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Behind the scenes of the beauty contest: window dressing and the G-SIB framework

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Abstract

This paper illustrates that systemically important banks reduce a range of activities at year-end, leading to lower additional capital requirements in the form of G-SIB buffers. The effects are stronger for banks with higher incentives to reduce the indicators, and for banks with balance sheet structures that can more easily be adjusted. The observed reduction in activity may imply an overall underestimation of banks' systemic importance as well as a distortion in their relative ranking, with implications for banks' ability to absorb losses. Moreover, a reduction in the provision of certain services at year-end may adversely affect overall market functioning.

Keywords: bank regulation, window dressing, systemically important banks

JEL classification: G20, G21, G28

Non-technical summary

This paper investigates whether window dressing behaviour affects additional capital requirements imposed on Global Systemically Important Banks (G-SIBs) according to the post-crisis financial regulatory framework. Window-dressing is the practice by which regulated entities adjust their activity around an anticipated reporting or disclosure date, with the objective of appearing safer or, in the case of the G-SIB framework, less systemically important to the regulator, supervisor, or market participants. The G-SIB assessment is conducted once a year, and the calculation of G-SIB scores relies on year-end data. Thus, banks involved in the exercise could have an incentive to reduce activities affecting the G-SIB score in the last quarter of the year, with the intention to reduce additional capital buffer requirements arising from the G-SIB framework.

The findings of the paper suggest that banks participating in the G-SIB exercise are more likely to reduce activities affecting the additional buffer requirements for G-SIBs at the end of the year, relative to the other banks in the sample. Furthermore, the effects are stronger for banks that are relatively close to a threshold between two buckets associated with different additional buffer requirements (which may have stronger incentives to window dress), and for banks with a larger amount of repo market activities that can be terminated relatively easily at reporting dates. In particular the former result supports the view that it is indeed the G-SIB framework that is incentivizing the reduction in activities affecting the G-SIB score at year-end, rather than other factors such as contributions to the Single Resolution Fund or bank levies in a number of countries that are also based on year-end balance sheet data.

Our findings have important policy implications, since window-dressing behaviour in the G-SIB framework could have detrimental effects on financial stability for at least two reasons: first, it may imply an underestimation of banks' overall systemic importance and a distortion of the relative ranking in favour of banks that engage in more window-dressing behaviour. Consequently, higher capital requirements for systemically important banks would incorrectly reflect the actual risks emanating from these institutions, resulting in potential underestimation or misallocation of capital requirements in the banking system. Second, the functioning of markets may be adversely affected if banks reduce the provision of certain services towards the end of the year. In particular, this may imply potential disruptions and undesirable instability in the smooth provision of financial services at reporting dates. For both reasons, regulators may want to explore potential measures that could help to address possible window dressing behaviour, e.g. the usage of monthly or daily averages rather than end-of quarter values for certain indicators.

1 Introduction

In response to the 2008-09 financial crisis, regulators around the world have implemented a comprehensive reform programme with the intention to increase the banking sector's resilience against shocks. An essential part of this reform programme is the new macroprudential framework, which aims at addressing systemic risk and inter alia includes additional capital buffer requirements for Global Systemically Important Banks (G-SIBs). These additional requirements are meant to mitigate negative externalities which G-SIBs may impose on the global financial system in case of their failure, where the level of the requirement depends on the risk emanating from the specific institution (see Basel Committee on Banking Supervision 2018a). For example, the failure of a larger or more interconnected bank is assumed to have a greater impact on the global financial system, and consequently such banks are subjected to higher additional capital requirements. While the intuition for the framework is simple and straightforward, it confronts regulators with practical challenges related to determining banks' systemic importance and mapping this systemic importance into higher capital requirements.

In this paper we examine one of these challenges in greater detail, namely the possibility that banks game the framework by engaging in so-called window-dressing behaviour. Window-dressing is the practice by which regulated entities adjust their activity around an anticipated reporting or disclosure date, with the objective of appearing safer or, in the case of the G-SIB framework, less systemically important to the regulator, supervisor, or market participants. Specifically, G-SIB buffers depend on the so-called G-SIB score, which is a composite of twelve risk indicators and allows the classification of G-SIBs into five equally-sized buckets, each corresponding to a different buffer rate. The scores are calculated during the G-SIB assessment exercise, which is conducted once a year and based on year-end data. Consequently, banks participating in the exercise could have an incentive to reduce activities affecting the G-SIB score on the reporting date, with the intention to reduce additional capital requirements arising from the G-SIB framework.[1]

To analyse whether banks participating in the G-SIB exercise engage in window dressing

[1]As explained in more detail in Section 2.1, banks participating in the exercise are the 75 largest institutions worldwide, and all banks with a Leverage Ratio exposure measure larger than EUR 200 billion. Since these banks need to report their G-SIB indicator values at the end of each year as part of the G-SIB exercise, we refer to them as 'reporting banks' throughout the paper.

behaviour we make use of a granular supervisory data set for euro area banks that is of higher frequency than the annual G-SIB data and thus allows us to build quarterly proxy variables for the indicators forming the basis for the G-SIB score. We use this data set to implement multivariate panel regression models, comparing year-end variation in G-SIB scores for banks participating in the G-SIB exercise with variation in scores for banks that do not participate. To improve identification, we make use of further variation across banks with respect to (i) the incentives to reduce risk indicators, exploiting the proximity of banks to a threshold separating banks into buckets associated with different requirements (and assuming that banks that are closer to such a threshold have greater incentives to reduce their scores); and (ii) the ability to reduce risk indicators, exploiting variation in banks' repo market activities and assuming that such activities can be adjusted more flexibly than other activities (see, e.g., Adrian and Shin 2010), and thus facilitate window dressing behaviour.

Our results suggest a significant impact of window dressing behaviour on the G-SIB framework: while the G-SIB score for the average bank in our sample is relatively constant over the year, banks that participate in the G-SIB assessment exercise reduce their scores by about 3 basis points at year-end, and banks that are identified as G-SIBs in the exercise reduce their scores by an additional 8 basis points. The magnitudes of these effects are economically large, considering that G-SIB buffer requirements increase in intervals of 100 basis points of the G-SIB score. Moreover, we document that effects are significantly stronger for banks that are close to a bucket threshold (and thus may have stronger incentives to window dress), and for banks with a larger amount of repo market activities that can be terminated relatively easily at reporting dates. In particular the former result supports the view that it is indeed the G-SIB framework that is incentivizing the reduction in activities affecting the G-SIB score at year-end, rather than other factors such as contributions to the Single Resolution Fund or bank levies in a number of countries that are also based on year-end balance sheet data.

Our findings have important policy implications, since window-dressing behaviour in the G-SIB framework could have detrimental effects on financial stability for at least two reasons: first, it may imply an underestimation of banks' overall systemic importance and a distortion of the relative ranking in favour of banks that engage in more window-dressing behaviour. Consequently, higher capital requirements for systemically important banks would incorrectly reflect the actual risks emanating from these institutions, resulting in potential underestimation or misallocation of capital requirements in the banking system. Second, the functioning of markets may be adversely affected if banks reduce the provision of certain services towards the end of the year. In particular, this may imply potential disruptions and undesirable instability in the smooth provision of financial services at reporting dates (see, e.g., Munyan 2017 for evidence from repo markets). For both reasons, regulators may want to explore potential measures that could help to address possible window dressing behaviour, e.g. the usage of monthly or daily averages rather than end-of quarter values for certain indicators, as already implemented in some jurisdictions (notably the U.S. and the U.K.) and currently being discussed at an international level for the Leverage Ratio (see, e.g., Basel Committee on Banking Supervision 2018b).

This paper adds to a growing literature on window dressing behaviour in the financial sector. Early papers often focused on the fund industry, illustrating that fund managers had a tendency to change portfolio composition at reporting or disclosure dates in order to appear safer or better performing (see, e.g., Lakonishok et al. 1991, Musto 1997, 1999, Ng and Wang 2004, Agarwal et al. 2014b). For the banking sector, Allen and Saunders (1992) are the first to provide evidence that U.S. banks adjust their balance sheets at reporting dates for the Call Reports. In the post-crisis period, discussion mainly focused on possible effects of the newly introduced Leverage Ratio on repo market functioning.[2] In particular, several studies have shown significant declines in repo market activity at the end of a quarter, which may be explained by banks' attempting to improve their Leverage Ratio at reporting dates in order to appear more resilient (see, e.g., Grill et al. 2017 and Bank for International Settlements 2018). There is also significant evidence of regional differences, illustrating that window-dressing behaviour is much more pertinent in Europe where the Leverage Ratio is based on end-of-quarter exposures rather than monthly or even daily averages as in other jurisdictions (see, e.g., Munyan 2017, Anbil and Senyuz 2018, Kotidis and Van Horen 2018).[3] Our paper adds to this literature by illustrating that not only the Leverage Ratio but also other regulatory requirements such as the G-SIB framework may incentivize window dressing behaviour and could benefit from using an averaging concept rather than relying on end-of-quarter reporting.

[2] Attention was mainly on the Leverage Ratio (LR) since repo transactions are collateralised and hence typically receive very low risk weights, so that changes in their volume do not have a big impact on risk-based capital ratios. In contrast, the full amount of a repo transaction is included in the denominator of the LR.

[3] On the effects of inconsistent implementation of regulatory requirements across different regulatory authorities, see also Agarwal et al. (2014a). Further, Smith (2016) explains how differences in the implementation of the Leverage Ratio rule helped European banks to gain market shares on U.S. repo markets.

The paper also adds to a literature on regulatory arbitrage and gaming of regulation in the financial sector more broadly. Using a large and granular data set for German banks, Behn et al. (2016) show that large institutions systematically underestimate default risk parameters that are used to calibrate capital requirements under the so-called internal ratings-based approach, which implies an unjustified reduction in the requirements (see also Mariathasan and Merrouche 2014, Firestone and Rezende 2016, Berg and Koziol 2017, Plosser and Santos 2018).[4] Koijen and Yogo (2015, 2016) present similar evidence for the insurance sector, inter alia showing that insurance companies try to avoid regulation by moving certain activities to unregulated and off-balance sheet 'shadow insurance' entities within the same insurance group. We contribute to this literature by pointing out an additional channel that enables banks to circumvent regulation to a certain extent, thus identifying a potential gap in the regulatory framework.[5]

The remainder of the paper is structured as follows: Section 2 describes the data used and the current institutional set-up to calculate the G-SIB risk score; Section 3 introduces the methodology to investigate whether banks have been incentivised to window-dress, and the potential role played by capital market activities. Section 4 reports the empirical findings and Section 5 concludes with some final remarks.

2 Institutional background and data

In this section we briefly describe the international G-SIB framework which forms the institutional background for our study. We then introduce the granular supervisory data set that we use in order to calculate quarterly proxy variables for the G-SIB indicators and provide descriptive evidence for window dressing behaviour at year-end.

[4]The most recent reform package agreed by the Basel Committee on Banking Supervision (2017) aims to address such problems by introducing a so-called 'output floor' that limits the amount by which banks can reduce capital requirements under the internal ratings-based approach, relative to the simpler standardized approach that does not rely on internal risk models.

[5]The findings in our paper document a potential shortcoming of the G-SIB framework. Another article that discusses potential pitfalls in the G-SIB framework is the one by Benoit et al. (2019), who argue that the methodology is biased towards indicators that are more volatile in the cross-section, and point out that depreciation of a currency with respect to the Euro mechanically lowers the score of the banks headquartered in this particular currency zone.

2.1 The international G-SIB framework

During the 2008-09 financial crisis, the failure or near-failure of several systemically important banks (SIBs) created enormous stress in the financial system and eventually harmed the real economy in a large number of countries. Problems in individual large institutions often caused massive public sector interventions, imposing huge costs on taxpayers and leading to moral hazard problems as banks were considered as 'too-big-to-fail'. To address these issues, the international framework for Global Systemically Important Banks (G-SIBs) imposes additional capital requirements on such institutions, thereby increasing their resilience against shocks and reducing their probability of failure (see Basel Committee on Banking Supervision 2014).

The G-SIB framework relies on an indicator-based approach in order to calibrate additional own funds requirements for the banks participating in the exercise. The so-called G-SIB score aggregates information from five individual risk categories and is used to sort banks into five buckets, each associated with a different capital buffer requirement (ranging from 1 to 3.5 percent of risk-weighted assets). The five risk categories are meant to capture banks' systemic importance through (a) their size, (b) their interconnectedness, (c) the substitutability of financial infrastructure or services they provide, (d) their cross-jurisdictional activity, and (e) their complexity. Each of the five risk categories is broken down further into two or three risk indicators, resulting in a total of twelve indicators that affect the banks' G-SIB scores and hence the additional buffer requirements imposed on them (see Annex I for further information on the risk indicators).

The risk indicators that are used for allocating banks into buckets need to be reported by all banks that are participating in the G-SIB assessment exercise (labelled as 'reporting banks' throughout our paper).[6] The framework is defined in relative terms, i.e. each of the twelve risk indicators for a bank is calculated by dividing the individual bank amount (expressed in EUR) by the aggregate amount for the indicator summed across all banks in the sample. Risk category scores are then obtained as weighted averages of the indicator scores in the respective category, and the overall G-SIB score is the simple average of the five category scores. The G-

[6]The sample varies according to regional criteria. Banks headquartered in the Banking Union are included in the sample if (i) they belong to the 75 largest banks worldwide (measured the Basel III Leverage Ratio exposure measure); (ii) they have a Basel III Leverage Ratio exposure measure larger than EUR 200 billion; or (iii) they were designated as a G-SIB in the previous year. Overall, this implies that 39 banks headquartered in the Banking Union need to report their risk indicators as part of the G-SIB assessment exercise.

SIB assessment exercise is conducted once a year, based on end-of-year data, and the resulting G-SIB scores are used to allocate banks into the five buckets with different buffer requirements, based on pre-defined thresholds for the score (see Annex I). The resulting allocation of banks into buckets is published on the FSB website.[7]

2.2 Data

The G-SIB score is calculated based on year-end data which reporting banks have to submit to the relevant authorities. To follow the evolution of the underlying indicators throughout the year, we use granular supervisory information (FINREP) for banks headquartered in the European Banking Union to calculate quarterly proxy variables for eight of the twelve indicators: the total Leverage Ratio exposure (size category), intra-financial system assets, intra-financial system liabilities and securities outstanding (interconnectedness category), over-the-counter (OTC) derivatives and level-3 assets (complexity category), cross-jurisdictional claims and cross-jurisdictional liabilities (cross-jurisdictional activity category).[8] We are unable to build quarterly proxies for the three indicators in the substitutability category, assets under custody, payment activity and underwriting activity, as well as the trading and available-for-sale securities indicator in the complexity category, due to lack of granular data. To build a quarterly proxy for the G-SIB score itself, we aggregate the information for the available indicators by equally redistributing the weights for the missing ones to the other indicators and risk categories. Annex I provides further details on the calculation of the quarterly proxy variables and also includes a comparison between our proxy variables and the official year-end scores published on the EBA website, illustrating that we manage to replicate the official scores very well.

The final dataset includes quarterly data for 97 banks (22 banks with reporting obligations of which 8 are G-SIBs, and 75 banks with no reporting obligations), from the third quarter of

[7]For the 2018 list, see: `http://www.fsb.org/wp-content/uploads/P161118-1.pdf`.

[8]To calculate indicator values each bank's amount needs to be divided by the respective denominator, reflecting the aggregate amount of the indicator for all banks in the G-SIB sample. Since we do not have information on banks outside the Banking Union, we use the publicly available denominators of the previous year to normalise the indicator values for the fourth quarter of a year and the first three quarters of the following year (see Section 4.3 for robustness checks on this assumption). To note, it is possible that banks outside the Banking Union engage in similar window dressing behaviour as the banks within our sample, which would mean that denominators would also change over quarters, with an impact on scores and the relative ranking of banks. Investigating the extent to which window dressing occurs for banks outside our sample is beyond the scope of this paper, although we note that for institutional reasons window dressing seems to be less likely in some other major jurisdictions (see discussion in the introduction). All denominators are available at: `https://www.bis.org/bcbs/gsib/denominators.htm`.

2014 to the last quarter of 2017. Overall, the sample includes almost EUR 19 trillion in terms of 2017 Total Assets (TA), thus representing approximately 67 percent of the euro area banking system. Most importantly, all the eight G-SIBs located in Europe are included in the sample; these 8 banks alone account for approximately one third of the overall euro area total assets. A breakdown of banks and bank assets by country is provided in Table 1.

[Table 1 here]

Table 2 reports summary statistics for the eight risk indicators (columns 2-4), the G-SIB scores and the category scores (columns 5-7) for which we obtain quarterly proxy variables: the derived category and G-SIB risk scores shown in the table also distinguish between banks with and without reporting obligations. The averages reported in the table illustrate that there is considerable heterogeneity with respect to the indicator values, reflecting diversity of the banks in our sample and the fact that G-SIBs and banks with reporting obligations tend to dominate many of the activities captured by the G-SIB score: this is also confirmed by the average risk score of the eight G-SIBs, which is more than double the average risk score of all the reporting banks in the sample.

[Table 2 here]

2.3 Descriptive evidence

Before we formalize the analysis in the next sections, we provide descriptive evidence on the evolution of the G-SIB scores and indicators over the calendar year. The left-hand panel of Figure 1 plots the development of the average G-SIB score for the eight banks that were classified as G-SIBs throughout our sample period.[9] In addition, the figure also plots the evolution of aggregate assets for these banks, since a number of indicators directly relate to the total amount of assets. Window dressing patterns are clearly visible in both series: while exhibiting a long-term decreasing trend, both G-SIB scores and aggregate assets tend to decline at year-end and rebound thereafter. This pattern occurs for all of the three year-end points that are embedded in our sample period. Moreover, the right-hand panel of Figure 1 shows that the same pattern

[9]Deutsche Bank, BNP Paribas, BPCE, Crédit Agricole, ING, Santander, Société Générale, and Unicredit.

also emerges for three out of the four risk category scores: the scores for size, cross-jurisdictional activity and interconnectedness decrease at the end of each year, while the pattern is less clear for the complexity category. Although the descriptive analysis included in the chart does not provide conclusive evidence, it illustrates that window dressing patterns are present already when looking at the data at very high level, and that economic magnitudes are quite substantial (since aggregate assets of the eight G-SIBs fluctuate by up to EUR 100 billion within a year).

[Figure 1 here]

3 Estimation strategy

This section explains the empirical methodology which we use in order to analyze whether the G-SIB framework is inducing window dressing behaviour among banks with reporting obligations. The first set of specifications exploits variation in banks' incentives to window dress, while the second set of specifications investigates the role of capital market activities as a possible driver of window dressing behaviour.

3.1 Variation in the incentives to window dress

Albeit illustrative, the reduction in activities affecting the G-SIB score documented in Figure 1 is not conclusive evidence of window-dressing behaviour among G-SIBs, since there could be other factors explaining the evolution of banks' activities over the year. For example, the contributions to the Single Resolution Fund (SRF) and bank levies in a number of euro area jurisdictions are based on year-end data and may provide similar incentives to window dress as the G-SIB framework (see, e.g., Grill et al. 2017). To account for these concerns and improve identification, we use banks that do not participate in the G-SIB exercise as a control group and investigate whether the reduction in G-SIB scores and underlying indicators at year-end (relative to other quarters) is systematically stronger for G-SIBs or banks with reporting obligations. Specifically, we estimate the following equation:

$$\Delta Score_{i,t} = \alpha_i + \alpha_t + \beta_1 \cdot [Q4_t \times GSIB_i] + \beta_2 \cdot [Q4_t \times RepBank_i] + \Gamma' \mathbf{V}_{i,t} + \epsilon_{i,t} \tag{1}$$

where $Q4$ is a dummy variable equal to one in the last quarter of each year, $GSIB$ is a dummy variable identifying the eight banks in our sample that are classified as G-SIBs, and $RepBank$ is a dummy variable identifying banks that are required to report their G-SIB scores at the end of each year. The set $\mathbf{V}$ of control variables includes the Common Equity Tier 1 ratio (CET1), the Liquidity Coverage Ratio (LCR), and the logarithm of total repurchase agreement activities (Repos). Our most stringent specifications include bank fixed effects (α_i) and time fixed effects (α_t), which control for both observed and unobserved heterogeneity across banks and over time. The dependent variable in Eq. (1) is the quarter-on-quarter change in either the proxy for the overall G-SIB score, or in any of the four proxies for the various risk categories. Standard errors in all regressions are robust to heteroscedasticity and adjusted for clustering at the bank level.

While a positive finding on Eq. (1) would provide stronger evidence for window-dressing behaviour, the specification is still unable to control for potential other differences between banks with and without reporting obligations that could explain a stronger reduction in scores at year-end for the former group. To systemically address such concerns, we further improve the identification strategy and develop an additional test that exploits variation in the incentives to reduce risk scores at year-end *within* the group of banks with reporting obligations. In particular, we rationalize that banks for which the G-SIB score in the previous year (as disclosed by the EBA) was closer to a bucket threshold have stronger incentives to reduce their indicator values at year-end, since it is more likely that doing so has an impact on the bucket allocation and hence the additional capital requirement for such banks.[10] To test this assertion, we define a dummy variable that identifies banks that are close to a bucket threshold and estimate the following equation:

[10] As explained in Section 2.1 and Annex I, banks are sorted into five buckets with different buffer requirements, based on threshold values of 130, 230, 330, 430 and 530 basis points for the G-SIB score. Our identification strategy assumes that banks that are closer to such a threshold have stronger incentives to window dress.

$$
\begin{aligned}
\Delta Score_{i,t} = \alpha_i + \alpha_t + \beta_1 \cdot [Q4_t \times RepBank_i] + \beta_2 \cdot [RepBank_i \times Close_{i,t-1}] \\
+ \beta_3 \cdot [Q4_t \times RepBank_i \times Close_{i,t-1}] + \Gamma' \mathbf{V}_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

where all variables are defined as above, and $Close_{i,t}$ is a dummy equal to one if a bank's G-SIB score in the previous year is at most 20 [30] basis points below or above a bucket threshold.[11] In a variation of this test, we further distinguish between banks with scores directly above and banks with scores directly below a bucket threshold, to explore whether window dressing patterns are stronger for either of these groups. Importantly, the test exploits variation in the incentives to window dress *within* the group of banks with reporting obligations and is therefore not affected by potential differences between banks with and without such reporting obligations.

3.2 Variation in the ability to window dress

Besides differences in the incentives to window dress there may also be variation in banks' ability to easily reduce some of their activity at year-end. In particular, banks' ability to engage in window dressing behaviour is likely to depend on the composition of their balance sheets, since certain types of activities (such as capital market activities) can more easily be terminated at year-end and may also have a greater impact on the bank's G-SIB score. Recent evidence presented by Munyan (2017) illustrates considerable window dressing activity in the market for repurchase agreements (repos). Repos are typically overnight transactions that can easily be scaled back, and Munyan (2017) shows that roughly 10 percent of the overall tri-party repo market vanishes at the end of each quarter (when banks have to report their capital ratios).[12] Since repos often occur between financial institutions and represent a considerable share of cross-border transactions, they have an impact on the size as well as the interconnectedness and the

[11] The dummy variables *Close* and *RepBank* are constant within a bank and hence absorbed by the bank fixed effect; similarly, the dummy $Q4$ is absorbed by the time fixed effect. The interaction $[Close \times Q4]$ is omitted from the regression since it is identical to the triple interaction (since there are, by definition, no banks without reporting obligations that are close to a bucket threshold).

[12] Repurchase agreements (repos) are short-term transactions in which the seller of a security (the collateral) agrees to buy it back at a specified price and time. Given their typically extremely short maturity, repos are considered as highly liquid and can facilitate the flow of cash and securities around the financial system. Nevertheless, an excessive use of repos can have detrimental effects on financial stability, since they contribute to increasing leverage and can lead to a massive use of unstable short-term funding to finance long-term assets (as underlined by Grill et al. 2017 and Financial Stability Board 2013).

cross-jurisdictional indicator of the G-SIB framework. Therefore, to test whether repos are a driver of possible window dressing behaviour among G-SIBs, we estimate the following equation:

$$\Delta Score_{i,t} = \alpha_i + \alpha_t + \beta_1 Repos_{i,t-1} + \beta_2 \cdot [Q4_t \times Repos_{i,t-1}] + \Gamma' \mathbf{V}_i + \epsilon_{i,t}, \tag{3}$$

where all variables are defined as before and the variable $Repos_{i,t-1}$ captures the logarithm of bank i's total repo activity at time $t-1$. The idea behind Eq. ((3)) is to test whether banks with higher levels of repo activity reduce their activities at year-end relatively more. However, the equation does not distinguish between banks with reporting obligations and other banks in the sample, so that stronger effects for banks with higher repo activity could still be driven by other factors, as explained before. Therefore, as a final test we run a similar specification as in the previous section, testing whether the impact of higher repo activity on G-SIB scores is particularly pronounced for banks with reporting obligations:

$$\begin{aligned}\Delta Score_{i,t} = {} & \alpha_i + \alpha_t + \beta_1 Repos_{i,t-1} + \beta_2 \cdot [Q4_t \times Repos_{i,t-1}] + \beta_3 \cdot [Q4_t \times RepBank_i] \\ & + \beta_4 \cdot [RepBank_i \times Repos_{i,t-1}] + \beta_5 \cdot [Q4_t \times RepBank_i \times Repos_{i,t-1}] + \Gamma' \mathbf{V}_i + \epsilon_{i,t}\end{aligned} \tag{4}$$

where the dependent variable is again the quarter-on-quarter change in either the G-SIB score or one of the four risk category scores, and all variables are defined as before.

4 Results

In this section we present the results of our empirical analysis: first, we describe the role of the G-SIB framework as an incentive for window dressing behaviour; second, we show the results of the analysis testing the impact of capital market activities on banks' window dressing; third, we provide a number of additional tests and robustness checks.

4.1 Window dressing in the G-SIB framework

Our analysis aims at testing whether the G-SIB framework has incentivized G-SIBs or banks with reporting obligations to systemically reduce activities affecting their G-SIB scores at the end of a calendar year. A (temporary) reduction in such activities could help to avoid additional capital requirements for G-SIBs, as it reduces [increases] the likelihood of being allocated to a higher [lower] bucket with more [less] stringent capital requirements.

Results for Eq. (1) are shown in Table 3 and indicate a considerable reduction in G-SIB scores at the end of a year. This reduction is significantly stronger for G-SIBs and banks with reporting obligations: while the average bank reduces its score in the fourth quarter by 0.3 basis points on average, the reduction is 3.1 basis points stronger for the average bank with reporting obligations, and an additional 8.2 basis points stronger for G-SIBs.[13] The coefficients for the interaction terms are remarkably stable when we saturate the specification with bank control variables, time fixed effects and bank fixed effects. In addition, magnitudes are economically meaningful: a total reduction of 11.6 basis points for G-SIBs constitutes about 9 percent of the current threshold for the first bucket (130 basis points) and 11.6 percent of the 100 basis point interval according to which buckets and hence capital requirements increase further.

[Table 3 here]

To investigate which of the components is driving the reduction in the overall G-SIB score at year-end, we re-estimate Eq. (1) for the individual risk category scores. Results are presented in Table 4 and show that the year-end decrease in the scores for size, interconnectedness and cross-jurisdictional activity is significantly stronger for G-SIBs and banks with reporting obligations. Magnitudes are particularly large in the cross-jurisdictional category, where G-SIBs tend to reduce their scores in the last quarter by more than 20 basis points (sum of the coefficients for the two interactions), relative to other quarters. Somewhat surprisingly, we find the opposite sign for the complexity category, which we will investigate further in Section 4.3.

[Table 4 here]

[13]Since G-SIBs are a subset of banks with reporting obligations, the coefficient on $[Q4 \times GSIB]$ should be understood as showing the additional effect for G-SIBs, relative to the group of banks with reporting obligations.

We further improve identification by checking whether the reduction in G-SIB scores at year-end is stronger for banks that have stronger incentives to engage in such window-dressing behaviour. As explained in Section 2.1, the determination of additional capital buffer requirements for G-SIBs is based on a bucketing approach, where banks move to a higher bucket with higher buffer requirements whenever their G-SIB score crosses a specific threshold value. Movements in the risk score are more likely to affect additional capital buffer requirements for banks for which the risk score in the previous year was relatively close to a bucket threshold, so that such banks could have higher incentives to window dress. Eq. (2) tests this assertion, and results are shown in Table 5.[14]

The results confirm that the G-SIB scores of banks with reporting obligations strongly decrease in the last quarter of the year (Q4 $\times$ Reporting Bank). As shown by the negative and significant coefficient on the triple interaction, this effect is particularly pronounced for banks with scores that are relatively close to a bucket threshold, where the effect is robust to the inclusion of time and bank fixed effects, and to using different variants of the closeness dummy. Again, economic magnitudes are large: the additional reduction in G-SIB scores at year-end is about 8 basis points stronger for banks with scores close to a bucket threshold, compared with other banks with reporting obligations. As shown in Table 6, these effects are driven in particular by the size and the cross-jurisdictional categories. Overall, the results illustrate that observed window dressing is stronger when the incentives to engage in such behaviour are higher.

[Table 5 here]

[Table 6 here]

Finally, Table 7 reports the results for regressions where we distinguish between banks with scores closely above ($Close_{+}$) and closely below ($Close_{-}$) a bucket threshold. Effects are more pronounced for banks with scores closely above a threshold, as indicated by the negative and significant coefficient on the triple interaction. That is, incentives to reduce scores in order to be allocated to a lower bucket seem to be stronger than incentives to reduce scores in order to

[14] The regressions reported in Table 5 focus on the Reporting Bank dummy; similar results are obtained when using the GSIB dummy, but power issues prevent the (negative) coefficient of the triple interaction term from being significant.

avoid being allocated into a higher bucket. However, we note that also the coefficient for the second triple interaction is negative, with very similar magnitude of the coefficient, so that the differences in significance between the $Close-$ and $Close+$ interaction may mainly be due to statistical power issues.

[Table 7 here]

4.2 The impact of repo market activity

As explained in Section 3.2, capital market activities such as repo transactions may facilitate window-dressing behaviour since they typically have very short maturities and can relatively easily be terminated at the end of a quarter or year. Consequently, previous research has identified such transaction as one of the main drivers of window dressing behaviour (e.g., Munyan 2017). To assess whether this also holds for the G-SIB framework, Table 8 reports regression results for Eq. (3), testing whether the reduction in G-SIB scores at year-end is stronger for banks with a greater amount of repo transactions.

Estimates in columns 1-3 illustrate this is indeed the case, as confirmed by the negative and significant coefficient for the interaction term. Moreover, columns 4-7 show that a larger amount of repos is associated with a stronger reduction in the size, interconnectedness and cross-jurisdictional activity categories at year-end, which is as expected given that the amount of repo transaction affects all of the indicators in these categories (see Section 3.2). In contrast, one would not necessarily expect a strong relation between the amount of repos and the indicators in the complexity category (OTC derivatives and Level-3 assets), so that the positive coefficient for the interaction term in column 6 is somewhat surprising.

[Table 8 here]

For the final estimation we employ a similar identification strategy as in the previous section, investigating whether the stronger reduction in the G-SIB score for banks with more repos in the last quarter of a year is more pronounced for banks with reporting obligations under the G-SIB framework. As before, the analysis is performed for both the G-SIB score (Table 9, columns 1-3) and the risk category scores (columns 4-7). Results confirm the hypothesis that a high level of repo market activities facilitates a reduction in G-SIB scores at year-end for banks with reporting obligations, as indicated by the negative and significant coefficient for the triple interaction. In line with previous results, the size and cross-jurisdictional activity categories seem to be the main drivers for such window-dressing behaviour, while the coefficient is negative but insignificant for interconnectedness.

[Table 9 here]

4.3 Further tests and robustness

This section provides a number of additional tests and robustness checks for our main results. One of the more surprising findings among our main results is the positive coefficient for the interaction term between the year-end dummy and the dummy for reporting banks when using the complexity category score as a dependent variable (see, e.g., column 3 in Table 4). The result is surprising because one of the indicators in the complexity category is the amount of OTC derivatives, which is usually believed to be among the main drivers of window-dressing behaviour (see, e.g., Basel Committee on Banking Supervision 2018b; money market activities are believed to be another main driver of window dressing, as explained above). To investigate this issue in more detail we re-estimate our main specifications at the indicator rather than the aggregate or category score level, and provide the corresponding results in columns 1-8 of Table 10. Results for the indicators in the complexity category are shown in columns 5-6 and illustrate that the positive interaction for complexity in Table 4 is mainly driven by the indicator for Level 3 assets, while the interaction terms are insignificant for the OTC derivatives indicator (in contrast to Table 4, the coefficient for the interaction between Q4 and the G-SIB dummy is *negative* and insignificant).[15] While this result is somewhat reassuring and more in line with the conventional wisdom on OTC derivatives, it still needs to be investigated further why the amount of Level 3 assets tends to increase in relative terms for banks with reporting obligations towards the end of

[15] A possible reason why we do not observe significant effects for OTC derivatives could be that banks reduce these exposures in a similar manner at the end of *each* quarter, so that we are unable to capture any window-dressing behaviour at year-end with our quarterly data (as noted before, our data allows capturing only variation in indicators and scores *between* quarters, and not *within* quarters).

a year.[16] For the remaining three categories – size, interconnectedness, and cross-jurisdictional activity – effects are relatively evenly distributed across the respective indicators.

[Table 10 here]

An additional robustness check we conduct concerns the definition of the indicator denominators. As explained in Section 2.2, to calculate indicator values each bank's amount needs to be divided by the respective denominator, reflecting the aggregate amount of the indicator for all banks in the G-SIB sample. Since we do not have information on banks outside the Banking Union, we use the publicly available denominators of the previous year to normalise the indicator values for the fourth quarter of a year and the first three quarters of the following year. That is, denominators are updated in the fourth quarter of each year, and then held constant over the subsequent three quarters. To investigate whether this assumption is affecting our results we alter it in a number of alternative specifications. In particular, in columns 9-11 of Table 10, we re-estimate our main specification (Eq. 1), but differently from baseline results in column 4 of Table 3 we use the denominator applicable in the fourth quarter of a year also in (i) the previous three quarters (column 9), (ii) the previous two and the subsequent quarter (column 10), and (iii) the previous one and the two subsequent quarters (column 11). The results are very robust to these changes, which makes us comfortable that our findings are not driven by changes in the denominator. In any case, as the denominators are obtained as an aggregate over a sample of 75 large banking institutions, they tend to be rather stable across different years.

As a final robustness check, we assess whether results are affected by a number of observations for which the proxy variables that we use do not match well with the officially reported indicator values of the banks. As mentioned before, Table A.3 in the Appendix illustrates that for the majority of banks and indicators our quarterly proxy variables closely match the official scores that are reported on the EBA website. Exceptions to this are Danske Bank and Caixa Económica Montepio Geral, for which we significantly underestimate the official scores. Column 12 of Table 10 illustrates that our main result is robust to the exclusion of observations for these banks, indicating that our findings are not affected by poorly matched data.

[16] One possible explanation could be a declining trend in the aggregate amount of Level 3 assets over the sample horizon, which reflects into a decline in the denominator for this indicator.

5 Conclusions

This paper presents evidence of window-dressing behaviour in the international G-SIB framework. Both G-SIBs and banks that are obliged to report their scores as part of the assessment exercise are more likely to reduce activities affecting the G-SIB score at the end of a calendar year, compared with other banks in our sample. Moreover, the effect is stronger (i) for banks with G-SIB scores closer to a threshold between two G-SIB buckets, which arguably have stronger incentives to window dress; and (ii) for banks with a larger amount of repo activities that can more easily be reduced at reporting dates.

Our estimates compare year-end values of the G-SIB score and risk category scores with values observed for these indicators at the end of other quarters. As such, we are able to observe window dressing effects between quarters, but not within the same quarter. As illustrated by e.g. Grill et al. (2017), there are significant reductions in repo market activity at the end of *each* quarter; our analysis indicates that these reductions are more pronounced at the end of the *last* quarter, relative to other quarters, which is likely due to the additional incentives to window dress stemming from the G-SIB framework. To capture the amount of window dressing at year-end relative to other dates within the same quarter, data at higher frequency would be necessary. Hence, our estimates may be seen as lower bounds for the amount of window dressing that is actually occurring, where a quantification of the additional effects coming from within-quarter variation is left for future research.

Overall, our study illustrates that G-SIB scores tended to decline over the sample period, in line with the G-SIB framework's intention to reduce banks' systemic footprint. However, at the same time the regulatory context might have incentivised some banks to window dress. This may imply a distortion in the relative ranking of banks' systemic importance, and it may also have adverse effects on the functioning of capital markets and the provision of financial services as banks reduce certain activities towards the end of the year. Against this background, further investigation could be warranted to understand whether an alternative metric for the risk score calculation – e.g. based on averaging rather than year-end data – might help to avoid the unintended consequences of the G-SIB framework while guaranteeing a smooth decreasing trend in banks' systemic importance. Such alternative metrics are already being explored for the leverage ratio framework, and could be extended further throughout the regulatory framework.

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Tables and Figures

Table 1: Banks in the sample

	Reporting banks		*of which G-SIB*		Total Sample	
Country	TA (EUR bn)	No. Banks	TA (EUR bn)	No. Banks	TA (EUR bn)	No. Banks
AT	220	1	0	0	417.8	5
BE	259.5	1	0	0	683.3	7
CY	0	0	0	0	6.8	1
DE	2798.7	5	1480	1	3716.8	15
EE	0	0	0	0	16.2	2
ES	2103.8	2	1431	1	2682	10
FI	27.1	1	0	0	144.6	2
FR	6152.3	6	5259	4	6492.3	10
GR	0	0	0	0	250.5	4
IE	0	0	0	0	82.7	3
IT	1510.1	2	861.7	1	2019.5	9
LT	0	0	0	0	24.4	4
LU	0	0	0	0	59	3
LV	0	0	0	0	13.8	4
MT	0	0	0	0	19.8	3
NL	1839.7	3	846.2	1	2040.6	5
PT	20.2	1	0	0	232.6	4
SI	0	0	0	0	15.9	2
SK	0	0	0	0	48.1	4
Total sample	14931.4	22	9877.9	8	18966.6	97

Note: the sample used in this study includes quarterly data for 97 euro area banks (22 banks with reporting obligations, of which 8 G-SIBs, and 75 banks with no reporting obligations). The total assets (TA) refer to year-end 2017 and are expressed in EUR billion: they show that the sample represents approximately 67% of the euro area banking system, while the 8 G-SIBs alone account for one third of the euro area total assets, and half of the total assets in the sample. Calculation based on FINREP data.

Table 2: Indicator and category scores

Risk indicator	Mean	Median	S.D.	Category score by bank type		
				Rep. Banks	*of which G-SIBs*	Non Rep. Banks
Size				91.55	*174.89*	8.02
Total Exposures	28.12	8.16	50.11			
Interconnectedness				120.11	*222.18*	10.05
Intra-financial assets	47.98	8.02	98.45			
Intra-financial liab.	42.17	10.19	74.50			
Complexity				101.13	*232.08*	6.77
Securities outstanding	24.18	3.22	41.32			
OTC derivatives	29.80	0.49	110.43			
Level3 Assets	34.06	6.93	71.51			
Cross-jurisdict. activities				165.48	*345.48*	8.95
Cross-jurisd. claims	58.57	7.25	130.96			
Cross-jurisd. liabilities	58.11	6.98	129.26			
G-SIB risk score				114.49	*243.68*	8.15

Note: for each risk indicator and in each quarter we have derived the corresponding risk score at the bank-level, and reported their summary statistics aggregated over the period Q3 2014 - Q4 2017 and over the entire sample of banks. The risk scores have then been aggregated at the risk-category level, and reported here distinguishing between Banks with reporting obligations, G-SIBs only and banks with no reporting obligations. The last row shows statistics for the overall G-SIB score. Calculation based on FINREP data.

Table 3: Baseline regressions – G-SIB score

	Δ GSIB risk scores			
	(1)	(2)	(3)	(4)
Q4	-0.280**	-0.226		
	(0.135)	(0.139)		
RepBanks	0.501***	0.855***	0.792***	
	(0.183)	(0.258)	(0.271)	
Q4 × RepBanks	-3.14***	-3.48***	-3.36***	-3.27***
	(0.685)	(0.669)	(0.677)	(0.658
G-SIBs	-0.023	0.399	0.362	
	(0.674)	(0.728)	(0.731)	
Q4 × GSIBs	-8.176*	-8.073*	-8.208*	-8.308*
	(4.560)	(4.545)	(4.550)	(4.543)
CET1		-1.763	-1.911	-8.892
		(1.961)	(1.979)	(8.652)
LCR		0.050	0.074**	0.159
		(0.033)	(0.036)	(0.130)
Repos		-0.128**	-0.103	-0.62***
		(0.062)	(0.063)	(0.216)
Time FE	No	No	Yes	Yes
Bank FE	No	No	No	Yes
Observations	784	784	784	784
R-squared	0.135	0.135	0.212	0.206
Number of banks	78	78	78	78

Note: results of the multivariate panel regression analysing the quarterly variations of the G-SIB risk scores as a function of a dummy variable identifying the last quarter of the year ($Q4$), two dummy variables identifying G-SIBs ($G-SIBs$), banks with reporting obligations ($RepBanks$) and the corresponding interaction terms with $Q4$, and three control variables (the CET1 ratio, the liquidity coverage ratio and repos). The table provides evidence of a significant reduction of the G-SIB risk scores in the last quarter of the year, which is considerably more pronounced for banks with reporting obligations, and even more for G-SIBs. Calculation based on FINREP, COREP and EBA data (Q3 2014 to Q4 2017). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level.

Table 4: Baseline regressions – category scores

	Δ *Category risk scores*			
	(1) Size	(2) Interconn.	(3) Complex.	(4) Cross-jurisd.
Q4 × RepBank	-3.245***	-8.498***	1.649**	-2.834***
	(0.535)	(2.055)	(0.712)	(0.678)
Q4 × GSIBs	-6.641**	-10.43	2.440	-18.62***
	(2.945)	(9.232)	(2.591)	(5.953)
CET1	-9.643*	-3.594	-10.28	-19.72
	(5.369)	(8.700)	(15.45)	(20.58)
LCR	0.120	0.224	0.201	0.406
	(0.073)	(0.152)	(0.211)	(0.465)
Repos	-0.441**	-1.421***	-0.180	-0.549
	(0.174)	(0.378)	(0.233)	(0.382)
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	784	784	784	555
R-squared	0.315	0.249	0.059	0.223
Number of banks	78	78	78	58

Note: results of the multivariate panel regression analysing the quarterly variations of the categories' risk scores as a function of a dummy variable identifying the last quarter of the year ($Q4$), two dummy variables identifying G-SIBs ($G-SIBs$), banks with reporting obligations ($RepBanks$) and the corresponding interaction terms with $Q4$, and three control variables (the CET1 ratio, the liquidity coverage ratio and repos). The results show a significant year-end decrease in the categories representing size, interconnectedness and cross-jurisdictional activities: such decreases are stronger for banks with reporting obligations, and are even more pronounced for G-SIBs. Calculation based on FINREP, COREP and EBA data (Q3 2014 to Q4 2017). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level.

Table 5: Closeness to threshold – G-SIB score

	Δ *GSIB risk scores*					
	Closeness 1 (20bps)			Closeness 2 (30bps)		
	(1)	(2)	(3)	(4)	(5)	(6)
Q4	-0.226			-0.223		
	(0.140)			(0.140)		
RepBanks	0.983***	0.927***		0.858***	0.809**	
	(0.335)	(0.340)		(0.302)	(0.315)	
Q4 $\times$ RepBanks	-4.621***	-4.632***	-4.565***	-3.553***	-3.485***	-3.447***
	(1.185)	(1.160)	(1.094)	(0.751)	(0.745)	(0.736)
RepBank $\times$ Close	0.943	0.926	2.915	0.588	0.513	3.475
	(1.232)	(1.214)	(3.443)	(0.831)	(0.843)	(2.172)
Q4 $\times$ RepBank $\times$ Close	-8.059*	-7.693*	-8.086*	-8.141*	-8.142*	-8.139*
	(4.256)	(4.329)	(4.724)	(4.645)	(4.749)	(4.788)
CET1	-0.063	-0.021	-7.420	-0.181	-0.086	-7.297
	(1.966)	(2.016)	(8.392)	(1.964)	(2.034)	(8.835)
LCR	0.021	0.046	0.150	0.024	0.050	0.163
	(0.034)	(0.036)	(0.131)	(0.034)	(0.036)	(0.129)
Repos	-0.183*	-0.162	-0.602***	-0.147**	-0.120*	-0.624***
	(0.106)	(0.101)	(0.209)	(0.066)	(0.064)	(0.213)
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes
Observations	774	774	774	774	774	774
R-squared	0.122	0.196	0.197	0.133	0.210	0.205
Number of banks	78	78	78	78	78	78

Note: results of the multivariate panel regression analysing the quarterly variations of the G-SIB risk scores as a function of a dummy variable identifying the last quarter of the year ($Q4$), a dummy variables identifying banks with reporting obligations ($RepBanks$) and its corresponding interaction term with $Q4$, and a dummy variable identifying banks whose risk score in the previous year was no more than 20 (Closeness 1) or 30 (Closeness 2) basis points above or below the threshold between two different HLA buckets ($Close$). The regression also includes three control variables (the CET1 ratio, the liquidity coverage ratio and repos). The results show that the G-SIB score of banks with reporting obligations has been stronger for banks with a risk score close to the threshold between two HLA buckets. Calculation based on FINREP, COREP and EBA data (Q3 2014 to Q4 2017). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level. 20 observations are close to the threshold according to definition $Closeness1$, and 31 observations are close to the threshold according to definition $Closeness2$.

Table 6: Closeness to threshold – category scores

	Δ *Category risk scores*							
	Closeness 1 (20bps)				Closeness 2 (30bps)			
	(1) Size	(2) Interconn.	(3) Complex.	(4) Cross-jurisd.	(5) Size	(6) Interconn.	(7) Complex.	(8) Cross-jurisd.
Q4 × RepBank	-4.434***	-9.851***	4.633**	-8.894***	-3.475***	-7.904***	1.924*	-4.455***
	(0.867)	(2.376)	(2.188)	(2.809)	(0.564)	(1.824)	(1.046)	(1.056)
RepBank × Close	1.625	6.681	3.783	-0.567	1.572	4.454	0.125	7.841*
	(1.867)	(5.945)	(3.552)	(4.020)	(1.445)	(4.153)	(1.043)	(4.238)
Q4 × RepBank × Close	-5.648**	-11.73	-10.48	-4.281	-6.233*	-12.54	1.659	-15.02**
	(2.626)	(8.733)	(6.998)	(4.537)	(3.167)	(9.572)	(2.278)	(6.502)
CET1	-8.355*	-1.727	-9.574	-17.72	-8.105	-0.900	-10.58	-17.92
	(5.016)	(9.033)	(13.70)	(22.62)	(5.212)	(9.469)	(15.74)	(20.48)
LCR	0.114	0.214	0.173	0.407	0.126*	0.237	0.190	0.395
	(0.074)	(0.163)	(0.196)	(0.485)	(0.073)	(0.146)	(0.212)	(0.455)
Repos	-0.424**	-1.419***	-0.240	-0.310	-0.436**	-1.429***	-0.210	-0.477
	(0.163)	(0.375)	(0.231)	(0.337)	(0.171)	(0.376)	(0.235)	(0.373)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	774	774	774	550	774	774	774	550
R-squared	0.295	0.249	0.076	0.164	0.309	0.259	0.058	0.203
Number of banks	78	78	78	58	78	78	78	58

Note: results of the multivariate panel regression analysing the quarterly variations of the categories' risk scores as a function of a dummy variable identifying the last quarter of the year ($Q4$), a dummy variables identifying banks with reporting obligations ($RepBanks$) and its corresponding interaction term with $Q4$, and a dummy variable identifying banks whose risk score in the previous year was no more than 20 (Closeness 1) or 30 (Closeness 2) basis points above or below the threshold between two different HLA buckets ($Close$). The regression also includes three control variables (the CET1 ratio, the liquidity coverage ratio and repos). The results show that the scores associated with the size and cross-jurisdictional activity categories have been more likely to decrease in the last quarter of the year for banks with reporting obligations and whose risk score was close to the threshold between two HLA buckets. Calculation based on FINREP, COREP and EBA data (Q3 2014 to Q4 2017). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level. 20 observations are close to the threshold according to definition $Closeness1$, and 31 observations are close to the threshold according to definition $Closeness2$.

Table 7: Closeness to threshold – below vs. above threshold

	Δ *GSIB risk scores*					
	Closeness 1 (20bps)			Closeness 2 (30bps)		
	(1)	(2)	(3)	(4)	(5)	(6)
Q4	-0.225			-0.223		
	(0.141)			(0.141)		
RepBank	1.123***	1.063**		1.000***	0.942***	
	(0.420)	(0.413)		(0.333)	(0.337)	
Q4 × RepBank	-4.80***	-4.81***	-4.81***	-4.62***	-4.63***	-4.54***
	(1.345)	(1.319)	(1.350)	(1.185)	(1.162)	(1.070)
RepBank × Close+	-0.162	-0.159	-0.332	-0.162	-0.159	-0.295
	-1.101	-1.053	-0.959	(1.101)	(1.053)	(0.946)
RepBank × Close-	1.757	1.721	5.69	1.757	1.721	5.733
	-1.734	-1.73	-5.884	(1.734)	(1.730)	(5.895)
Q4 × RepBank × Close+	-8.337**	-7.781**	-7.830**	-8.154**	-7.600**	-7.468**
	(3.934)	(3.824)	(3.424)	(3.788)	(3.709)	(3.488)
Q4 × RepBank × Close-	-6.055	-5.903	-5.377	-7.767	-7.579	-8.246
	(5.520)	(5.655)	(5.189)	(7.122)	(7.255)	(8.292)
CET1	-0.0539	0.0120	-7.122	-0.545	-0.468	-8.094
	(2.329)	(2.482)	(8.408)	(2.222)	(2.338)	(8.393)
LCR	0.022	0.046	0.154	0.029	0.053	0.164
	(0.0395)	(0.0421)	(0.127)	(0.0383)	(0.0402)	(0.129)
Repos	-0.168**	-0.148*	-0.589***	-0.189*	-0.168*	-0.605***
	(0.0838)	(0.0806)	(0.180)	(0.106)	(0.101)	(0.191)
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes
Observations	774	774	774	774	774	774
R-squared	0.122	0.196	0.192	0.124	0.197	0.202
Number of banks	78	78	78	78	78	78

Note: results of the multivariate panel regression analysing the quarterly variations of the G-SIB risk scores as a function of a dummy variable identifying the last quarter of the year ($Q4$), a dummy variables identifying banks with reporting obligations ($RepBanks$) and its corresponding interaction term with $Q4$, and a dummy variable identifying banks whose risk score in the previous year was no more than 20 (Closeness 1) or 30 (Closeness 2) basis points above ($Close+$) or below ($Close-$) the threshold between two different HLA buckets. The regression also includes three control variables (the CET1 ratio, the liquidity coverage ratio and repos). The results indicate that reporting banks whose risk score was above the threshold between two HLA buckets have been more likely to window-dress with respect to the other banks. However, the coefficients associated with the interaction term $Q4 * RepBank * Close-$ are also negative and quite big in absolute terms: their lack of significance might thus be due to mere power issues. Calculation based on FINREP, COREP and EBA data (Q3 2014 to Q4 2017). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level. According to definition $Closeness1$, 9 observations are above and 11 observations are below the threshold between two HLA buckets; according to definition $Closeness2$, 14 observations are above and 17 observations are below the threshold between two HLA buckets.

Table 8: Impact of repo market activities – all banks

	Δ *GSIB Risk scores*			Δ *Category risk scores*			
	(1)	(2)	(3)	(4) Size	(5) Interconn.	(6) Complex.	(7) Cross-jurisd.
Q4	25.46**						
	(10.31)						
Repos	0.050	0.068	-0.172	-0.033	-0.621*	-0.347	0.208
	(0.047)	(0.054)	(0.172)	(0.137)	(0.370)	(0.217)	(0.336)
Q4 × Repos	-1.263**	-1.274**	-1.276**	-1.168***	-2.378**	0.491**	-2.179***
	(0.492)	(0.500)	(0.502)	(0.334)	(0.993)	(0.200)	(0.769)
CET1	1.365	1.307	-6.808	-7.890	0.266	-11.10	-17.94
	(2.456)	(2.601)	(9.741)	(6.190)	(10.19)	(15.43)	(23.00)
LCR	0.006	0.031	0.203	0.160*	0.310	0.184	0.521
	(0.048)	(0.049)	(0.148)	(0.090)	(0.193)	(0.207)	(0.489)
Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	784	784	784	784	784	784	555
R-squared	0.091	0.168	0.168	0.264	0.208	0.056	0.161
Number of banks	78	78	78	78	78	78	58

Note: results of the multivariate panel regression analysing the quarterly variations of the G-SIB risk scores (columns 1 to 3) and the categories' risk scores (columns 4 to 7) as a function of a dummy variable identifying the last quarter of the year ($Q4$), a variable identifying the amount of repo transactions (*Repos*) and its corresponding interaction term with $Q4$, and two control variables (the CET1 ratio and the liquidity coverage ratio). The results in columns (1)-(3) confirm that banks with high level of repos are more likely to decrease their G-SIB risk score at the end of the year than the other banks. Columns (4)-(7) also show that the impact of repos is stronger on the risk categories representing size, interconnectedness and cross-jurisdictional activities. Calculation based on FINREP, COREP and EBA data (Q3 2014 to Q4 2017). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level.

Table 9: Impact of repo market activities – reporting banks

	Δ *GSIB Risk scores*			Δ *Category risk scores*			
	(1)	(2)	(3)	(4) Size	(5) Interconn.	(6) Complex.	(7) Cross-jurisd.
Q4	1.212						
	(1.535)						
RepBank	0.789	-3.210					
	(2.612)	(2.904)					
Q4 × RepBank	63.23	65.99	68.64	52.60**	114.8	2.954	110.9**
	(39.49)	(40.80)	(42.01)	(26.12)	(85.82)	(16.71)	(54.39)
Q4 × Repos	-0.068	-0.059	0.003	-0.114*	0.038	0.235*	0.008
	(0.076)	(0.081)	(0.096)	(0.063)	(0.211)	(0.121)	(0.262)
RepBank × Repos	-0.001	0.168	0.076	0.065**	0.138	-0.054	0.179
	(0.113)	(0.126)	(0.049)	(0.028)	(0.113)	(0.054)	(0.115)
Q4 × RepBank × Repos	-2.883*	-2.997*	-3.115*	-2.408**	-5.291	-0.044	-5.014**
	(1.699)	(1.754)	(1.806)	(1.122)	(3.685)	(0.717)	(2.342)
Repos	-0.045**	-0.065*	-0.546***	-0.341**	-1.325***	-0.269	-0.377
	(0.019)	(0.033)	(0.191)	(0.156)	(0.340)	(0.235)	(0.382)
CET1	-0.683	-0.709	-9.816	-10.41*	-5.527	-10.25	-22.19
	(1.763)	(1.843)	(9.116)	(5.672)	(8.339)	(15.40)	(22.48)
LCR	0.038	0.059*	0.157	0.122*	0.221	0.189	0.440
	(0.030)	(0.034)	(0.131)	(0.073)	(0.154)	(0.214)	(0.482)
Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	784	784	784	784	784	784	555
R-squared	0.136	0.212	0.209	0.320	0.271	0.058	0.194
Number of banks	78	78	78	78	78	78	58

Note: results of the multivariate panel regression analysing the quarterly variations of the G-SIB risk scores (columns 1-3) and the categories' risk scores (columns 4-7) as a function of a dummy variable identifying the last quarter of the year (*Q4*), a dummy variables identifying banks with reporting obligations (*RepBanks*) and its corresponding interaction term with *Q4*, and a variable identifying the amount of repo transactions (*Repos*). The regression also includes two control variables (the CET1 ratio and the liquidity coverage ratio). The results in columns (1)-(3) show that banks with both reporting obligations and high levels of capital market activities are more likely to reduce their G-SIB risk score at the end of the year: columns (4)-(7) also confirm that the size and cross-jurisdictional activity categories are the main drivers for such window-dressing behaviour. Calculation based on FINREP, COREP and EBA data (Q3 2014 to Q4 2017). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level.

Table 10: Further results and robustness checks

	Size	Interconnectedness			Complexity		Cross-jurisdictional		G-SIB score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Tot. LRE	IFS assets	IFS liab.	Sec.	OTC deriv.	L3 assets	Claims	Liab.	[t-3,t]	[t-2,t+1]	[t-1,t+2]	Ex. bad match
Q4 × RepBanks	-3.245***	-8.540***	-13.33***	-3.629***	0.829	2.469*	-2.952***	-2.717***	-2.947***	-3.016***	-2.976***	-3.487***
	(0.535)	(2.854)	(3.420)	(1.238)	(0.618)	(1.461)	(0.652)	(0.744)	(0.719)	(0.722)	(0.722)	(0.680)
Q4 × GSIBs	-6.641**	-18.11	-13.46	0.277	-0.561	5.426	-20.24***	-17.01***	-8.002*	-7.990*	-7.989*	-8.108*
	(2.945)	(11.34)	(13.76)	(4.394)	(3.785)	(6.376)	(6.072)	(5.854)	(4.585)	(4.580)	(4.583)	(4.547)
CET1 Ratio	-9.643*	6.065	-10.71	-4.978	-25.41	6.917	-8.441	-31.00	-0.409	-1.565	-1.630	-9.515
	(5.369)	(13.42)	(23.05)	(7.459)	(39.48)	(14.83)	(13.11)	(31.09)	(7.020)	(7.563)	(5.133)	(8.729)
LR	0.120	0.290	0.222	0.0732	0.409	-0.00212	0.263	0.550	0.163	0.0212	0.0424	0.168
	(0.0729)	(0.257)	(0.251)	(0.106)	(0.354)	(0.252)	(0.384)	(0.575)	(0.165)	(0.108)	(0.118)	(0.130)
Repos	-0.441**	-1.736***	-2.440***	-0.0696	0.0380	-0.484	-0.751	-0.347	-0.728***	-0.579***	-0.612***	-0.616***
	(0.174)	(0.564)	(0.613)	(0.230)	(0.485)	(0.439)	(0.475)	(0.321)	(0.262)	(0.216)	(0.218)	(0.216)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	784	784	784	766	776	743	555	555	784	784	784	777
R-squared	0.315	0.217	0.224	0.081	0.022	0.086	0.259	0.183	0.191	0.190	0.192	0.207
Number of banks	78	78	78	76	77	75	58	58	78	78	78	76

Note: the table provides further results and robustness checks for our main regression. Columns 1-8 provide additional results on G-SIB indicators. That is, the category scores (results in Tables 4 and 6) are broken down further into individual indicators, i.e. the total Leverage Ratio Exposure measure for size, intra-financial system assets and liabilities as well as securities outstanding for interconnectedness, OTC derivatives and Level 3 assets for complexity, and cross-jurisdictional claims and liabilities for the cross-jurisdictional category. In columns 9-11 we use the Q4 denominator for Q4 and (i) the previous three quarters (column 9), (ii) the previous two and the subsequent quarter (column 10), and (iii) the previous one and the two subsequent quarters (column 11), instead of Q4 and the subsequent three quarter as in the baseline regressions. Finally, in column 12 we re-estimate the baseline specification, excluding those banks for which the match between our proxy score and the officially reported EBA scores is not particularly good (Danske Bank and Caixa Economica Montepio Geral, see Table A.3). The reported R-squared is the intra-group one. The standard errors in parenthesis are robust and adjusted for clustering at the bank level.

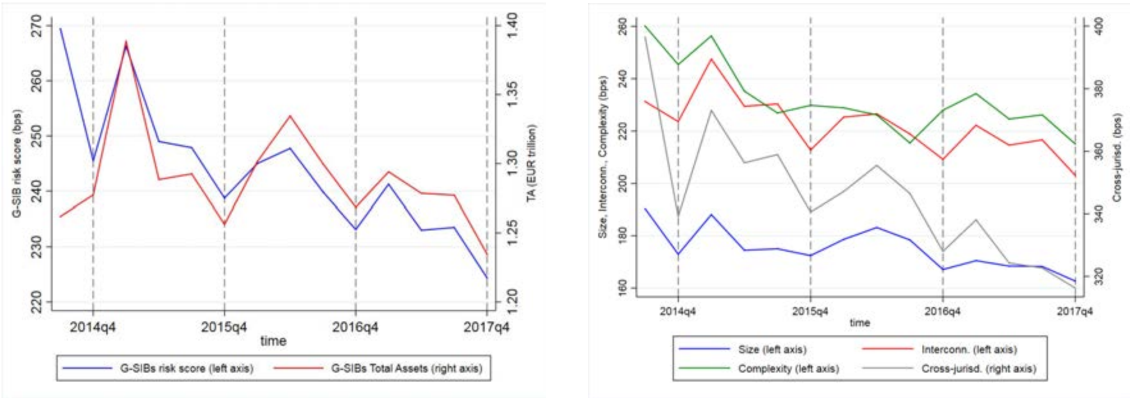

Figure 1: Evolution of risk scores and total assets. The left-hand panel shows the evolution of the average G-SIB score and aggregate assets (in EUR trillion) for the eight G-SIBs included in our sample. the right-hand panel shows the evolution of the four risk category scores that we are able to proxy with quarterly data: size, interconnectedness, complexity and cross-jurisdictional activity. Dashed vertical lines indicate the last quarter of each year. Calculations based on FINREP and EBA data, period from 2014Q3 to 2017Q4.

Annex I: BCBS indicator-based approach for G-SIBs

The BCBS indicator-based measurement approach used to derive the banks' risk scores is based on five risk categories: they have been designed to capture the systemic importance of banks through (a) their size, (b) their interconnectedness, (c) the lack of readily available substitutes or financial institution infrastructure for the services they provide, (d) their global (cross-jurisdictional) activity and (e) their level of complexity. The BCBS guidelines assign an equal weight of 20 percent to each of these five risk categories. The score of each risk category, with the exception of the size category, results from the combination of several risk indicators, each of them equally weighted within its own category.[17] The weights of the risk categories and indicators are shown in Table A.1. Since we are unable to calculate proxy variables for all of the indicators, we reallocate the weights assigned to indicators that we are unable to approximate to the other indicators within the category (or to the other categories for the substitutability category, that we are unable to proxy at all, see columns 5-6).

In order to calculate a bank's overall risk score, the values of the twelve indicators are normalised using sample totals. The sample consists of the largest banks worldwide, and it includes (a) all the banks with a Basel III leverage ratio exposure exceeding EUR 200bn, and (b) all the other banks, if any, that were designated as G-SIBs in the previous year but not exceeding the EUR 200bn leverage exposure measure. The sample totals, or denominators, represent the sum of the activity for each of the twelve indicators reported by all the banks in the sample. The indicator scores, expressed in basis points (bps), are thus calculated as follows:

$$\frac{Bank\ Indicator\ (EUR)}{Indicator\ sample\ total\ (EUR)} \cdot 10,000 = Indicator\ score\ (bps) \tag{1}$$

The final risk scores are calculated by averaging the five risk category scores (or, alternatively, the twelve indicator scores) according to the weights reported in Table A.1 (columns 3 and 4 for the complete BCBS/EBA methodology; columns 5 and 6 for the approximation used in this

[17]According to this methodology, if there are two indicators within a risk category, each indicator is given a 10 percent weight, corresponding to the 20 percent weight assigned to the risk category, equally divided among the two indicators; similarly, if there are three indicators within a risk category, each indicator has a weight of 6.67 percent. Detailed reporting instructions for banks on how to calculate their risk scores can be found at this BIS webpage.

paper).

The final G-SIB risk score is then translated into a Higher Loss Absorbency (HLA) requirement using the score ranges shown in Table A.2. The current cut-off score for the G-SIB designation is 130 bps, and each of the five buckets has a range of 100 bps: each bucket implies higher loss-absorbency requirements, and the bucket thresholds have been set such that bucket 5 is empty.[18]

As illustrated in column 5 of Table A.1, we are able to obtain quarterly proxy variables for eight of the 12 indicator variables used in the G-SIB methodology. To assess how good our proxy variable captures the actual G-SIB score, we compare the risk scores calculated in this paper with the risk scores annually published by the EBA. The results reported in Table A.3 refer to the euro area banks with reporting obligations that are also included in the sample used in this study (23 banks overall), and represent the ratio between the risk category scores estimated in this study and the official risk category scores disclosed by the EBA. All numbers refer to year-end 2017 (the results referred to 2014, 2015 and 2016 are very similar). Overall, the risk scores estimated in this study replicate well the official risk scores published by the EBA, and this is particularly true for the eight G-SIBs in the sample.

[18]Hypothetically, if the highest bucket should become populated in the future, a new bucket would be introduced to maintain the incentive for banks to avoid becoming more systemically important.

Table A.1: BCBS indicator-based approach for G-SIBs

		Weights			
		BCBS methodology (annual data)		this study (quarterly data)	
(1) Category	(2) Individual indicator	(3) Indicator	(4) Category	(5) Indicator	(6) Category
Size	Total exposure	20%	20%	25%	25%
Interconnectedness	Intra-financial system assets	6.67%	20%	8.33%	25%
	Intra-financial system liabilities	6.67%		8.33%	
	Securities outstanding	6.67%		8.33%	
Substitutability	Assets under custody	6.67%	20%	X	X
	Payment activity	6.67%		X	
	Underwritten transaction in debt and equity market	6.67%		X	
Complexity	Notional amount of OTC derivatives	6.67%	20%	12.50%	25%
	Trading and AFS securities	6.67%		X	
	Level 3 assets	6.67%		12.50%	
Cross-jurisdictional activity	Cross-jurisdictional claims	10%	20%	12.50%	25%
	Cross-jurisdictional liabilities	10%		12.5%	

Note: the five risk categories (column 1), overall including twelve risk indicators (column 2), are associated with their corresponding weights as prescribed by the BCBS methodology to derive the G-SIB risk score (columns 4 and 5). These weights are compared with the weights implemented in the current study (columns 5 and 6), where the differences between the two are due to lack of granular data to apply the BCBS framework at quarterly frequencies.

Table A.2: Score ranges and HLA requirements

Bucket	Score range	HLA requirement
5	530 - 629	+3.5% CET1
4	430 - 529	+2.5% CET1
3	330 - 429	+2.0% CET1
2	230 - 329	+1.5% CET1
1	130 - 229	+1.0% CET1

Note: The table shows the relation between the G-SIB score and the Higher Loss Absorbency (HLA) requirement associated with each of the five buckets of the G-SIB framework.

Table A.3: Comparison between the official EBA risk scores and the “approximated” risk scores calculated in this study

Bank	Country	Size	Interconnect.			Complexity		Cross-jurisd.		Median
		Total assets	Intra-finan. assets	Intra-finan. liabilities	Securities outstanding	OTC derivatives	Level 3 assets	Cross-jurisd. claims	Cross-jurisd. liabilities	
ABN AMRO Group	NL	0.81	0.60	1.03	0.59	0.61	0.92	0.51	0.46	0.60
BNP Paribas	FR	0.93	1.72	2.00	0.64	0.64	1.06	0.88	1.06	0.99
Banco Bilbao Vizcaya Argentaria	ES	0.87	0.82	0.89	0.34	1.02	1.25	0.87	0.75	0.87
Banco Santander	ES	1.02	1.41	1.41	0.42	1.03	1.06	1.05	1.02	1.04
Bayerische Landesbank	DE	0.94	0.77	0.70	0.63	0.27	0.92	0.23	1.19	0.74
Commerzbank	DE	0.92	0.76	0.73	0.51	1.03	1.03	0.47	0.54	0.75
Caixa Económica Montepio Geral	PT	0.06	0.09	0.21	0.01	1.03	0.02			0.08
Confédération Nationale du Crédit Mutuel	FR	0.97	1.27	1.11	0.84	0.91	1.20	0.76	0.94	0.95
Coöperatieve Rabobank	NL	0.88	2.20	1.10	0.76	0.85	0.81	0.58	0.88	0.87
Crédit Agricole	FR	0.84	2.99	1.16	0.70	1.04	1.00	0.86	1.62	1.02
DZ Bank	DE	0.94	0.82	0.92	0.71	0.92	0.86	0.44	1.15	0.89
Danske Bank	FI	0.06	0.08	0.08	0.00	0.07	0.02			0.07
Deutsche Bank	DE	1.09	1.32	0.77	0.82	0.84	1.34	1.20	1.32	1.15
Erste Group Bank	AT	0.98	0.70	0.89	0.40	0.83	0.95	0.98	0.91	0.90
Groupe BPCE	FR	1.00	2.17	1.47	0.58	0.89	0.60	0.59	0.93	0.91
ING Groep	NL	0.77	0.92	0.77	0.49	0.83	0.94	0.85	0.83	0.83
Intesa Sanpaolo	IT	1.02	0.84	1.16	0.61	0.83	1.07	0.70	0.70	0.83
KBC Group	BE	1.02	0.47	0.49	1.27	0.77	0.73	0.78	0.42	0.75
La Banque Postale	FR	0.97	0.73	3.59	0.73	0.32	0.48			0.73
Landesbank Baden-Württemberg	DE	0.93	1.04	0.99	0.80	0.17	1.16	0.37	0.71	0.86
Société générale.	FR	0.93	1.24	1.00	0.69	0.98	1.09	0.89	0.82	0.95
UniCredit	IT	0.88	1.00	0.88	0.44	0.88	0.98	1.11	1.27	0.93
Median		0.93	0.88	0.95	0.62	0.85	0.96	0.78	0.91	

Note: calculation based on FINREP, COREP and EBA data (Q4 2017). The reported values have been calculated as the ratio between the risk-category scores estimated in this study and the EBA ones.

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