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Is window dressing by banks systemically important?*

Luis Garcia[a], Ulf Lewrick[b,c], Taja Sečnik[a]

[a] *European Banking Authority, Europlaza 20 Avenue André Prothin, 92927 Paris La Défense, France*
[b] *Bank for International Settlements, Centralbahnplatz 2, 4051 Basel, Switzerland*
[c] *University of Basel, Peter Merian-Weg 6, 4052 Basel, Switzerland*

Abstract

We study banks' year-end window dressing in the European Union to assess how it affects the identification of global systemically important banks (G-SIBs) and the associated capital surcharges. We find that G-SIBs compress their balance sheet at year-end to an extent that they can reduce their surcharges or avoid G-SIB designation altogether. G-SIBs use several levers to adjust their balance sheets. Most notably, they compress intra-financial system assets and liabilities as well as their derivative books at year-end. Moreover, G-SIBs that are more tightly constrained by capital requirements window dress more than their peers. Our findings underscore the importance of supervisory judgement in the assessment of G-SIBs and call for greater use of average as opposed to point-in-time data to measure banks' systemic importance.

Keywords: Systemically important bank, systemic risks, regulatory arbitrage, financial stability
JEL: G20, G21, G28

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1. Introduction

Effective supervision of banks builds on accurate data. If supervisory information is flawed, the assessment of risks becomes unreliable.[1] Window dressing by banks is one factor that can blur supervisory data and thus affect regulatory outcomes.[2]

The internationally agreed methodology to identify global systemically important banks (G-SIBs) is a case in point. Developed by the Basel Committee on Banking Supervision (BCBS) in 2011 and seen as a pillar of regulatory reforms in the aftermath of the Great Financial Crisis, the assessment largely relies on balance sheet information as of the end of the banks' financial year (BCBS (2011, 2018)). For each bank in the assessment sample, the BCBS calculates a G-SIB score every year. This score reflects a weighted average of the banks' market share across 12 indicators of banking activity. Banks with a sufficiently high score are designated as G-SIBs and, depending on their score, are allocated into different buckets, which determine the regulatory capital surcharge.

Banks that temporarily compress their balance sheet ahead of the end-year reporting date can manage down their G-SIB score and reduce their capital surcharges. While the balance sheet compression at year-end is not a novelty, we investigate in this paper whether it occurs at a sufficiently large scale that it could misinform supervisors' assessment and result in a misalignment of capital surcharges across G-SIBs.

We study how the G-SIB scores vary around the reporting dates by approximating the scores at a quarterly frequency. We have access to harmonised supervisory data for 166 large banks in the European Union (EU) from 2014 to 2020, including all EU G-SIBs and all other EU banks that are required to report their indicator values for the annual G-SIB assessment ('reporting banks'). This allows us to match closely the balance sheet items that constitute the annual G-SIB assessment.

Our analysis uncovers a large and systematic contraction in the scores of EU G-SIBs at year-end. Up to 13 banks in the EU would have faced more intense supervision and higher capital requirements in the absence of window dressing. Of these, three banks would have been added to the G-SIB list, whereas 10 banks would have been allocated to a higher G-SIB bucket in at least one year. Several banks repeatedly 'dip into' into a lower bucket at year-end, suggesting a systematic approach to their balance sheet compression. These numbers are likely to reflect a lower bound. For instance, previous research (e.g. Aldasoro et al. (2019), Grill et al. (2017), Munyan (2015)) based on higher-frequency data points to sizeable reductions in banks' repo exposures ahead of quarter-end reporting dates.

[1] Equally important are the consistency and comparability of supervisory data across market participants to ensure consistent microprudential and macroprudential decisions.

[2] Allen and Saunders (1992) define window dressing as the use of short-term financial transactions to manipulate accounting values around reporting dates. Accrual activities, such as strategic choices of accounting methods as well as earnings and loss estimates (see, e.g., Fields et al. (2001)), can add to inconsistencies in supervisory data across banks.

This implies that banks' year-end compression is even more pronounced than what our quarter-end to quarter-end comparison uncovers.

Our approximation requires assumptions about the unobserved behaviour of non-EU banks and of individual indicators that cannot be matched. The G-SIB score is based on the relative share of a bank in the measured banking activity. If unobserved banks compress their balance sheet at year-end, this raises the scores of the banks in our sample. To assess the robustness of our findings, we thus consider several alternative scenarios of how these unobserved banks and indicators may have evolved. These scenarios support the above findings. For instance, even under the assumption of wide-spread window dressing by unobserved banks, we find that several EU G-SIBs compress their balance sheet by enough to move into a lower bucket at year-end.

We explore the drivers of G-SIBs' window dressing in a formal regression setup to complement our matching results. Even though year-end contractions are most pronounced for G-SIBs, they are not confined to these banks. Indeed, we find an average decline in scores at year-end of around 5 basis points (bps) for the entire sample of banks. Reporting banks exhibit a contraction by an additional 4 bps. G-SIBs, finally, compress their score by another 12 bps, for a total compression by these banks of nearly 20 bps, on average, at year-end. However, the average compression across G-SIBs masks reductions in scores by more than 70 bps for some G-SIBs. To put these numbers into perspective, we note that G-SIB scores are mapped into five buckets, with each bucket covering a range of 100 bps. Banks that manage to reduce their score by enough to move into a lower bucket benefit from a Common Equity Tier-1 (CET1) capital relief equivalent to 0.5% of their total risk-weighted assets (RWA). Banks that push their score below 130 bps drop off the G-SIB list and unlock a capital relief of 1% CET1 capital.[3] For the 13 banks which, absent window dressing, would have moved into a higher G-SIB bucket, the estimated annual relief amounts to more than EUR 31 billion of CET1 capital (equivalent to 0.6% of RWA) based on these banks' total RWA in the first quarter of 2020.

G-SIBs window dress their balance sheet by pulling several levers. Relative to their peers, G-SIBs compress almost all categories included in the G-SIB assessment methodology. Even so, reductions in G-SIBs' intra-financial assets (notably loans and advances to banks and other financial firms), their intra-financial liabilities (particularly deposits from banks and other financial firms), and their notional amounts of OTC derivatives stand out. Year-end compression of the latter has further increased over recent years, suggesting that OTC derivatives markets are increasingly exposed to withdrawals by key counterparties around year-end reporting dates.

[3] Although the designation of G-SIBs is generally rules-based, supervisory authorities can, in exceptional cases, apply judgement and designate banks as G-SIBs even if their score is below the threshold. For banks allocated to buckets 2 or higher, the capital relief would exceed 1% CET1 capital if the bank manages to avoid G-SIB designation.

We find that G-SIBs that are more tightly constrained by capital requirements compress their balance sheet by more than other G-SIBs at year-end. This contrasts with banks designated as systemically important at the national level – referred to as 'other systemically important institutions' (O-SIIs) in the EU. Given their significant domestic market share, these banks have little leeway to manage down their O-SII capital surcharge. Accordingly, they exhibit no systematically different behaviour compared with other reporting banks. This is also the case for those G-SIBs for which the O-SII capital surcharge is at least as high as the one imposed by the G-SIB framework, in which case it supersedes the latter.

Finally, we show that the year-end contraction in G-SIBs' scores influences other regulatory ratios. It is associated with a more modest increase in G-SIBs' Liquidity Coverage Ratio (LCR) relative to other banks. G-SIBs and other reporting banks, on average, raise their LCR by about 15 percentage points at year-end. The LCR of other banks in our sample, by comparison, increases by as much as 30 percentage points on average. Seen through the lens of our previous results on the evolution of the scores, this implies that G-SIBs' compression of their balance sheet may prevent them from raising their LCR by as much as their peers at year-end.

Our findings have several implications for policy. Admittedly, many factors could be driving banks' year-end adjustments. Tax incentives, annual contributions to deposit insurance schemes or resolution funds, as well as a wind-down of positions by banks' counterparties could all be contributing to the observed behaviour. Yet regardless of the driver, the observed input to the annual G-SIB exercise appears to twist the assessment of banks' systemic importance. This underscores the value of supervisory judgement as complementary to a mechanistic application of the G-SIB methodology to the G-SIB designation process or bucket allocation. It also warrants consideration of a more robust calculation of the G-SIB scores, such as greater reliance on averages as opposed to year-end values. In this sense, our findings highlight the difficulty in striking a balance between relying on simple rules and containing the scope for regulatory arbitrage.

Our analysis relates to an active research agenda on banks' window dressing and the effects of post-crisis financial reforms to mitigate systemic risks.[4]

Most closely related to our analysis, Behn et al. (2019) assess year-end balance sheet adjustments by euro area banks against the backdrop of the G-SIB framework. Consistent with our findings, they document a reduction in G-SIBs' scores by around 12 bps relative to non-reporting banks. Leveraging on a larger dataset, we expand their analysis along

[4]A different strand of the literature discusses the adequacy of bank capital requirements to mitigate systemic risk (see Dagher et al. (2020) for a discussion). The analysis in Passmore and von Hafften (2019), for example, suggests that G-SIB capital surcharges would need to be raised considerably to account for the risk of failure of these banks. Another strand assesses the impact of the G-SIB framework on banks in the medium term (e.g. Violon et al. (2020), Goel et al. (2019, 2021).

several dimensions. Most importantly, we show that window dressing undermines the identification of G-SIBs and reduces the regulatory requirements for some of them. We also explore how the varying tightness of capital constraints shapes the banks' year-end balance sheet contraction. Furthermore, we consider the interaction of G-SIBs' window dressing with the O-SII framework and the Liquidity Coverage Ratio.

Berry et al. (2021) study window dressing by US G-SIBs. They find that, relative to other US banks, US G-SIBs mainly compress the notional amount of OTC derivatives at year-end. This compression has become more pronounced since the introduction of the G-SIB framework. While our results reveal that EU G-SIBs adjust along several additional margins, we also find that OTC derivatives are one important margin of adjustment, where the year-end compression has intensified over the past years.

A consistent finding of the literature is that short-term borrowing, such as through repurchase agreements (repos), is particularly prone to window dressing. Several studies find that large European banks retrench from repo markets around reporting dates, supporting the banks' regulatory ratios at the expense of reduced market depth (e.g. Aldasoro et al. (2019), Grill et al. (2017), Munyan (2015)). In line with this stream of research, we show that reductions in (short-term) intra-financial assets and liabilities account for a notable share of G-SIBs' year-end adjustments. We add to this literature by showing that other financial instruments, notably OTC derivatives, also feature prominently in the G-SIBs' balance sheet compression.

The claim that some banks window dress is not new. Indeed, regulators and newspaper columnists accused national banks of window dressing in the aftermath of the American Civil War (Hoag (2016)). In one of the first empirical assessments, Allen and Saunders (1992) point to window dressing behaviour by US banks in the late 1970s and during the 1980s. Similar to our findings, they show that banks that are more constrained by regulation are more likely to reduce the size of their balance sheet around reporting dates. They also document that changing the calculation of regulatory metrics towards greater use of quarterly averages (as opposed to quarter-end values) undid much of the previously observed window dressing of capital ratios.

Kotomin and Winters (2006) provide an alternative explanation for the observed quarter-end contraction in balance sheets. They argue that banks' activity is driven by their customers' preference for holding cash at year-ends. The compression in banks' balance sheets would thus reflect a passive response to their customers' window dressing. Our paper focuses on the implications of window dressing for the assessment of banks' systemic importance. We study the characteristics of banks that compress their balance sheet most strongly. Yet a comprehensive study of the drivers of banks' year-end adjustments is outside the scope of our paper as it would require data at a higher frequency than the quarterly supervisory reports. Even so, our finding that G-SIBs lower their scores significantly more than their peers at year-end lends some support to our interpretation that these adjustments reflect an active balance sheet management by these banks.

We organise the remainder of this paper as follows. Section 2 provides an overview of the G-SIB assessment methodology and the window-dressing incentives it creates. In Section 3, we present the data and present our matching approach. Section 4 presents the results of our analysis, starting with an examination of G-SIBs hidden bucket changes before turning to the discussion of year-end adjustment patterns and drivers. Section 5 explores the interaction of the G-SIB framework with the one for O-SIIs and the LCR. We conclude with Section 6.

2. G-SIB framework and window-dressing incentives

Regulatory reforms to mitigate the systemic risks that arise from G-SIBs span a variety of measures, centred on the assessment methodology to identify G-SIBs (BCBS (2013)).[5] The methodology comprises 12 indicators, grouped into five categories of systemic importance (Table 1).[6] For each indicator, a bank's indicator score is calculated as the bank's indicator value divided by the sum of the corresponding values of all the banks in the BCBS assessment sample (currently around 80 institutions). The indicator scores can thus be thought of as a bank's global market share in the corresponding business activity. The final G-SIB score is equal to the weighted average of the bank's 12 indicator scores based on the weights reported in Table 1.

Table 1: G-SIB score categories and indicators

Category	Indicator	Weight	Reporting
Size	Basel III leverage ratio total exposure	20%	end of year
Cross-jurisdictional activity	Cross-jurisdictional claims	10%	end of year
	Cross-jurisdictional liabilities	10%	end of year
Interconnectedness	Intra-financial system assets	6.67%	end of year
	Intra-financial system liabilities	6.67%	end of year
	Securities outstanding	6.67%	end of year
Complexity	Notional amount of OTC derivatives	6.67%	end of year
	Level 3 assets	6.67%	end of year
	Trading and available-for-sale securities	6.67%	end of year
Substitutability	Assets under custody	6.67%	end of year
	Payments activity	6.67%	annual volume
	Underwritten transactions in debt and equity markets	6.67%	annual volume

Notes: See BCBS (2013). Each category has a weight of 20% in the calculation of the G-SIB score.

[5] In addition to the G-SIB assessment methodology and the attendant capital surcharges, the regulatory reforms encompass enhanced supervision of G-SIBs and measures to improve the banks' resolvability.

[6] A revised assessment methodology, taking effect in 2021, adds the volume of banks' trading activities as an additional indicator (BCBS (2018)).

G-SIB designation is based on a simple threshold approach. All banks with a score of at least 130 bps are designated as G-SIBs and thus subject to more stringent regulatory requirements. In addition, regulation allocates G-SIBs into different buckets depending on their score. These buckets, which each span a range of 100 bps in terms of scores, determine the amount of the G-SIBs' capital surcharge (so-called Higher Loss Absorbency requirements). Starting from a level of 1% CET1 capital to RWA in the first bucket for the G-SIBs with the lowest scores (130 to 229 bps), the surcharges increase by increments of 0.5 percentage points up to the fourth bucket. From there onwards, surcharges increase by increments of 1 percentage point. The BCBS calculates the scores annually, and the Financial Stability Board (FSB) publishes the list of G-SIBs and the bucket allocation every year in November. Phase-in of the capital surcharges started in 2016, with full implementation as of the beginning of 2019.

The design of the assessment methodology and capital surcharges provide incentives for banks to adjust their balance sheets ahead of the reporting date. In addition to bolstering G-SIBs' resilience, the regulation intends to discourage G-SIBs from further raising their systemic importance by imposing higher capital surcharges for banks with higher scores. However, the calculation of the scores largely relies on a snapshot of the balance sheet at the end of the bank's financial year: 10 out of the 12 indicators rely on year-end data (Table 1). These 10 indicators account for nearly 87% of the banks' G-SIB score. A bank that temporarily compresses the indicator values ahead of the reporting date can reduce its score. If the compression is sufficiently large, the bank moves into a lower bucket and therefore benefits from a discrete decline in its capital requirements by at least 0.5 percentage points. Some banks could even drop off the G-SIB list. Since a bank's score increases by design if other banks reduce their indicator values, window dressing by peers reinforces banks' incentives to compress their balance sheet.

3. Data and empirical strategy

Our empirical strategy to assess the magnitude of G-SIBs' year-end balance sheet compression relies on matching the G-SIB indicators with closely related balance sheet items available at a quarterly frequency.

Our main dataset comprises quarterly information from 166 EU banks based on the harmonised Financial Reporting (FinRep) and Common Reporting (CoRep), which are the backbones of supervisory data collection from EU banks.[7] Data are available from the fourth quarter of 2014 up to the first quarter of 2020. A second dataset comprises

[7]All banks are comprised in the EBA's list of reporting institutions (EBA (2020b)). This list also includes banks that compile solo-level data which are not available to the EBA and thus not included in our sample. The supervisory reporting for all banks in the EU follows the EBA reporting framework, which is regularly updated to reflect any changes in regulatory requirements (EBA (2020a)).

monthly data on the Liquidity Coverage Ratio (LCR), which is available for 165 out the 166 banks. This dataset starts in October 2016, with the final observation in March 2020.

A total of 37 banks have reported year-end data to the BCBS at least once for the calculation of the G-SIB score during the period of observation. One additional bank disclosed the same data under the European Banking Authority's (EBA) guidelines for the disclosure of systemic importance indicators (EBA (2016)). Of these, 32 banks consistently reported data in each year. This sub-sample includes all 13 banks that were designated as a G-SIB in at least one year. We use the sub-sample of 32 banks (henceforth referred to as 'reporting banks') in our matching analysis in order to identify hidden bucket changes (see next section).

The remaining banks do not regularly compile or disclose G-SIB indicator values. However, they report quarterly data to the EBA that can be used to approximate the G-SIB indicators and the score. We use this larger group of banks and attendant proxy scores in our regression analysis to shed light on the bank characteristics that are associated with window dressing.

Our approximation of the quarterly indicator scores proceeds in two steps. First, we map FinRep and CoRep data to the indicators based on the detailed reporting instructions for the G-SIB assessment exercise (see the Appendix for a complete overview of the matched time series). This yields matched indicators for all 10 indicators for which the G-SIB assessment relies on year-end data (recall Table 1 above). We cannot match the two indicators that record a bank's activity over the course of the entire financial year (*Payments activity* and *Underwritten transactions in debt and equity markets*). However, these two indicators are less prone to window dressing exactly because they do not rely on year-end snapshots of the balance sheet. Omitting these indicators is thus unlikely to affect our results. If anything, our approximation of banks' window dressing would appear to be biased downward since we disregard the possibility that banks might also window dress these two indicators to some extent.

Second, we approximate the denominators to calculate the indicator scores. Each bank's indicator value is divided by the sum of indicator values across all banks in the G-SIB sample, the BCBS global denominator, to calculate the indicator scores. Since the denominator is only available at year-end, we approximate the denominators for the first three quarters of the year based on linear interpolation of the neighbouring year-end values in our baseline approach. We explore alternative scenarios for the evolution of the denominators to confirm the robustness of our results in the next section.

The equations below summarise how the quarterly indicator scores for bank i and indicator z are computed for each of the first three quarters and for the fourth quarter (i.e. year-end), Q_j, respectively:

$$\begin{aligned}\text{Indicator score}_{i,z,Qj} &= \frac{\text{Matched indicator}_{i,z,Qj}}{\text{Interpolated global denominator}_{z,Qj}} \quad \text{for } j \in \{1,2,3\}, \\ \text{Indicator score}_{i,z,Qj} &= \frac{\text{Matched indicator}_{i,z,Qj}}{\text{BCBS global denominator}_{z,Qj}} \quad \text{for } j = 4. \end{aligned} \tag{1}$$

We calculate category scores based on weighted averages of the indicator scores of the same category.[8] The final score is given by the weighted average of the category scores based on the weights reported in Table 1.

We evaluate the accuracy of our approximation to ensure the robustness of the results in the remainder of the paper. For each reporting bank, we divide the approximated scores at year-end by the actual scores from the G-SIB assessment. Next, we calculate the standard deviation of this ratio for each bank to assess whether we consistently approximate the scores for individual banks at year-ends.

Table 2 reports the summary statistics of the banks' standard deviations. The standard deviation of this ratio is 9% on average for the reporting banks, suggesting that the approximated score tightly mimics the evolution of the reported score. Importantly, we find neither a systematic difference in the matching accuracy for G-SIBs nor for the banks that we identify as shifting into lower buckets at year-end (see next section).

Table 2: Matching accuracy

	Mean	P10	P25	P50	P75	P90
Reporting banks	0.09	0.04	0.04	0.08	0.09	0.13
of which G-SIBs	0.07	0.04	0.04	0.08	0.09	0.10
of which non-G-SIBs	0.09	0.04	0.05	0.07	0.09	0.15
Banks with hidden bucket changes	0.09	0.04	0.05	0.08	0.09	0.10

Notes: The table reports the summary statistics, mean as well as the 10th (P10), 25th (P25), 50th (P50), 75th (P75), and 90th (P90) percentiles, of the standard deviation of the ratio of the approximated Q4 score divided by reported Q4 score for each bank and year of observation. The statistics are shown for the reporting banks, G-SIBs, non-G-SIB reporting banks, and banks with hidden bucket changes as marked in Table 4, respectively.

We conclude this section by presenting summary statistics of the scores for the 10 matched indicators, distinguishing between the scores of G-SIBs and those of the

[8] Since we can only match *Assets under custody* out of the three indicators in the *Substitutability* category at a quarterly frequency, we proceed as follows for the calculation of the corresponding category score: for reporting banks, we apply linear interpolation to infer from the year-end indicator values the quarterly values for the two unobserved indicators (*Payments activity* and *Underwritten transactions in debt and equity markets*); for all other banks, we approximate the category score based on the matched *Assets under custody* indicator values.

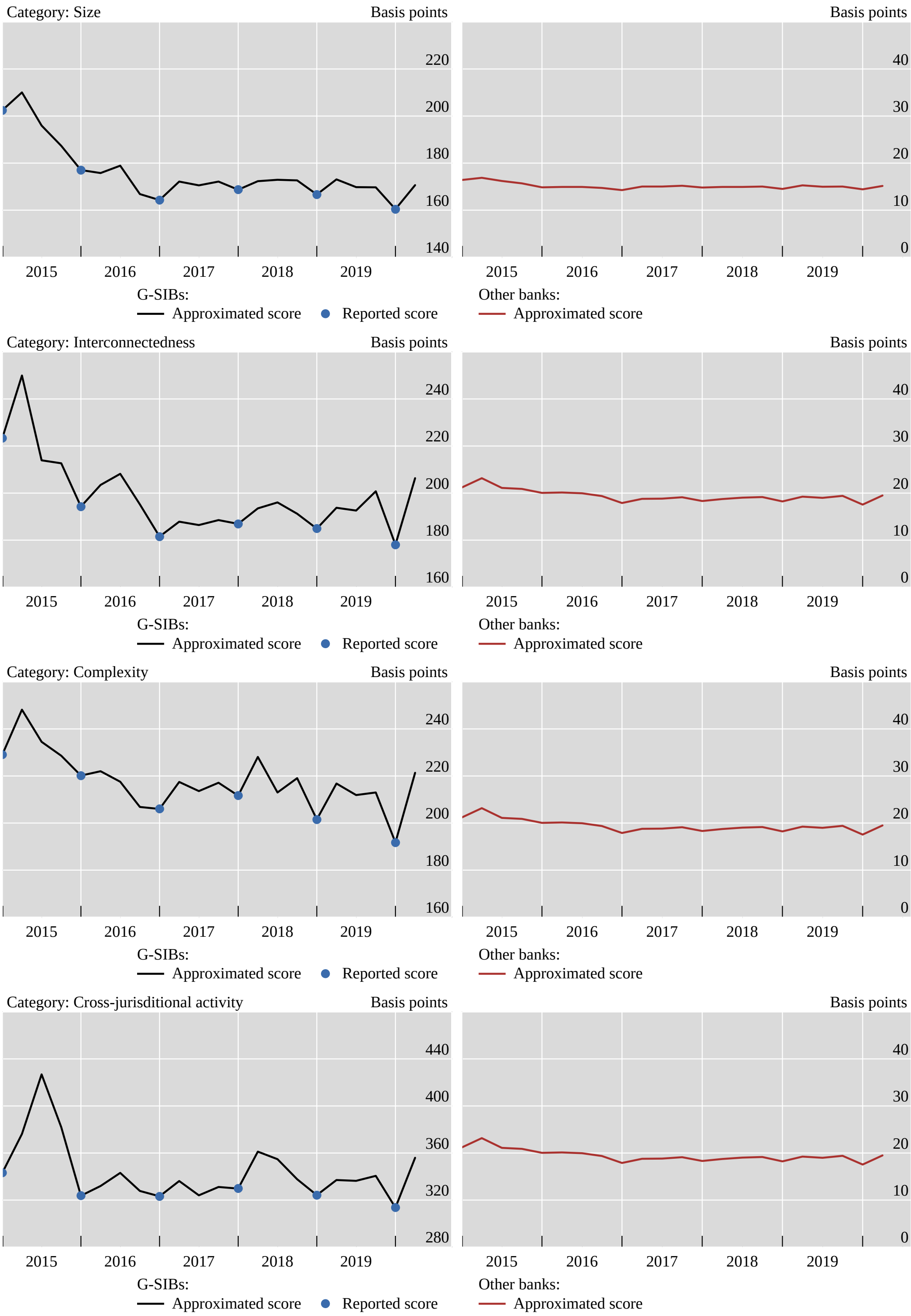
other banks, respectively (Table 3). We also summarise the bank data that we use in the regression analysis. G-SIBs exhibit markedly higher scores than their peers for all indicators. They also tend to be more leveraged (both in risk-weighted and unweighted terms), while, on average, also reporting lower return-on-equity despite lower shares of non-performing loans.

Table 3: Summary statistics

	P10	P25	P50	P75	P90	StDev	Mean	Obs
G-SIBs (13 banks)								
MATCHED INDICATORS (basis points)								
Assets under custody	6	12	54	148	393	158	124	286
Cross-jurisdictional claims	67	176	261	512	627	213	328	286
Cross-jurisdictional liabilities	71	181	267	509	679	217	329	286
Intra-financial assets	225	262	447	787	921	295	513	286
Intra-financial liabilities	164	243	333	631	821	248	435	286
Level 3 assets	42	62	125	293	481	164	199	286
Notional amount of OTC derivat.	67	97	157	436	660	234	284	286
Securities outstanding	68	122	165	198	221	52	157	286
Total exposures	91	131	161	199	293	67	173	286
Trading & AFS securities	249	306	443	621	936	341	533	286
Overall G-SIB score	149	161	224	387	503	139	274	286
BANK CHARACTERISTICS (per cent)								
Leverage ratio (fully loaded)	3.92	4.21	4.96	5.24	5.46	0.59	4.75	195
Liquidity Coverage Ratio	119.9	128.5	140.9	151.5	162.2	17.9	141.6	556
CET1 capital ratio (fully loaded)	10.57	11.42	13.02	14.46	15.64	2.12	13.07	286
Non-performing loans ratio	1.21	1.7	2.68	3.71	5.82	2.38	3.22	286
Short-term wholesale funding	24.42	26.87	33.48	39.94	46.75	8.22	34.19	286
Return on equity	0.91	4.26	6.39	8.44	10.39	4.59	5.78	286
Total assets (EUR billion)	605	867	1,242	1,490	1,930	477	1,253	286
Other banks (153 banks)								
MATCHED INDICATORS (basis points)								
Assets under custody	0	0	1	7	18	31	10	2,310
Cross-jurisdictional claims	0	0	0	6	31	23	9	3,085
Cross-jurisdictional liabilities	0	0	0	6	33	23	9	3,085
Intra-financial assets	0	0	2	20	85	57	26	3,085
Intra-financial liabilities	0	0	2	21	78	52	24	3,085
Level 3 assets	0	0	2	13	58	57	19	3,085
Notional amount of OTC derivat.	0	0	0	3	14	30	8	3,085
Securities outstanding	0	0	4	22	61	31	18	3,085
Total exposures	1	3	7	19	45	22	16	3,085
Trading & AFS securities	0	2	11	38	87	53	32	3,085
Overall G-SIB score	1	2	5	18	45	25	16	3,085
BANK CHARACTERISTICS (per cent)								
Leverage ratio (fully loaded)	3.86	4.77	6.29	8.46	11.22	6.99	7.54	2,219
Liquidity Coverage Ratio	125.20	139.70	171.10	239.80	388.40	312.10	244.50	6,267
CET1 capital ratio (fully loaded)	11.11	12.73	15.48	19.93	27.60	13.34	18.67	3,251
Non-performing loans ratio	0.54	1.62	3.60	8.39	18.30	9.31	7.10	2,811
Short-term wholesale funding	5.55	15.30	24.84	34.01	43.32	21.03	26.42	3,118
Return on equity	–0.41	3.78	7.45	11.34	15.06	10.37	7.06	2,880
Total assets (EUR billion)	8	19	48	141	276	151	110	2,880

Notes: Data are based on the harmonised Financial Reporting (FinRep) and Common Reporting (CoRep) by EU banks.

Figure 1: Approximated category scores for reporting banks: G-SIBs vs other banks



Notes: The left-hand (right-hand) panels depict the quarterly category score in bps averaged across EU G-SIBs (other EU banks). The dots represent the corresponding value of the reported score at year-end that is used in the G-SIB assessment. The approximated G-SIB scores for year-end periods have been adjusted to reflect the reported scores for all reporting banks. The non-year-end adjustment factors were obtained by interpolating the corresponding year-end adjustment factors. For each reference period, an average adjustment factor based on all banks for which the G-SIB assessment data are available is used for the rest of the banks in the sample.

Year-end compressions abound in the visual inspection of the category scores. Figure 1 illustrates the evolution of the average score of G-SIBs and other banks, respectively, for each of the four categories for which the underlying indicators can be closely matched. Notwithstanding the caveats that encompass the approximation, a pronounced V-shape adjustment of the scores at year-end (dots) is observed for G-SIBs in each of the four categories. This stands in contrast to the evolution of other banks' scores, for which one needs to zoom in very closely to find a marginal reduction in the scores at year-end. We test the significance of these year-end patterns more formally in the next section.

4. Results

The key policy question from the perspective of the G-SIB framework is whether the year-end compression is sufficiently large to have banks drop off the G-SIB list or to have them allocated into a lower G-SIB bucket. These hidden bucket changes undermine supervisors' ability to evaluate banks' systemic importance. The second policy question is what drives the compression in balance sheets. We consider each of these questions in turn.

4.1. Hidden bucket changes

We assess the impact of window dressing on the G-SIB scores by comparing the reported scores at year-end with the approximated scores in the third and first quarter (Table 4). Our approximation points to up to 13 different banks across the six years studied which would have faced higher capital requirements in the absence of year-end adjustments. Of these, three banks would have been added to the G-SIB list, whereas 10 banks would have been allocated to a higher G-SIB bucket. The estimated annual relief amounts to more than EUR 31 billion of CET1 capital (equivalent to 0.6% of RWA) based on the 13 banks' total RWA in the first quarter of 2020. Several alternative scenarios for the evolution of the score denominators, detailed below, confirm the robustness of these results.

Several banks cross the bucket threshold year after year, suggesting a systematic approach to their balance sheet compression. However, for Bank 09 we observe a bucket shift only in Q3 2015 with no corresponding shift in Q1 2016 (indicated by the symbol ↘ in Table 4). Likewise, Bank 14 and Bank 21 exhibit bucket shifts only in the first quarters of the year, but not in the preceding third quarter (indicated by the symbol ↗). For these banks, we can thus not rule out a continued contraction (Bank 09) or expansion (Bank 14 and Bank 21) of the balance sheet that would justify a higher score in the third quarter and first quarter, respectively. This stands in contrast to the other banks, which 'dip into' a lower bucket at year-end, but immediately expand their activity in the following quarter (indicated by "V").[9]

[9] Given the absence of data for Q3 2014, only the Q1 2015 adjustment by banks can be observed. For

Table 4: Hidden bucket changes: estimated Q3 and Q1 scores vs reported scores in Q4

Year-end:	2014	2015	2016	2017	2018	2019
Bank 01						
Bank 02						
Bank 03						
Bank 04						
Bank 05 (G-SIB)	↗	V	V	V	V	V
Bank 06						
Bank 07						
Bank 08				↗	V	
Bank 09		↘				
Bank 10 (G-SIB)	↗	V	V	V	V	V
Bank 11						
Bank 12 (G-SIB)	↗	V	V			
Bank 13 (G-SIB)	↗	V	V	V	V	V
Bank 14 (G-SIB)	↗					
Bank 15						
Bank 16 (G-SIB)		V	V	V	V	
Bank 17						
Bank 18 (G-SIB)	↗	V	V	V	V	V
Bank 19 (G-SIB)	↗	V	V	V	V	V
Bank 20 (G-SIB)	↗	V	V	V	V	V
Bank 21	↗					
Bank 22 (G-SIB)						
Bank 23 (G-SIB)	↗	↘	V	V	V	V
Bank 24						
Bank 25 (G-SIB)						
Bank 26						
Bank 27						
Bank 28 (G-SIB)						
Bank 29						
Bank 30						
Bank 31						
Bank 32						
Sum of bucket changes	10	10	9	9	9	7

Notes: "V" indicates that the bank's estimated score in Q3 of year t and Q1 of year $t+1$ corresponds to a higher G-SIB bucket allocation than the bank's actual allocation based on Q4 of year t (a V-shaped adjustment by the bank). The symbol ↘ (↗) indicates that the bank's score in Q3 of year t (Q1 of $t+1$) corresponds to a higher bucket, but not in Q1 of $t+1$ (Q3 of t). For non-G-SIBs, a higher bucket allocation implies that the bank would have been designated as a G-SIB (see Bank 08, Bank 09, Bank 21). Since data are not available for Q3 2014, a V-shaped adjustment by banks cannot be identified for the year 2014.

Our baseline scenario, which underpins the results in Table 4, uses a linear interpolation. This implies that the denominator for each indicator grows at a constant – although indicator-specific – rate from one reported year-end value to the next. However, if unobserved banks also window dress their balance sheet, the linear interpolation would underestimate the denominator for the first three quarter-ends of each year. This, in turn, would overestimate the scores of the observed banks.

2014, the data thus do not allow identification of a V-shaped adjustment.

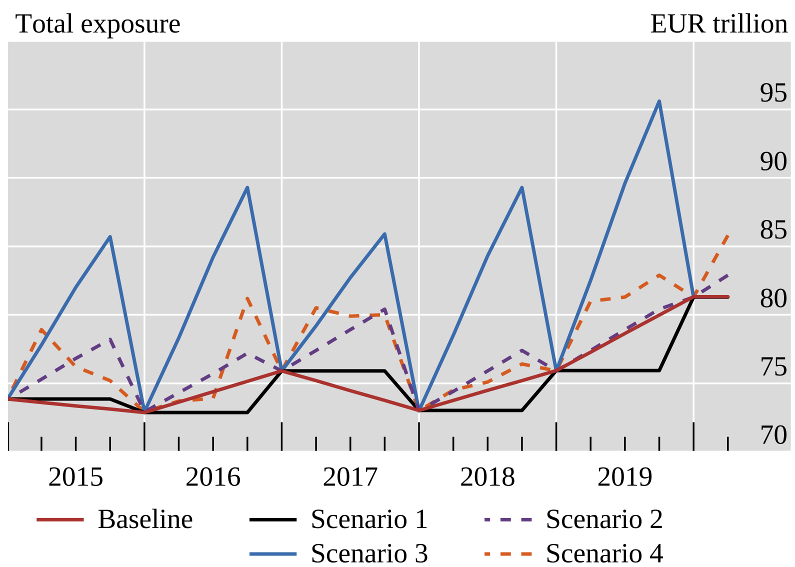
We consider four alternative scenarios for the evolution of the denominators to test the robustness of our results (Figure 2). In Scenario 1, we assume that the denominator remains at its previous year-end level for all quarters until the following year-end, creating a jump from the third to the fourth quarter.

Scenario 2 is based on calculating the compounded annual growth rate of the year-end denominators from 2014 to 2019 for each indicator. This growth rate is then used to inflate the denominators up to the third quarter of the year, thus mirroring the assumption that a drop in the denominators would be observed and concentrated at year-ends.

Scenario 3 assumes that the denominator increases at a constant rate from its year-end value up to the third quarter, before contracting by 15% (i.e. two standard deviations above the average annual growth rate across indicators) from the third to the fourth quarter. Under this extreme scenario, the average score across EU G-SIBs actually increases at year-end, given the assumed steep contraction by their non-EU competitors.

Finally, in Scenario 4, the quarterly denominators reflect the quarter-on-quarter growth in the scores of all the 166 banks in our sample, similar to the approach taken by Behn et al (2019) in their approximation of the G-SIB scores.

Figure 2: Robustness check: scenario assumptions for the G-SIB denominators



Notes: The panel illustrates the evolution of the denominator (in EUR), based on the example of the indicator Total exposures, for the baseline scenario (linear interpolation of the reported year-end denominator values) and four alternative ones. Scenario 1: The denominator is kept constant at its previous year-end level for all quarters until the following year-end, creating a jump from the third to the fourth quarter. Scenario 2: The denominator grows up to the third quarter of the year by the compounded annual growth rate of the year-end denominators from 2014 to 2019 before jumping to the level of the year-end BCBS global denominator. Scenario 3: The denominator increases at a constant rate from its year-end value up to the third quarter, before contracting by 15% from the third to the fourth quarter. Scenario 4: The quarterly denominators reflect the quarter-on-quarter growth in the scores of all the 166 EU banks in the sample.

Table 5: Robustness checks: alternative scenarios for the denominators

Scenario	**Baseline**	**1**	**2**	**3**	**4**
Banks shifting into higher buckets					
based on approx. scores (Q1/Q3) vs. reported Q4 scores	13	13	12	11	11
of which banks added to G-SIB list	*3*	*3*	*2*	*1*	*2*
based on approx. scores (Q1/Q3) vs. approx. Q4 scores	9	9	8	5	6
of which banks added to G-SIB list	*3*	*3*	*2*	*1*	*2*
Change in G-SIBs' approx. scores (Q3 vs. Q4)					
Average	–16 bps	–19 bps	–15 bps	+30 bps	–11 bps
25th percentile	–25 bps	–30 bps	–26 bps	+16 bps	–25 bps

Notes: The following assumptions about the evolution of the G-SIB denominators underpin the different scenarios. Baseline: linear interpolation of the year-end BCBS global denominators. Scenario 1: The denominator is kept constant at its previous year-end level for all quarters until the following year-end, creating a jump from the third to the fourth quarter. Scenario 2: The denominator grows up to the third quarter of the year by the compounded annual growth rate of the year-end denominators from 2014 to 2019 before jumping to the level of the year-end BCBS global denominator. Scenario 3: The denominator increases at a constant rate from its year-end value up to the third quarter, before contracting by 15% from the third to the fourth quarter. Scenario 4: The quarterly denominators reflect the quarter-on-quarter growth in the scores of all the 166 EU banks in the sample. The average change and the 25th percentile change in G-SIBs' approximated score is calculated as the average across all banks that have been designated as a G-SIB in at least one year.

The four different scenarios support the robustness of our main result (Table 5). Even under the underlying assumption of marked window dressing by all reporting banks – i.e. EU and non-EU banks contributing to the global denominator – under Scenario 3, we estimate that a total of 11 banks move into a higher bucket at least once.

To complement these robustness checks, we assess how our findings change if we compare the approximated scores in Q1 and Q3 with the scores that would result from also approximating the scores in Q4 based on the matched indicators rather than using the reported G-SIB scores.

This alternative comparison confirms our finding of systematic window dressing by G-SIBs under each scenario, notwithstanding a decline in the number of banks shifting buckets (Table 5, lines 3 and 4). Even under the assumption of widespread window-dressing by banks that underpins Scenario 3, we find that 5 G-SIBs would move to a higher bucket, and one bank would be added to the G-SIB list. This is despite the fact that several G-SIBs exhibit an increase of their scores at year-end under this scenario, pushing the average change in G-SIBs' scores to as much as +30 bps (Table 5).[10]

4.2. Year-end balance sheet contraction

We now turn to the drivers of banks' window dressing. We first assess the magnitude of banks' window dressing based on a formal regression setup to complement the visual inspection and bank-level results discussed above. This allows us to control for potential confounding factors that could be driving year-end adjustments of the balance sheet.

[10]Under the even more extreme assumption of a 25% contraction in the denominators from Q3 to Q4, we find that 3 G-SIBs would move into a higher bucket at year-end.

Our baseline regression to assess changes in the score at year-end is as follows:

$$\Delta score_{i,t} = \alpha_i + \beta_{GSIB}\ (G\text{-}SIB_i \times Q4) + \beta_{RepB}\ (RepB_i \times Q4) + Q4 + X_{i,t} + \gamma_t + \varepsilon_{i,t}. \tag{2}$$

where $\Delta score_{i,t}$ represents the quarter-on-quarter difference in bank i's score in quarter t. We define $Q4$ as an indicator variable with value 1 (zero otherwise) in the fourth quarter of the year. Our interest lies in the coefficients β_{GSIB} and β_{RepB}, which measure the change in G-SIBs' and reporting banks' (RepB) scores at year-end relative to other banks. Here, the G-SIB indicator comprises all banks that were designated a G-SIB in at least one year, such that the composition of G-SIBs, reporting banks, and the remaining banks is constant over time. We also include $Q4$ as a standalone variable to estimate the average contraction by all banks in the sample at year-end.

$X_{i,t}$ accounts for time-varying differences across banks, such as the banks' riskiness or profitability. Specifically, we include in the regression the banks' ratio of non-performing loans to total loans (NPL ratio), the return on equity, short-term wholesale funding as a share of total funding (SWTF), the (fully-loaded) CET1 capital ratio, and the ratio of and (log) total assets. These bank-level controls are available for 148 out of the 166 banks in our sample, including all G-SIBs and other reporting banks. Furthermore, we saturate our model with bank fixed-effects (α_i) and quarter fixed-effects (γ_t), respectively, to ensure that neither unobserved differences in the fundamental characteristics of banks nor time trends affect our measures. The inclusion of quarter fixed-effects in addition to the $Q4$ variable implies that the latter measures the base effect that is common to all end-year observations in our sample. $\varepsilon_{i,t}$ is the error term. Throughout our analysis, we calculate and report robust standard errors clustered at the bank-level.[11]

Our estimates point to a notable contraction by all banks at year-end, with an even larger contraction by reporting banks and, among those, by G-SIBs. This is despite the fact that we are using quarter-end balance sheet information, which is likely to be window-dressed as well. Indeed, several studies using higher frequency data document that major banks wind down their exposures to other financial intermediaries ahead of quarterly reporting dates (e.g. Aldasoro et al. (2019), Grill et al. (2017), Munyan (2015)). All else equal, this pattern implies a reduction of the approximated G-SIB scores at quarter-ends. Thus, our estimates can be considered lower bounds of the true magnitude of banks' window dressing at year-end.

Table 6 depicts the results of our baseline regression. While all banks reduce their scores at year-end relative to their third quarter proxy by around 5 bps, we estimate that reporting banks reduce their score by an additional 4 bps on average at year-end

[11] Our results are robust for alternative choices, such as using a time-varying measure of G-SIB status, dropping Q4 as a standalone variable or substituting quarter fixed effects by a linear trend.

relative to other banks (Columns (3) and (4)). However, G-SIBs stand out with an average contraction – on top of the former – of more than 12 bps. These findings accord with those in Behn et al. (2019), who report a year-end contraction of 3 basis points for reporting banks, with an additional contraction of 8 basis points for G-SIBs, although based on only about half the number of banks.

Table 6: Banks' year-end contraction

Dependent variable: Δ G-SIB score

	(1)	(2)	(3)	(4)	(5)
Q4	–6.35***	–4.58***	–4.58***	–4.67***	–4.77***
	(1.57)	(1.04)	(1.04)	(1.11)	(1.16)
RepB × Q4		–8.58***	–3.67***	–3.72***	–3.44***
		(2.69)	(0.58)	(0.59)	(0.64)
G-SIB × Q4			–12.09**	–12.10**	–3.67**
			(6.07)	(6.10)	(1.79)
Bucket change × Q4					–13.47*
					(7.29)
NPL ratio				6.22**	5.91**
				(2.95)	(2.97)
Return on equity				0.62	0.76
				(0.82)	(0.79)
STWF				0.53	0.58
				(0.86)	(0.89)
CET1 ratio				–5.02***	–4.71**
				(1.87)	(1.82)
Total assets (logs)				–0.64	–0.60
				(0.74)	(0.75)
R2	0.07	0.11	0.14	0.15	0.17
Observations	3,371	3,371	3,371	2,895	2,895
Banks	166	166	166	148	148
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: */**/*** indicates statistical significance at the 10/5/1% level. Coefficient estimates based on equation (2) with robust standard errors, clustered by bank, in parentheses. Bank controls comprise the ratio of non-performing loans (NPL), return on equity, the short-term wholesale funding ratio (STWF), the CET1 ratio, and log total assets.

The average contraction masks considerable variation across G-SIBs. Some banks reduce their scores by more than 70 bps at year-end. We thus explore whether the contraction is particularly strong for those banks that are estimated to dip into a lower bucket or avoid G-SIB designation at year-end. Column (5) of Table 6 considers the addition of an indicator variable that is equal to one for these banks. We find an additional reduction in the score of more than 13 bps, providing further evidence that hidden bucket changes result from systematic reductions in the scores of these banks at year-end.

4.3. Margins of adjustment

Our next step is to assess which categories and indicators of the G-SIB framework are subject to the largest contractions. Table 7 reports the estimated year-end contraction for each of the four categories that rely on year-end reporting by the banks.

Table 8: Banks' year-end contraction at *indicator* level

Dependent variable: Δ indicator score

	Cross-j. claims	Cross-j. liabilities	Intra-fin. assets	Intra-fin. liabilities	Securit. outst.	OTC derivat.	Level 3 assets	Trading & AFS sec.	Assets u. custody
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Q4	–4.39***	–4.35***	–14.62***	–13.18***	–2.49***	–2.45**	–4.77***	–11.20***	–1.61*
	(1.51)	(1.66)	(3.53)	(3.16)	(0.53)	(1.01)	(1.54)	(3.10)	(0.88)
RepB × Q4	–4.47***	–3.64***	–11.02***	–13.92***	–2.06***	–2.15**	–2.36	–7.59***	0.04
	(1.12)	(0.95)	(2.59)	(2.60)	(0.55)	(0.98)	(1.62)	(1.84)	(0.42)
G-SIB × Q4	–10.81*	–12.28*	–53.90**	–34.58**	1.30	–26.19***	0.16	–16.42	–4.82
	(6.05)	(6.85)	(21.82)	(15.89)	(1.11)	(8.92)	(4.03)	(18.25)	(4.87)
R2	0.08	0.09	0.18	0.17	0.07	0.05	0.03	0.08	0.02
Obs.	2,895	2,895	2,895	2,895	2,895	2,895	2,895	2,895	2,392
Banks	148	148	148	148	148	148	148	148	131

Notes: * / ** / *** indicates statistical significance at the 10/5/1% level. Coefficient estimates based on equation (2) with robust standard errors, clustered by bank, in parentheses. All regressions include time-varying bank controls (non-performing loans ratio, return on equity, short-term wholesale funding ratio, CET1 ratio, and log total assets) as well as bank fixed effects and quarter fixed effects. Regressions based on excluding time-varying bank controls in order to include the entire sample of 166 banks yield very similar results (available upon request from the authors).

We find that reporting banks compress their balance sheet along the full range of categories at year-end. For each of these categories, we also find that G-SIBs reduce their scores over and above the reporting banks' compression. The difference is most pronounced for *Interconnectedness*, which comprises banks' intra-financial assets and liabilities, such as interbank loans and deposits, which can be wound down relatively quickly and at limited cost. This may imply that G-SIBs that are more heavily engaged in lending to the real economy as opposed to being more tightly interconnected with the rest of the financial industry are potentially penalised by the relative nature of the framework.

Table 7: Banks' year-end contraction at *category* level

Dependent variable: Δ category score

	Size		Complexity		Cross-jur. activity		Interconnectedness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Q4	–2.89***	–2.43***	–5.77***	–6.14***	–4.17***	–4.37***	–9.44***	–10.10***
	(0.55)	(0.54)	(1.44)	(1.62)	(1.46)	(1.58)	(2.21)	(2.32)
RepB × Q4	–1.67***	–1.92***	–4.01***	–4.03***	–4.04***	–4.05***	–8.97***	–9.00***
	(0.36)	(0.34)	(0.95)	(0.96)	(1.00)	(1.01)	(1.73)	(1.75)
G-SIB × Q4	–4.11*	–4.10*	–14.16*	–14.15*	–11.53*	–11.55*	–29.03**	–29.06**
	(2.42)	(2.43)	(8.33)	(8.37)	(6.38)	(6.41)	(12.68)	(12.74)
R2	0.14	0.15	0.06	0.06	0.08	0.09	0.17	0.18
Observations	3,371	2,895	3,371	2,895	3,371	2,895	3,371	2,895
Banks	166	148	166	148	166	148	166	148
Bank controls	No	Yes	No	Yes	No	Yes	No	Yes
Bank & quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * / ** / *** indicates statistical significance at the 10/5/1% level. Coefficient estimates based on equation (2) with robust standard errors, clustered by bank, in parentheses. Bank controls comprise the ratio of non-performing loans, return on equity, the short-term wholesale funding ratio, the CET1 ratio, and log total assets. Results for the *Substitutability* category are not reported since out of the three indicators in this category only *Assets under custody* can be matched. The results for this indicator are reported in Table 8.

Zooming in even closer, we consider banks' adjustment for each of the approximated indicators. Consistent with the findings at the category level, Table 8 points to a large contraction in G-SIBs' *Intra-financial assets* and *Intra-financial liabilities* on top of the contraction observed for reporting banks. Furthermore, we find a notable compression in G-SIBs' *Notional amounts of OTC derivatives* relative to their peers. This finding tallies with the results for US G-SIBs reported by Berry et al. (2021). However, in contrast to the US G-SIBs, we find that EU G-SIBs reduce their year-end scores along several margins, also including their *Cross-jurisdictional claims* and *Cross-jurisdictional liabilities.*

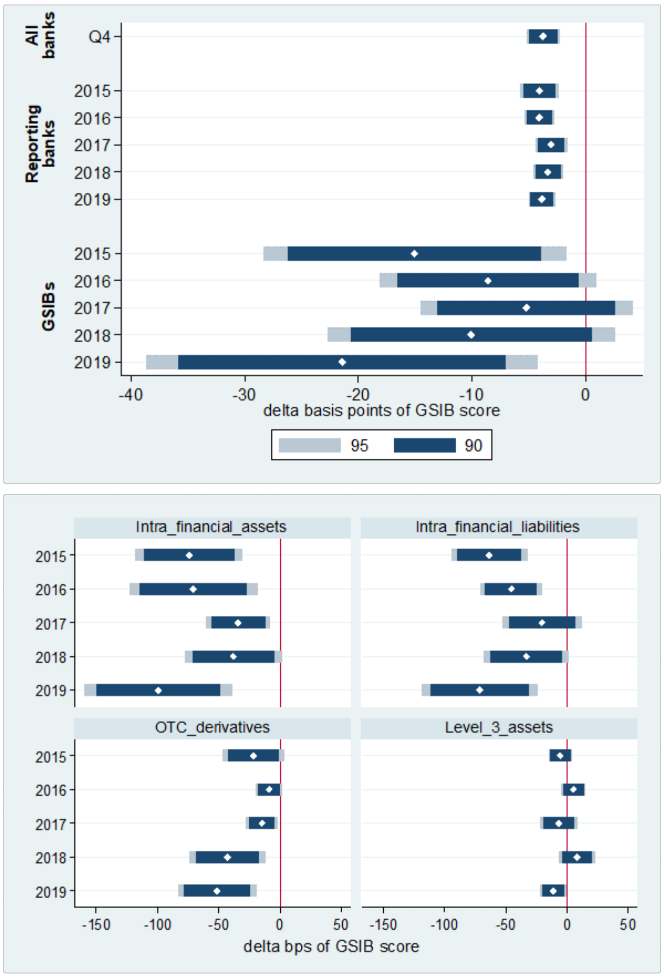
Has the year-end contraction intensified over time? More stringent capital requirements could incentivise banks to window dress more aggressively. The G-SIB capital surcharges have been phased in since 2016, gradually raising the regulatory requirements for G-SIBs. To test how the year-end contraction has evolved, we loosen the assumption in our baseline regression and allow for the year-end effect ($Q4$) to vary every year, y:

$$\begin{aligned}\Delta score_{i,t} \;=\; & \alpha_i + \sum_{y=2015}^{2019} \beta_{GSIB,y}\,(G\text{-}SIB_i \times Q4_y) + \sum_{y=2015}^{2019} \beta_{RepB,y}\,(RepB_i \times Q4_y) \\ & + \; Q4 + X_{i,t} + \gamma_t + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

Figure 3 (upper panel) illustrates the yearly estimates for the corresponding fourth quarter interaction terms. The year-end contraction by reporting banks relative to other banks, at around 4 bps on average, is stable over time with little variation across banks. For G-SIBs, by contrast, the additional contraction is not only larger (12 bps) but also much more dispersed and appears to have increased in the most recent year of observation. However, the limited number of and large variation across G-SIBs limits the ability to test the statistical significance of these changes over time.

We plot in Figure 3 (lower panel) the estimates for G-SIBs' year-end contraction for those indicators for which we observed particularly large compressions among G-SIBs on average: *Intra-financial assets* (top left), *Intra-financial liabilities* (top right), and the *Notional amount of OTC derivatives* (bottom left). In line with our above finding, the estimates point to a recent increase in G-SIBs' window dressing for each of these indicators. Other indicators, such as those recording banks' share of *Level-3 assets* (bottom right), remain little changed. Flexibility in accounting standards, which enable banks to book profits and conceal losses by reclassifying less liquid assets (Milbradt (2012)), thus appear to play only a limited role in G-SIBs' score adjustments at year-end.

Figure 3: G-SIBs' year-end window dressing intensifies over time



Notes: Coefficient estimates based on equation (3) with robust standard errors, clustered by bank. The light (dark) bars indicate the 95% (90%) confidence intervals.

4.4. Regulatory tightness

The tightness of capital requirements likely reinforces window-dressing incentives for banks. A temporary contraction of the balance sheet raises the reported regulatory capital ratios, which benefits capital-constrained banks most. This effect has been noticed at quarter-end for banks with comparatively low regulatory Leverage Ratios (e.g. BCBS (2018b)). However, an outsized compression at year-end would also accord with an additional impetus provided by the G-SIB assessment. Indeed, by driving down their G-SIB score sufficiently strongly, banks can reduce their capital requirements, closing any perceived gap to their regulatory target level.

We test whether banks that are more tightly constrained by capital requirements compress their G-SIB score by more than their peers. We run the following regression based on different measures of capital tightness:

$$\begin{aligned}\Delta score_{i,t} &= \alpha_i + \beta_{GSIB}\,(G\text{-}SIB_i \times Q4) + \beta_{GSIB,tight}\,(G\text{-}SIB_i \times tight_{i,t-1} \times Q4)\\ &+ \beta_{RepB}\,(RepB_i \times Q4) + \beta_{RepB,tight}\,(RepB_i \times tight_{i,t-1} \times Q4)\\ &+ \beta_{tight}\,tight_{i,t-1} + \beta_{tight,Q4}\,(tight_{i,t-1} \times Q4) + Q4 + X_{i,t} + \gamma_t + \varepsilon_{i,t}. \quad (4)\end{aligned}$$

We define tightness as an indicator variable, *tight*, that is to equal one if the bank's (fully loaded) Leverage Ratio, its Common Equity Tier-1 (CET1) capital ratio, or both of these ratios, respectively, fall into the bottom quartile of the sample distribution in the previous quarter. Using a relative and lagged measure of banks' capitalisation addresses concerns that these measures are also window-dressed at year-end.

Table 9: Tightness of capital requirements

Dependent variable: Δ G-SIB score

	(1)	(2)	(3)	(4)	(5)	(6)
Q4	−3.94***	−3.62***	−5.18***	−4.53***	−4.06***	-3.50***
	(1.01)	(1.00)	(1.06)	(1.04)	(0.94)	(0.92)
RepB × Q4		−3.11***		−4.10***		-3.67***
		(0.68)		(0.55)		(0.63)
G-SIB × Q4	−6.63***	−3.86*	−6.40***	−2.91*	−6.94***	-3.83**
	(1.89)	(1.99)	(1.45)	(1.53)	(1.53)	(1.61)
Tight	−0.42	−0.53	−0.19	−0.16	1.60	1.71
	(0.54)	(0.51)	(0.59)	(0.59)	(1.18)	(1.20)
Tight × Q4	−1.59***	−0.59*	0.23	0.06	−1.29	-0.84
	(0.43)	(0.35)	(0.36)	(0.29)	(0.89)	(0.73)
RepB × tight × Q4		−1.18		1.32		-0.96
		(0.80)		(0.83)		(1.65)
G-SIB × tight × Q4	−26.49*	−26.32*	−22.25*	−23.40*	−37.59**	-37.09**
	(14.30)	(14.37)	(12.51)	(12.52)	(16.63)	(16.62)
Tightness measure	Leverage Ratio	Leverage Ratio	CET1 ratio	CET1 ratio	Leverage & CET1 ratio	Leverage & CET1 ratio
Bank controls & bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.26	0.26	0.19	0.19	0.31	0.31
Observations	1,946	1,946	2,895	2,895	1,946	1,946
Banks	146	146	148	148	146	146

Notes: */**/*** indicates statistical significance at the 10/5/1% level. Coefficient estimates based on equation (4) with robust standard errors, clustered by bank, in parentheses. All regressions include time-varying bank controls (non-performing loans ratio, return on equity, short-term wholesale funding ratio, CET1 ratio, and log total assets) as well as bank fixed effects and quarter fixed effects. Tightness is an indicator variable equal to one (zero otherwise) if the bank's Leverage Ratio (columns (1) and (2)), its CET1 capital ratio (columns (3) and (4)), or both of these ratios (columns (5) and (6)), respectively, fell into the bottom quartile of the sample distribution in the previous quarter of observation.

Consistent with our conjecture, G-SIBs that are more tightly constrained by capital requirements compress their balance sheet by more than other G-SIBs at year-end. Table 9 presents the estimates based on equation (4), with Columns (1) and (2) presenting results based on approximating tightness by the Leverage Ratio, whereas Columns (3) and (4) depict the corresponding results based on using the CET1 capital ratio. Our findings imply an additional year-end contraction in the scores of tightly constrained G-SIBs in a range of 22 to 27 bps – on top of the average contraction by G-SIBs. Columns (5) and (6), finally, show the results for those G-SIBs that are constrained by both ratios. For these G-SIBs the contraction is strongest, at around 37 bps. The results are statistically significant for each measure of tightness, notwithstanding the limited number of tightly constrained G-SIBs.

5. Interaction of regulatory requirements

We conclude our empirical analysis by considering how other regulatory requirements interact with the G-SIB capital surcharges. First, we assess how the introduction of the EU framework for other systemically important banks (O-SIIs) has affected banks' window dressing. Second, we explore how the compression in banks' balance sheets at year-end interacts with the banks' Liquidity Coverage Ratio.

5.1. O-SII framework

The O-SII framework represents the counterpart to the G-SIB framework for banks that are systemically important at the level of individual EU member states. The O-SII framework includes three steps. The first step builds a parallel with the G-SIB framework. For each bank, an O-SII score is computed as the weighted average of each institution's score across 10 indicators. These indicators are closely tied to those used in the G-SIB assessment methodology. Banks above a certain threshold score are designated as O-SIIs. In a second step, authorities calibrate the O-SII buffer requirement.

The O-SII framework provides little leeway for G-SIBs to manage down their O-SII capital surcharges. Given its focus on systemic importance from a national perspective, G-SIBs are benchmarked against much smaller peers than in the G-SIB assessment methodology. Accordingly, all EU G-SIBs have also been designated as O-SIIs, and it would require an unrealistically large year-end reduction in their domestic market share to lower their O-SII surcharge. We note that many O-SIIs are not reporting banks since their Leverage Ratio Exposure Measure is below the EUR 200 billion threshold for inclusion in the BCBS's G-SIB assessment sample (BCBS (2013)).

For EU G-SIBs, the higher of the G-SIB and O-SII capital requirement applies under the EU framework. To assess window dressing incentives created by the G-SIB framework, we thus have to account for the bindingness of the G-SIB capital surcharge relative to the O-SII buffer.

We evaluate the O-SIIs' behaviour at year-end based on the following specification:

$$\begin{aligned}\Delta score_{i,t} &= \alpha_i + \beta_{OSII}\,(O\text{-}SII_{it} \times Q4) + \beta_{GSIB}\,(G\text{-}SIB_i \times Q4) + \beta_{RepB}\,(RepB_i \times Q4)\\ &+ Q4 + X_{i,t} + \gamma_t + \varepsilon_{i,t}. \qquad (5)\end{aligned}$$

The indicator variable $O\text{-}SII_{it}$ is equal to one (zero otherwise) starting in the first year in which the bank has been designated an O-SII.

Table 10: Interaction with O-SII capital requirements

Dependent variable: Δ G-SIB score

	(1)	(2)	(3)	(4)
Q4	–5.11***	–4.88***	–4.87***	–4.67***
	(1.18)	(1.13)	(1.13)	(1.12)
O-SII × Q4	–2.38**	0.31	0.31	
	(0.95)	(0.21)	(0.20)	
RepB × Q4		–8.74***	–3.82***	–3.72***
		(2.69)	(0.59)	(0.59)
G-SIB × Q4			–12.10**	–15.04*
			(6.10)	(8.43)
O-SII ≥ G-SIB surcharge × Q4				9.56
				(9.23)
Bank controls & bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R2	0.08	0.12	0.15	0.16
Observations	2,895	2,895	2,895	2,895
Banks	148	148	148	148

Notes: */**/*** indicates statistical significance at the 10/5/1% level. Coefficient estimates based on equation (5) with robust standard errors, clustered by bank, in parentheses. All regressions include time-varying bank controls (non-performing loans ratio, return on equity, short-term wholesale funding ratio, CET1 ratio, and log total assets) as well as bank fixed effects and quarter fixed effects.

Table 10 presents the estimates for different variations of this specification. In the simplest setup, we benchmark O-SIIs against all other banks (Column (1)). Even though the sub-sample of O-SIIs comprises all the G-SIBs, we observe only a small additional contraction in the scores of O-SIIs relative to other banks. O-SIIs which are not designated as G-SIBs exhibit a markedly different behaviour than G-SIBs (recalling Table 6). This finding is consistent with the fact that the O-SII framework, with its jurisdiction-specific assessment sample, leaves banks with a large footprint at the national level little opportunity to reduce their O-SII buffers. Controlling for the window dressing of reporting banks and G-SIBs, we find no notable difference in the year-end adjustment of the remaining O-SIIs relative to other reporting banks (Columns (2) and (3)).

As a next step, we identify those G-SIBs for which the O-SII capital surcharge is at least as high as (or "super-equivalent" to) the G-SIB surcharge. For these banks, moving into a lower G-SIB bucket would not lead to a reduction in capital requirements.[12] Column (4) of Table 10 reports our estimates for the year-end contraction by these O-SIIs (bottom line, *O-SII* $\geq$ *G-SIB surcharge* $\times Q4$), relative to their peers. Consistent with the reduced incentives of these G-SIBs to window-dress their G-SIB score, we find that these banks lower their scores by less than other G-SIBs, although the statistical significance of this opposing effect cannot be established given the limited number of such O-SIIs.

[12]The surcharges have become additive with the implementation of the EU Capital Requirements Directive V. The new rules, implemented after our period of observation, could thus reinforce the incentives for some O-SIIs to compress their balance sheets at year-end.

5.2. *Interaction with the Liquidity Coverage Ratio*

We conclude our analysis by exploring whether G-SIBs' year-end balance sheet compression has any implications for other regulatory bank metrics. We focus on the Liquidity Coverage Ratio (LCR), which would appear to be most directly affected by the observed decline in intra-financial assets and liabilities. One additional advantage of studying the LCR is that data are available at a monthly frequency. This allows us to study how G-SIBs' LCR evolves in the immediate run-up to the year-end reporting of the G-SIB indicators, which provides some additional, albeit indirect, insights into banks' compression of the G-SIB scores.

We run the following regression to evaluate the month-on-month changes in the Liquidity Coverage Ratio, $\Delta LCR_{i,m}$:

$$\Delta LCR_{i,m} = \alpha_i + \beta_{GSIB}\ (G\text{-}SIB_i \times m12) + \beta_{RepB}\ (RepB_i \times m12) + m12 + \gamma_m + \varepsilon_{i,m}. \tag{6}$$

Our main interest lies in the change at year-end, *m12*, for which we consider the LCR adjustment by all banks, reporting banks, and G-SIBs, respectively. Given the large variation in banks' reported LCRs on a monthly basis, we winsorisze the LCR on both sides at 1%. We control for bank fixed effects (α_i) and month fixed effects (γ_m) in the absence of relevant observable bank controls at a monthly frequency. Table 11 reports our estimates.

Table 11: Year-end contractions of the Liquidity Coverage Ratio

Dependent variable: Δ Liquidity Coverage Ratio	(1)	(2)	(3)
m12	29.11**	31.43**	31.43**
	(13.93)	(14.85)	(14.85)
RepB × m12		–17.52*	–18.00*
		(9.04)	(9.33)
G-SIB × m12	–14.50*		1.18
	(8.09)		(4.05)
R2	0.01	0.01	0.01
Observations	6,627	6,627	6,627
Banks	165	165	165
Bank & time FE	Yes	Yes	Yes

Notes: */**/*** indicates statistical significance at the 10/5/1% level. Coefficient estimates based on equation (6) with robust standard errors, clustered by bank, in parentheses. All regressions include time-varying bank controls (non-performing loans ratio, return on equity, short-term wholesale funding ratio, CET1 ratio, and log total assets) as well as bank fixed effects and quarter fixed effects.

G-SIBs raise their LCR by less than non-reporting banks at year-end. The latter increase their LCR by as much as 30 percentage points. However, we find a partially off-setting effect for G-SIBs and other reporting banks, with their LCR only increasing by roughly half this amount at year-end. Seen through the lens of our previous results on the G-SIB scores, this implies that G-SIBs' window dressing at year-end – most notably the compression of intra-financial assets and liabilities that directly affect the LCR – comes at the cost of not being able to raise the LCR by as much as their peers. This also accords with the fact that, at an average value of more than 140% (see also Table 3), the LCRs of most G-SIBs have been well above the regulatory minimum requirement of 100%, suggesting limited incentives for these banks to substantially raise the LCR at year-end.

6. Conclusion

In this paper, we evaluate whether banks' window dressing at year-end undermines the assessment of banks' systemic importance, as measured by their G-SIB scores. We show that several banks in the EU compress their scores ahead of their regulatory reporting to an extent that it lowers their G-SIB capital surcharges – some banks even manage to avoid G-SIB designation altogether. Our estimates reveal that EU G-SIBs pull several levers to reduce their scores, with the most notable year-end contractions observed in the banks' intra-financial assets and liabilities and their OTC derivatives business. The G-SIBs that are most tightly constrained by capital requirements lower their scores more than other G-SIBs. By comparison, banks that are designated as O-SIIs at the national level do not lower their scores by more than other banks.

We note that the approximation of G-SIB scores is subject to caveats. Our proxies rely on a tight matching of the G-SIB indicators with consistent supervisory data at quarterly frequency. Our dataset comprises all the major EU banks, but does not track the adjustment by banks outside the EU. Collecting consistent data to assess the extent of window dressing across all G-SIBs would provide an important step towards supporting the supervisory assessment of banks' systemic importance.

Our findings have several implications for policy. First, they caution against a mechanistic application of the G-SIB methodology. As such, they underscore the value of making use of supervisory judgement in designating G-SIBs. Yet, in current supervisory practice, the application of such judgement is typically limited to adding banks to the G-SIB list. Our analysis argues in favour of expanding supervisory judgement to also empower supervisors to allocate banks to higher G-SIB buckets. In addition, enhancements to the calculation of the G-SIB indicators warrant consideration. Rather than relying exclusively on year-end values, the use of averaging could be a first step towards improving the robustness of the assessment. More generally, our analysis highlights the difficulty in striking the right balance between using simple rules-based approaches in banking regulation and limiting the risk of regulatory arbitrage.

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Appendix. Mapping of G-SIB indicators

Category	Indicator	Formulas used for proxied derived from ITS data
Size	Total exposures as defined for use in the Basel III leverage ratio	For periods up to and including Q2 2016: Sum of C 45.00.a c030 r010, C 45.00.a c030 r020, C 45.00.a c030 r030, C 45.00.a c030 r040, C 45.00.a c030 r050, C 45.00.a c030 r060, C 45.00.a c030 r070, C 45.00.a c030 r080, C 45.00.a c030 r090 and C 45.00.a c030 r100 For periods from Q3 2016 onwards: C 47.00 c010 r300
Cross-jurisdictional activity	Cross-jurisdictional claims	Sum of F 20.01 c020 r320 across all sheets (z axis) except for the domestic country of the bank
	Cross-jurisdictional liabilities	Sum of F 20.02 c020 r220 across all sheets (z axis) except for the domestic country of the bank
Interconnectedness	Intra-financial assets	Sum of F 20.04 c010 r020, F 20.04 c010 r030, F 20.04 c010 r050, F 20.04 c010 r060, F 20.04 c010 r110, F 20.04 c010 r120, F 20.04 c010 r170 and F 20.04 c010 r180 across all sheets (z axis)
	Intra-financial liabilities	Sum of F 20.06 c010 r020, F 20.06 c010 r030, F 20.06 c010 r050, F 20.06 c010 r060, F 20.06 c010 r100, F 20.06 c010 r110) across all sheets (z axis)
	Securities outstanding	Sum of F 01.02 c010 r050, F 01.02 c010 r065, F 01.02 c010 r090, F 01.02 c010 r130, F 01.02 c010 r143, F 01.03 c010 r010, F 01.03 c010 r040, and F 01.03 c010 r050
Substitutability	Assets under custody	F 22.02 c010 r060
	Payments	No proxy available
	Values of underwritten transactions in debt and equity markets	No proxy available
Complexity	Notional amount of over-the-counter (OTC) derivatives	Sum of F 10.00 c030 r300, F 10.00 c030 r310, F 10.00 c030 r320, F 11.01 c030 r510, F 11.01 c030 r520, and F 11.01 c030 r530
	Level 3 assets	Sum of F 14.00 c030 r010, F 14.00 c030 r051, F 14.00 c030 r056, F 14.00 c030 r060, F 14.00 c030 r100, F 14.00 c030 r101, F 14.00 c030 r121, F 14.00 c030 r125, and F 14.00 c030 r140
	Trading and available-for-sale securities	Sum of F 01.01 c010 r070, F 01.01 c010 r080, F 01.01 c010 r093, F 01.01 c010 r094, F 01.01 c010 r110, F 01.01 c010 r120, F 01.01 c010 r142, F 01.01 c010 r143, F 01.01 c010 r150 and F 01.01 c010 r160

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