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Banks' window-dressing of the G-SIB framework: causal evidence from a quantitative impact study

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Banks’ window-dressing of the G-SIB framework: causal evidence from a quantitative impact study

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Executive Summary

Banks' market activity is commonly observed to contract around period-end dates. This behaviour by banks, known as “window-dressing”, has micro- and macro-prudential implications, as well as potential repercussions for financial stability and the operationalisation of monetary policy. However, data limitations have constrained the capability of studies to attribute incentives for this behaviour to *specific* policies, restricting policymakers' scope to impose on banks costly mitigating reporting reforms. Exploiting a novel and uniquely extensive bank-level dataset, this study employs a difference-in-differences empirical strategy to test whether the response of banks to the introduction of the G-SIB framework – a key component of the Basel III macroprudential reforms – directly contributes to window-dressing behaviour. It finds causal evidence that it does. Window-dressing incentivised by the G-SIB framework is responsible for around *half* of the observed year-end contractions in notional over-the-counter derivatives, accounting for aggregate reductions of €30 trillion – equating to around 5% of total global activity per year. These results indicate that banks’ attempts to lower their G-SIB capital requirements are a significant contributor of year-end window-dressing behaviour and highlight the potential broader implications of this behaviour on market volatility.

Keywords: Banks, macroprudential regulation, window-dressing, regulatory arbitrage, market volatility

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1. Introduction

In the wake of the global financial crisis in 2008, the Basel Committee on Banking Supervision (BCBS) implemented a sweeping package of "Basel III" macroprudential reforms to increase banking sector resilience to shocks. These reforms require banks to hold higher levels of regulatory capital and liquidity to be able to absorb shocks and mitigate systemic risks. These systemic risks are often measured by regulatory metrics that are based on point-in-time (often period-end) data reported or disclosed by banks. Such frameworks can be sensitive to regulatory arbitrage behaviour by banks, known as "window-dressing".

Window-dressing is defined as the temporary reduction in market activity and balance sheet items by banks in anticipation of period-end reporting dates in order to appear safer or less systemically important than they may actually be. A report by the Committee on the Global Financial System (CGFS) in 2017 concluded that such a "pattern of … market disruption near period-end reporting dates is fairly well established" and "occurs with a degree of predictability" (CGFS (2017)).

Window-dressing has evident micro- and macro-prudential consequences. A range of accounting standards and regulatory policies such as annual disclosures, bank levies, stress tests, contributions to the Single Resolution Fund for banks in the European Union (EU), leverage, liquidity, and regulatory capital (for Global Systemically Important Banks (G-SIB), and Domestic Systemically Important Banks (D-SIB)) frameworks are (and have been) based on period-end reported data.[2] Contractions in activity around these reporting dates result in misleading bank disclosures and misrepresentation of bank risk. These implications have been particularly well documented for the leverage ratio and G-SIB frameworks. Bassi et al (2023) find that EU banks' repo volumes fall by around 12.5% in the few days before quarter-end, significantly skewing perception of banks' leverage ratios from the true figure during the quarter. In relation to the G-SIB framework, Garcia et al (2023), Behn et al (2022) Torstensson and Welz (2023) and Berry et al (2021) each find that contractions in year-end activity result in misidentification of G-SIBs and a misallocation of capital.

Window-dressing also has potential broader implications for financial stability and the operationalisation of monetary policy. Sharp contractions in financial market activity around period-end reporting dates increase market volatility and reduce market access for clients. This has the potential to disrupt market functioning, impact the transmission of monetary policy, and amplify shocks that coincide with period-ends (Du et al (2018), Brand et al (2019), and Bassi et al (2023)).

Action has been taken by some policymakers in recent years. In 2018, the BCBS described window-dressing behaviour as "unacceptable, as it undermines … intended policy objectives … and risks disrupting the operations of financial markets" (BCBS (2018b)), and in 2019 introduced measures seeking to reduce window-dressing incentives in the leverage ratio framework by increasing the frequency at which banks are required to disclose data (see BCBS (2019)). However, imposing more stringent reporting and disclosure requirements on banks entails an increase in their reporting burden, and other regulatory metrics – such as the G-SIB framework – have continued to be based on point-in-time data.

To date, data limitations have constrained empirical studies' ability to attribute period-end contractions to *active* efforts by banks to arbitrage specific regulatory metrics. Doing so requires both disentangling window-dressing behaviour from seasonal demand-side dynamics (particularly at year-end), as well as disentangling incentives originating from different possible regulatory policies and accounting standards that are each based on data at the same point-in-time. Absent strong evidence identifying the primary sources of this behaviour, it is difficult for policymakers to know how to most efficiently mitigate the micro- and macro-prudential, as well as potential broader financial stability and monetary policy implications of this behaviour.

[2] Domestic Systemically Important Banks and Global Systemically Important Banks receive higher loss absorbing capital requirements (D-SIB or G-SIB capital surcharge) based on the degree to which they are deemed to be respectively domestically or globally systemically important.

This study utilises a novel and uniquely extensive dataset to determine whether the G-SIB framework is a material driver of window-dressing behaviour. The G-SIB framework assigns regulatory capital requirements to banks based on their global systemic importance. Banks report data across 13 different indicators (capturing activity in a range of markets, such as notional over-the-counter (OTC) derivatives and repos), based on which a "G-SIB score" is calculated for each bank in the assessment sample, reflecting their global systemic importance. Based on these scores, banks are categorised into "buckets" with fixed thresholds that determine their G-SIB capital requirement.[3] Crucially, data reported by banks are as at year-end.

A number of studies have found evidence that is *consistent* with G-SIB-incentivised window-dressing behaviour (Berry et al (2021), Behn et al (2022), Garcia et al (2023)). However, data limitations in the sample size of banks and time-period have constrained the strength of the conclusions drawn. The dataset used in our study contains nearly the *entire* sample of global banks that have been part of the assessment sample in the G-SIB exercise (70 of the largest banks across 16 jurisdictions, accounting for 97% of global notional OTC derivatives activity) and spans the time-period between 2010 and 2022, crucially, stretching back to *before* the implementation of the G-SIB framework in 2016. This provides us with a unique opportunity to answer this research question.

We adopt an empirical strategy that exploits the fact that the G-SIB framework generates heterogeneous window-dressing incentives across banks. Specifically, incentives depend on banks' proximity to the fixed bucket thresholds that determine G-SIB capital requirements. These buckets are relatively large and crossing a threshold implies a significant change in capital requirements that banks are subject to (between 0.5% and 1% of total risk-weighted assets). Banks that find themselves closer to these thresholds are more likely to be able to materially reduce their capital requirements by cutting year-end activity and dipping (or remaining) below these thresholds. Thus, these banks face greater incentives to window-dress their activity for the purposes of saving G-SIB-incurred capital costs. Crucially, this is an exogenous source of G-SIB-*specific* window-dressing incentives.

Using quarterly data between 2010 and 2022, we employ a difference-in-differences empirical strategy to compare the window-dressing behaviour of global banks before and after the implementation of the G-SIB framework, distinguishing between banks based on their proximity to G-SIB bucket thresholds.

We find that banks with greater G-SIB-specific window-dressing incentives began to window-dress notional OTC derivatives significantly more than peers *after* the implementation of the framework, having previously exhibited broadly similar behaviour. We confirm that this finding is a *causal* relationship by showing that the parallel trends hypothesis holds conditioning on important bank balance sheet characteristics such as size, business model, level of Tier 1 capital, and location of headquarters. This result is robust to a host of checks. We also find a positive association between the G-SIB framework and window-dressing of repos. However, these results are less statistically robust than are those for notional OTC derivatives, so we are more cautious in drawing strong conclusions in relation to repos.

We find that the incentives to window-dress notional OTC derivatives generated by the G-SIB framework are economically, as well as statistically, significant. Conditioning on the abovementioned bank balance sheet characteristics, the response of banks to the G-SIB framework is directly responsible for year-end contractions of notional OTC derivatives activity in the order of magnitude of €30 trillion. This equates to approximately 5% of global notional OTC derivatives activity, and explains around *half* of the contractions observed at year-end. The magnitude of this effect is particularly striking given that notional OTC derivatives contribute only 6.67% of banks' G-SIB scores. That is, *despite* the relatively small weight, the G-SIB framework is nevertheless incentivising such a distortion in behaviour.

The policy implications are clear. Banks' attempts to lower their G-SIB scores are a material driver of year-end window-dressing activity. Efforts to reduce incentives to window-dress for G-SIB purposes

[3] Details of the G-SIB framework methodology are provided in Section 3.

would not only reduce the risk of misidentifying G-SIBs and misallocating regulatory capital within the G-SIB framework, but it would potentially have positive spillovers for the accurate provision of risk in other regulatory frameworks and materially reduce year-end volatility in certain markets. Indeed, in conjunction with the publication of this working paper, the BCBS has published a consultative document setting out potential measures to address window-dressing behaviour in the G-SIB framework (BCBS (2024)).[4]

This paper is structured as follows. We provide a review of the literature in the next section, before detailing the G-SIB methodology in Section 3. We describe the data and empirical strategy in Section 4, present the results in Section 5, and conclude in Section 6.

2. Related literature

While window-dressing by banks has long been a known phenomenon (see Allen and Saunders (1992)), it has become an increasingly studied activity since the implementation of the Basel III regulatory reforms. In particular, the research literature has focused recently on two specific sources of window-dressing activity. The first, which has received most attention, is quarter-end window-dressing of repo market activity, relating to the leverage ratio framework. The second is year-end window-dressing relating to the G-SIB framework. Across these two sources, studies have sought to answer two distinct questions. First, what is the impact of window-dressing on the effectiveness of these regulatory frameworks? The motivation for this research question is to understand the possible micro- and macro-prudential consequences of window-dressing behaviour. Second, what are the primary drivers of window-dressing behaviour? The motivation here lies in the potential broader impacts of this behaviour beyond prudential effectiveness, for market volatility, market functioning, financial stability (Munyan (2017), Du et al (2018), Brand et al (2019), Bassi et al (2023)) and the operationalisation of monetary policy (Duffie and Krishnamurthy (2016), Banegas and Tase (2020)).

In relation to the leverage ratio framework, the sharp contraction in repo market activity at quarter-ends is widely documented. Bassi et al (2023) estimate that repo volumes across EU banks fall by around 12.5% in the few days before quarter-end. Munyan (2017) finds that the removal of quarter-end repo positions by non-US banks in the US repo market averages $170 billion, equating to 10% of the entire global repo market. This has clear consequences for banks' leverage ratios.

Additionally, studies have found strong empirical evidence *attributing* quarter-end window-dressing of repo market activity specifically to the leverage ratio framework. Aldasoro et al (2022) exploit the fact that the inconsistent implementation of leverage ratio regulations across jurisdictions has meant that while EU banks can calculate their leverage ratio based on quarter-end positions, other jurisdictions are mandated to average over daily positions (see BCBS (2014)). They find strong evidence that EU banks withdraw from repo markets at quarter-end significantly more than those in other jurisdictions. They also find that this has a significant impact on pricing in these markets. Grill et al (2017) similarly link quarter-end window-dressing of repo market activity to the leverage ratio framework and identify an effect on prices. Munyan (2017) finds that the quarter-end contraction of repos has spillover effects on bond markets, money market funds, and market liquidity each quarter.

On the back of this evidence, the BCBS overhauled leverage ratio disclosure requirements in 2019 (see BCBS (2019)), asking firms to disclose *daily* averaged values for Securities Financing Transactions (SFTs, a key component of leverage exposures), alongside the traditional quarter-end disclosures.[5]

In relation to the G-SIB framework, studies consistently find that year-end contractions in activity materially reduce the accuracy with which the framework measures systemic risk. Garcia et al (2023)

[4] The decision to develop potential measures to address window-dressing behaviour by some banks in the context of the framework for G-SIBs, was announcement by the BCBS in December 2023 (BCBS (2023)).

[5] SFTs are largely made up of repos and reverse repos.

compare EU banks' G-SIB scores (which reflect their systemic risk) as calculated at year-end by the G-SIB framework, with estimated scores calculated based on data at adjacent quarter-ends. They find that G-SIBs' year-end scores are *materially* lower, on average, than if calculated at adjacent quarter-ends, and that this reduction in scores results in the misidentification of G-SIBs and the misallocation of capital requirements. Between 2014 and 2020, Garcia et al (2023) estimate that up to 13 banks faced lower capital requirements, with three banks avoiding G-SIB designation altogether. Berry et al (2021) and Behn et al (2022) find similar evidence in studies based on EU and US banks, respectively. Bassi et al (2023) find that repo volumes (which contribute to a number of G-SIB indicators) fall by 25% at year-end (compared to 12.5% at quarter-end). Furthermore, these studies indicate that year-end contractions in activity are heterogeneous across banks, with capital market banks better *able* to window-dress than retail banks. Given that systemic importance is measured, in the G-SIB framework, *relative* to other banks, this heterogeneity results in both winners *and* losers from this year-end activity.[6]

However, attributing year-end contractions in activity specifically to the G-SIB framework has proved more difficult than attributing quarter-end contractions to the leverage ratio framework. There are two primary identification challenges. First, observed reductions in activity around regulatory reporting dates must be identified as originating from banks' own reduced *demand* for activity, rather than a result of cyclical *supply*-side dynamics.[7] This is more challenging at year-end than at quarter-end, given festive period complications (see Kotomin and Winters (2006)). Secondly, there is a much broader *range* of regulatory and accounting frameworks that are based on year-end, rather than quarter-end, data. These include, for example, annual disclosures, bank levies, contributions to the Single Resolution Fund for EU banks, stress tests, leverage, Liquidity Coverage Ratio, D-SIB, and G-SIB frameworks. Identifying window-dressing incentives generated by specific regulatory (eg G-SIB) frameworks requires disentangling those framework-specific incentives from incentives originating from other sources.

Some studies have sought to glean insights into whether the G-SIB framework, specifically, might be driving observed year-end contractions in activity. However, thus far, data limitations have restricted the strength of the conclusions drawn. Garcia et al (2023) (in the EU) and Berry et al (2021) (in the US) compare window-dressing behaviour between G-SIBs and non-G-SIBs. Each find that G-SIBs window-dress to a greater degree than non-G-SIBs. They also find that this discrepancy has become more pronounced since the implementation of the G-SIB framework in 2016. However, although these findings are *consistent* with G-SIB framework-driven incentives, G-SIBs and non-G-SIBs are two inherently different groups of banks. G-SIBs are more likely to have different business models and face other contributory regulatory requirements, some of which may have been implemented around the same time as the G-SIB framework. Without doing more to account for these possible systematic differences between the two groups of banks, as Garcia et al (2023) themselves advise, it is difficult to draw more concrete conclusions.

Studies have sought to go further than this, by comparing window-dressing behaviour across G-SIBs, based on the degree to which they are tightly *constrained* by G-SIB capital requirements.[8] Consistent with the hypothesis that the G-SIB framework incentives this behaviour, Behn et al (2022) and Garcia et al (2023) find a positive association between proximity to G-SIB bucket thresholds and the degree of window-dressing. However, the authors caution that data limitations (relating each to sample size, timeframe, and level of granularity) constrain the conclusions drawn.

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6 Those banks that are less able to window-dress their year-end activity will have an *over-estimated* systemic importance.

7 Allen and Saunders (1992) distinguish between active (or endogenous) and passive (or exogenous) window dressing, where the latter "results from forces external to the bank, such as corporate incentives to reduce quarter-end borrowing in order to window dress their balance sheets".

8 The G-SIB framework creates different window-dressing incentives depending on how close banks happen to find themselves to the bucket thresholds that determine capital requirements. Banks that lie close to G-SIB bucket thresholds may seek to maintain (or push) their score below the threshold by window-dressing, and thereby lower their capital surcharge. In contrast, banks that lie far away from a bucket threshold are less likely to be able to materially benefit from doing so, and so face smaller G-SIB-specific incentives.

A more statistically robust finding is that identified by Bassi et al (2023). They exploit daily transaction-level repo market data to find that G-SIBs that are "close" to bucket thresholds significantly reduce repo volumes specifically on positions that appear on the balance sheet (and thus contribute to the G-SIB score) in the last four days of the year, while maintaining volumes on positions that do not. In contrast, G-SIBs that are further away from bucket thresholds maintain all positions. Intuitively, this is a convincing finding. Proximity to G-SIB bucket thresholds is an *exogenous* source of GSIB-*specific* window-dressing incentives. In theory, there should not exist an endogenous factor that could explain this result. However, in practice, this study is limited by a very small sample, which comprises only of six G-SIBs (three that are "close", and three that are "not close" to bucket thresholds). With such a small sample of banks, it is difficult to categorically rule out that, entirely by chance, there exists some systematic differences between the banks, which may happen to correlate with this behaviour. Additionally, their sample period focuses only on periods *after* the implementation of the G-SIB framework; preventing us from testing whether this behaviour existed also prior to implementation.

The novel and uniquely extensive dataset we use in our study allows us to overcome these limitations. Our dataset contains nearly the entire sample of global banks that have been part of the assessment sample in the G-SIB exercise, and stretches between 2010 and 2022. The sheer breadth of the sample of banks and extensive time-period covered is unparalleled, providing the unique opportunity to robustly identify a causal relationship between the G-SIB framework and window-dressing behaviour. Doing so represents a significant contribution to the literature, being the first study to robustly identify an economically and statistically significant *causal* impact of the G-SIB framework on year-end window-dressing.

3. G-SIB framework

The G-SIB framework requires banks identified as globally systemically important to hold additional capital to protect against the negative externalities that would result from their default. The level of capital that G-SIBs are required to hold depends on their degree of systemic importance. The G-SIB framework was implemented in 2013, with the requirement to hold more Common Equity Tier 1 (CET1) capital being gradually phased-in from 2016 to 2019. The methodology underlying the framework is detailed in BCBS (2011), BCBS (2013), and BCBS (2018a), and summarised in this section.

Banks with leverage exposures greater than €200 billion take part in the annual "G-SIB assessment exercise". For most of those banks, this entails submitting a wide range of data to the BCBS that are aggregated into 13 main indicators of banking activity, grouped across five broad categories: size, interconnectedness, complexity, substitutability, and cross-jurisdictional activity.[9] A G-SIB assessment sample of the largest 75 global banks is then identified to be used as a proxy for the global banking sector.[10] For each bank in this sample, across each indicator, an "indicator score" is calculated to reflect a banks' market share of activity in that indicator. That is, scores are calculated *relative* to global activity in that indicator. Indicator scores are then aggregated, according to their relative weighting specified in Table 1, to generate a total "G-SIB score" for each bank. This can be thought of as reflecting a banks' market share of systemic importance.

9 Banks in the "assessment sample" are required to submit this data to BCBS. Those not in the "assessment sample" are required only to disclose the aggregated main indicators.

10 Banks fulfilling any of the following criteria are included in the G-SIB assessment sample: (i) banks that the BCBS identifies as the 75 largest global banks, based on the financial year-end Basel III leverage ratio exposure measure, including exposures arising from insurance subsidiaries; (ii) banks that were designated as G-SIBs in the previous year (unless supervisors agree that there is compelling reason to exclude them); and (iii) banks that have been added to the sample by national supervisors using supervisory judgment.

Indicator-based measurement approach		Table 1
Category (and weighting)	Individual indicator	Indicator weighting
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the Basel III leverage ratio*	20%
Interconnectedness (20%)	Intra-financial system assets*	6.67%
	Intra-financial system liabilities*	6.67%
	Securities outstanding*	6.67%
Substitutability/financial institution infrastructure (20%)	Assets under custody	6.67%
	Payments activity	6.67%
	Underwritten transactions in debt and equity markets	3.33%
	Trading volume	3.33%
Complexity (20%)	Notional amount of over-the-counter derivatives*	6.67%
	Level 3 assets*	6.67%
	Trading and available-for-sale securities	6.67%

* Extended scope of consolidation to include insurance activities.

Source: Basel Committee on Banking Supervision.

Banks' G-SIB scores determine whether they are identified as a "G-SIB" and the associated G-SIB capital requirement they are subject to. Banks with a G-SIB score greater or equal to 130 basis points are identified as G-SIBs and are subject to a range of G-SIB "buffer rates" (capital surcharges). Table 2 outlines the categorisation of banks, based on their G-SIB scores, into "buckets" with associated capital requirements. Banks with a G-SIB score between 130 basis points and 229 basis points fall in "bucket 1", and are required to hold a G-SIB capital surcharge of 1.0% of risk-weighted assets. This capital surcharge increases in increments of 0.5% of risk-weighted assets, with buckets that are 100 basis points wide, until bucket 4. Above bucket 4, the capital surcharge increases by 1 percentage point resulting in a 3.5% associated G-SIB buffer rate in bucket 5.[11]

G-SIB assessment methodology: buckets		Table 2
Capital surcharge bucket	Score range (basis points)	G-SIB buffer rate (% of risk-weighted assets)
Bucket 5	530-629	3.5%
Bucket 4	430-529	2.5%
Bucket 3	330-429	2.0%
Bucket 2	230-329	1.5%
Bucket 1	130-229	1.0%

Source: Basel Committee on Banking Supervision.

There are two features of the framework that are particularly important for the rest of this paper. First, data submitted by banks are based on a single point-in-time value; with the reference date (financial year-end) known by the bank ex ante.[12] Second, the capital surcharges associated with each bucket are applied as a percentage of a bank's total risk-weighted assets. So, an increase in G-SIB score from, for

11 The G-SIB framework also allows for jurisdictions to exercise supervisory judgment to designate a bank that has a score of less than 130 basis points as a G-SIB, or move a bank into a different bucket. This application must be approved by the BCBS, and the criteria for downgrading a bank into a lower bucket than that assigned by the quantitative assessment exercise are stricter than those for upgrading to a higher bucket.

12 Some of the data used for the calculation of the G-SIB indicators are cumulative amounts over the financial year.

example, 229 basis points to 230 basis points would require the bank to hold additional capital equal to 0.5% of its total risk-weighted assets. This is a rather costly consequence for the bank. Taking these features together, one might expect banks to have relatively strong incentives around these thresholds to window-dress their activity at year-end in order to maintain a materially lower capital surcharge.

In the rest of the paper, we detail how we exploit these features to causally identify the G-SIB framework as driving observed year-end window-dressing behaviour.

4. Data, descriptive evidence, and empirical strategy

4.1 Data

We leverage a novel and confidential supervisory dataset collected by the BCBS as part of a quantitative impact study it carried out in 2023. The dataset comprises quarterly data between Q1 2010 and Q2 2022 on 70 global banks across 16 jurisdictions.[13] The banks in the sample have all, in at least one period, taken part in the G-SIB assessment exercise. In other words, their leverage exposures have exceeded €200 billion in at least one period since the introduction of the G-SIB framework. Of these banks, 24 have been identified as G-SIBs in at least one year.

The dataset covers a wide range of variables. These include variables that directly contribute to banks' G-SIB scores (notional OTC derivatives and repos) for the purpose of measuring window-dressing behaviour.[14] We focus on these variables as they have been identified as most sensitive to window-dressing behaviour, in part due to the high frequency and liquid nature of the markets they are traded in.[15] The dataset also includes bank balance sheet data, which we use to capture (and, in our empirical strategy, control for) bank-specific characteristics such as size, business model, and level of Tier 1 capital. The full set of variables is outlined in Appendix A.

With our sample consisting of nearly the entire population of global banks, our data encompass the vast majority of global activity for each of these variables. For instance, aggregate notional OTC derivatives across our sample in Q2 2022 are €618 trillion – more than 97% of the €632 trillion of total global activity.[16]

The data submitted are generally of good quality, and particularly so for the variables used to measure window-dressing. For many of the other balance sheet variables, data availability becomes significantly more comprehensive after 2015.

4.2 Descriptive evidence

First, we plot the raw aggregate evolution of our variables of interest in a number of major jurisdictions (the European Banking Union, the United Kingdom and the United States). Graphs 1a-1c show the time series for notional OTC derivatives and repos. Across the board, we observe a tendency for contractions

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[13] The jurisdictions are: Australia, Brazil, Canada, European Banking Union (Belgium, France, Germany, Italy, Netherlands, Spain), India, Japan, Singapore, Sweden, Switzerland, the United Kingdom and the United States. Data for most jurisdictions are available back to 2010. An exception is data for European Banking Union banks, which are available from 2014. Data are collected from all jurisdictions as at their respective financial quarter-ends. That is, for jurisdictions who have non-standard financial period ends (such as Canada and Japan), data is collected on a basis that is consistent with their BCBS submissions.

[14] Proxies for these variables are used for some banks.

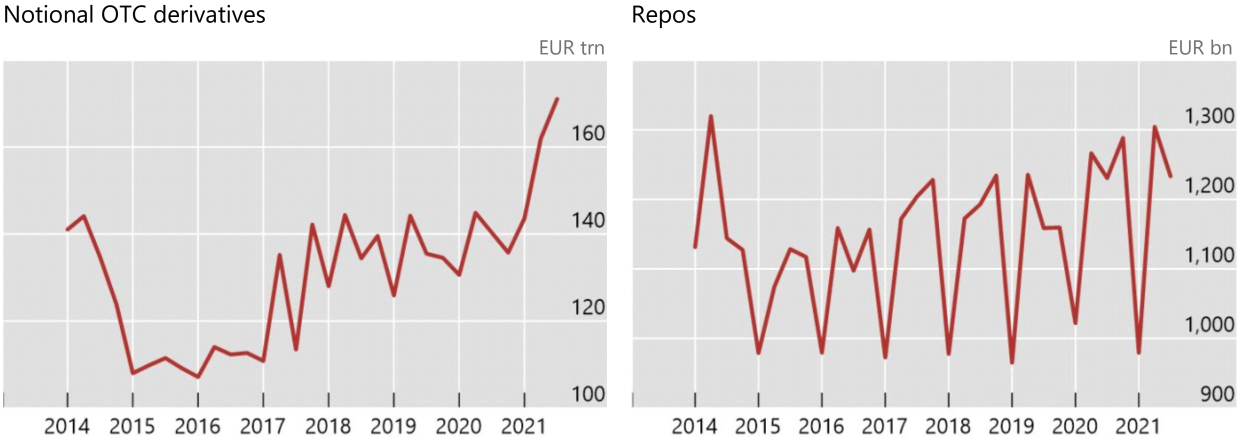
[15] Notional OTC derivatives contribute to a specific G-SIB indicator in the *Complexity* category. Repos are not a separate indicator, but contribute to several in the *Cross-Jurisdictional* and *Interconnectedness* categories.

[16] Statistics on total global notional OTC derivatives activity are reported by the Bank for International Settlements, www.bis.org/publ/otc_hy2311.htm.

in activity at year-end (identified by the vertical white lines) relative to adjacent quarter-ends, after the implementation of the G-SIB framework in 2016.[17] These contractions are particularly striking across banks in the European Banking Union (BU) for both notional OTC derivatives and repos, and across US banks for notional OTC derivatives. For each, the year-end contractions follow rather sharp "V-shapes" and are in the order of magnitude of several trillions of euros for notional OTC derivatives, and €100 billion for repos. Appendix B depicts figures across other jurisdictions in our sample.

Aggregate evolution of notional OTC derivatives and repos

European Banking Union — Graph 1a

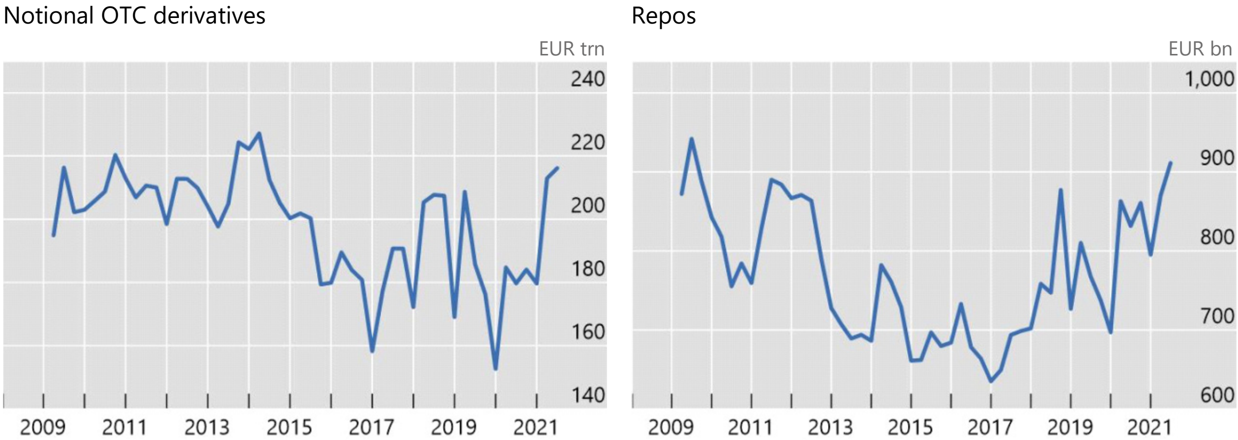


Note: The tick marks on the x-axis denote year-end values.

Source: Basel Committee on Banking Supervision, authors' calculations.

Aggregate evolution of notional OTC derivatives and repos

United States — Graph 1b



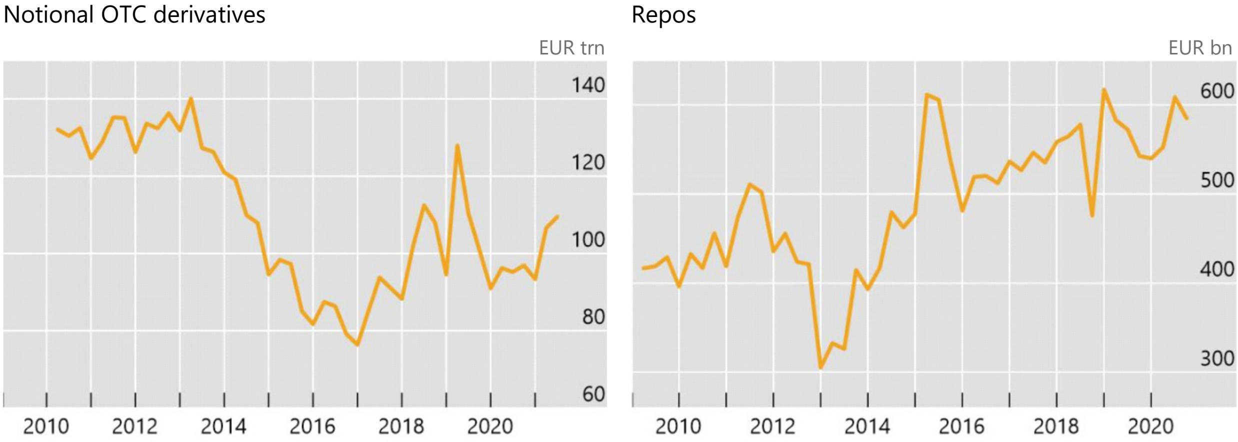
Note: The tick marks on the x-axis denote year-end values.

Source: Basel Committee on Banking Supervision, authors' calculations.

[17] In some jurisdictions, we observe typically weaker contractions in year-end activity prior to 2016. This is consistent with the discussion in Section 2 that there are also other contributing factors to this behaviour, such as cyclical supply-side dynamics, that are independent of the G-SIB framework.

Aggregate evolution of notional OTC derivatives and repos

United Kingdom Graph 1c



Note: The tick marks on the x-axis denote year-end values.

Source: Basel Committee on Banking Supervision, authors' calculations.

The raw data depict behaviour that is consistent with window-dressing. The next question we ask is whether there is any raw correlation between observed window-dressing by banks and incentives originating from the G-SIB framework. We follow studies described in Section 2 to focus on banks' proximity to bucket thresholds as an exogenous G-SIB-specific source of variation for window-dressing incentives. Specifically, we test the correlation between how close to a bucket threshold banks *expect* to be in the upcoming G-SIB assessment exercise, and their level of window-dressing at year-end.[18] We capture banks' *expected* proximity by their proximity in the previous assessment exercise, adjusted to account also for banks' growth rate relative to the market and exchange rate dynamics, since the previous assessment exercise.[19] We measure window-dressing as:

$$\text{Window Dressing}_{i,t,y} = \frac{(Q3_{i,t,y} - Q4_{i,t,y}) + (Q1_{i,t+1,y} - Q4_{i,t,y})}{0.5 \times (Q3_{i,t,y} + Q1_{i,t+1,y})} \times 100 \qquad (1)$$

This captures the proportional fall (given as a percentage) in bank i's activity of variable y in the fourth quarter of year t ($Q4_t$) relative to the adjacent quarters $Q3_t$ and $Q1_{t+1}$.[20] Greater values of $\text{Window Dressing}_{i,t,y}$, reflect greater contractions in the fourth quarter of the year.

Graph 2 shows a scatterplot with banks' expected proximity in a given period on the x-axis, and their degree of window-dressing of notional OTC derivatives in that same period on the y-axis. The plot shows observations for each bank in each period since 2016, when the G-SIB capital requirement began to be gradually phased in.

There are a few interesting remarks to make. First, most of the observations (ignoring their colour or size, for now) are above the horizontal dotted line. This indicates that Q4 activity of notional OTC

18 US banks are subject to an alternative G-SIB methodology imposed by the Federal Reserve Board, known as "US Method 2". This methodology is similar to the BCBS methodology, but (typically) more stringent in the capital requirements that it levies, and is thus the binding framework for US banks. To account for this, we calculate US banks' "proximity" based on their distance to bucket thresholds in the US Method 2 G-SIB methodology (see Fed (2015)).

19 Banks' expected proximity can be measured in several ways. For instance, we could simply take their proximity in the previous assessment exercise, which banks will likely use as a gauge. Adjusting this for the additional information that banks will have when it comes to potentially 'deciding' how much to window-dress, generates a more sophisticated measure. We present similar evidence based on simpler measures in Appendix C. See notes to Graph 2 for a formal representation of the expected proximity measure.

20 We also use other measures of window-dressing for robustness. These are specified in Appendix C.

derivatives is lower than that in adjacent quarters for most banks in most periods, suggesting some degree of window-dressing across the board.

Second, we observe a bunching of particularly sharp window-dressing just to the left of the vertical dotted line. That is, when banks expect to be *just below* a bucket threshold, they seem to window-dress significantly more. Intuitively, this makes sense. These are the banks that, were they not to window-dress, may find themselves being moved up into the higher bucket. Thus, they window-dress to prevent this by increasing the distance to the bucket threshold.[21] Meanwhile, when banks find themselves either far away from bucket thresholds, or just above a bucket threshold, they seem to window-dress less. The latter observation suggests that incentives to window-dress may not be symmetric above and below a threshold. A possible explanation is that banks who find themselves just above a bucket threshold may expect supervisory judgment to be used to reallocate them back up if they did dip just below and are, thus, resigned to the higher bucket.[22] Hence, the costs of forgoing trade and activity by window-dressing outweighs the benefits in these cases. This could also explain the small grouping of banks who expect to be above or very marginally below a bucket threshold but do not window-dress – potentially reflecting banks that have *already* been moved up by supervisory judgment, and expect the same to happen again.

Third, the fact that most observations of significant window-dressing lie to the left of the vertical dotted line, indicates that banks that seek to remain below G-SIB bucket thresholds – by window-dressing – indeed manage to do so successfully. This is corroborated in Graph C.1 in Appendix C, where we plot window-dressing against where banks *actually* end up with their G-SIB scores. We show that banks who window-dress most significantly manage to end up just below G-SIB bucket thresholds.

Fourth, comparing the dots of different size, we distinguish between banks that are constrained by the G-SIB buffer (the big circles) and those that are instead constrained by the D-SIB buffer (smaller circles). That is, while all the banks in our sample take part (or have taken part) in the G-SIB assessment exercise, some banks, including G-SIBs, may also be subject to a D-SIB capital surcharge. Under the Basel III standards, the higher of the D-SIB and G-SIB buffer binds for any given bank. Hence, those banks that are subject to a higher D-SIB than G-SIB buffer, will not be "constrained" by the capital requirements that result from the G-SIB framework, while peers (in theory) would.[23] This group of banks should, thus, be less incentivised to window-dress for G-SIB purposes, as the G-SIB requirements have no implications for their capital requirements. Indeed, we observe that "D-SIB constrained" banks do seem to, on average, window-dress *less* than "G-SIB constrained" peers.

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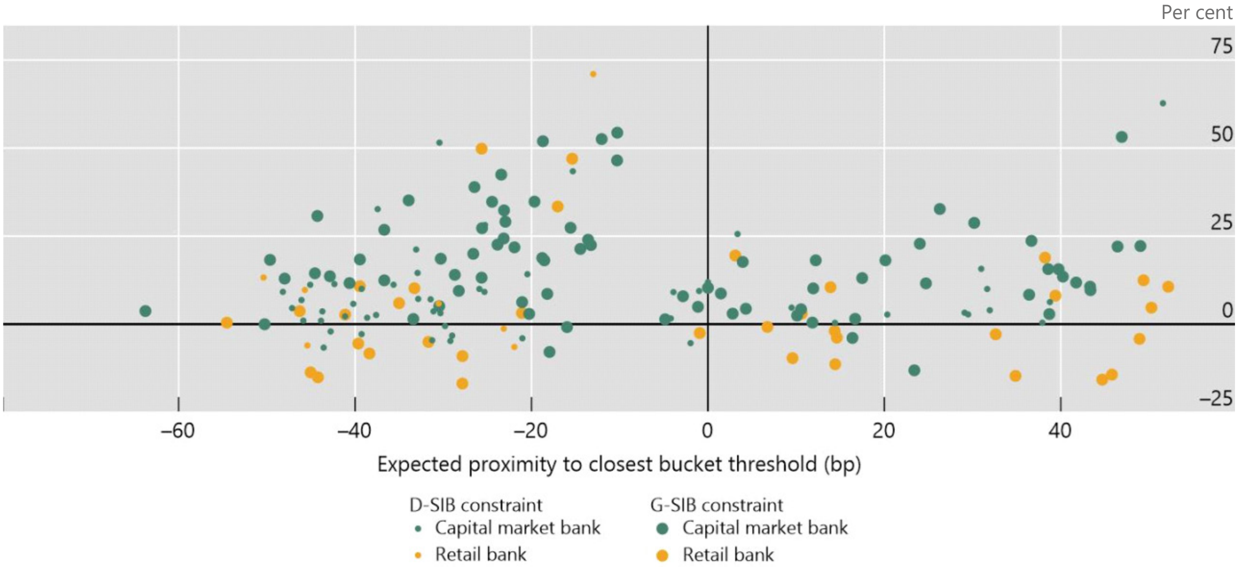
21 The relative nature of the framework means there is always a degree of uncertainty around G-SIB scores. Indeed, we see that the banks just below a threshold who window-dress significantly, seem to aim for a healthy buffer below the threshold, to reduce the risk of being moved up.

22 In contrast, it indicates that those banks just below do not expect supervisory judgment to be used to bump them back down if they did end up being pushed into the higher bucket. This is consistent with the fact that the criteria for exercising supervisory judgment is itself asymmetric for upgrading and downgrading a bank.

23 We define a bank as 'G-SIB constrained' if its G-SIB buffer rate is greater or equal to their D-SIB buffer rate. In these cases, this bank would, in theory, be concerned about an increase to its G-SIB capital surcharge.

Association between proximity to G-SIB bucket thresholds and window-dressing of notional OTC derivatives

Since implementation of the G-SIB framework | Graph 2



Note: The y-axis reports the degree of window-dressing by a bank, calculated according to Equation (1) in the main text. Expected proximity measures how close a bank i expects to be to a bucket threshold at time t. A value of 0 bp suggests they will be exactly on a threshold, -30 bp indicates they expect to be 30 bp *below*, with +30 bp indicating *above*. Formally: $Expected\ Proximity_{i,t} = Proximity_{i,t-1} \times \left[\frac{1+sign(Proximity_{i,t-1})x growth_{i,t}}{1+sign(Proximity_{i,t-1})x\frac{1}{N}\sum_i growth_{i,t}}\right] \times \left[1+\left(1-\frac{BIS\ FX(Q3_{i,t})}{BIS\ FX(Q4_{i,t-1})}\right)\right]$, where ($sign(Proximity_{i,t-1})$ ensures the same sign is maintained. $Growth_{i,t}$ refers to the growth rate of bank i's size in year t. BIS $FX_{i,t}$ refers to bank i's respective official BIS exchange rate to the Euro, in a specific period. We show observations for banks that were within at least 50 bp of a bucket threshold in at least one year. We also remove (the very few) anomalous observations of -100% window-dressing (indicating that a bank more than doubled their activity in Q4) on data quality grounds.

Source: Basel Committee on Banking Supervision, authors' calculations.

Graph 3 corroborates these observations. It shows the average contraction of notional OTC derivatives at year-end, relative to adjacent quarters, for different groups of banks. Specifically, it shows that, since the implementation of the G-SIB framework in 2016, year-end activity across all banks is, on average, 9% lower than at adjacent quarters. The 70 banks in our sample were responsible for €618 trillion of notional OTC derivatives activity in Q2 2022, so a 9% fall equates to year-end contractions that are in the order of magnitude of several 10 trillion. The degree of year-end contractions increases as we sequentially filter down to banks which have: (i) a capital market business model (14% year-end contraction across 36 banks); (ii) are also G-SIB (rather than D-SIB) constrained (18% contraction across 17 banks); and (iii) are typically just below a G-SIB bucket threshold (22% contraction across 10 banks). The latter group were responsible for €302 trillion of notional OTC derivatives activity in Q2 2022 (accounting for nearly 50% of total global activity).

Additionally, Graph 3 indicates that the average degree of window-dressing *increased* after the implementation of the G-SIB framework in 2016 (increasing from 7% over the full sample period to 9% after 2016).

Descriptive evidence from Graphs 1, 2 and 3 depict both the existence of window-dressing, and, in relation to notional OTC derivatives, a correlation with incentives derived specifically from the G-SIB

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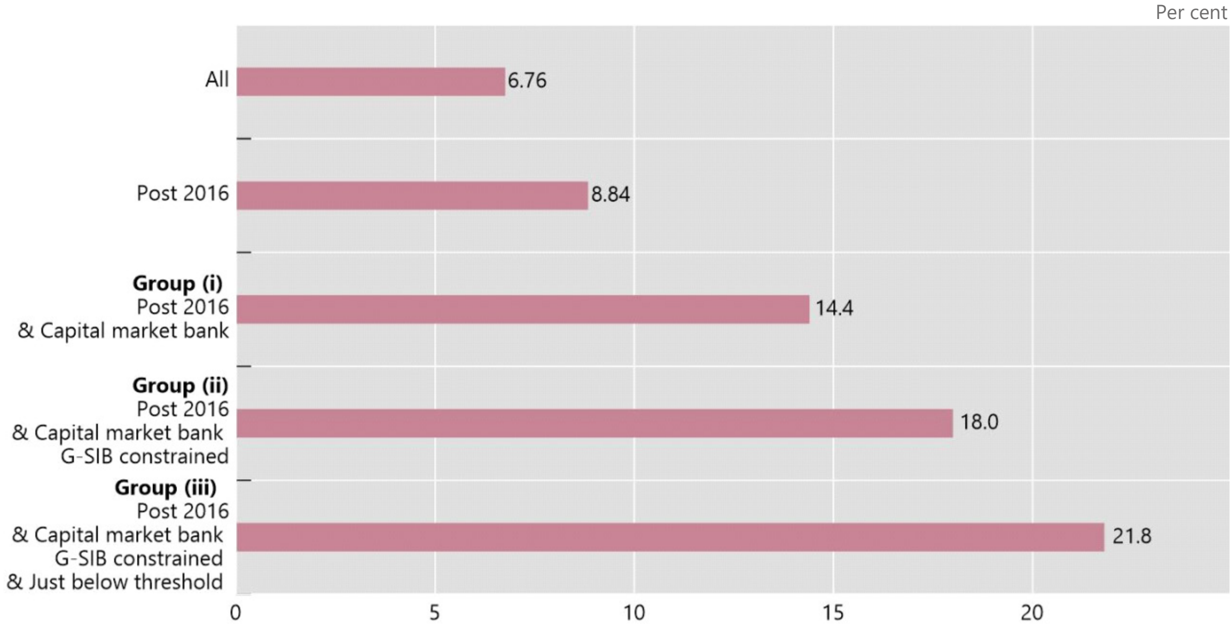
[24] We distinguish between retail and capital market banks based on their ratio of trading book to total assets. Banks with above median trading book to total assets ratios are defined as capital market banks.

framework. However, to draw causal inferences, we need a robust empirical strategy to appropriately account for potential confounding factors. We describe this strategy in the next subsection.

Average window-dressing of notional OTC derivatives

Graph 3



Note: "Average Window-Dressing (%)" is given by the average degree of window-dressing for notional OTC derivatives across banks and time, where window dressing is measured as in Equation (1) in the main text. The full sample contains 70 banks and accounts for approximately 97% of total global notional OTC derivatives activity. Group (i) consists of 36 and accounts for around 85% of global activity, group (ii) 17 banks and 70% of global activity, and group (iii) 10 banks and 50% of global activity.

Source: Basel Committee on Banking Supervision, authors' calculations.

4.3 Empirical Strategy

Causal effects could be identified by two different empirical methods. The first would rely on the fact that our sample includes nearly the entire population of global banks which have, in at least one period, taken part in the G-SIB assessment exercise. Focusing on the period after the implementation of the G-SIB framework we could directly test the association of banks' proximity to G-SIB bucket thresholds with window-dressing behaviour. As discussed above, banks' proximity to bucket thresholds should not, in theory, be systematically correlated with any other sources of window-dressing incentives. Although the sample size is not so large as to *rule out* some factors correlating (by chance) with proximity, the breadth of banks should provide us with sufficient natural variation such that bank-specific characteristics such as size, business model, or country-level differences that may impact window-dressing behaviour can be appropriately and robustly controlled for. Controlling for *all* possible endogenous factors should allow us to identify causal effects.

The second method, which we use for our analysis, goes one step further and makes use of the fact that our dataset stretches back to *before* the implementation of the G-SIB framework. This allows us to run a difference-in-differences empirical strategy comparing the behaviour of banks with different proximities to G-SIB bucket thresholds, pre- and post-implementation of the G-SIB framework.[25] This has several advantages. First, as we saw in Graph 2, window-dressing incentives may not be symmetric or linear. Thus, a standard linear regression model may not be best suited to capturing the association. Instead, *grouping* banks by the degree to which they have G-SIB-specific window-dressing incentives more

[25] Specifically, banks are designated into one of the groups for the entirety of the sample period. This is necessary to be able to compare any *changes* in behaviour between banks in the two groups.

directly tests the correlation observed in Graph 2. Second, in this set up, the importance of meticulously controlling for any, and all, potential endogenous factors is relaxed. An observation that the group of banks which have greater G-SIB-specific window-dressing incentives begin to window-dress significantly more than peers after the implementation of the G-SIB framework, having exhibited similar behaviour beforehand, would be sufficient to identify a *causal* effect *unless* there exists some unobserved factor that simultaneously satisfies each of the following conditions:

1. It is systematically correlated with year-end contractions in activity.
2. It is systematically correlated with banks in one group and not the other.
3. These systematic correlations began only *after* the implementation of the G-SIB framework.

There exist factors that satisfy condition (1): cyclical supply-side dynamics, compression processes for risk management purposes, and other regulatory policies and accounting standards. Additionally, some of these factors, such as regulatory policies relating to Basel III, may have been implemented at a similar time to the G-SIB framework. However, as described above, in theory, banks' proximity to G-SIB bucket thresholds should be an *independent* source of variation. It should not be systematically correlated with other factors common to one group and not the other (condition (2)), let alone beginning only after the implementation of the G-SIB framework (condition (3)). Hence, there should exist no factor, beyond the G-SIB framework, that simultaneously satisfies each of these conditions and can explain the observation above.

To reduce the likelihood that some unobserved factor *happens* to satisfy these conditions *entirely by chance* in our sample, we do, naturally, control for possible systematic differences between our two groups of banks. But the difference-in-differences setup allows us to be more sparing in our use of controls and prioritise degrees of freedom for causal inferences. Specifically, we run the following baseline regression:

$$\text{Window Dressing}_{i,p,t,y,c} = \beta_1 \text{ Post G-SIB}_t \text{ x Just Below}_i + \delta \text{ Bank Controls}_{i,t} + \gamma_c + \varepsilon_{i,t} \quad (2)$$

Where $\text{Window Dressing}_{i,p,t,y,c}$ is the degree of window-dressing for bank i in group $p = \{0,1\}$, which depends on its proximity to a bucket threshold, in period $t = [2010, 2021]$, across variable y = {notional OTC derivatives, repos}, in country (or region) c. $\text{Just Below}_i = \{0,1\}$ takes the value of 1 in our baseline regression if a banks' median proximity to a bucket threshold over the sample period is in the range [-40 bp, 0 bp].[26] $\text{Post G-SIB}_t = \{0,1\}$ takes the value 0 if t is before the implementation of the G-SIB framework in 2016, and 1 if t is after. $\text{Bank Controls}_{i,t}$ account for bank i's size, business model (whether it is a capital market or retail bank), its level of Tier 1 capital, and whether it is constrained by the G-SIB or D-SIB framework.[27] γ_c are country fixed effects.

[26] This specific range is motivated by the observations in Graph 2. We also test this specification using alternate ranges, including: [+/- 25 bp], [+/- 15 bp], [-20 bp, +15 bp], [-25 bp, +5 bp], [-30 bp, 0 bp] as well as distinguishing between whether a bank is a G-SIB, and whether its closest bucket is bucket 1 (where supervisory judgment to identify a G-SIB below the threshold may be more likely), to account for any further asymmetric incentives. The results are similar across all specifications, presented in Appendix C. For US banks, we again calculate their "proximity" based on their distance to bucket thresholds in the US Method 2 G-SIB methodology, as this is the binding framework for these banks.

[27] Size and Tier 1 capital are time-varying. To account for whether a bank is G-SIB or D-SIB constrained and whether a bank is capital market or retail, we use interaction terms: $\text{Post G-SIB}_t \text{ x G-SIB constrained}_i$ and $\text{Post G-SIB}_t \text{ x Capital market bank}_i$. In the former case, this allows us to account for any other systematic changes in behaviour amongst banks that became constrained by the G-SIB framework after its implementation, independent of their proximity to bucket thresholds. In the latter case, we are able to account for any systematic changes in behaviour amongst capital market banks that may have arisen at the same time as the G-SIB framework was implemented, but independently of it, for instance by changes to compression or derivative clearing practices, which may impact these banks more. A $\text{Capital market bank}_i = \{0,1\}$ is defined as such, taking the value of 1, if the bank has above median trading book to total assets ratio in the sample.

5. Results

5.1 Notional OTC Derivatives

We split banks into two groups. The first group of banks lie, more often than not, just below a bucket threshold through the sample period.[28] The second group consists of banks that lie either above or far away from a bucket threshold. If the G-SIB framework generates window-dressing incentives and is responsible for the behaviour observed in Graph 2, we would expect the first group of banks to begin to engage in greater window-dressing behaviour than peers only *after* the implementation of the framework.

This is exactly what we see. Graph 4 plots the evolution of window-dressing of notional OTC derivatives across these two groups of banks from Q4 2010 to Q4 2021.[29,30] Prior to the implementation of the G-SIB framework, both groups of banks exhibit similar trends. On average, each group contracts their year-end activity by about 5% relative to adjacent quarters. However, after the implementation of the G-SIB framework in Q4 2016, the group of banks who lie "Just Below" bucket thresholds begin to window-dress significantly more, on average, while the behaviour of their peers remains unchanged. Indeed, window-dressing amongst the "Just Below" group increases to above 20% in 2019. The aggregate notional OTC derivatives across the 15 banks in this group were €351 trillion in Q2 2022, which accounted for 55% of global activity. Hence, a 20% contraction in activity at year-end relative to adjacent quarters implies a fall in the order of magnitude of €70 trillion in that year (or, approximately 10% of global activity). While the degree of window-dressing then falls slightly in 2020 and 2021, it remains at nearly 15%, and remains visibly greater than peers.

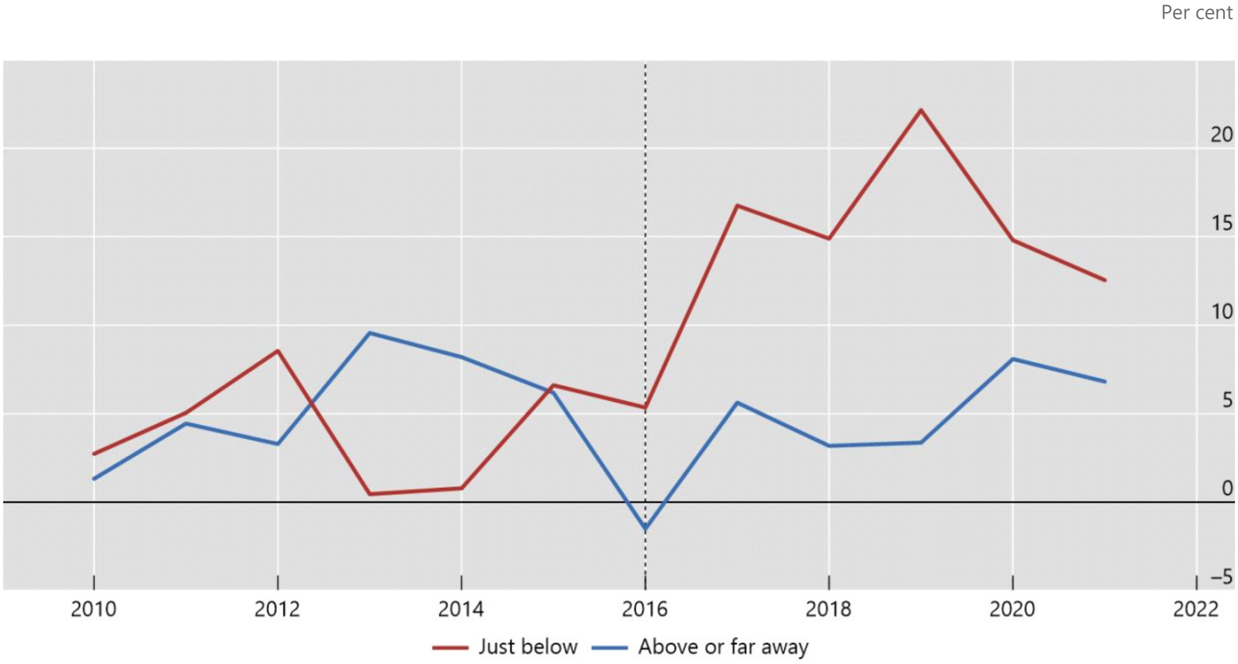
28 Specifically, this group of banks were "Just Below" a bucket threshold in at least half of the periods in the sample. We define "Just Below" in a number of different ways, described below.

29 For this plot, we define the "Just Below" group as those banks who were within [-40 bp, 0 bp] of the next bucket for the majority of periods in the sample. For robustness, we plot this using several different variations of this range and find similar observations. These are described in Appendix C.

30 Using this definition, there are 15 banks (11 G-SIBs) in our "Just Below" group, and 55 banks (13 G-SIBs) in the control group. Amongst the "Just Below" group, 12 banks report data in all periods, while three banks report only from 2015.

Evolution of window-dressing of notional OTC derivatives

For banks "Just Below" and "Above or Far Away" from a bucket threshold | Graph 4



Note: The y-axis reports window dressing, measured according to Equation (1) in the main text. The tick marks on the x-axis refer to the fourth quarter of that year. A bank is grouped as "Just Below" if, more often than not, its proximity to a bucket threshold was within the range [-40 bp, 0 bp]. There are 15 banks in this group (11 G-SIBs), and 55 banks in the "Above or Far Away" group (13 G-SIBs). The 15 banks in the "Just Below" group accounted for 55% of global notional OTC derivatives activity in Q2 2022. Data for CA, JP, UK, and US banks are available back to 2010 Q4, data for BU banks are available from 2014 Q4. We winsorise the group of banks depicted, removing the 10% tails. We do this because of a small number of highly anomalous window-dressing observations (in both directions) amongst some of the smaller banks. The dotted vertical line indicates the implementation date of the G-SIB framework.

Source: Basel Committee on Banking Supervision, authors' calculations.

We test whether this observation holds once we account for possible systematic differences between the two groups of banks, by running the regression specification outlined in Section 4.3. Table 3 presents the results of the regression results for notional OTC derivatives.[31] Column 1 represents the simple bivariate association without any controls. We then add controls one-by-one to account for whether a bank is G-SIB rather than D-SIB constrained (column 2), its business model (column 3), size (column 4), and capitalisation level (column 5). We also add country-level fixed effects in column 6 to strip out any systematic differences between jurisdictions. We see that the Post G-SIB_t x Just Below_i term of interest is statistically significant in each specification.[32,33]

The magnitude of the coefficient on Post G-SIB_t x Just Below_i also indicates that this effect is economically significant. The coefficient in column 6 (the most conservative specification) tells us that, on average, a bank just below a G-SIB bucket threshold began to window-dress by an additional 8 percentage points relative to peers after the implementation of the G-SIB framework. Global activity in Q2 2022 was €632 trillion, of which "Just Below" banks account for more than half. This tells us that the response of banks to the G-SIB framework is *directly* responsible for year-end contractions in notional OTC derivatives

[31] To note, we winsorise the sample, removing the 5% tails. We do this because of highly anomalous window-dressing observations amongst a small number of the smaller banks.

[32] We also test the robustness of this result against a battery of balance sheet variables to account for potential differences in banks' liquidity, density ratio, profitability, provisions, non-performing loans, and dividends. Our results remain across each.

[33] We have observations for five periods prior to the implementation of the framework, and six periods after.

activity, on average, in the order of magnitude of €30 trillion (8% of €351 trillion) each year – approximately 5% of global activity.[34,35]

Baseline regression results

Table 3

	Window-Dressing of notional OTC derivatives							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Post G-SIB}_t \times \text{Just Below}_i$	0.09***	0.08***	0.08***	0.08***	0.08***	0.08***	0.06***	0.11***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
$\text{Post G-SIB}_t \times \text{G-SIB constrained}_i$		0.02	0.02	0.02	0.02	0.02	0.09***	0.10***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
$\text{Post G-SIB}_t \times \text{Capital market bank}_i$			0.01	0.01	0.01	0.02	0.05**	0.02
			(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)
$\text{Size}_{i,t}$				-0.00	-0.00	0.01	0.01	0.01
				(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
$\text{Level of Tier 1 Capital}_{i,t}$					0.09	0.11	0.10	0.11
					(0.16)	(0.19)	(0.28)	(0.47)
Country Fixed Effects	No	No	No	No	No	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full	Full	Total Assets > €400bn	Total Assets > €800bn
Adj R^2	0.06	0.07	0.10	0.10	0.10	0.13	0.24	0.23
Num. obs.	535	535	535	529	527	527	319	172

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. In the regressions window-dressing is measured in decimals, rather than as a %, as in Graphs 2-4.

Source: Basel Committee on Banking Supervision, authors' calculations.

We plot in Graph 5 the estimated coefficients of a variant of our baseline regression (column 6), where instead of a {0,1} Post G-SIB_t dummy, we interact Just Below_i with each *year*.[36] This allows us to test whether there were any fundamental differences in the behaviour of our two groups of banks (accounting for the abovementioned bank-specific characteristics) prior to the implementation of the G-SIB framework. We see that between 2011 and 2015, the degree of window-dressing between the two groups of banks was not statistically significantly different (at the 10% level).[37] However, after implementation, we see that the "Just Below" group window-dresses statistically significantly more than peers in 2017, 2018 and 2019. While this is not then statistically significant in 2020 and 2021 (consistent with the downtick we see in

[34] Note also that the R-squared increases as we add the set of controls and fixed effects. In the baseline regression with the full sample (column 6), our model explains 13% of the variation in year-end contractions. This then increases to nearly 25% as we restrict the sample to the largest banks only in columns 7 and 8, which is rather large for panel data.

[35] One might wonder whether this simply reflects a *substitution* of activity from "Just Below" banks to peers at year-end. That is, whether the reduction in activity amongst 'Just Below' banks is offset by an *increase* in activity by other banks. If this were the case, we would expect the degree of window-dressing amongst the "Above or Far Away" group to have *fallen* after 2016, as they increase their year-end activity to offset the reduction amongst peers. This is clearly *not* what we see in Graph 2. Their behaviour remains unchanged pre- and post-implementation. Thus, we infer that this result reflects an absolute fall in activity, rather than simply a substitution away from "Just Below" banks.

[36] This provides us with an estimated coefficient for the difference in window-dressing between our two groups of interest in each year, rather than simply an average of before and an average for after.

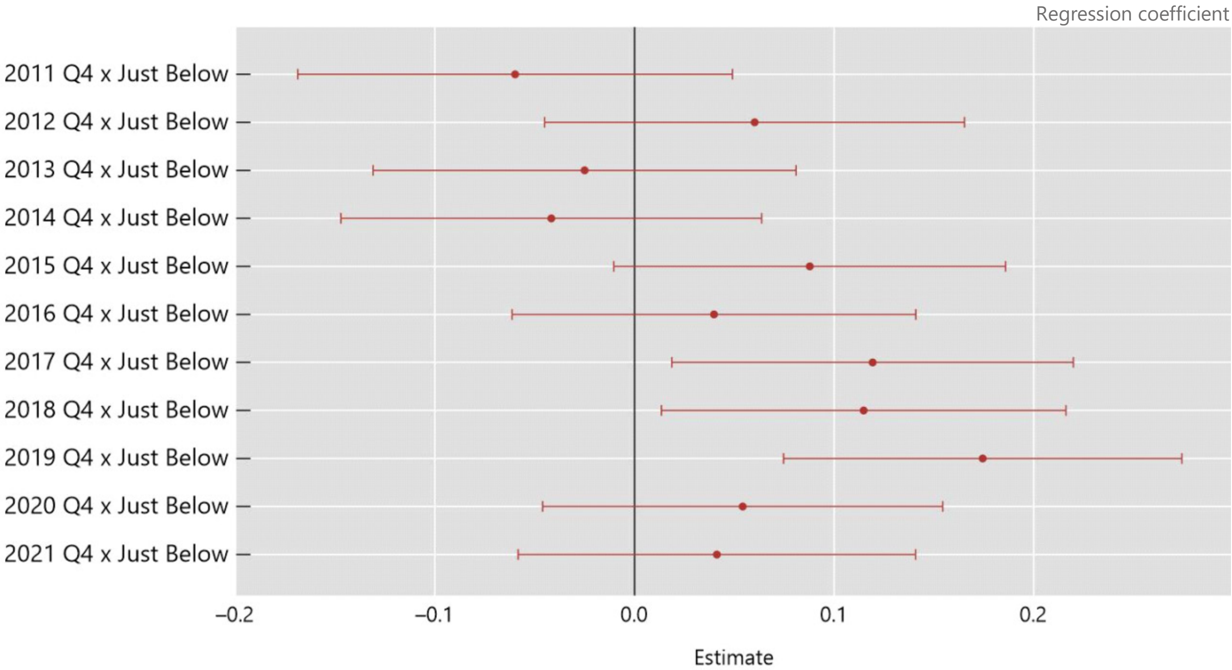
[37] The estimated coefficient seems to become consistently positive from around 2015 (albeit only statistically significantly so from 2017). This may reflect banks acting pre-emptively from 2015, in anticipation of the implementation of the framework in 2016.

Graph 4), the estimated coefficient still indicates that the “Just Below” group window-dressed by approximately 5 percentage points more than peers, on average, in these periods.

One potential explanation for the reduction in average window-dressing amongst the “Just Below” group towards the end of the sample period is that the estimated coefficients in our difference-in-differences specification are downward biased. That is, the true extent of the window-dressing incentivised by the G-SIB framework is *downplayed* in our empirical setup. Our difference-in-differences empirical strategy requires that we keep the banks in each group constant throughout the entire sample period. We define banks as “Just Below” if they are just below a threshold in the majority of the periods in the sample. If these banks were indeed just below a threshold in every single period, our estimated coefficients would be unbiased. However, if in some periods some of these banks were not just below a threshold, and thus were not incentivised to window-dress in that period, the “treatment” group is not entirely “treated”. Similarly, in some periods some banks in the “Above or Far Away” group may actually be just below a bucket threshold, resulting in some “control” group banks actually being treated in some periods. Each of these cases would bias the estimated coefficient downward, *below* the true degree of incentivised window-dressing. Indeed, Table B.2.4 shows that fewer banks in the “Just Below” group were indeed just below a threshold in 2021, dragging down on the average window-dressing amongst this group in that period. This downward bias makes our finding of a statistically and economically significant difference between the two groups even more striking.

Parallel trends hypothesis for baseline specification with notional OTC derivatives

Estimated coefficients of baseline regression in each period — Graph 5



Note: The red lines indicate the 10% confidence intervals. Window dressing is measured as in Equation (1) in the main text. A bank is grouped as “Just Below” if, more often than not, its proximity to a bucket threshold was within the range [-40 bp, 0 bp]. There are 15 banks in this group (11 G-SIBs). Coefficient estimates measure the window-dressing of the “Just Below” group relative to the “Above or Far Away” group in decimal points.

Source: Basel Committee on Banking Supervision, authors’ calculations.

We test the causal relationship identified against a host of robustness checks. For instance, one potential concern may be that the smaller banks in the “Above or Far Away” group might be skewing the observed behaviour of this group.[38] We seek to account for this by controlling for bank size in our baseline specification, but also go one step further in limiting the sample of banks to those with total assets of at least €400 billion (Table 3, column 7) and €800 billion (Table 3, column 8).[39] This reduces the risk that particularly "small" global banks are skewing the observed behaviour of the control group. Indeed, we see from column 8 that the difference in window-dressing between our two groups of banks becomes even more significant when we compare only the largest banks; banks just below the threshold window-dress by an additional 13 percentage points post-implementation relative to peers. Additionally, the R-squared increases in the regression specifications based on the restricted sample, with our models explaining nearly 25% of the variation in year-end contractions.

We also test the robustness to different ranges of proximity to thresholds as well as different measures of window-dressing. Our results, presented in Appendix C, are robust across the board.

5.2 Repos

The results presented so far have focused on notional OTC derivatives. In relation to repos, we similarly observe striking year-end contractions (Graph 1), in the order of magnitude of €100 billion. This behaviour also seems to correlate with banks' proximity to bucket thresholds, in particular if we focus on G-SIB constrained capital market banks (who are best *able* to window-dress and subject to G-SIB surcharges) (Graph D.1). Moreover, in our baseline difference-in-differences regression specification, we also obtain a positive coefficient for our Post G-SIB_t x Just Below_i variable of interest, estimating that banks in the "Just Below" group increased the degree to which they window-dressed repos after the implementation of the G-SIB framework by 13 percentage points, relative to peers (Table D.1).[40] However, this result is only marginally significant at the 10% level, and not as statistically robust as the finding on Notional OTC Derivatives. Thus, we conclude that, while there seems to be an association present between the G-SIB framework and window-dressing of repos, we treat these with more caution.

One potential explanation for why our results on repos are less statistically powerful than those on notional OTC derivatives may be related to the quarterly frequency of our dataset.[41] Repos are traded at typically higher frequencies than notional OTC derivatives, and so may be less costly to window-dress at very short notice. Thus, more banks are incentivised to engage in this behaviour, even if they are not necessarily just below a bucket threshold. Bassi et al (2023) exploit granular, high frequency transaction level data to compare window-dressing behaviour of specific repo positions. In particular, they identify a causal effect with the G-SIB framework by comparing volumes of one-week repo positions with overnight positions in the last four days of a quarter. Thus, our dataset may simply be insufficiently granular to robustly identify this behaviour for repos.

6. Conclusions

Banks have long been known to contract their market activity around period-end reporting dates. Empirical studies have consistently found that this regulatory arbitrage behaviour, known as "window-dressing", results in misleading representations of banks' activity and miscalculation of systemic risk in a number of regulatory metrics, with both micro- and macro-prudential implications. However, data

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38 Table B.2 in Appendix B presents the summary statistics for these two groups.

39 Filtering down to banks with total assets > €400 billion, we have 43 banks in total, accounting for 91% of global activity. Of these, 14 are in the "Just Below" group. Filtering down to banks with total assets > €800 billion, we have 23 banks in total, accounting for 67% of global activity. Of these, nine are in the "Just Below" group.

40 Graphs D.1 and D.2 in Appendix D depict this.

41 Indeed, the fact that we *are* able to identify this causal relationship in relation to notional OTC derivatives is rather striking.

limitations have constrained the capability of studies to attribute incentives for this behaviour to *specific* policies, restricting policymakers' scope to impose on banks costly mitigating reporting reforms.

In this paper, we exploit a novel and uniquely extensive dataset to causally identify banks' response to the G-SIB framework – imposed by the BCBS after the Great Financial Crisis – as a material driver of year-end window-dressing behaviour. Using quarterly data between 2010 and 2022 on nearly the *entire* sample of global banks to have taken part in the G-SIB assessment exercise, we are able to employ a difference-in-differences empirical strategy exploiting the fact that the G-SIB framework generates exogenous heterogeneous window-dressing incentives across banks. We find that banks with greater G-SIB-*specific* window-dressing incentives began to window-dress notional OTC derivatives significantly more than peers *after* the implementation of the framework, having previously exhibited broadly similar behaviour. This result is economically, as well as statistically, significant. Window-dressing by banks incentivised by the G-SIB framework is directly responsible for year-end contractions of notional OTC derivatives activity in the order of magnitude of €30 trillion – equating to approximately 5% of global notional OTC derivatives activity and explaining around *half* of the contractions observed at year-end.

The policy implications are clear. Banks' attempts to lower their G-SIB scores are a material driver of year-end window-dressing activity. Efforts to reduce incentives to window-dress for G-SIB purposes would not only reduce the risk of misidentifying G-SIBs and misallocating regulatory capital within the G-SIB framework, but would potentially have positive spillovers for the accurate provision of risk in other regulatory frameworks and materially reduce year-end volatility in certain markets. Indeed, in conjunction with the publication of this working paper, the BCBS has published a consultative document setting out potential measures to address window-dressing behaviour in the G-SIB framework (see BCBS (2024)).

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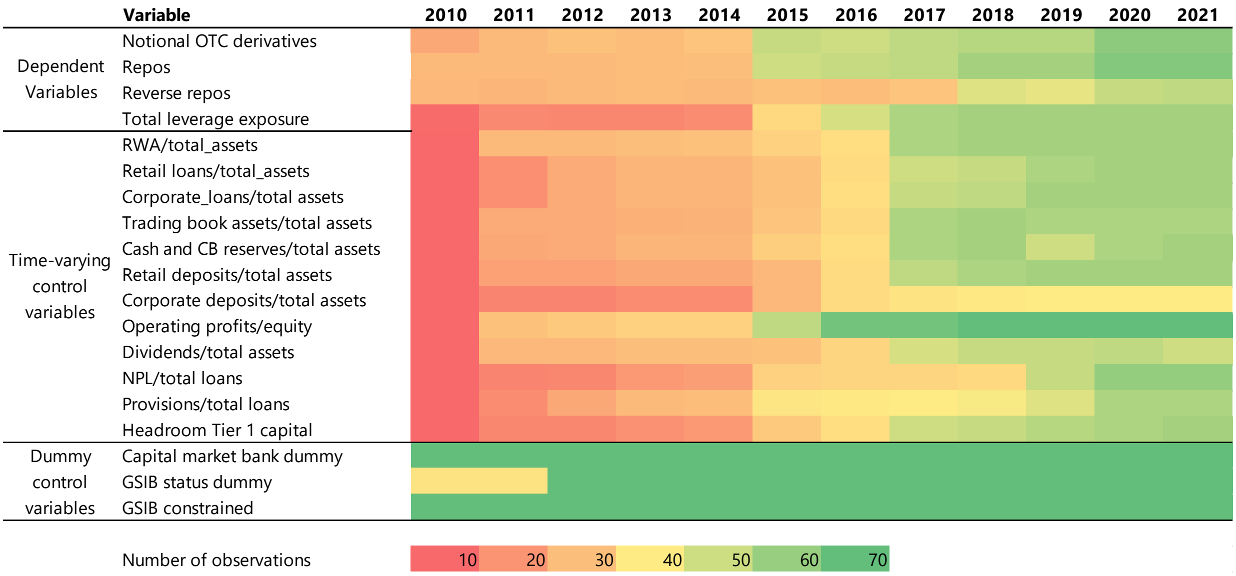
Appendix A: Data collected

Heat map for data availability

Graph A.1

Number of observations



Note: For European Union banks, total leverage exposure is used as scaling variable instead of total assets.

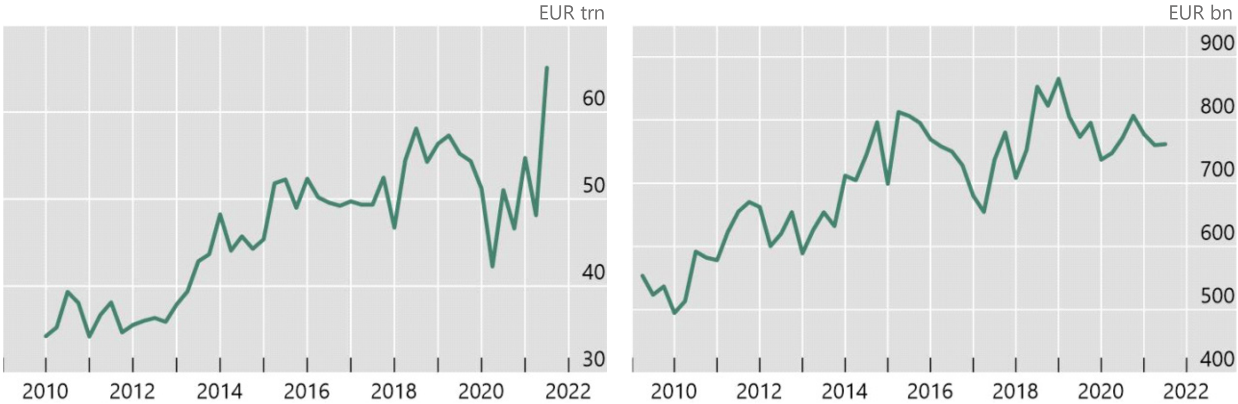
Source: Basel Committee on Banking Supervision, authors' calculations.

Appendix B: Further descriptive statistics

Aggregate evolution of notional OTC derivatives and repos

Japan | Graph B.1.1

Notional OTC derivatives | Repos



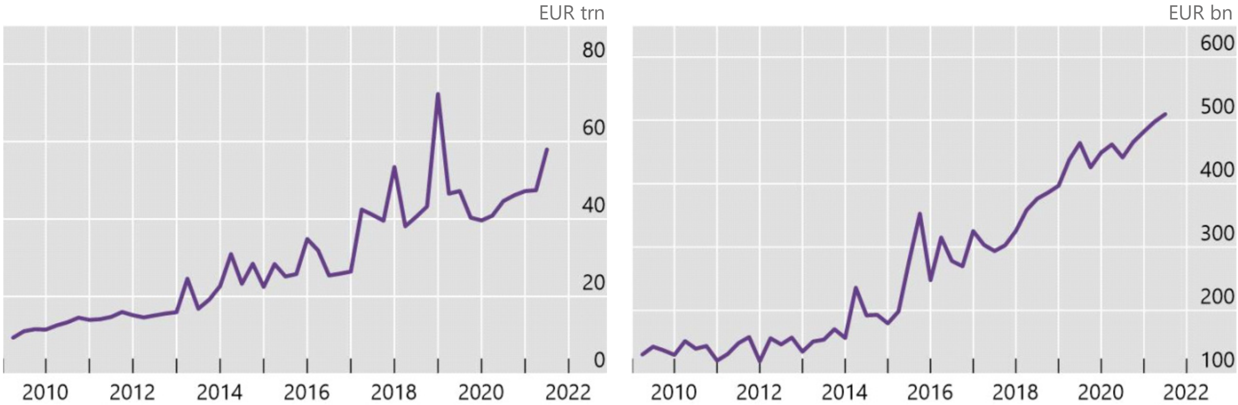
Note: The tick marks on the x-axis denote year-end values.

Source: Basel Committee on Banking Supervision, authors' calculations.

Aggregate evolution of notional OTC derivatives and repos

Canada | Graph B.1.2

Notional OTC derivatives | Repos



Note: The tick marks on the x-axis denote year-end values.

Source: Basel Committee on Banking Supervision, authors' calculations.

Summary statistics for banks "Just Below" and "Above or Far Away"

Full sample[1]

Table B.2.1

	Just Below				Above or Far Away			
Variable	N	Mean	Min	Max	N	Mean	Min	Max
NOTCD	15	19,436	242	42,383	55	4,441	0	48,204
Repos	15	132	54	293	55	33	0	213
Total assets	15	1,617	312	3,308	55	698	201	2,775
Total lev exp	15	1,720	385	4,084	55	703	169	2,938

[1] Mean, Min, Max in € bn.

Source: Basel Committee on Banking Supervision, authors' calculations.

Summary statistics for banks "Just Below" and "Above or Far Away"

Total Assets > EUR 400 bn[1]

Table B.2.2

	Just Below				Above or Far Away			
Variable	N	Mean	Min	Max	N	Mean	Min	Max
NOTCD	14	19,219	242	42,383	29	7,469	48	48,204
Repos	14	135	54	293	29	52	1	213
Total assets	14	1,762	788	3,308	29	1,052	449	2,775
Total lev exp	14	1,815	671	4,084	29	1,075	345	2,938

[1] Mean, Min, Max in EUR bn.

Source: Basel Committee on Banking Supervision, authors' calculations.

Summary statistics for banks "Just Below" and "Above or Far Away"

Total Assets > EUR 800 bn[1]

Table B.2.3

	Just Below				Above or Far Away			
Variable	N	Mean	Min	Max	N	Mean	Min	Max
NOTCD	9	21,005	5,475	42,383	14	11,619	686	48,204
Repos	9	150	60	293	14	74	5	213
Total assets	9	2,304	920	3,308	14	1,558	783	2,775
Total lev exp	9	2,201	874	4,084	14	1,410	767	2,938

[1] Mean, Min, Max in EUR bn.

Source: Basel Committee on Banking Supervision, authors' calculations.

Summary statistics for banks "Just Below" and "Above or Far Away" — Table B.2.4

Period	Number of banks "Just Below"
2016 Q4	13
2017 Q4	16
2018 Q4	15
2019 Q4	14
2020 Q4	12
2021 Q4	7

Source: Basel Committee on Banking Supervision, authors' calculations.

Appendix C: Robustness checks for baseline notional OTC derivatives

Different measures of window-dressing

We repeat our analysis with several different measures of $WindowDressing_{i,t,y}$. Our baseline measure is given by (i), whilst (ii) - (v) are modifications. Our results for notional OTC derivatives hold for each.

i. $$WindowDressing_{i,t,y} = \frac{(Q3_{i,t,y} - Q4_{i,t,y}) + (Q1_{i,t+1,y} - Q4_{i,t,y})}{0.5 \times (Q3_{i,t,y} + Q1_{i,t+1,y})} \times 100$$

ii. $$WindowDressing_{i,t,y} = \frac{(Q2_{i,t,y} - Q4_{i,t,y}) + (Q2_{i,t+1,y} - Q4_{i,t,y})}{0.5 \times (Q2_{i,t,y} + Q2_{i,t+1,y})} \times 100$$

iii. $$WindowDressing_{i,t,y} = \frac{Q3_{i,t,y} - Q4_{i,t,y}}{Q3_{i,t,y}} \times 100$$

iv. $$WindowDressing_{i,t,y} = \frac{Q2_{i,t,y} - Q4_{i,t,y}}{Q2_{i,t,y}} \times 100$$

v. $$WindowDressing_{i,t,y} = \frac{\frac{1}{3}(Q1_{i,t,y} + Q2_{i,t,y} + Q3_{i,t,y}) - Q4_{i,t,y}}{\frac{1}{3}(Q1_{i,t,y} + Q2_{i,t,y} + Q3_{i,t,y})} \times 100$$

Robustness results with different measure of window dressing — Table C.1

	Window-dressing of notional OTC derivatives				
	(1)	(2)	(3)	(4)	(5)
Post G-SIB$_t$ x Just Below$_i$	0.08***	0.10***	0.06***	0.06***	0.08***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Post G-SIB$_t$ x G-SIB constrained$_i$	0.02	0.05**	-0.01	-0.00	0.00
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
Post G-SIB$_t$ x Capital market bank$_i$	0.02	0.02	-0.01	0.01	-0.02
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Size$_{i,t}$	0.01	-0.01	0.00	-0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Level of Tier 1 Capital$_{i,t}$	0.11	-0.03	-0.05	-0.42	-0.23
	(0.19)	(0.24)	(0.12)	(0.17)	(0.16)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full
WD version	i	Ii	iii	iv	v
Adj. R^2	0.13	0.09	0.09	0.09	0.10
Num. obs.	527	515	528	517	514

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. In the regressions window-dressing is measured in decimals, rather than as a %, as in Graphs 2-4.

Source: Basel Committee on Banking Supervision, authors' calculations.

Different definitions of proximity to bucket thresholds

We also test our baseline results using different grouping definitions for the difference-in-differences set up. Our baseline is given by v1, while versions v2-v5 are alternative iterations. Our difference-in-differences results are robust to most definitions.

- v1: 1 if expected proximity to threshold is in range [-40 bp, 0], 0 otherwise
- v2: 1 if expected proximity to threshold is in range [-30 bp, 0 bp], 0 otherwise
- v3: 1 if expected proximity to threshold is in range [-25 bp, +5 bp], 0 otherwise
- v4: 1 if expected proximity to threshold is in range [$\pm$ 25 bp], 0 otherwise
- v5: 1 if expected proximity to threshold is in range [-20 bp, +15 bp], 0 otherwise

Robustness results with different definitions of proximity to bucket thresholds — Table C.2

	Window-dressing of notional OTC derivatives				
	(1)	(2)	(3)	(4)	(5)
Post G-SIB$_t$ x Just Below$_i$	0.08***	0.12**	0.08**	0.04	0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Post G-SIB$_t$ x G-SIB constrained$_i$	0.02	0.03	0.03	0.03	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Post G-SIB$_t$ x Capital market bank$_i$	0.02	0.01	0.05**	0.04	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Size$_{i,t}$	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Level of Tier 1 Capital$_{i,t}$	0.11	0.11	0.19	0.17	0.17
	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	Full
Close definition	v1	v2	v3	v4	V5
Adj. R^2	0.13	0.135	0.13	0.12	0.12
Num. obs.	527	527	527	527	528

Note: ***p < 0.01; **p < 0.05; *p < 0.1. In the regressions window-dressing is measured in decimals, rather than as a %, as in Graphs 2-4.

Source: Basel Committee on Banking Supervision, authors' calculations.

Different samples of banks

As discussed in Section 4, we test whether our results hold for different cuts of the sample. We filter out the smaller banks to compare only the larger banks in our sample. As shown in columns 7 and 8 of Table 3, our results hold.

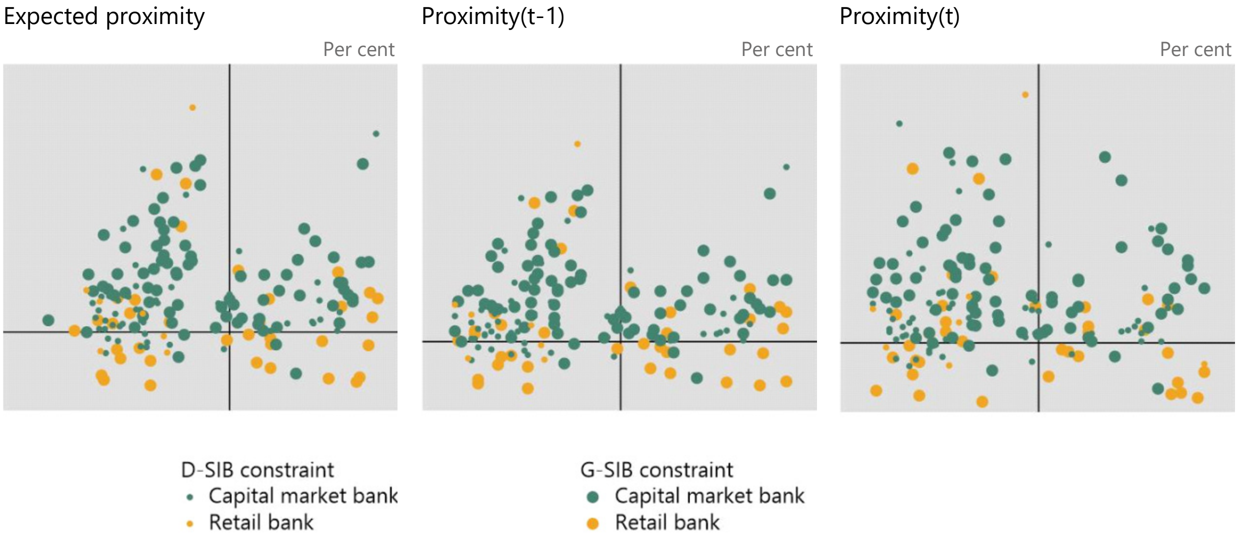
Different definition of "expected proximity"

We show in Graph 2 a scatterplot of banks' 'expected proximity' to a bucket threshold against their degree of window-dressing. The measure we used was not only based on banks' proximity in the previous assessment exercise, but also accounts for their growth rate in that year relative to the market, and exchange rate dynamics. This was given by: $Expected\ Proximity_{i,t} = Proximity_{i,t-1} \times \left[\frac{1+sign(Proximity_{i,t-1})xgrowth_{i,t}}{1+sign(Proximity_{i,t-1})x\frac{1}{N}\sum_i growth_{i,t}}\right] \times \left[1+\left(1-\frac{BIS\ FX(Q3_{i,t})}{BIS\ FX(Q4_{i,t-1})}\right)\right]$.We also depict this relationship based on two simpler measures: (ii) $Proximity_{i,t-1}$ (the latest observed proximity figure); and $Proximity_{i,t}$ (the actual realised proximity figure). The correlations are shown below, with very similar findings across the three. We use (ii) in our baseline regression results, but our findings are similar across each measure.

Association between proximity to G-SIB bucket thresholds and window-dressing of notional OTC derivatives

Since implementation of the framework

Graph C.1



Note: The y-axis reports window dressing, measured according to Equation (1) in the main text. Expected proximity is defined as per above. $Proximity_{i,t-1}$ is the proximity in the previous period, whilst $Proximity_{i,t}$ is that in the same period as the data for notional OTC derivatives. We show observations for banks that were within at least 50 bp of a bucket threshold in at least one year. We also remove (the very few) anomalous observations of -100% window-dressing (indicating that a bank more than doubled their activity in Q4) on data quality grounds. Axes values are removed for bank anonymisation purposes.

Source: Basel Committee on Banking Supervision, authors' calculations.

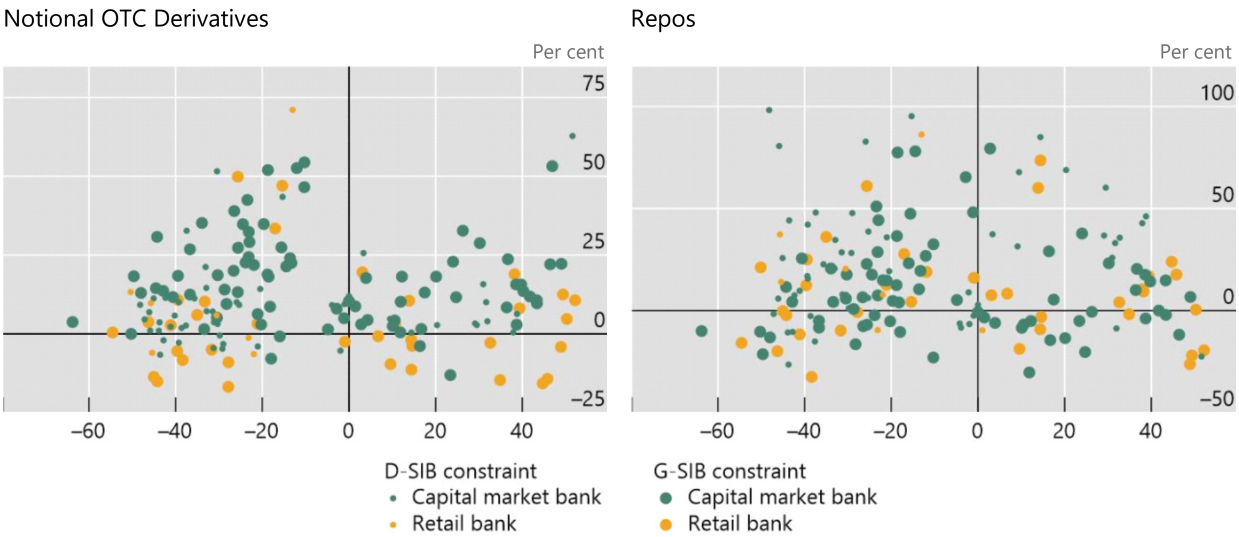
Appendix D: Results for repos

Graph D.1 shows the raw correlations between banks' expected proximity to bucket thresholds and their degree of window-dressing each year. The left-hand chart depicts this for notional OTC derivatives, as depicted in Graph 2 in Section 3, while the right-hand chart depicts this for repos. Focusing on the latter, we see that most observations are above the 0% horizontal dotted line, indicating that (similarly to notional OTC derivatives) most banks reduce repos at year-end relative to adjacent quarter-ends. We also see a rather striking magnitude of window-dressing, with many observations around or even above 50% (more so than observed for notional OTC derivatives). The correlation with proximity, in particular focusing on the large green dots (G-SIB constrained capital market banks), we again see a cluster of observations with high window-dressing just below a bucket threshold (the vertical 0 line).

Association between proximity to G-SIB bucket thresholds and window dressing

Since the implementation of the G-SIB framework

Graph D.1



Note: The y-axis reports window dressing, measured according to Equation (1) in the main text. Expected proximity is used in each case, as defined above. We show observations for banks that were within at least 50 bp of a bucket threshold in at least one year. We also remove (the very few) anomalous observations of -100% window-dressing (indicating that a bank more than doubled their activity in Q4) on data quality grounds.

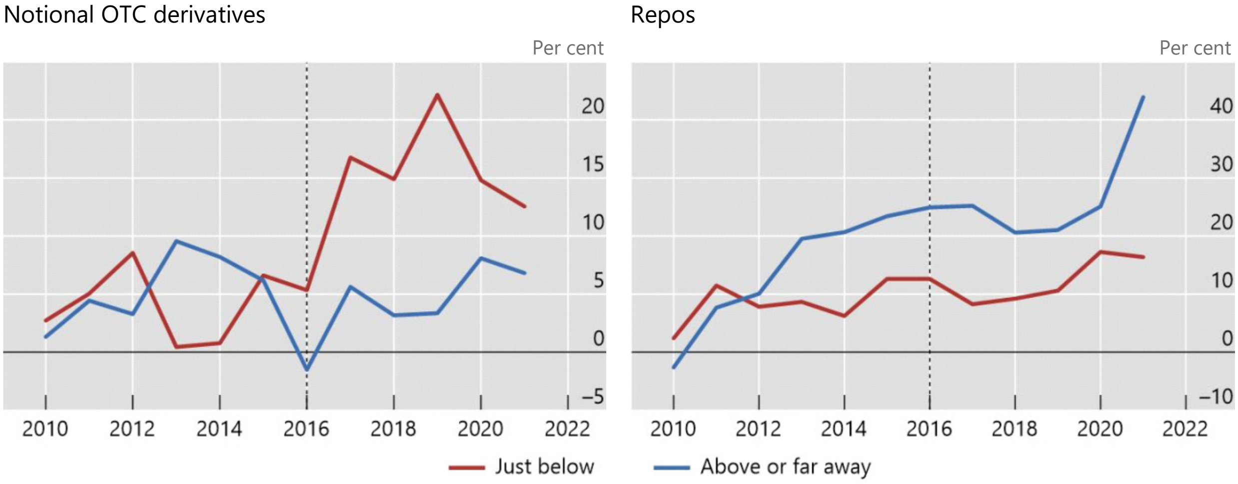
Source: Basel Committee on Banking Supervision, authors' calculations.

Graph D.2 depicts the evolution of window-dressing across our two variables of interest, using our baseline "Just Below" definition. We see in the left chart is the same as that depicted in Graph 4, relating to notional OTC derivatives. The right hand chart depicts the evolution of year-end window-dressing of repos. On the latter, there are two observations to make. First, window-dressing is strikingly high across both groups, with Q4 values consistently between 10% and 20% lower than in adjacent periods. Second, we see in the raw data that the control group actually seem to window-dress more than the "Just Below" group. This, however, does not (observationally) seem to change systematically pre- and post-implementation and does not hold once we account for the standard controls (size, business model, G-SIB constrained, and capitalisation), as shown in Table D.1. In fact, the coefficient on our dummy variable of interest "$\text{Post G-SIB}_t \times \text{Just Below}_i$" is positive (0.13) and marginally significant, indicating that banks just below the threshold started window-dressing by more than banks above or far away after the implementation of the framework (consistent with our results for notional OTC derivatives), accounting for the respective bank balance sheet characteristics.

Evolution of window-dressing between our two groups of interest

For banks "Just Below" and "Above or Far Away" from a bucket threshold

Graph D.2



Note: The y-axis reports window dressing, measured according to Equation (1) in the main text. The tick marks on the x-axis refer to the fourth quarter of that year. A bank is grouped as "Just Below" if, for at least half of the periods in the sample, its proximity to a bucket threshold was within the range [-40 bp, 0 bp]. There are 15 banks in this group (11 G-SIBs), and 55 banks in the "Above or Far Away" group (13 G-SIBs). The 15 banks in the "Just Below" group accounted for 55% of global notional OTC derivatives activity in Q2 2022. Data for CA, JP, UK, and US banks are available back to 2010 Q4, data for BU banks are available from 2014 Q4. We winsorise the group of banks depicted, removing the 10% tails. We do this because of highly anomalous window-dressing observations (in both directions) amongst some of the smaller banks.

Source: Basel Committee on Banking Supervision, authors' calculations.

Baseline regression results for all variables

Table D.1

	Window dressing					
	Notional OTC Derivatives			Repos		
	(1)	(2)	(3)	(4)	(5)	(6)
Post G-SIB$_t$ x Just Below$_i$	0.08***	0.06**	0.11***	0.13*	0.07	0.11
	(0.03)	(0.03)	(0.04)	(0.07)	(0.06)	(0.07)
Post G-SIB$_t$ x G-SIB constrained$_i$	0.02	0.09***	0.10**	-0.12*	0.00	-0.11
	(0.02)	(0.03)	(0.04)	(0.06)	(0.06)	(0.08)
Post G-SIB$_t$ x Capital market bank$_i$	0.02	0.05**	0.02	-0.18***	-0.00	-0.10
	(0.02)	(0.03)	(0.05)	(0.07)	(0.06)	(0.09)
Size$_{i,t}$	0.01	0.01	0.01	-0.02	0.05**	0.07**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
Level of Tier 1 Capital$_{i,t}$	0.11	0.10	0.11	0.51	0.61	0.68
	(0.19)	(0.28)	(0.47)	(0.58)	(0.63)	(0.86)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Total Assets > EUR400bn	Total Assets > EUR800bn	Full	Total Assets > EUR400bn	Total Assets > EUR800bn
Adj. R^2	0.13	0.24	0.23	0.20	0.11	0.05
Num. obs.	527	319	172	510	315	173

Note: ***p < 0.01; **p < 0.05; *p < 0.1. In the regressions window-dressing is measured in decimals, rather than as a %, as in Graphs 2-4.

Source: Basel Committee on Banking Supervision.