to one in the first quarter of each year during our observation period, and zero otherwise.	Own calculation
$Q4$	Indicator variable equal to one in the fourth quarter of each year during our observation period, and zero otherwise.	Own calculation
<i>Bank-specific controls:</i>		
$Leverage$	Banks' volume of total equity capital divided by total assets.	Standard & Poor's Global Market Intelligence
$Cost-to-Income$	Banks' cost to income ratio.	Standard & Poor's Global Market Intelligence
$ROAA$	Banks' return on average assets.	Standard & Poor's Global Market Intelligence
$Liquidity$	Difference between banks' loan and deposit volume, divided by their total assets.	Standard & Poor's Global Market Intelligence
$NII-to-OpIncome$	Banks' net interest income divided by their operating income.	Standard & Poor's Global Market Intelligence
<i>Country-specific controls:</i>		
$GDPGrowth$	Growth rate of the real gross domestic product at the country level.	Refinitiv EIKON/Datastream
$Inflation$	Growth rate of average consumer prices (seasonally adjusted) at the country level.	Refinitiv EIKON/Datastream

This table gives an overview of the variables and data sources used in our empirical analyses.

Table 2: Descriptive statistics.

Variable	N	Mean	SD	p10	p25	p50	p75	p90
<i>G-SIB indicators:</i>								
$\Delta TAssets$ (bp)	1,873	-0.83971	12.36369	-11.62250	-3.45259	-0.09721	2.70209	7.85094
$\Delta DebtIssued$ (bp)	1,384	-1.05469	18.85782	-14.99487	-5.37150	-0.30140	3.87599	12.46808
$\Delta Derivatives$ (bp)	378	-3.70101	56.23506	-17.93146	-1.16181	0.22407	2.23752	13.38946
$\Delta L3Assets$ (bp)	807	-3.51709	31.08986	-30.40337	-7.44194	-0.12593	5.03946	17.67002
$\Delta Trading$ (bp)	889	-1.78869	39.24377	-19.02899	-3.75651	0.39304	4.20532	15.93448
<i>Main explanatory variables:</i>								
<i>GSIB</i>	1,942	0.50206	0.50012	0.00000	0.00000	1.00000	1.00000	1.00000
<i>Q1</i>	1,942	0.22863	0.42006	0.00000	0.00000	0.00000	0.00000	1.00000
<i>Q4</i>	1,942	0.28218	0.45018	0.00000	0.00000	0.00000	1.00000	1.00000
<i>Bank-specific controls:</i>								
<i>Leverage (%)</i>	1,925	6.96807	2.31006	4.51078	5.39132	6.46161	7.87533	10.65690
<i>NPL (%)</i>	1,304	2.58735	2.64359	1.00000	1.00000	2.00000	3.00000	6.00000
<i>Cost-to-Income (%)</i>	1,688	56.80896	17.38503	33.00000	46.00000	57.00000	66.00000	78.00000
<i>ROAA (%)</i>	1,921	0.66845	0.52689	0.09000	0.32000	0.63000	1.01000	1.32000
<i>Liquidity (%)</i>	1,723	-7.59442	17.97024	-24.58447	-18.15006	-8.84910	4.94094	14.38867
<i>NII-to-OpIncome (%)</i>	1,648	61.97572	16.99198	42.04617	50.89356	63.17674	74.31585	81.69132
<i>Country-specific controls:</i>								
<i>GDPGrowth (%)</i>	1,942	0.71519	0.71548	-0.07218	0.26323	0.62756	1.19081	1.71390
<i>Inflation (%)</i>	1,942	0.40213	0.46743	-0.08101	0.13521	0.39025	0.59095	0.80542

This table reports the descriptive statistics for the variables used in our analysis. To retain the largest possible number of observations for our regression analysis, we do not standardize the number of observations for each variable. Variables are described in Table 1. N refers to the number of observations, SD means standard deviation. p10, p50, and p90 represent the tenth, fiftieth, and the ninetieth percentile. Bp refers to basis points. Bank-specific controls are winsorized at the 1% and 99% levels.

its indicator value by the aggregate amount of that indicator across all banks in the sample. This approach mirrors the G-SIB assessment methodology, ensuring that changes in a bank's indicator reflect not only its own movements but also those of other banks (see Equation 3). Using these indicators, we compute quarter-on-quarter differences to capture changes between the third and fourth quarters, as well as between the fourth and the first quarters of each year. Our dependent variables can be interpreted as changes in market shares that are calculated as follows:

$$\Delta Y_{i,j,t} = \frac{\text{Bank indicator proxy}_{i,j,t}}{\sum_{i=1}^I \text{Bank indicator proxy}_{i,j,t}} - \frac{\text{Bank indicator proxy}_{i,j,t-1}}{\sum_{i=1}^I \text{Bank indicator proxy}_{i,j,t-1}}, \quad (3)$$

where $\Delta Y_{i,j,t}$ is the quarterly change in the market share between $t - 1$ and t in the specific indicator proxy j used to calculate the G-SIB score for bank i . To mitigate bias due to missing observations, which could distort the aggregate amounts and subsequent calculations of deltas, we maintain a constant number of banks for each time period. For missing observations, we apply linear interpolation solely for determining aggregate amounts, while individual banks' indicator values remain missing for those instances.

In order to prove the validity of our indicator approximations, we conduct a correlation analysis and compare the time series of our year-end indicator proxies with the official BCBS indicators. Overall, for *TAssets*, *Derivatives* and *L3Assets*, we find high positive correlations for the majority of banks in our sample. For *DebtIssued* and *Trading*, results are slightly weaker and the correlation with the original data depends on the individual bank, being high with around 90 % for some banks, but also lower for other banks.

5.3 Control variables

In our empirical setting, we control for many different bank- and country-specific characteristics to make sure that the observed differences between G-SIBs' and non-G-SIBs' behavior are indeed driven by window dressing. At the bank level, we consider controls from the CAMELS rating system, which was developed in the U.S. as a supervisory tool to comprehensively eval-

uate banks' overall condition (e.g., [Lopez, 1999](#)). CAMELS is an acronym and includes six components: Capital adequacy, Asset quality, Management ability, Earnings, Liquidity, and Sensitivity to market risk. Several studies that aim at explaining bank balance sheet positions use these components as control variables as well (e.g., [Özlem Dursun-de Neef and Schandlbauer, 2020](#)).

We incorporate banks' capital adequacy using the volume of total equity capital divided by total assets (*Leverage*). The volume of non-performing loans divided by total loans serves as a proxy for banks' asset quality (*NPL*). Banks' management ability is inferred from their cost-to-income ratio (*Cost-to-Income*), and earnings from their return on average assets (*ROAA*). We consider banks' liquidity by calculating the difference between the loan and deposit volume and dividing this difference by total assets (*Liquidity*). The net interest income divided by the operating income is applied as proxy for banks' sensitivity to market risk (*NII-to-OpIncome*). We winsorize our bank control variables at the 1% and 99% levels to consider the non-linearities of ratios.

As country-specific controls, we use the growth rate of the real gross domestic product (GDP) (*GDPGrowth*) to consider a country's current economic strength. Moreover, we apply the growth rate of consumer prices to incorporate a country's inflation (*Inflation*).

Table [A.5](#) in the Online Appendix reports the pairwise correlations of all our bank- and country-specific control variables. We also determine variance inflation factors (VIFs) to test for multicollinearity. However, all VIFs suggest that multicollinearity is not an issue in our empirical setting.

6 Results

6.1 Univariate analyses

Before presenting our regression results, we outline some univariate findings. In Figure [1](#), we plot the development of our five mean G-SIB indicator proxies over time, separately for G-SIBs and non-G-SIBs. Across all five indicators, it appears that the relevant balance sheet positions

of G-SIBs are substantially more volatile between quarters as compared to non-G-SIBs. This is most pronounced for derivatives. Moreover, we observe that particularly G-SIBs seem to decrease their positions in the fourth quarter of most years. This is again most clearly visible for derivatives, but also for level 3 assets during the first years in our observation period. Only the volume of trading and available-for-sale securities tends to increase for both G-SIBs and non-G-SIBs in the fourth quarter in several years.

With regard to our identification strategy explained in Section 5, it is important to highlight that G-SIBs in total still exhibit higher mean volumes across all five indicator proxies. This underpins the need to only include non-G-SIBs in our sample that have been at least once part of the G-SIB assessment sample because those banks are the most similar to G-SIBs. Otherwise, the volume differences would be much higher. In our empirical model, remaining differences in size between banks shall be captured with bank fixed effects (see Section 5.1). Additionally, time-fixed effects are necessary as well because some positions, such as total assets, show a trend over time.

Building on the graphical analysis, we present the mean differences for our dependent variables (i.e., $\Delta TAssets$, $\Delta TDebt$, $\Delta Derivatives$, $\Delta L3Assets$, and $\Delta Trading$) in Table 3. We again distinguish between G-SIBs and non-G-SIBs, as well as the third and the fourth quarter (see upper panel) and the fourth and the first quarter (see bottom panel). We find that G-SIBs, on average, reduce all five indicators in the fourth quarter as compared to the third quarter, whereas for non-G-SIBs, we observe a reduction only in three indicators, namely, the total assets, debt issued, and trading indicators. Across all five indicators, G-SIBs show a significantly stronger reduction than non-G-SIBs in the fourth quarter. In the first quarter, we observe that both G-SIBs and non-G-SIBs increase all indicators on average. This increase is more pronounced for G-SIBs as compared to non-G-SIBs and statistically significant for the total assets, debt issued, and derivatives indicators.

The results of our univariate analyses already give a slight indication that G-SIBs engage in window dressing by reducing certain activities at the end of the year that have an impact on the G-SIB score. In addition to the incentive for window dressing aimed at minimizing additional

Figure 1: Development of mean G-SIB indicator proxies for G-SIBs and non-G-SIBs over time.

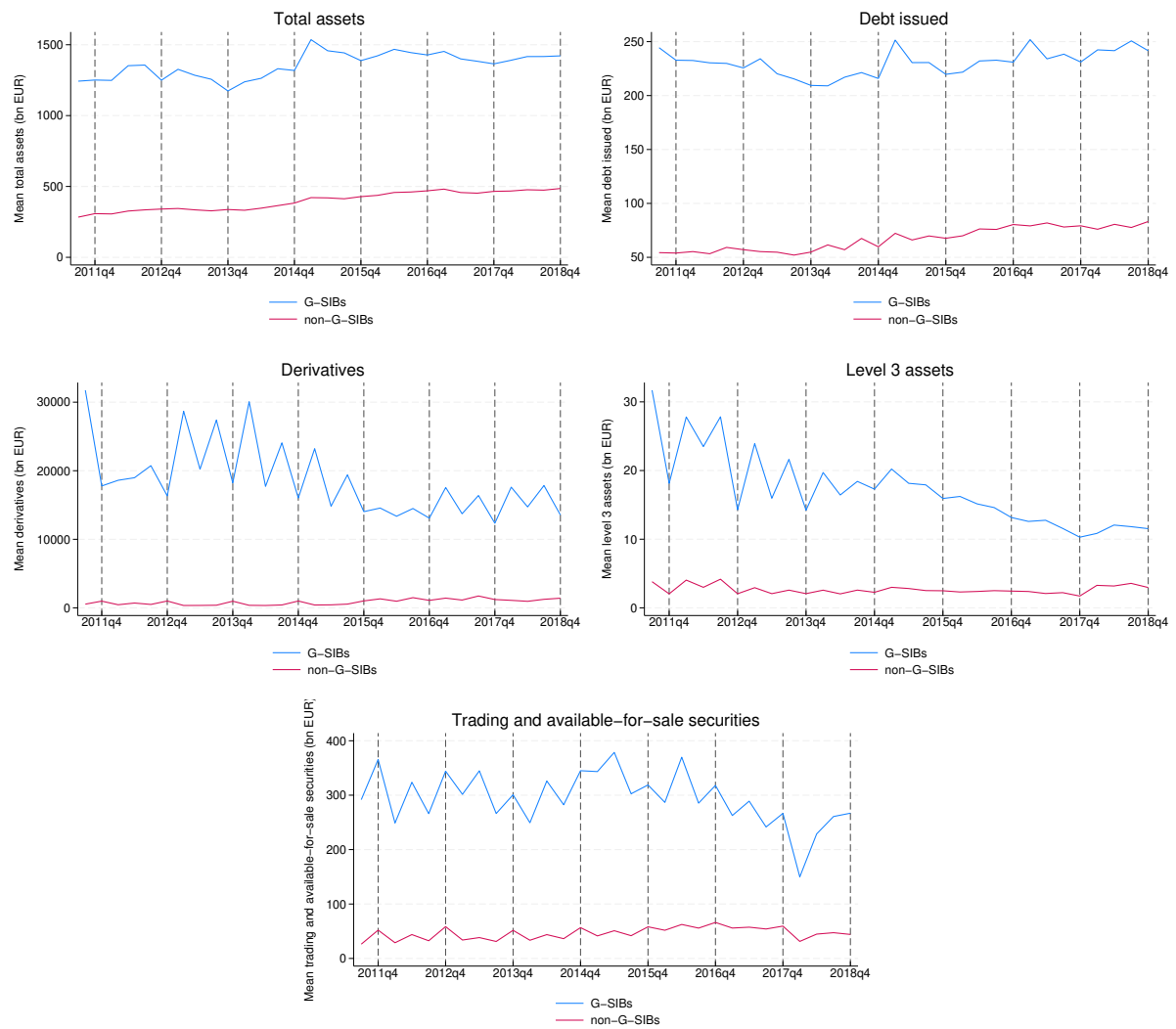


Table 3: Results of univariate tests to compare G-SIBs and non-G-SIBs.

<i>Q4</i>	Non-G-SIBs	G-SIBs	Difference between these groups
<i>$\Delta TAssets$</i>			
Mean	-1.676	-13.864	-12.188 ***
N (t-statistics)	272	265	(11.241)
<i>$\Delta DebtIssued$</i>			
Mean	-1.087	-12.931	-11.844***
N (t-statistics)	223	182	(5.649)
<i>$\Delta Derivatives$</i>			
Mean	2.595	-64.547	-67.142***
N (t-statistics)	87	35	(4.467)
<i>$\Delta L3Assets$</i>			
Mean	1.101	-18.019	-19.120***
N (t-statistics)	133	109	(4.261)
<i>$\Delta Trading$</i>			
Mean	-0.313	-20.560	-20.247 ***
N (t-statistics)	137	121	(4.938)
<i>Q1</i>	Non-G-SIBs	G-SIBs	Difference between these groups
<i>$\Delta TAssets$</i>			
Mean	3.269	11.985	8.716***
N (t-statistics)	220	224	(-7.314)
<i>$\Delta DebtIssued$</i>			
Mean	2.268	12.576	10.308***
N (t-statistics)	174	151	(-4.335)
<i>$\Delta Derivatives$</i>			
Mean	1.428	48.406	46.977***
N (t-statistics)	67	24	(-4.334)
<i>$\Delta L3Assets$</i>			
Mean	2.452	7.007	4.555
N (t-statistics)	98	89	(-0.875)
<i>$\Delta Trading$</i>			
Mean	0.225	14.047	13.822
N (t-statistics)	117	112	(-1.632)

This table reports tests on the mean differences between G-SIBs and non-G-SIBs in the fourth quarter (upper panel) and the first quarter (bottom panel). Variables are described in Table 1. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

capital buffer requirements, banks may have several other motivations for optimizing balance sheet positions at year-end. These include enhancing investor confidence, mitigating perceived risk around reporting dates, and strategically positioning the institution for future activities such as capital issuance or mergers and acquisitions. We will examine this further in our regression analyses below.

6.2 Regression results

Baseline specification:

First, we present the results of our baseline specification where we compare the behavior of G-SIBs and non-G-SIBs (see Equation 2). As dependent variables, we use the quarterly changes in our five indicator proxies (see Section 5.2). To underpin that our results are not driven by single control variables, we first conduct each regression with bank- and time-fixed effects only and subsequently add bank- and country-specific control variables (see Section 5.3).

Table 4 reports our results for the fourth quarter. The coefficient of highest interest is the one for the interaction, $GSIB \times Q4$, which is significantly negative across all indicators, both with and without control variables. This means that at the end of the year, G-SIBs reduce their activities that are relevant for calculating the G-SIB score significantly more than non-G-SIBs. In all specifications, except for $\Delta Derivatives$ in specification (8), we also find significantly negative coefficients for $Q4$. This shows that on average, all banks reduce their activities at year-end, however, the interaction, $GSIB \times Q4$, reveals that this effect is more pronounced for G-SIBs. More specifically, as shown for $\Delta TAssets$ in specification (6), the indicator declines, on average, by approximately 13 basis points in $Q4$. G-SIBs experience, on average, an additional decline of 13 basis points.

Next, we analyze banks' behavior in the first quarter and present our results in Table 5. The interaction, $GSIB \times Q1$, is significantly positive across all indicators, except for $\Delta L3Assets$ in specification (9). This suggests that at the beginning of the year, G-SIBs increase their indicators significantly more than non-G-SIBs. Again, we mostly find significantly positive coefficients also for $Q1$, meaning that all banks in our sample increase their indicators on average in the first

Table 4: Baseline specification (Q4).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>GSIB x Q4</i>	-13.57*** (1.767)	-13.22*** (4.354)	-76.74** (34.80)	-12.86*** (3.878)	-26.32*** (7.315)	-12.98*** (1.966)	-13.27*** (4.131)	-112.7** (39.69)	-12.84** (5.824)	-22.27*** (5.353)
<i>Q4</i>	-16.83*** (2.290)	-17.90*** (4.940)	-111.8** (50.53)	-39.42*** (14.17)	-27.22*** (8.199)	-12.83*** (2.471)	-16.85*** (5.101)	-116.4 (69.41)	-46.07** (20.40)	-11.46* (5.865)
<i>Leverage</i>						1.496*** (0.428)	1.838** (0.794)	2.517 (4.986)	1.934 (1.893)	2.373 (2.248)
<i>NPL</i>						-0.0643 (0.237)	-0.503 (0.439)	5.112 (3.681)	-0.481 (1.977)	-1.452 (1.658)
<i>Cost-to-Income</i>						0.0383 (0.0444)	0.0630 (0.122)	1.053 (0.891)	0.300 (0.320)	-0.688 (0.483)
<i>ROAA</i>						0.531 (1.086)	1.231 (2.055)	-2.456 (12.73)	3.589 (6.709)	-10.08 (12.07)
<i>Liquidity</i>						-0.124* (0.0695)	-0.0652 (0.128)	1.693 (1.532)	0.309 (0.541)	-0.0681 (0.351)
<i>NII-to-OpIncome</i>						0.0503 (0.0572)	0.00681 (0.0704)	0.259 (0.286)	0.346 (0.204)	0.489* (0.267)
<i>GDPGrowth</i>						0.519 (0.590)	0.700 (1.723)	16.43 (10.71)	-3.337 (4.189)	4.612* (2.503)
<i>Inflation</i>						1.205** (0.490)	1.086 (0.803)	11.31** (4.685)	-3.646 (2.365)	5.657 (3.736)
<i>Constant</i>	-0.0971 (0.436)	0.339 (0.911)	-4.137 (6.228)	3.107 (2.102)	-2.856 (6.157)	-19.10*** (5.061)	-18.31* (9.585)	-125.0 (98.92)	-47.69 (33.13)	-15.59 (38.61)
N	1,873	1,384	378	807	889	1,112	882	217	477	570
R-squared	0.505	0.196	0.357	0.192	0.162	0.529	0.240	0.434	0.201	0.186
# Banks	69	58	23	40	53	59	45	15	29	41
# Treated banks	34	25	7	19	27	31	21	5	14	21
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs decrease those activities at the end of the year that affect the G-SIB score. All specifications include time- and bank-fixed effects. Specifications (1) to (5) include fixed effects only. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

quarter, but this effect is larger for G-SIBs as shown by the interaction, $GSIB \times Q1$. Regarding the economic impact, the results from $\Delta TAssets$ in specification (6) indicate that, on average, banks increase their total assets indicator by around 13 basis points in Q1. For G-SIBs, this effect is even more pronounced, with an additional increase of approximately 14 basis points. Interestingly, bank characteristics appear to play only a minor role in Q4 and Q1.

Taking together our findings in Tables 4 and 5, we provide evidence for a “V-shape” adjustment, that is, banks reduce relevant activities at year-end before increasing them again at the beginning of the subsequent year. This “V-shape” adjustment is particularly strong (twice as large) for G-SIBs as compared to other banks in our sample and suggests that the reductions observed at year-end are not driven by strategic, more sustainable balance sheet adjustments, but rather by short-term window-dressing behavior.

Close-to-threshold analysis:

Building on our baseline specification, we refine our identification strategy to make sure that our results are not driven by differences between G-SIBs and non-G-SIBs (see Section 6.1). Hence, we vary our treatment group and focus on banks that are particularly close to a bucket threshold, independent of being classified as G-SIB.¹⁰ Those banks are expected to have a high incentive for window dressing because the probability of moving to a higher or lower bucket is particularly large. We define *Close-to-Threshold* as an indicator variable equal to one for banks whose G-SIB score was at least once during our observation period either 15 below or above a bucket threshold.¹¹ The bucket thresholds are currently set at 130, 230, 330, 430, and 530 (see Table A.2 in the Online Appendix). 28 banks in our sample satisfy this condition, of which 24 are G-SIBs and 4 are other banks. 10 banks in our sample are G-SIBs but during our observation period never close to a bucket threshold.

Table 6 reports our results for the fourth quarter, where we interact $Q4$ with our indicator variable *Close-to-Threshold*. We find significantly negative coefficients for the interaction,

¹⁰ As an alternative, we could also conduct the close-to-threshold analysis for the full sample in one step via a triple interaction term, that is, $GSIB \times [Q1 \text{ or } Q4] \times Close-to-Threshold$. If we do so, our findings are very similar.

¹¹ In order to underpin the relevance of our time-invariant *Close-to-Threshold* dummy, we calculate the standard deviations of the distances to a bucket threshold per bank. Overall, we do not find much variation over time.

Table 5: Baseline specification (Q1).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>GSIB x Q1</i>	14.40*** (1.869)	16.78*** (5.095)	79.81** (36.02)	15.72** (7.249)	32.37*** (9.392)	13.83*** (2.354)	14.18** (5.277)	120.9* (60.51)	7.522 (9.528)	33.66*** (9.452)
<i>Q1</i>	16.49*** (2.214)	16.74*** (4.056)	129.3** (57.79)	29.20* (16.26)	31.49* (17.76)	12.73*** (2.746)	13.62*** (4.534)	149.8 (94.06)	44.51* (24.66)	23.65 (22.17)
<i>Leverage</i>						1.733*** (0.397)	2.214*** (0.769)	5.698 (4.603)	1.919 (1.906)	2.332 (2.170)
<i>NPL</i>						-0.0739 (0.227)	-0.511 (0.447)	3.852 (6.022)	-0.460 (1.851)	-1.985 (1.731)
<i>Cost-to-Income</i>						0.0399 (0.0424)	0.0748 (0.123)	0.776 (0.694)	0.289 (0.315)	-0.681 (0.479)
<i>ROAA</i>						0.754 (1.009)	0.967 (1.952)	14.83 (24.84)	3.271 (6.834)	-9.193 (11.35)
<i>Liquidity</i>						-0.150** (0.0680)	-0.0929 (0.127)	1.127 (1.326)	0.305 (0.549)	0.00333 (0.331)
<i>NII-to-OpIncome</i>						0.0377 (0.0488)	-0.00155 (0.0710)	0.421 (0.550)	0.352 (0.209)	0.447* (0.255)
<i>GDPGrowth</i>						0.608 (0.580)	0.895 (1.746)	16.93 (12.18)	-3.354 (4.317)	4.942* (2.532)
<i>Inflation</i>						1.494*** (0.464)	1.452* (0.791)	10.08** (3.925)	-3.792 (2.374)	5.422 (3.502)
<i>Constant</i>	-23.76*** (2.709)	-23.78*** (4.686)	-145.3** (60.77)	-42.83*** (13.92)	-43.16*** (9.319)	-40.47*** (5.509)	-45.49*** (12.53)	-311.8 (200.0)	-100.2** (46.26)	-35.31 (41.08)
N	1,873	1,384	378	807	889	1,112	882	217	477	570
R-squared	0.505	0.207	0.353	0.195	0.174	0.542	0.244	0.444	0.196	0.211
# Banks	69	58	23	40	53	59	45	15	29	41
# Treated banks	34	25	7	19	27	31	21	5	14	21
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs increase those activities at the beginning of the year that affect the G-SIB score. All specifications include time- and bank-fixed effects. Specifications (1) to (5) include fixed effects only. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Close-to-Threshold x *Q4*, except for $\Delta Derivatives$ in specification (3), and significantly negative coefficients for *Q4* across all specifications. Hence, we conclude that although all banks in our sample on average reduce relevant activities, this reduction is particularly strong for banks that are close to a bucket threshold.

In Table 7, we present the results for the first quarter. The interaction, *Close-to-Threshold* x *Q1*, is significantly positive in 8 out of 10 specifications, and *Q1* in 9 out of 10 specifications. This again provides evidence for a “V-shape” adjustment and is in line with previous results. Also, it underpins that our baseline results are most likely not driven by differences between G-SIBs and non-G-SIBs because in this analysis, we define our treatment group independent of banks’ G-SIB status.

To further support our line of argumentation, we restrict our sample to G-SIBs only and again use banks that are close to a bucket threshold as treatment group. We present our results in Tables 8 and 9. Although this reduces our sample size,¹² we still yield significantly negative coefficients for the interaction, *Close-to-Threshold* x *Q4*, in five specifications, namely for $\Delta DebtIssued$, $\Delta L3Assets$, and partly $\Delta Trading$, and also mostly significantly negative coefficients for *Q4*. Moreover, the interaction, *Close-to-Threshold* x *Q1*, is significantly positive in six specifications, namely for $\Delta TAssets$, $\Delta DebtIssued$, and partly $\Delta Trading$. The coefficients for *Q1* are predominantly significantly positive. Taking those results together, we provide evidence that G-SIBs that are close to a bucket threshold reduce relevant activities more than other G-SIBs. This strengthens our hypothesis that banks close to a bucket threshold are more likely engaged in window-dressing behavior because the probability of moving to a higher or lower bucket is particularly large for those banks.

In additional analyses, we vary our indicator variable, *Close-to-Threshold*, and use either a higher or lower distance to the threshold to provide evidence for the robustness of our finding. We use a distance of either 10 or 20 and re-estimate our regressions (see Tables A.6 to A.9 in the Online Appendix). Overall, our results hold and thus do not depend on the specific definition of

¹² Due to this reduction in our sample size, it is not possible to estimate the interaction terms, *Close-to-Threshold* x *Q4* and *Close-to-Threshold* x *Q1*, with $\Delta Derivatives$ as dependent variable and additional control variables (see specification (8) in Tables 8 and 9).

Table 6: Close-to-threshold analysis (Q4).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>Close-to-Threshold</i> x <i>Q4</i>	-10.07*** (2.312)	-15.23*** (5.177)	-30.82 (41.20)	-13.76*** (4.302)	-12.71* (7.444)	-11.80*** (2.216)	-17.27*** (4.449)	-103.6** (38.80)	-19.35*** (6.810)	-23.17*** (6.449)
<i>Q4</i>	-19.54*** (2.798)	-18.58*** (5.111)	-136.3** (62.46)	-40.37*** (13.94)	-35.83*** (10.92)	-15.41*** (3.252)	-17.97*** (5.711)	-121.7* (68.32)	-45.66** (20.11)	-16.38** (6.342)
<i>Leverage</i>						1.552*** (0.434)	1.811** (0.769)	3.619 (5.343)	1.731 (1.854)	2.332 (2.279)
<i>NPL</i>						0.0208 (0.231)	-0.392 (0.386)	4.829 (3.655)	-0.483 (1.993)	-1.074 (1.620)
<i>Cost-to-Income</i>						0.0384 (0.0447)	0.0683 (0.120)	1.086 (0.889)	0.307 (0.323)	-0.704 (0.484)
<i>ROAA</i>						0.132 (1.097)	0.711 (2.049)	-4.827 (12.26)	2.987 (6.950)	-11.23 (12.11)
<i>Liquidity</i>						-0.139* (0.0697)	-0.0766 (0.123)	1.739 (1.576)	0.301 (0.534)	-0.123 (0.347)
<i>NII-to-OpIncome</i>						0.0499 (0.0574)	-0.00578 (0.0688)	0.309 (0.295)	0.337 (0.205)	0.502* (0.271)
<i>GDPGrowth</i>						0.536 (0.594)	0.736 (1.710)	17.38 (10.65)	-3.345 (4.183)	4.703* (2.502)
<i>Inflation</i>						1.214** (0.514)	1.047 (0.838)	10.79** (4.325)	-3.793 (2.419)	5.312 (3.711)
<i>Constant</i>	-0.165 (0.463)	0.300 (0.947)	-4.527 (4.796)	3.014 (2.021)	-2.530 (6.140)	-19.47*** (5.176)	-17.45* (9.350)	-134.7 (100.9)	-45.03 (32.84)	-14.57 (38.91)
N	1,873	1,384	378	807	889	1,112	882	217	477	570
R-squared	0.474	0.201	0.293	0.194	0.140	0.516	0.253	0.421	0.210	0.187
# Banks	69	58	23	40	53	59	45	15	29	41
# Treated banks	28	21	7	17	23	23	15	4	10	15
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether banks that are close to a bucket threshold decrease activities at the end of the year that affect the G-SIB score. All specifications include time- and bank-fixed effects. Specifications (1) to (5) include fixed effects only. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 7: Close-to-threshold analysis (Q1).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>Close-to-Threshold</i> x <i>Q1</i>	11.94*** (2.373)	19.11*** (6.197)	43.79 (44.74)	14.14* (8.348)	21.84** (10.79)	13.56*** (2.592)	20.88*** (6.119)	96.28* (54.46)	15.04 (10.91)	41.54*** (11.16)
<i>Q1</i>	18.78*** (2.733)	17.65*** (4.222)	144.3** (65.50)	31.11* (16.26)	37.85* (19.18)	14.86*** (3.313)	14.00*** (4.904)	154.8 (94.77)	43.09* (23.95)	27.39 (22.55)
<i>Leverage</i>						1.592*** (0.394)	2.055*** (0.742)	5.499 (4.819)	1.653 (1.946)	1.871 (2.201)
<i>NPL</i>						0.0509 (0.253)	-0.464 (0.439)	2.997 (5.068)	-0.545 (1.832)	-1.788 (1.759)
<i>Cost-to-Income</i>						0.0462 (0.0444)	0.0864 (0.116)	0.799 (0.734)	0.284 (0.307)	-0.767 (0.489)
<i>ROAA</i>						0.747 (0.987)	1.033 (1.914)	10.98 (19.75)	3.801 (7.141)	-8.599 (11.07)
<i>Liquidity</i>						-0.144** (0.0644)	-0.0945 (0.122)	1.345 (1.448)	0.297 (0.517)	-0.0780 (0.333)
<i>NII-to-OpIncome</i>						0.0162 (0.0470)	-0.0465 (0.0744)	0.439 (0.498)	0.320 (0.210)	0.387 (0.244)
<i>GDPGrowth</i>						0.707 (0.582)	1.022 (1.723)	16.79 (11.96)	-3.260 (4.297)	5.302** (2.620)
<i>Inflation</i>						1.462*** (0.473)	1.506* (0.800)	10.36** (3.851)	-3.708 (2.403)	5.626 (3.612)
<i>Constant</i>	-23.78*** (2.773)	-23.76*** (4.678)	-149.4** (63.91)	-43.17*** (13.85)	-43.34*** (9.564)	-38.84*** (5.937)	-42.42*** (11.73)	-307.8 (193.7)	-95.74** (44.83)	-25.23 (41.90)
N	1,873	1,384	378	807	889	1,112	882	217	477	570
R-squared	0.483	0.214	0.301	0.193	0.151	0.534	0.270	0.403	0.202	0.226
# Banks	69	58	23	40	53	59	45	15	29	41
# Treated banks	28	21	7	17	23	23	15	4	10	15
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether banks that are close to a bucket threshold increase activities at the beginning of the year that affect the G-SIB score. All specifications include time- and bank-fixed effects. Specifications (1) to (5) include fixed effects only. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 8: Close-to-threshold analysis for G-SIBs only (Q4).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>Close-to-Threshold x Q4</i>	-4.009 (3.642)	-14.30* (7.464)	61.49 (83.77)	-17.74** (8.107)	5.076 (19.28)	-5.290 (4.694)	-17.69** (8.009)		-23.01** (9.356)	-18.81** (7.283)
<i>Q4</i>	-37.55*** (4.844)	-35.53*** (9.841)	-320.9** (90.24)	-64.72*** (22.19)	-78.59*** (24.58)	-27.70*** (6.438)	-28.10** (11.84)	-283.0*** (52.97)	-62.63 (37.42)	-29.53*** (10.37)
<i>Leverage</i>						2.392** (1.097)	3.758** (1.469)	-5.270 (41.17)	2.221 (2.886)	3.049 (3.442)
<i>NPL</i>						-0.498 (0.366)	-2.087** (0.848)	5.783 (17.04)	-4.305 (6.764)	-3.012 (2.624)
<i>Cost-to-Income</i>						0.0215 (0.0634)	0.161 (0.234)	5.707*** (1.085)	0.0908 (0.599)	-1.357 (1.043)
<i>ROAA</i>						-1.119 (1.813)	-1.367 (3.835)	133.0*** (12.07)	-6.679 (17.28)	-26.42 (24.74)
<i>Liquidity</i>						-0.191 (0.241)	0.538 (0.548)	9.985* (4.499)	1.858* (1.014)	1.593* (0.826)
<i>NII-to-OpIncome</i>						0.0268 (0.131)	-0.266 (0.209)	-1.505 (1.324)	1.104** (0.397)	0.994 (0.770)
<i>GDPGrowth</i>						0.615 (1.082)	2.820 (3.770)	135.4*** (9.852)	-1.561 (6.080)	7.486 (7.055)
<i>Inflation</i>						1.540 (1.129)	-0.927 (2.575)	31.11 (49.61)	-25.20 (14.69)	20.29 (15.56)
<i>Constant</i>	0.146 (0.736)	1.705 (1.841)	-20.58 (22.12)	3.971 (4.135)	-3.089 (10.96)	-22.83 (14.42)	-8.900 (15.48)	-496.3* (208.5)	-5.955 (70.15)	39.22 (89.26)
N	941	637	108	382	431	558	435	57	237	299
R-squared	0.630	0.287	0.624	0.323	0.237	0.668	0.368	0.827	0.351	0.295
# Banks	34	25	7	19	27	31	21	5	14	21
# Treated banks	24	17	5	14	20	21	13	3	9	14
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs that are close to a bucket threshold decrease activities at the end of the year that affect the G-SIB score. All specifications include time- and bank-fixed effects. Specifications (1) to (5) include fixed effects only. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 9: Close-to-threshold analysis for G-SIBs only (Q1).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>Close-to-Threshold</i> x <i>Q1</i>	7.129* (3.982)	20.93** (8.379)	-35.46 (66.64)	15.64 (14.50)	8.589 (19.36)	8.716* (4.953)	24.28*** (8.434)		14.30 (11.39)	39.52*** (12.33)
<i>Q1</i>	35.76*** (5.052)	33.13*** (8.427)	338.3** (95.68)	42.95 (25.57)	91.61** (44.33)	24.66*** (6.788)	15.47 (10.15)	481.1*** (23.37)	43.35 (34.57)	44.07 (55.46)
<i>Leverage</i>						2.338** (1.083)	3.645** (1.547)	-5.270 (41.17)	2.146 (3.184)	2.620 (3.510)
<i>NPL</i>						-0.462 (0.401)	-2.393** (0.985)	5.783 (17.04)	-4.562 (6.613)	-3.308 (2.628)
<i>Cost-to-Income</i>						0.0409 (0.0654)	0.205 (0.226)	5.707*** (1.085)	0.111 (0.597)	-1.404 (1.054)
<i>ROAA</i>						-0.681 (1.741)	-0.0849 (3.765)	133.0*** (12.07)	-3.472 (17.33)	-23.58 (23.64)
<i>Liquidity</i>						-0.164 (0.236)	0.578 (0.546)	9.985* (4.499)	1.815 (1.047)	1.508* (0.812)
<i>NII-to-OpIncome</i>						-0.0222 (0.124)	-0.376 (0.224)	-1.505 (1.324)	1.053** (0.433)	0.768 (0.689)
<i>GDPGrowth</i>						0.781 (1.038)	3.184 (3.774)	135.4*** (9.852)	-1.397 (6.354)	7.705 (7.149)
<i>Inflation</i>						1.715 (1.118)	-0.265 (2.528)	31.11 (49.61)	-23.26 (14.99)	21.86 (15.22)
<i>Constant</i>	-40.18*** (3.763)	-43.07*** (7.924)	-300.7** (99.12)	-73.48*** (22.04)	-78.54*** (14.52)	-52.34*** (12.16)	-43.92*** (14.10)	-779.2** (188.7)	-86.24 (89.69)	12.93 (95.63)
N	941	637	108	382	431	558	435	57	237	299
R-squared	0.635	0.300	0.614	0.321	0.237	0.676	0.387	0.827	0.344	0.316
# Banks	34	25	7	19	27	31	21	5	14	21
# Treated banks	24	17	5	14	20	21	13	3	9	14
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs that are close to a bucket threshold increase activities at the beginning of the year that affect the G-SIB score. All specifications include time- and bank-fixed effects. Specifications (1) to (5) include fixed effects only. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

our *Close-to-Threshold* variable. Finally, we examine the relationship between banks' distance to a bucket threshold and quarterly indicator changes by generating scatter plots for the first and fourth quarters (see Figures A.1 and A.2 in the Online Appendix). Generally, banks closer to a bucket threshold exhibit more negative indicator proxy changes in the fourth quarters and more positive changes in the first quarters. This pattern provides further empirical support for our findings.

High-surcharge analysis:

Beside being close to a bucket threshold, another incentive for banks to engage in window dressing could be a high G-SIB surcharge. In the literature, saving equity capital has turned out as an important driver for bank behavior (e.g., Begley et al., 2017; Berg and Koziol, 2017; Plosser and Santos, 2018; Behn et al., 2022a). Hence, we again vary our treatment group to analyze whether particularly those G-SIBs with a high surcharge engage in window dressing. For that purpose, we assign a dummy variable, *HighSurcharge*, equal to one for banks with a G-SIB surcharge larger than 1 percentage point (pp), and zero otherwise. In total, this applies to 19 G-SIBs during our observation period, whereas the surcharges for 15 G-SIBs are always equal to 1 pp.

Table 10 presents our results for the fourth quarter, where we apply the interaction term between *HighSurcharge* and *Q4* as main explanatory variable. Across all specifications, we find significantly negative coefficients both for the interaction, *HighSurcharge* x *Q4*, and for *Q4*. The latter result is in line with previous findings and underpins that banks generally reduce certain exposures relevant for the calculation of the G-SIB score at the end of the year. The interaction term additionally reveals that G-SIBs with a high surcharge reduce their exposures more than banks with a lower or no surcharge.

In Table 11, we summarize our results for the first quarter. The interaction, *HighSurcharge* x *Q1*, is significantly positive in all specifications, with the exception of $\Delta L3Assets$ in specification (9), and *Q1* is significantly positive in 8 out of 10 specifications. This again provides tentative evidence that G-SIBs specifically affected by the G-SIB framework due to a high surcharge increase relevant activities at the beginning of the year more than

Table 10: High-surcharge analysis (Q4).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>HighSurcharge</i> x <i>Q4</i>	-14.19*** (2.638)	-15.30** (6.389)	-142.4*** (34.77)	-18.63*** (4.123)	-33.74*** (10.21)	-11.21*** (2.805)	-13.32** (6.509)	-152.6*** (8.645)	-18.55*** (6.712)	-22.81*** (7.141)
<i>Q4</i>	-19.57*** (2.654)	-19.42*** (5.017)	-108.6** (46.70)	-38.23*** (14.05)	-27.96*** (8.428)	-16.18*** (3.112)	-20.02*** (5.368)	-122.9* (68.71)	-45.72** (20.20)	-15.76** (6.542)
<i>Leverage</i>						1.535*** (0.437)	1.855** (0.783)	5.526 (5.247)	1.815 (1.839)	2.430 (2.291)
<i>NPL</i>						0.0627 (0.230)	-0.297 (0.396)	4.942 (3.492)	-0.414 (1.977)	-1.054 (1.613)
<i>Cost-to-Income</i>						0.0365 (0.0429)	0.0598 (0.122)	0.984 (0.900)	0.293 (0.320)	-0.696 (0.480)
<i>ROAA</i>						0.558 (1.094)	1.414 (2.021)	3.753 (10.22)	3.752 (6.800)	-9.870 (12.02)
<i>Liquidity</i>						-0.147** (0.0710)	-0.0881 (0.125)	1.036 (1.368)	0.268 (0.527)	-0.178 (0.358)
<i>NII-to-OpIncome</i>						0.0470 (0.0566)	-0.00144 (0.0707)	-0.00560 (0.299)	0.339 (0.201)	0.464* (0.263)
<i>GDPGrowth</i>						0.519 (0.600)	0.684 (1.705)	13.98 (10.38)	-3.276 (4.180)	4.624* (2.491)
<i>Inflation</i>						1.331** (0.512)	1.239 (0.821)	12.52** (4.502)	-3.495 (2.346)	5.957 (3.859)
<i>Constant</i>	-0.0494 (0.440)	0.313 (0.968)	-5.181 (7.134)	3.015 (1.965)	-4.134 (6.305)	-19.60*** (5.010)	-18.59* (9.407)	-131.5 (98.42)	-46.61 (32.83)	-16.81 (38.64)
N	1,873	1,384	378	807	889	1,112	882	217	477	570
R-squared	0.498	0.199	0.457	0.201	0.173	0.509	0.235	0.480	0.208	0.185
# Banks	69	58	23	40	53	59	45	15	29	41
# Treated banks	19	15	3	12	16	17	13	3	9	12
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs with a high surcharge decrease activities at the end of the year that affect the G-SIB score. All specifications include time-fixed effects. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

other banks, suggesting a “V-shape” relationship.

In Tables 12 and 13, we restrict our analysis to G-SIBs and only compare G-SIBs with higher and lower surcharges with each other. This again allows us to mitigate potential effects from the fact that higher G-SIB scores can vary more in a linear setting in terms of absolute changes than lower scores. Although our results are slightly weaker as compared to the full sample, we still corroborate previous results. Since this analysis compares G-SIBs with higher and lower surcharges, we confirm that our baseline results are most likely not driven by differences between G-SIBs and non-G-SIBs.

7 Robustness checks

In addition to the aforementioned specifications, we conducted several robustness checks, the results of which are consistent with previous findings.

Exclude countries where banks already use averages for measuring systemic importance:

First, we exclude two countries, the United Kingdom and the United States, from our sample. In those two countries, banks are partly already required to calculate measures for their systemic impact based on intra-year averages, as opposed to year-end exposures.¹³ Therefore, banks from these two countries may adversely impact our findings. We report our results for the fourth quarter in Table A.10, and for the first quarter in Table A.11 in the Online Appendix. Overall, although the sample size is now substantially smaller, our results are still in line with our baseline specification.

Use shorter observation periods:

Second, we shorten our observation period, originally reaching from 2011 until 2018 in our baseline specification, and drop all observations before 2013. The rationale for shortening our sample period is due to potential confounding factors possibly prevalent during the first years. G-SIBs were first identified in 2011 and published on the FSB website. However, the first G-SIB

¹³ In the United Kingdom, averages of the leverage exposures based on quarter-ends are used to determine buffer rates in the framework for domestic systemically important banks (D-SIBs) (Bank of England, 2016). Banks in the United States have to calculate averages based on intra-year data for the size indicator and their national short-term wholesale funding indicator (Federal Reserve, 2025)

Table 11: High-surcharge analysis (Q1).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>HighSurcharge</i> x <i>Q1</i>	15.75*** (2.642)	21.35*** (7.056)	133.0*** (39.71)	21.34** (8.764)	43.97*** (12.40)	14.93*** (3.320)	18.72** (7.994)	193.4*** (10.98)	9.882 (11.04)	44.59*** (12.63)
<i>Q1</i>	19.23*** (2.557)	18.19*** (4.085)	127.6** (56.45)	29.01* (15.99)	33.65* (18.11)	15.63*** (3.093)	15.99*** (4.601)	156.8 (93.61)	45.21* (23.92)	27.87 (22.51)
<i>Leverage</i>						1.531*** (0.397)	2.005** (0.755)	6.096 (4.181)	1.816 (1.931)	2.384 (2.233)
<i>NPL</i>						0.0649 (0.257)	-0.402 (0.436)	10.27* (5.686)	-0.429 (1.843)	-1.551 (1.704)
<i>Cost-to-Income</i>						0.00603 (0.0376)	0.0156 (0.125)	0.482 (0.547)	0.259 (0.289)	-0.808 (0.490)
<i>ROAA</i>						1.103 (1.116)	1.384 (1.910)	35.56 (23.71)	3.620 (7.028)	-9.594 (10.89)
<i>Liquidity</i>						-0.156** (0.0663)	-0.106 (0.127)	0.877 (1.223)	0.280 (0.527)	-0.145 (0.339)
<i>NII-to-OpIncome</i>						0.0275 (0.0421)	-0.0136 (0.0769)	0.765 (0.589)	0.372* (0.215)	0.501* (0.252)
<i>GDPGrowth</i>						0.465 (0.576)	0.647 (1.652)	16.88 (11.70)	-3.317 (4.295)	4.908* (2.496)
<i>Inflation</i>						1.322*** (0.457)	1.249 (0.797)	10.82** (4.691)	-3.702 (2.338)	5.771 (3.596)
<i>Constant</i>	-23.77*** (2.728)	-23.76*** (4.643)	-144.8** (59.00)	-42.53*** (13.83)	-42.76*** (9.146)	-36.79*** (5.335)	-40.33*** (11.75)	-352.6 (202.8)	-99.21** (45.43)	-34.12 (42.31)
N	1,873	1,384	378	807	889	1,112	882	217	477	570
R-squared	0.505	0.220	0.426	0.204	0.196	0.537	0.254	0.535	0.197	0.230
# Banks	69	58	23	40	53	59	45	15	29	41
# Treated banks	19	15	3	12	16	17	13	3	9	12
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs with a high surcharge increase activities at the beginning of the year that affect the G-SIB score. All specifications include time-fixed effects. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 12: High-surcharge analysis G-SIBs only (Q4).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>HighSurcharge x Q4</i>	-7.666** (3.076)	-9.854 (6.999)	-155.8*** (40.37)	-20.14** (7.100)	-26.20** (11.16)	-2.789 (3.696)	-5.592 (6.878)	-187.6*** (8.464)	-16.59* (7.864)	-9.335 (7.143)
<i>Q4</i>	-35.97*** (3.777)	-38.24*** (8.764)	-192.9* (82.00)	-60.90** (23.49)	-55.98*** (13.49)	-29.28*** (5.387)	-34.83*** (9.212)	-96.44 (54.16)	-66.17 (38.03)	-32.19*** (9.737)
<i>Leverage</i>						2.404** (1.105)	3.853** (1.513)	-7.388 (56.87)	2.453 (2.958)	3.317 (3.478)
<i>NPL</i>						-0.524 (0.365)	-2.389*** (0.794)	10.88 (9.360)	-4.231 (6.784)	-3.364 (2.623)
<i>Cost-to-Income</i>						0.0223 (0.0634)	0.168 (0.238)	5.397*** (1.146)	0.0972 (0.597)	-1.320 (1.036)
<i>ROAA</i>						-0.790 (1.816)	0.237 (4.034)	145.3** (39.60)	-4.597 (17.01)	-24.52 (24.72)
<i>Liquidity</i>						-0.201 (0.238)	0.513 (0.563)	6.208 (3.681)	1.767 (1.049)	1.476* (0.825)
<i>NII-to-OpIncome</i>						0.0338 (0.131)	-0.235 (0.221)	-3.294* (1.236)	1.088** (0.405)	0.974 (0.765)
<i>GDPGrowth</i>						0.617 (1.091)	2.821 (3.805)	145.5*** (10.47)	-1.382 (6.260)	7.651 (7.173)
<i>Inflation</i>						1.688 (1.089)	-0.343 (2.554)	46.97 (63.43)	-23.01 (13.77)	22.51 (15.66)
<i>Constant</i>	0.245 (0.723)	1.765 (1.819)	-23.05 (34.57)	3.753 (4.059)	-5.162 (11.14)	-23.78 (14.37)	-13.15 (16.55)	-457.9 (243.5)	-12.98 (72.37)	30.49 (89.11)
N	941	637	108	382	431	558	435	57	237	299
R-squared	0.638	0.280	0.716	0.326	0.249	0.665	0.349	0.895	0.346	0.291
# Banks	34	25	7	19	27	31	21	5	14	21
# Treated banks	19	15	3	12	16	17	13	3	9	12
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs with a high surcharge increase activities at the beginning of the year that affect the G-SIB score. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 13: High-surcharge analysis G-SIBs only (Q1).

VARIABLES	(1) $\Delta TAssets$	(2) $\Delta DebtIssued$	(3) $\Delta Derivatives$	(4) $\Delta L3Assets$	(5) $\Delta Trading$	(6) $\Delta TAssets$	(7) $\Delta DebtIssued$	(8) $\Delta Derivatives$	(9) $\Delta L3Assets$	(10) $\Delta Trading$
<i>HighSurcharge</i> x <i>Q1</i>	9.306*** (3.211)	16.38** (7.793)	161.4** (51.60)	21.26* (11.35)	36.27** (13.57)	7.885* (4.468)	13.28 (8.457)	217.6*** (22.84)	6.837 (9.563)	35.88** (14.09)
<i>Q1</i>	35.53*** (3.774)	36.58*** (7.229)	210.7* (91.81)	38.05 (23.60)	74.62* (40.04)	25.67*** (5.599)	23.61*** (7.463)	236.7** (58.73)	48.02 (35.42)	41.90 (57.26)
<i>Leverage</i>						2.292** (1.087)	3.753** (1.492)	38.80 (21.25)	2.543 (3.110)	3.568 (3.551)
<i>NPL</i>						-0.510 (0.403)	-2.499** (0.908)	32.53** (9.300)	-4.590 (6.733)	-3.208 (2.548)
<i>Cost-to-Income</i>						-0.000835 (0.0539)	0.105 (0.241)	2.388** (0.787)	0.0713 (0.569)	-1.497 (1.061)
<i>ROAA</i>						-0.403 (1.819)	0.419 (3.876)	88.46** (24.12)	-4.357 (16.88)	-25.65 (23.60)
<i>Liquidity</i>						-0.191 (0.237)	0.542 (0.567)	5.296 (3.157)	1.845 (1.048)	1.238 (0.810)
<i>NII-to-OpIncome</i>						0.00915 (0.121)	-0.262 (0.248)	1.707 (1.018)	1.139** (0.383)	1.133 (0.758)
<i>GDPGrowth</i>						0.518 (1.054)	2.579 (3.705)	120.1*** (19.71)	-1.554 (6.322)	7.976 (7.333)
<i>Inflation</i>						1.463 (1.049)	-0.841 (2.607)	-24.56 (40.42)	-24.00 (14.85)	23.19 (15.62)
<i>Constant</i>	-40.18*** (3.728)	-42.83*** (7.987)	-301.0** (90.90)	-72.62*** (22.23)	-77.75*** (14.18)	-50.99*** (11.43)	-44.00*** (14.34)	-890.0*** (130.3)	-89.10 (91.11)	-9.209 (95.07)
N	941	637	108	382	431	558	435	57	237	299
R-squared	0.642	0.290	0.707	0.326	0.260	0.674	0.359	0.895	0.341	0.313
# Banks	34	25	7	19	27	31	21	5	14	21
# Treated banks	19	15	3	12	16	17	13	3	9	12
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the analysis on whether G-SIBs with a high surcharge increase activities at the beginning of the year that affect the G-SIB score. In specifications (6) to (10), we additionally control for different bank- and country-specific characteristics (see Section 5.3). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels.

surcharges were communicated to the public only in late-2012. Thus, by excluding observations before 2013, we want to make sure that our results hold when only focusing on the time period where G-SIBs were classified according to their systemic importance based on the G-SIB score. We present our results in Tables A.12 and A.13 in the Online Appendix. Again, our sample size is reduced, but our findings remain qualitatively the same.

To further underpin that our findings do not depend on the volatility observed in the early years of our sample period, we conduct two additional robustness checks and exclude both the first three years (2011 to 2013) and the first four years (2011 to 2014). We report the results in Tables A.14 to A.17 in the Online Appendix. Overall, our findings are weaker due to the reduced sample size, but still remain robust.

Exclude banks with an unbalanced number of observations throughout the quarters:

Third, we exclude banks for which less than 75% of all observations are available for the analyzed period. This exclusion helps prevent bias towards data in the fourth quarter, which is more readily available due to the fiscal year ending in the fourth quarter for most banks. Smaller, non-listed banks might not report data for each quarter, so this robustness check also ensures that our sample is not biased towards larger banks. The results, presented in Tables A.18 and A.19 in the Online Appendix, show that although the sample size is reduced, our findings are broadly confirmed.

Exclude countries where the financial year-end is not December:

Fourth, we exclude banks from countries where the financial year does not end in December. This exclusion helps avoid potential interference from window-dressing activities that might occur at different times of the year, rather than in the first and fourth quarters. The results are shown in Tables A.20 and A.21 in the Online Appendix. Although the sample size is reduced, our findings remain consistent.

Inclusion of a dummy for the introduction of the Basel III framework:

Fifth, we introduce a dummy variable starting in 2013 to account for the implementation of the Basel III framework. In addition to the G-SIB framework, several other regulatory measures were introduced shortly after the financial crisis of 2007-09 that could incentivize banks to

engage in window-dressing. Notably, the leverage ratio phased in from 2013 is a candidate that might have interfered with the G-SIB framework. This interference was also evident in our baseline regression, as we observed a significant coefficient for the leverage ratio (see Tables 4 and 5). The results, presented in Tables A.12 and A.13 in the Online Appendix, confirm our findings.

Analysis on individual geographical areas:

Sixth, we analyze banks within specific geographical regions, that are, America, Asia, and Europe, to ensure that our results are not disproportionately influenced by any single region.¹⁴ This approach also implicitly accounts for potential interference from national frameworks for D-SIBs, as American and Asian banks are classified as D-SIBs to a lesser extent than European banks.¹⁵ The results for each region are presented in the Online Appendix: America in Tables A.24 and A.25, Asia in Tables A.26 and A.27, and Europe in Tables A.28 and A.29. Although the sample sizes are substantially reduced, our findings remain consistent with the baseline specification.

Riskiness of the business model:

Seventh, we examine how banks' business models influence our results. Banks with riskier business models, irrespective of their G-SIB status, may face stronger incentives to engage in window dressing due to greater risk exposure and more active risk management needs. Specifically, we investigate whether the observed results are primarily driven, from an idiosyncratic perspective, by banks with higher risk appetite and riskier business models. We classify banks with average risk weights and NPL ratios above the median as risky banks. It turns out that our previous results on G-SIBs are broadly confirmed after explicitly controlling for business-model risk (see Tables A.30 to A.33 in the Online Appendix), though the magnitudes of some effects slightly decrease and their significance weakens. An exception arises for level 3 assets

¹⁴ Regions are defined as follows. America include USA, Brazil, and Canada. Asia contains China, India, Singapore, South Korea, and Russia. Europe consists of Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, and the United Kingdom.

¹⁵ In 2022, the European Banking Authority (EBA) classified 180 banks as D-SIBs (European Banking Authority, 2023). This is substantially more than the designations for other regions shown in the Regulatory Consistency Assessment Programmes (RCAPs). For instance, the USA did not classify any additional banks as D-SIBs beyond those already designated as G-SIBs (Basel Committee on Banking Supervision, 2016).

in Table A.33, where the interaction $GSIB \times Q1$ turns negative, likely due to limited observations complicating estimation. Notably, our results indicate that riskier G-SIBs exhibit stronger window-dressing tendencies, suggesting that riskier business models amplify such behavior.

Alternative dependent variable based on changes in growth rates:

The dependent variables employed so far are based on changes in market shares (see Equation (3) in Section 5.2). Given that higher indicator proxy levels are more likely to exhibit greater absolute fluctuations than lower ones, we implement an alternative relative measure as a robustness check. Specifically, we compute the growth rates of individual indicators and subsequently determine the difference in growth rates between two consecutive points in time for each bank. This two-step approach enables us to account for relative changes while mitigating the influence of disproportionately high changes that may arise when the initial level is very low. The results presented in Tables A.34 and A.35 in the Online Appendix corroborate our primary findings, particularly for the fourth quarter. While the positive sign remains consistent in the first quarter, the effect is no longer statistically significant.

8 Conclusion

This paper examines whether G-SIBs engage in window dressing more strongly than other banks. The G-SIB framework aims at reducing the probability and severity of issues emanating from the failure of large and globally active banks by posing an additional capital buffer requirement for such banks. The amount of this additional capital surcharge mostly depends on year-end exposures, which may incentivize banks to window dress those exposures to appear less risky and save capital. However, window dressing undermines regulatory requirements and may lead to banks holding too little capital and thus being more vulnerable to shocks. Therefore, detecting window-dressing behavior is of particular relevance for a sound financial system.

Based on a global bank sample and many different robustness analyses, we indeed provide some evidence for window-dressing behavior. Our study reveals that the year-end reduction in certain exposures is both economically meaningful and substantially larger for G-SIBs (by

approximately a factor of two) compared to other banks. The exposures affected include total assets, debt issued, derivatives, level 3 assets, as well as trading and available-for-sale securities, all of which are relevant for calculating the G-SIBs score and determining the additional capital buffer requirement. These reductions in exposures do not appear to be risk reductions of a longer term and sustainable nature because our findings also reveal that G-SIBs increase these exposures again more strongly, i.e. roughly twice as large as other banks, at the beginning of the subsequent year. This behavior is also of economic significance. By way of example, banks exhibit in the fourth quarter a decline in their total assets indicator by approximately 13 basis points, while G-SIBs exhibit an even larger reduction, with an additional decline of 13 basis points. This behavior is reversed in the first quarter, as the total assets indicator increases by 13 basis points for all banks and by additional 14 basis points for G-SIBs. This indicates a “V-shape” relationship and thus points to window-dressing behavior. We find that this behavior is particularly pronounced for G-SIBs where a reduction in exposures is particularly worthwhile, that is, G-SIBs whose scores are close to a threshold and for G-SIBs with a high surcharge. It is noteworthy that this behavior can also have significant implications for financial markets, as large-scale exposures are sold and then repurchased in the following quarter. In this regard non-bank financial intermediaries often serve as counterparts, typically taking opposite positions, particularly in the context of derivatives.¹⁶

Although the systemic importance of G-SIBs has declined after the financial crisis of 2007-09 (e.g., [Goel et al., 2019](#)), which is likely at least partially attributable to the G-SIB framework, the unintended consequence of banks’ window-dressing behavior may be a reason to consider changes to the framework. One potential solution is to base G-SIB scores on averages, similar to the national methodologies used in the United Kingdom and the United States. However, the public support in the take-over of Credit Suisse by UBS may impose some more fundamental questions on the framework. Specifically, the G-SIB framework should have mitigated incentives for merging two G-SIBs, as the combined UBS and Credit Suisse entity has significantly increased in size and poses more systemic risk than the two individual banks did separately.

¹⁶ This behavior is evident in the European swap market ([European Central Bank, 2022](#)).

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