Basel II and Operational Risk

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Abstract

In a setting where private information goes public for the first time, we study the real effects of the Basel II Accord requiring banks to calculate operational risk capital, and disclose qualitative and quantitative information. Using a difference-in-differences setup featuring partial US implementation relative to full EU adoption, we find that the introduction of operational risk regulation resulted in a significant reduction in operational losses in treated EU banks. This effect, concentrated in internal losses and present in banks subject to supervisory approval, supports the idea that capital adequacy, supervisory review, and market discipline operate effectively on a complementary basis.

Keywords: Basel II, Market Discipline, Measurement Approach, Operational Risk, Pillar 3, Supervisory Disclosure, Risk Governance

JEL Classification: G21, G28, G32

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1. Introduction

We study the real effects of operational risk capital, first introduced in the 2007 Basel II Accord.[1] Operational risk is formally defined as the risk of loss from inadequate or failed internal processes, people, and systems, or from external events (Basel Committee on Banking Supervision, 2006a). Many of the largest and most newsworthy losses reported by banks fall under the umbrella of operational risk.[2] The Basel II Accord supplements traditional capital requirements with Pillar 3 disclosure which is intended to promote market discipline (Figure 1 highlights the relevant developments between Basel I and Basel II). The Pillar 3 framework entails a novel disclosure practice and information environment for banks by placing regulatory data in the public domain for the first time. Within this framework the notion of operational risk capital embodies two intertwined aspects: (1) calibrating and holding capital for operational risk, and (2) disclosure of a banks' risk profile and risk management practices in the novel Pillar 3 disclosure. The effects of the introduction of operational risk capital on banks' behaviour is an important empirical question, addressed in this paper, with wider implications for capital regulation.

Several unique features of operational risk makes it a worthwhile avenue to understand the consequences of capital regulation. First, in contrast to credit risk and market risk, there is no explicit risk-return tradeoff associated with operational risk.[3] Second, for most banks, the level of operational risk capital is set as a function of historical revenues rather than expected future losses. The implication is that there is limited motivation for management to focus on improving internal risk governance processes to reduce the quantity of operational risk capital required. Finally, it is unclear whether any changes in *ex-post* operational losses are attributable to heightened market discipline through Pillar

[1] A real effect is generally defined as a phenomenon in which disclosure can affect subsequent and observable decisions made internally or externally of the firm (Bourveau and Schoenfeld, 2017).

[2] Examples of large operational losses through unauthorized trading are probably best known, including losses of $1.3 billion in Barings Bank in 1995, $691 million in Allied Irish Banks in 2002 and of $7.2 billion in Societe Generale in 2008. Operational losses are not limited to unauthorized trading, however, but cover a wide spectrum of event types. For example, in recent times, many banks have had to pay large fines to regulators due to various irregularities, also under the umbrella of operational risk.

[3] Instead, an implicit link between operational risk and profitability may exist. Management may neglect to invest in improved processes, systems, risk management or compliance, resulting in greater short-term cash flows but leaving them exposed to long-term operational risks.

3 disclosure, as some banks already allocated capital for operational risk internally prior to the regulatory change and the introduction of operational risk capital was not intended to change the aggregate level of regulatory capital held by banks (Basel Committee on Banking Supervision, 2001). With these features pointing to limits to effectiveness for capital adequacy requirements relating to operational risk in isolation, we examine the combined effect of the three pillars of Basel II, capital adequacy, supervisory review, and market discipline, on banks' operational risk taking.

Employing a difference-in-differences (diff-in-diff) setup featuring partial US implementation relative to full EU adoption, we find that the implementation of operational risk regulation resulted in a significant reduction in operational losses. Results are shown to hold regardless of whether we study all banks in our sample, including those where there are no reported operational losses, or whether we condition upon banks with reported losses. The magnitude of the treatment effect is substantial: a reduction in operational losses of up to 96% for treated EU banks relative to an entropy-balanced sample of control US banks with similar characteristics. No link between operational risk regulation and external operational losses is found, providing support for the influence of strong internal control and risk governance processes. Using hand-collected data relating to the measurement approach adopted by banks to calibrate operational risk capital, we show that the treatment effect is present in banks that are subject to supervisory approval, specifically those that must satisfy requirements of demonstrating strong operational risk management when adopting either the standardized approach or the advanced measurement approach. This further highlights the importance of risk governance criteria, in addition to granularity of operational risk categorization, in influencing *ex-post* operational losses. Collectively, these findings suggest that capital adequacy, supervisory review, and market discipline operate effectively on a complementary basis.

Our findings are shown to be robust. The identifying assumptions underpinning the diff-in-diff analysis are confirmed to be met. Results are also in agreement for shorter time windows surrounding the regulatory change, alleviating concerns that our findings may be driven by either other regulatory changes or changes in market structure. The causal

impact of the operational risk regulation is further validated by a series of placebo and falsification tests. Findings are also consistent when we exclude losses emanating from the global financial crisis (including legal costs), control for concurrent media attention, use alternative loss measures, and remove potential outliers. Furthermore, our findings are robust to alternative matching choices including the use of an entropy-balanced sample based on higher-order moments of the covariates, a propensity-score-matched sample, and a sample without matching.

Our study builds upon and expands the current literature in several interrelated areas of research. First, our paper pertains to the literature considering outcomes resulting from changes in bank regulatory capital requirements (Fraisse et al., 2020; Gropp et al., 2019; Jiménez et al., 2017). As capital adequacy requirements in isolation may not be sufficient to influence bank risk, policymakers have sought to augment macroprudential policy in various ways. The complementary effect of regulation and supervision acts to reduce bank fragility (Delis and Staikouras, 2011). Increased disclosure requirements may also interact with capital adequacy to improve welfare (Biswas and Koufopoulos, 2022). This interaction has been little studied in an empirical context, with only Kovner and Van Tassel (2022) showing that banks' systematic risk is reduced in the post-crisis period, led by simultaneous changes in capital regulation and disclosure under the Dodd-Frank act. Our paper adds to the literature on bank transparency through risk disclosures (e.g., Bischof and Daske, 2013; Jorion, 2002; Cordella and Yeyati, 1998) by providing evidence on the transparency effects of Pillar 3 disclosure. Finally, our paper extends the literature specific to operational risk, especially that indicating that operational losses are associated with weak internal risk management and governance (Chernobai et al., 2021, 2011; De Fontnouvelle et al., 2006).

Our findings of the real effects of the Basel II operational risk regulation are both relevant and timely. We document the consequence of the operational risk regulation on *ex-post* operational losses in treated banks. As this is an introduction of a new capital regulation, rather than an adjustment to an existing rule, our findings provide a previously undocumented perspective into the capacity of bank regulation to influence

bank risk-taking behavior. Given the unique aforementioned features surrounding operational risk, evidence of successful implementation through integration of capital adequacy, supervisory review, and market discipline provides broad guidance for future bank regulation. Further, our findings are timely in light of the impending introduction of a new standardized approach to calculate operational risk capital, effective on 1 January 2023. The new standardized approach replaces internal modeling under the previous advanced measurement approach with a calibration using historical losses over the previous ten years combined with information relating to income across different business lines in determining capital requirements. This is supplemented by disclosure requirements for loss data and an operational risk management framework applicable across all banks. This new shift addresses the transparency issues associated with the use of internal modeling through improved disclosure of data and risk governance.[4]

The remainder of this paper is organized as follows: in Section 2, we describe the background and develop testable hypotheses. We then present the research design and data in 3. We report our main empirical findings in Section 4, and robustness test results in Section 5. Section 6 concludes.

2. Background and Hypotheses Development

2.1. Background

Introduced by the Basel Committee on Banking Supervision (BCBS) in 1992, the Basel I Capital Accord prescribes a minimum capital to risk-weighted assets ratio of 8% (Tier 1 regulatory capital ratio), which initially focused on credit risk, and was later amended in 1997 to include market risk. Implemented in 2007, Basel II attempted to strengthen minimum capital requirements by proposing a variety of extensions to the extant framework. Under Basel II, operational risk was formalized as a regulatory focus for the first time, with banks required to hold capital as a backstop for operational losses

[4]The review of banks' operational risk modeling practices and capital outcomes performed by Basel Committee on Banking Supervision (2016) revealed that the Committee's expectations failed to materialize due to the inherent complexity and lack of comparability arising from a wide range of internal modeling practices have exacerbated variability in risk-weighted asset calculations and eroded confidence in risk-weighted capital ratios.

and publicly disclose specific risk information for the first time. Figure 1 provides a summary of the relevant regulatory changes which occurred between Basel I and Basel II.

The Basel II framework is based on three complementary pillars. Pillar 1 relates to minimum capital requirements, ensuring that banks hold sufficient capital of high quality. While requiring changes to capital estimation for credit risk and market risk, Basel II did not necessarily require banks to raise new capital resulting from their operational risk exposures. As described by the Basel Committee on Banking Supervision (2001), the intention of the Basel II Accord was to "*leave the total capital requirement for an average portfolio broadly unchanged*". In fact, the quantitative impact assessment carried out in 2005 highlighted that the expected level of aggregate capital would drop by between 7.7% and 15.4% for European banks (Basel Committee on Banking Supervision, 2006b). Pillar 2 formalizes the importance of the supervisory review process in promoting safety and soundness in banks and financial systems. Pillar 3 encourages market discipline enabled by public disclosure of capital adequacy, risk profiles, and risk assessment processes (Basel Committee on Banking Supervision, 2006a).

Basel II prescribed three methods to calculate operational risk capital in a spectrum of increasing sophistication and risk sensitivity: the basic indicator approach (BIA), the standardized approach (TSA), and advanced measurement approach (AMA). Under BIA, operational risk capital is set as a function of three-year average gross income. For TSA, operational risk capital is calibrated using weights applied to three-year average revenue across different business lines. For AMA, operational risk capital is calculated based on internal operational risk measurement systems. One of the defining characteristics that distinguishes BIA from TSA and AMA is the active involvement of supervisory review and approval in the subscription to the latter two approaches. TSA and AMA adopting banks must demonstrate that strong and appropriate governance and risk management structures are in place *ex-ante*. Specifically, banks must, at the minimum, satisfy their supervisor that (1) their board of directors and senior management are actively involved in the oversight of the operational risk management framework; (2) they have an operational

risk management system that is conceptually sound and is implemented with integrity; and (3) they have sufficient resources in the use of the approach in the major business lines as well as the control and audit areas. In addition, supervisory review and approval are also at play after a bank adopts a measurement approach: First, a bank is subject to supervisory review when it reverts from a more advanced approach to a simpler one. Second, a bank using a more advanced approach may be required to revert to a simpler approach if the supervisory review suggests that the bank no longer meets the qualifying criteria for the approach initially adopted. The bank is allowed to switch back to a more advanced approach once it meets the qualifying criteria again (Basel Committee on Banking Supervision, 2006a).[5]

In 2016, the BCBS proposed an extensive overhaul to operational risk requirements through a modified methodology to quantify operational risk capital and an updated disclosure practice. The new standardized approach, replaces all operational risk measurement approaches originally introduced under Basel II. Under the new standardized approach, operational risk capital is computed as the product of the business indicator component (BIC) and bank-specific internal loss multiplier (ILM). BIC is a simple financial statement proxy of operational risk exposure that is stable and comparable across banks, leaving business volume the sole factor influencing operational risk exposure. According to the size of their BIC, banks are divided into five buckets. For banks in bucket 1, capital is an increasing linear function of the BIC and does not depend on ILM. For banks in buckets 2 to 5, capital is calibrated in two steps: (1) calculating a baseline level of capital using the BIC; and (2) multiplying up or down the portion of the BIC above the threshold separating buckets 1 and 2 by a function that depends on the banks' ILM to differentiate between banks with different risk profiles. Banks are required to disclose both quantitative and qualitative information on the operational risk framework. In the quantitative disclosure, all banks need to disclose each BIC sub-item for each of the three years of the BIC calculation window. In addition, banks with BIC over EUR 1 billion, or that use internal loss data to calculate operational risk capital, have to disclose their

[5]Although this is the rule applicable to switching, it rarely happens in practice, at least in our sample.

annual loss data for each of the ten years in the ILM calculation window. Of particular relevance to this study, the qualitative disclosure aspects of the new approach require banks to describe the main characteristics and elements of their operational risk management framework, which include: (1) policies, frameworks and guidelines for operational risk management; (2) the structure and organization of operational risk management and control function; (3) operational risk measurement system; (4) the scope and main context of their reporting framework on operational risk to executive management and the board of directors; and (5) the risk mitigation and risk transfer used in operational risk management (Basel Committee on Banking Supervision, 2016).

2.2. Capital Adequacy and Market Discipline

The conventional view on the relationship between capital regulation and bank risk holds that minimum capital requirements entail a risk-mitigating mechanism that makes banks' own capital risk sensitive thus internalizing possible losses. While not exhaustive, many empirical studies emphasize the importance of greater quantities of high quality capital in reducing bank risks (Berger and Bouwman, 2013; Iannotta et al., 2007; Furlong and Keeley, 1989) and improving stock performance (Demirgüç-Kunt et al., 2013; Beltratti and Stulz, 2012). This view has, however, been challenged given that research findings appear to be dependent on whether: (1) banks are viewed as value- or utility-maximizing firms operating in complete or incomplete markets and within a purely static or a more dynamic framework; (2) the limited liability of bank shareholders and the moral hazard problems arising from deposit insurance are fully accounted for; (3) information asymmetries and monitoring incentives on bank assets, bank ownership, and market structure are appropriately considered; and (4) supervisors have the ability to enforce capital regulation (Delis and Staikouras, 2011; Behr et al., 2010; VanHoose, 2007).

While capital regulation alone may not be sufficient to limit banking risk, the combined effect of the three pillars of Basel II might help to mitigate appropriate risk exposures. In particular, an increase in transparency and the resulting improvement in market discipline might contribute to banking stability by limiting information asymmetries, promoting private monitoring, facilitating supervisory oversight, and encouraging banks to

adopt more prudent risk-taking (Demirgüç-Kunt et al., 2008; Beck et al., 2006). Market discipline is a market-based incentive scheme in which market participants use available information to monitor and discipline banks' risk-taking behavior (Bushman, 2014; Nier and Baumann, 2006). Market discipline is less about the market *per se* and more about the institutional framework of information, incentives, and control employed to reduce the problems of asymmetric information and moral hazard in banking (Stephanou, 2010). Information disclosure enhances *ex-ante* market discipline under the premise that informed investors discern greater risk-taking by demanding higher returns on their investments (Nier and Baumann, 2006). Market discipline can also function through regulatory intervention triggered by market signals, such as price changes in bank securities (Stephanou, 2010; Flannery, 2001). A broad consensus reached in the literature on operational risk is that financial institutions experience reputational losses following operational risk events (Fiordelisi et al., 2014; Biell and Muller, 2013; Sturm, 2013; Gillet et al., 2010; Cummins et al., 2006; Perry and de Fontnouvelle, 2005), which suggests the existence of a possible mechanism through which market discipline might influence banks' operational risk taking.

Market discipline and capital requirements operate effectively on a complementary basis. Based on a spatial model of imperfect banking competition within which banks conduct deposit taking and loan making, Vauhkonen (2012) presents three scenarios: (1) Under the *baseline scenario* where both capital and disclosure requirements are absent, bank insiders' incentives to invest in the quality of risk management is lower than the social optimum because insiders are not fully rewarded for their private effort given that they have to share the returns from a successful loan project with depositors. The regulator hence requires banks to raise capital to better align the incentives of the insiders with social interests. (2) Under a *private information scenario* where the quality of a bank's risk management systems is unobservable to outsiders, market discipline does not work and the introduction of capital requirements is ineffective in improving the safety of the banking system because the cost of capital requirements is fully transferred to depositors, and the capital-at-risk effect does not operate in the absence of information

on the risk of individual banks. (3) Under a *partial or full information transparency scenario*, mandatory disclosure requirements (e.g., Pillar 3 disclosure) enable the quality of a bank's risk management systems to be either partially or fully observable to outsiders, which reduce cost of outside equity and foster banks' quality competition. In this case, the ultimate success of Pillar 1 minimum capital requirements depends on how well Pillar 3 disclosure functions (Gordy and Howells, 2006).

The Pillar 3 framework entails a novel disclosure practice and information environment for banks in two primary ways. First, it places regulatory data in the public domain for the first time, which provides financial market participants such as investors and depositors with the access to information on banks' risk profiles and detailed risk-based capital adequacy that previously was only available to the regulators. Second, Pillar 3 disclosure is parallel and complementary to standards-based financial reporting that has a longstanding tradition of being publicly accessible (Borio et al., 2004). Given the new disclosure requirements for operational risk introduced under Basel II and the theoretical prediction on the complementary relationship between capital requirements and market discipline in countering bank risk-taking, we propose the following hypothesis:

Hypothesis 1: *The Basel II operational risk regulation resulted in a reduction in realized operational risk for treated banks in the post treatment period.*

2.3. Supervisory Review and Risk Governance

Risk governance is an integral part of the Basel II framework. Risk governance refers to "*the means by which the board and management establish firm strategy; articulate and monitor adherence to risk appetite and risk limits; and identify, measure and manage risks*" (Financial Stability Board, 2013). Risk governance thus goes beyond traditional risk management and places risk at the heart of the corporate governance mechanism in financial institutions. This approach is explicitly incorporated in the minimum supervisory criteria for operational risk governance and management structures within the Basel II framework. The risk governance requirements embedded in the supervisory review and approval for TSA or AMA adopting banks may help reduce operational risk. First, effective supervision is complementary to market discipline requirements in reducing bank

risk. In the absence of supervisory review, capital adequacy (either directly or through its effective supervision) does not curtail bank risk but only affects those banks that hold a level of capital very close to the minimum capital adequacy threshold (Delis and Staikouras, 2011). Second, a focus upon risk management and governance may reduce banking risk in general (Anginer et al., 2018; Ellul and Yerramilli, 2013) and operational risk in particular (Chernobai et al., 2011). Focusing upon the influence of risk management and governance requirements and links with operational risk previously documented, we propose the following hypothesis:

Hypothesis 2: *Banks adopting the standardized approach or advanced measurement approach to calibrate operational risk capital have reduced realized operational risk in the post treatment period.*

3. Empirical Design and Data

3.1. Identification Strategy and Empirical Model

Our identification strategy has three key elements. The first element is based on variations in the implementation of Basel II across jurisdictions. Our sample comprises banks that are subject to full adoption in European countries in 2007, and partial implementation in the US. In the European Union, all banks were required to report operational risk capital calibrated using one of the three measurement approaches (i.e., BIA, TSA, and AMA). In the US, the federal banking agencies applied Basel II solely to the 19 very largest, internationally active "core" US banks with at least USD 250 billion of consolidated total assets or at least USD 10 billion of on-balance-sheet risk associated with foreign asset holdings. This setting enables us to perform a diff-in-diff analysis accompanied with placebo and falsification tests. The second element of our identification strategy is the application of entropy balancing, a matching technique that produces enhanced covariate balance and matching efficiency relative to the existing matching techniques such as propensity score matching (PSM) (Hainmueller, 2012). The third element of our identification strategy is a fixed-effects structure that controls for various sources

of observed and unobserved heterogeneity in operational losses, which helps minimize correlated omitted variable and related endogeneity concerns. In our main specification, we include bank and year fixed effects (FE) to control for the impact of unobservable time-invariant bank characteristics and economy-wide shocks on bank operational risk, respectively. Combining the three elements of our identification strategy, we estimate a series of difference-in-differences model specifications that are variants of the following form:

$$\begin{aligned} ln(OpLoss)_{i,t} = \alpha_0 + \alpha_1 Treated_i + \alpha_2 Post_t + \alpha_3 Treated_i \times Post_t \\ + \alpha_4 \text{Controls}_{i,t-1} + \text{FE} + \epsilon \end{aligned} \tag{1}$$

where $ln(OpLoss)_{i,t}$ are the operational losses of bank i at time t, measured as the natural logarithm of operational losses. *Treated* is a treatment group indicator that equals 1 for European banks, and 0 for US banks that did not implement Basel II. *Post* is a dummy indicator that equals to 1 after the Basel II implementation (from 2007) and 0 before this period. The coefficient of interest is α_3, which measures the difference-in-changes in operational losses for countries which implemented Basel II relative to countries that did not. If α_3 is statistically significant, then the Basel II operational risk regulation has an impact on bank operational losses. We also include a set of time-varying bank- and country-level characteristics associated with operational losses to rule out the possibility that the estimates are influenced by a contemporaneous shock to these characteristics. These control variables include bank size (the natural logarithm of total assets), deposit ratio (total deposits over total assets), equity ratio (book value of equity over total assets), mortgage exposure (mortgage loans over total assets), credit risk (net charge-offs over gross loans), business complexity (noninterest income over total operating income), profitability (return on equity), and yearly growth of total assets. The choice of this set of bank-level controls is informed by prior literature on the determinants of operational losses (Chernobai et al., 2021, 2011) and the literature on the drivers of market discipline (Nier and Baumann, 2006). As suggested by Nier and Baumann (2006), effective market discipline operates through three key factors: (1) government safety net (support); (2) the banks' funding structure (funding); (3) transparency of banks' risk choices (disclosure). Corresponding to these three factors: (1) all countries in our sample

has a longstanding explicit deposit guarantee scheme; (2) the deposit ratio and loans to assets ratio are included to control for banks' funding structure; (3) after accounting for the above two factors, the observed treatment effect can be attributed to disclosure as the main driver for the market discipline of Basel II. We also include yearly GDP per capita and the corresponding growth rate for each of the countries. The diff-in-diff approach ensures that model estimation is not influenced by permanent and unobserved differences between the treated and the control group or by common trends. Detailed variable definitions are reported in Appendix A.

3.2. Data and Sample

SAS OpRisk Global Data is the source for the operational loss data employed in this study. SAS OpRisk Global Data is the world's largest, most comprehensive, and most accurate repository of information on publicly reported cross-country operational losses greater than USD 100,000.[6] The vendor gathers information on operational losses from public sources such as news reports, court filings, and SEC filings. We take data from the 2018 reporting cycle of the SAS OpRisk Global Database, which includes losses recognized between 2000 and 2015. All reported loss values are denoted in US dollars and CPI-adjusted to 2018, which allows for comparison across currencies and time.

We select banks in Europe and US that have available data between 2000 and 2015 on all variables studied. After matching with accounting data based upon the accounting date of the loss,[7] excluding the "core" US banks, removing banks that did not survive the global financial crisis (i.e., 2007–2009), we also ensure that we have data available on all variables for the empirical tests. Two samples are created: the "zero+nonzero" sample and the "nonzero" sample. For the "zero+nonzero" sample, we begin with the universe of banks as reported in Bankscope and setting operational loss to zero for banks reporting no losses in particular years. This sample includes 18,567 bank-year observations for 1,462 banks, of which 937 banks are in the treatment group (11,612 bank-year observations)

[6]SAS OpRisk Global Data contains more than 35,000 operational loss events, of which 45% relate to financial services.

[7]The accounting date is the date at which the loss is booked in the income statement.

and 525 banks are in the control group (6,955 bank-year observations). For the "nonzero" sample, we only include banks with reported operational losses for the given year. The "nonzero" sample consists of 766 bank-year observations for 245 banks: 102 banks are in the treatment group (370 bank-year observations) and 143 banks are in the control group (396 bank-year observations).[8]

Table 1 reports the breakdown of the sample by country. Over 50% of bank-year observations are from the US, providing a sufficient control sample. Italy, Switzerland and the UK account for the largest proportion of losses outside the US. In Table 2 we detail statistics of losses on an annual basis.

[Tables 1 and 2 about here.]

3.3. Matching

To identify bank characteristics associated with operational loss severity, we estimate a Tobit regression model in the 2000–2006 period, accounting for the left-trunction of the AS OpRisk Global Data at a reporting threshold value of USD 100,000. Our identification of matching covariates are informed by prior literature on determinants of operational risk, which shows that firms that suffer from operational losses tend to be younger, more complex, and with greater *ex-ante* risk of financial distress (Chernobai et al., 2021, 2011). The model employed to assess the relevance of such characteristics to our loss data is as follows:

$$\begin{aligned} ln(OpLoss)_{i,t} = \beta_0 &+ \beta_1 ln(Total\ assets)_{i,t-1} + \beta_2 DEPO_{i,t-1} + \beta_3 DPO_{i,t-1} \\ &+ \beta_4 MORT_{i,t-1} + \beta_5 NCO_{i,t-1} + \beta_6 NII_{i,t-1} + +\beta_7 ROE_{i,t-1} \\ &+ \beta_8 \Delta Total\ assets_{i,t-1} + \beta_9 GDP_{i,t-1} + \beta_{10} \Delta GDP_{i,t-1} + \text{FE} + \epsilon \end{aligned} \tag{2}$$

where $ln(OpLoss)_{i,t}$ is as previously defined. We include the natural logarithm of total assets to proxy for bank size. Although larger banks generally have better internal control systems, they have to process a higher volume and more complex transactions, and thus are more likely to experience operational risk events (Chernobai et al., 2011). We include

[8] Operational losses are aggregated by bank-year to match with the yearly accounting data and to fit with the premise that capital levels are set as a backstop for aggregate losses.

deposit ratio (DEPO) to control for bank business model. The dividend payout ratio (DPO) and mortgage exposure (MORT) control for financial distress and banks' *ex-ante* exposure to the subprime mortgage crisis, respecitvely. We control for credit risk and any potential correlation between operational risk and credit risk due to common moral hazard channel or any potential misclassification of operational losses to credit losses prior to the formal introduction of operational risk using net chargeoffs (NCO). Noninterest income ratio (NII) is included to control for business complexity (Brunnermeier et al., 2020; Stiroh, 2006, 2004). The model also controls for return on equity (ROE) as a profitability measure. More profitable banks are less constrained and are able to invest more in internal controls. However, profitability can also be positively correlated with operational risk due to the presence of moral hazard (Chernobai et al., 2011). Annual growth of total assets (ΔTotal assets) controls for the impact of excessive growth especially heightened merger and acquisition activities. Moreover, we include the natural logarithm of annual GDP per capita (GDP) and annual growth of GDP per capita (ΔGDP) to account for the effect of the general economic environment. We also introduce year and country fixed effects (FE) to account for economy-wide shocks on bank operational losses and unobservable time-invariant country characteristics, respectively. All variables are measured at (financial) year-end. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles of their empirical distribution. Detailed variable definitions are reported in Appendix A. Table 3 reports results from the estimation of Equation (2). We identify three bank characteristics that are associated with future operational losses: bank size, noninterest income ratio, and return on equity. Any significant distributional disparity between these variables for treated and control banks can potentially weaken inference from our diff-in-diff framework.

[Table 3 about here.]

We employ entropy balancing (Hainmueller, 2012) to address this problem. Entropy balancing is a generalization of the well-known PSM that results in enhanced covariate balance relative to PSM (Hainmueller, 2012). Compared with other matching techniques,

entropy balancing appropriately reweights units to obtain balance, while keeping the weights as close as possible to the base weights. It thus retains valuable information in the processed data and improves efficiency for the subsequent analysis (Hainmueller, 2012). Compared with PSM, entropy balancing does not drop observations or generate random matches, and thus increases test power (King and Nielsen, 2019). For the purposes of entropy balancing, we employ these three significant bank characteristics emerging from the Tobit model regression as matching covariates. We match on the first and second moments of matching covariate distributions with a tolerance level of 0.015 (Hainmueller and Xu, 2013).[9] We match in the year before Basel II implementation (2006),[10] and use the same entropy balance weights in all years in the subsequent diff-in-diff analysis. Table 4 reports descriptive statistics on matching covariates for both unbalanced and entropy-balanced samples as of 2006. Panel B shows that the mean and variance of the treatment and weighted control groups are identical after entropy balancing, confirming the efficacy of our entropy balancing procedure. Statistics are similar for other years, but are not reported for brevity.

[Table 4 about here.]

4. Results

4.1. Evolution of Risk Capital Held by European Banks

Figure 1 provides some context for our analysis. This details the aggregate quantity of capital reported by European banks and is broken out into credit risk capital, market risk capital, and operational risk capital. Focusing on operational risk capital, in the post treatment period (2007) we observe a sharp increase in the quantities of capital held to USD 33 billion. A further large increase is observed in 2008, corresponding to the full European implementation of Basel II to calculate capital adequacy. Operational risk

[9] The tolerance level refers to the maximum deviation from the moment conditions across all the variables included in the set of covariates.

[10] Results remain qualitatively the same when other years in the pre-treatment period is used for the entropy balancing.

capital continues to increase up to 2011, with a small decrease observed after this point. The total operational risk capital held is economically meaningful, with 95 European banks holding EUR 123 billion in 2016. Figure 1 also shows aggregate credit and market risk capital. While operational risk capital is increasing over time, we find no evidence of an increase in either credit or market risk capital over the period examined. Furthermore, aggregate bank capital is not found to increase in the post-treatment period, which is in line with the intention of the Basel II Accord to leave the total capital requirement for an average portfolio broadly unchanged (Basel Committee on Banking Supervision, 2001).

[Figure 1 about here.]

4.2. The Effect of the Basel II Operational Risk Regulation on Operational Losses

We use the entropy-balanced sample to examine the difference in operational losses between treated and control banks. As shown in Equation (1), $ln(\text{OpLoss})$ is regressed on a treatment group dummy *Treated* that takes a value of 1 for European banks and 0 for US banks, a post treatment dummy *Post* that takes a value of 1 after 2007 and 0 before 2007, and an interaction term between the treatment group dummy and the post treatment dummy $Treated \times Post$. We report the baseline results on the effect of the Basel II operational risk regulation on operational losses in Table 5. The variable of interest is the interaction term, which captures the impact of the introduction of the Basel II operational risk regulation on bank operational losses. Columns 1 to 3 report the results in a setup using Tobit model estimates for a sample where banks with no reported losses are represented with a zero loss value. In column 1, only bank fixed effects are included. In columns 2 and 3, both bank and year fixed effects are included to further control for unobservable bank-specific characteristics that may have an impact on operational losses, with standard errors clustered at the bank and country levels, respectively. Across all specifications, the coefficient on $Treated \times Post$ is found to be significant and negative. This means that banks subject to the Basel II operational risk regulation experienced lower operational losses in the post treatment period. In columns 4 to 6, we examine a reduced dataset only containing banks with reported operational losses, using a truncated

regression to account for the fact that only losses greater than USD 100,000 are included in the sample. The interaction variable of interest, *Treated*×*Post*, is again found to be significant at a 1% level. In other words, (EU) treated banks experienced lower operational losses post treatment relative to (US) control banks. The economic magnitude of the findings is considerable. Compared to the control banks, the loss magnitude in treated EU banks is reduced by 96%. Similar findings are evident when bank and year fixed effects are included and for standard errors clustered at the bank and country level. These findings indicate that the Basel II operational risk regulation leads to a reduction in operational losses for European banks, providing support for Hypothesis 1.

[Table 5 about here.]

4.3. The Effect of the Basel II Operational Risk Regulation on Operational Losses Across Measurement Approaches

We next examine the role of supervisory review and risk governance in countering operational risk. In Table 6, we interact the measurement approach employed by treated banks with the *Post* dummy. Our earlier findings of a reduction in operational losses post treatment is borne out for banks employing either TSA or AMA to calibrate operational risk capital, but not for banks subscribing to the BIA approach. In other words, banks using TSA or AMA experienced lower operational losses in the post treatment period. Hence, Hypothesis 2 is supported.

[Table 6 about here.]

While there are differences in the approach to calculate required capital between AMA and TSA, common to both approaches is supervisory approval based on evidence of strong governance and risk management in order to be permitted to adopt these sophisticated approaches. Such requirements are not associated with BIA, supporting the notion that the prerequisite of strong risk governance contributed to the success of operational risk capital and disclosure in reducing realized losses. This inference resonates

with the findings of Chernobai et al. (2011) that strong governance and risk management are associated with reduced operational losses.

4.4. The Effect of the Basel II Operational Risk Regulation on Operational Losses Across Event Categories

We perform additional tests to further corroborate the channel of influence for the results reported in Tables 5 and 6. We perform subsample analyses based on the type of the operational risk events as defined by the Basel Committee (Appendix B). We first separate internal events from external events according to Basel II operational risk event categories. We define a loss as an internal event if it originated from one of business disruption and system failures (BDSF), clients, products, and business practices (CPBP), employment practices and workplace safety (EPWS), execution, delivery, and process management (EDPM), or internal fraud (IF). Losses arising from damage to physical assets (DPA) or external fraud (EF) are defined as external events. If the treatment effect of the Basel II operational risk regulation functions through improved risk governance and internal control, we should observe significant results for the internal events sample. This is indeed what we find, as reported in Table 7: Columns 1 and 2 detail results for internal events while columns 3 and 4 present results for external events. We find a negative and statistically significant treatment effect for internal events but not for external events, which suggests that the introduction of operational risk regulation functions through an improvement in internal control and risk governance in keeping with the earlier results detailed and previous work on the drivers of operational losses (Chernobai et al., 2011). We then perform tests for each of these event types when the number of observations for the subsample permits, with results reported for CPBP in columns 5 and 6, EDPM in columns 7 and 8, and IF in columns 9 and 10.[11] The treatment effect is evident for CPBP and partially for IF, both of which are the focus for internal control and risk management practices in banks.

[11] We do not have sufficient number of observations to perform subsample tests for BDSF, EPWS, DPA and EF.

[Table 7 about here.]

5. Robustness Tests

5.1. Identifying Assumptions

In order to obtain reliable diff-in-diff estimates, several assumptions must be satisfied. The first assumption to be met is that the treatment group is subject to the adoption of Basel II, but the control group is not. Defining our treatment/control groups as European versus US and by excluding US "core" banks that are subject to adopt Basel II in 2007 ensures that this assumption is valid. Second, the pre and post periods should be balanced in terms of having the same banks in both periods (Atanasov and Black, 2021). Our sample selection criterion of retaining only banks that survived through the 2007–2009 financial crisis period satisfies this condition. Third, the treatment should have a significant effect on the treatment group, as observed in Table 5. Finally, the outcome variable for treatment and control groups should exhibit parallel trends over the pre-treatment period (Atanasov and Black, 2021; Lennox, 2016). That is, in the absence of treatment, the average change in the outcome variable would have been the same for both the treatment and control groups. Because such counterfactual trends are not empirically observable, we perform a counterfactual analysis to compare operational losses of the treatment group with those of the control group. We estimate the counterfactual treatment effect by estimating the equation below:

$$ln(OpLoss)_{i,t} = \gamma_0 + \sum_{j=1}^{7} \gamma_j Treated_i \times Pre_j + \sum_{k=1}^{9} \gamma_k Treated_i \times Post_k + \text{Controls}_{i,t-1} + \text{FE} + \epsilon \tag{3}$$

We replace the interaction term $Treated \times Post$ in Equation (1) with separate interactions between Treated and year dummies (except for year 2006, which is used as the benchmark). Pre_1–Pre_7 refer to 1–7 years before the introduction of Basel II operational risk (2000–2006), and $Post_1$–$Post_9$ refer to 1–9 years after the treatment (2007–2015). The same set of bank-level control variables used in the baseline regression are included. FE

refer to year and bank fixed effects here. Our findings, reported in Table 8 and plotted in Figure 2, suggest that the counterfactual treatment effects do not build up in the pre Basel II period, which satisfies the parallel trends assumption and further supports our results in earlier diff-in-diff analysis. We also find that the treatment interaction coefficient is strongly negative and statistically significant for all years post treatment except for 2007. This suggests that the treatment effect takes time to be effective in operational risk mitigation since some banks start to publish Pillar 3 reports that disclose operational risk from 2008. Moreover, we note that the size of the treatment interaction coefficient decreases after 2011, indicating a diminishing treatment effect over time.

[Figure 2 about here.]

[Table 8 about here.]

In Table 9, we limit the sample to shorter time windows of three, two and one year surrounding Basel II mandates. Given that our sample period coincides with several milestone events that are relevant for banks such as amendment of Pillar 3 disclosure requirements (2015), the UK's "twin-peaks" model of financial regulation (2013), and the Dodd–Frank Wall Street Reform and Consumer Protection Act (2010), the use of a shorter window mitigates the concern that the effect that we find may be due to these changes taking place during the sample period. In addition, using a shorter window around the regulatory change also alleviates the concern that overall changes in market structure may be driving our results. Our coefficient of interest remains negative and statistically significant across all specifications in these shorter windows, which provides reassurance that the decrease in operational loss is attributable to the regulatory change imposed by Basel II.

[Table 9 about here.]

5.2. Placebo Tests

We further confirm the causal impact of the Basel II operational risk regulation on bank operational losses by performing two placebo tests based on the diff-in-diff model described in Equation (1). In the first test, we assume 2004 is the treatment year, and select both pre- and post-periods before the implementation of operational risk regulation (2000–2003 as the pre period; 2004–2006 as the post period). This test specification enables us to further corroborate whether the reduction in operational losses is the result of the the original disclosure requirements for operational risk set out in the 2004 Pillar 3 framework or the 2007 mandate that requires public disclosure of operational risk. In the second test, we assume 2012 is the treatment year, and select both pre- and post-periods after the implementation of operational risk regulation (2008–2011 as the pre period; 2012–2015 as the post period). For both tests, we perform entropy balancing again based on the three matching covariates in the year prior to the placebo treatment year. Results for these two tests are reported in Panel A and Panel B of Table 10, respectively. For both specifications, we do not find a significant and negative coefficient on the interaction term ($Treated \times Post$), providing further support for the causal impact of Basel II operational risk regulation on the realized operational losses.

[Table 10 about here.]

5.3. Falsification Tests

We perform falsification tests to address the concern that the treatment effect documented is attributable to factors such as unobservable differences between the EU and US rather than the Basel II operational risk regulation. We reestimate Equation (1) for a sample of US compliant banks and comparable EU banks. The US compliant banks are the very largest and internationally active "core" banks that are excluded from the control group in our baseline tests. If there is no significant difference in the reduction in operational losses between the US compliant banks and EU treated banks, it confirms the treatment effect of the Basel II operational risk regulation documented in the baseline results. As reported in Table 11, this is supported by our empirical findings. Panel A

is based on a sample of 15 US compliant banks and 13 EU systemically important (SI) banks[12] while Panel B is based on a sample of 8 US SI compliant banks and 13 EU SI banks. The coefficient on *Treated*×*Post* is insignificant across all specifications, suggesting the reduction in operational losses shown in our baseline findings is attributable to the implementation of Basel II operational risk regulation.

[Table 11 about here.]

5.4. Confounding Events

We check the robustness of our results to the confounding effect of the 2007 Subprime Mortgage Crisis and the 2008 Global Financial Crisis that coincided with introduction of Basel II. To ensure that our findings are not materially impacted by losses emanating from the crisis, we examine the following specifications with results reported in Table 12: (1) excluding losses originating in the 2007–2009 crisis period from our sample (columns 1 and 2); (2) excluding losses realized in the 2007–2009 crisis period from our sample (columns 3 and 4); (3) deducting associated legal liabilities from the operational loss amount to remove the impact of different litigation propensities across jurisdictions especially the severe US legal ramifications in the aftermath of the financial crisis (columns 5 and 6). In addition, the inclusion of the variable MORT throughout all test specifications further control for banks' exposure to subprime mortgage crisis. Results, detailed in Table 12, are again consistent with the baseline results and suggest that legal losses and losses related to problems emerging from the financial crisis are not behind our baseline findings.

[Table 12 about here.]

The potential effect of the interaction between media attention, operational risk event disclosure, and the size of the institution may help in explaining our findings (Chernobai et al., 2021). Given that operational risk events are often public events and large financial

[12]We define a bank as a systemically important bank using the list of global systemically important banks (G-SIBs) published by the Basel Committee.

institutions are naturally the focus of public scrutiny and thus attract more media coverage, we include a media-attention control variable to account for any potential media bias. Employing the Financial Times Historical Archive data, we compute the number of news articles that include a headline or paragraphs mentioning the names of our sample banks in a given year. We then include the news count as an additional control variable (*Media attention*) in our models for a formal robustness test. The results are reported in columns 7 and 8 of Table 12. The coefficients for *Media attention* are statistically significant in column 7 but economically small. Nevertheless, the economic and statistical significance of the treatment relating to Basel II operational risk remains robust.

5.5. Alternative Loss Measures

We check the robustness of our baseline results to the choice of the operational loss measure by examining the following alternatives: (1) the natural logarithm of operational losses scaled by gross income (columns 1 and 2); (2) the natural logarithm of operational losses scaled by total assets (columns 3 and 4); (3) the natural logarithm of annual average loss per event (columns 5 and 6); and (4) the natural logarithm of annual average loss per employee (columns 7 and 8).[13] All model specifications using alternative loss measures are estimated using ordinary least squares (OLS) to account for the scaled logarithmic-linear dependent variables. Results, reported in Table 13, indicate that treated banks have lower losses in the post treatment period for all alternative loss measures, confirming our earlier findings.

[Table 13 about here.]

5.6. Removing Potential Outliers

To ensure that our findings are not driven by potential large outliers, we remove the largest 5% of the loss distribution in our sample. Table 14 reports results for these tests: (1) removing the specified outliers in the full sample (columns 1 and 2); (2) removing

[13]This is to account for the possibility that loss severity drops but frequency increases as a result of the Basel II regulation.

the outliers in each year (columns 3 and 4); (3) removing the outliers in the treatment and the control groups (columns 5 and 6); and (4) excluding banks with total assets less than USD 10 billion (columns 7 and 8). Results across all specifications examined are consistent and support our finding of a reduction in realized operational losses for treated banks post treatment.

[Table 14 about here.]

5.7. Alternative Matching Choices

5.7.1. Entropy Balancing on Higher Order Moments

Entropy balancing works through obtaining convergence in matching based on a trade-off between the number of matching covariates, number of moments of the distribution of matching covariates (i.e., matching up to mean, variance or skewness), and the tolerance level. Our baseline results are based on an entropy-balanced sample matching upon three covariates (i.e., SIZE, NII and ROE) up to the second moment at the tolerance level of 0.015. To test the sensitivity of our findings to the matching criteria employed, we implement the entropy balancing based on the following combinations of parameters: (1) matching upon the three matching covariates up to the third moment of their distribution, with a tolerance level of 0.1; and (2) matching only upon bank size up to the third distributional moment with a tolerance level of 0.001. Balancing properties of matching covariates under these two specifications are reported in Appendix C1. Related diff-in-diff results, reported in Appendix C2, support our primary finding that operational losses are reduced for treated banks in the post treatment period.

5.7.2. Propensity Score Matching

We next employ propensity score matching (PSM) as an alternative matching technique to create a matched sample. The matching is performed based on data from 2006 using the same set of covariates. We first implement nearest neighbor matching (Rosenbaum and Rubin, 1983) by selecting a control bank (without replacement) for each treated bank that has the closest propensity score. We then perform radius matching that con-

siders all non-treated observations within a specified radius (0.1) around a treated bank's propensity as control units. Radius matching allows for higher precision than nearest neighbor matching (Huber et al., 2013). Matching is performed with replacement, which means that each non-treated bank can be used as a neighbor for multiple treated banks. Appendix D1 reports the balancing properties of the matching covariates under these two PSM specifications. No statistically significant differences are found between the treatment and control samples, providing support for balance between the two samples. Subsequent results, reported in Appendix D2, are strongly supportive of the baseline results, albeit there is an indication of reduced sample size and/or lower test efficiency using PSM due to the information loss in the preprocessing stage.

5.7.3. No Matching

In order to demonstrate our results are independent of the matching procedures selected, we examine a specification where no matching is performed to identify the group of control banks. Results reported in Appendix E are consistent with our baseline results.

5.8. Other Robustness Tests

We conduct a number of further robustness tests in this section and provide details in Appendix F. First, we exclude the year 2007 from our sample to account for any difference in the progress of initial implementation of Basel II across banks/countries as the European Union introduced Basel II in 2007 but allow for a transition period until 2008. We also utilize a balanced sample of pre (2000–2006) versus post period (2008–2014). Results in columns 1 and 2 indicate that our baseline results are not driven by the unbalanced pre- and post-sample periods. Second, as there may be a lag before losses are updated in the dataset, we look at a further specification removing the last three years in the sample period, where we can be reasonably confident that all relevant losses have been reported. Again, we find a consistent treatment effect for the treated banks (columns 3 and 4). Last, to address the potential for the standard error of the estimators being underestimated by diff-in-diff standard errors (Bertrand et al., 2004), we average all variables in the pre- and post-treatment periods to perform entropy balancing and the

subsequent regression. Results, reported in columns 5 and 6, remain qualitatively the same. These findings also support our earlier results that the introduction of operational risk regulation led to a reduction in operational losses.

6. Conclusions

Forming a significant element of the ongoing overhaul to the regulatory capital framework, operational risk has received increased attention from both academic researchers and policymakers. While much of the focus in the literature has been on modeling the distributional characteristics associated with and correlations between operational losses, this paper provides the first assessment of the effects of the introduction of the operational risk regulation under Basel II. The new regulation entails three key novel practices: (1) calculating operational risk capital using one of the three approaches (i.e., BIA, TSA and AMA), (2) reporting qualitative and quantitative information related to the risk capital in the novel Pillar 3 disclosure, and (3) supervisory approval of internal risk governance for banks adopting either TSA or AMA to calculate operational risk capital.

We find that treated banks experienced a reduction in operational losses after the regulation mandate. This effect is mostly pronounced for internal operational losses and for banks that are subject to supervisory approval of internal risk governance when employing either TSA or AMA to calculate operational risk capital. This highlights the importance of risk governance criteria, in addition to risk disclosure and granularity of operational risk categorization, in influencing *ex-post* operational losses.

While our findings shed light on the impact of operational risk regulation on banking risk, they are relevant to policymakers implementing the new standardized approach to calibrate operational risk capital. The inference from our analysis is also relevant for the design of future regulatory frameworks, combining elements of capital adequacy, disclosure, and supervisory review.

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Figure 1: An Overview of Basel I and Basel II Regulatory Frameworks

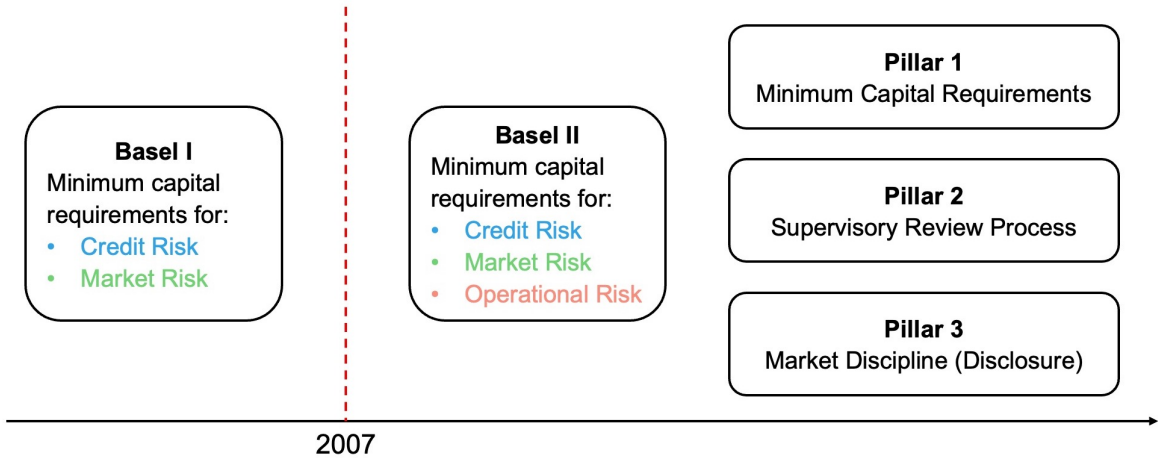

Figure 2: Risk Capital Held by Sample European Banks

This figure shows the evolution of risk capital held by 45 European banks with detailed data by risk category available throughout 2007–2015. CR, MR and OR refer to Credit Risk, Market Risk and Operational Risk, respectively. Risk capital data is hand-collected from annual reports and Pillar 3 disclosure.

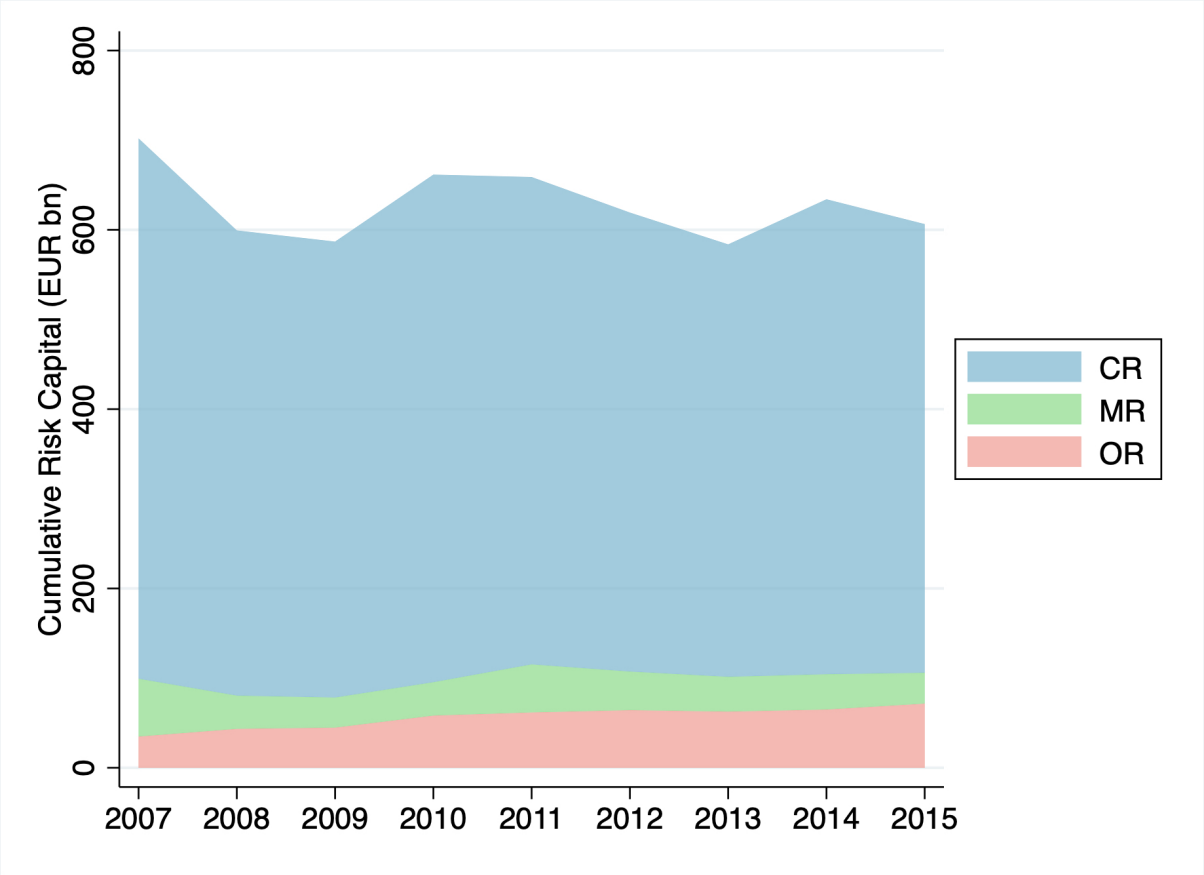

Figure 3: Counterfactual Treatment Effects

This figure depicts the counterfactual treatment effects. The year before the treatment (2006) is used as the benchmark (i.e., coefficient constrained to equal zero). The counterfactual treatment effects do not build up before the treatment, which satisfies the parallel trends assumption for reliable diff-in-diff estimates.

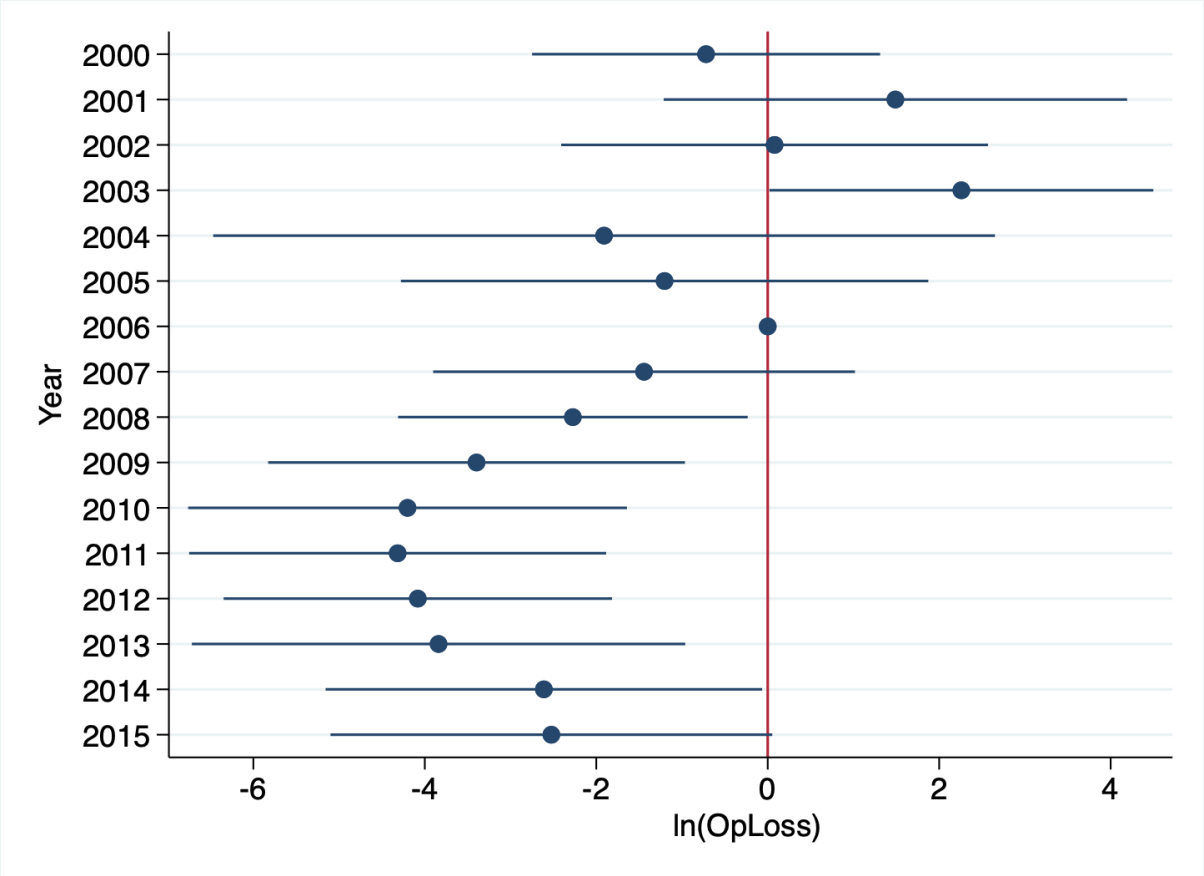

Table 1: Sample Composition by Country

This table outlines the sample of bank-year observations for each country examined in the paper. Panel A details the number of bank-year observations where all banks are included each year. Where there is no reported loss the loss magnitude is set equal to zero. Panel B details the number of bank-year observations where reported operational losses are non-zero.

	Panel A. Zero+Nonzero		*Panel B. Nonzero*	
Country	Frequency	Percent	Frequency	Percent
Austria	495	2.67	12	1.57
Belgium	70	0.38	11	1.44
Cyprus	64	0.34	7	0.91
Denmark	281	1.51	9	1.17
France	475	2.56	33	4.31
Germany	7,646	41.18	29	3.79
Greece	52	0.28	17	2.22
Hungary	29	0.16	6	0.78
Ireland	18	0.10	14	1.83
Italy	423	2.28	53	6.92
Netherlands	68	0.37	14	1.83
Norway	535	2.88	5	0.65
Poland	57	0.31	4	0.52
Portugal	50	0.27	6	0.78
Spain	266	1.43	21	2.74
Sweden	97	0.52	19	2.48
Switzerland	501	2.70	47	6.14
United Kingdom	485	2.61	63	8.22
United States	6,955	37.46	396	51.70
Total	**18,567**	**100.00**	**766**	**100.00**

Table 2: Loss Distribution by Year

This table reports the distribution of reported losses by year. Frequency and percent summarize the number of reported bank-year losses. Mean, median, min and max report the statistical characteristics of the loss magnitude per year. All losses are aggregated by bank-year, in USD million, and CPI-adjusted to 2018.

	Frequency	Percent	Mean	Median	Min	Max
2000	8	1.04	5.44	2.52	1.46	18.48
2001	8	1.04	103.82	6.70	0.18	635.32
2002	13	1.70	20.22	6.94	1.82	68.37
2003	21	2.74	31.50	5.32	0.13	252.85
2004	19	2.48	602.81	1.93	0.19	11,313.95
2005	27	3.52	68.23	1.87	0.12	951.64
2006	43	5.61	983.30	6.29	0.15	29,119.26
2007	86	11.23	140.54	8.80	0.14	2,760.76
2008	83	10.84	144.56	8.65	0.12	2,386.04
2009	84	10.97	79.09	5.50	0.12	1,292.92
2010	67	8.75	70.07	6.34	0.12	722.33
2011	63	8.22	96.71	5.79	0.12	2,152.48
2012	78	10.18	465.38	4.35	0.11	10,204.90
2013	57	7.44	348.85	5.72	0.12	9,616.25
2014	61	7.96	239.40	6.44	0.11	3,443.77
2015	48	6.27	909.57	10.45	0.13	21,811.00
Full Sample	**766**	**100.00**	**278.51**	**5.77**	**0.11**	**29,119.26**

Table 3: Characterizing Operational Losses

This table identifies bank characteristics associated with operational loss severity. A Tobit model with year and country fixed effects is estimated, where the dependent variable is the natural logarithm of aggregated bank-year operational losses. Standard errors are clustered at the bank level and robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Coefficient	t-statistic
Dependent variable: ln(OpLoss)		
ln(Total assets)	3.369***	(10.648)
Deposit ratio	-2.285	(-0.860)
Dividend payout ratio	0.012	(0.820)
Mortgage exposure	0.161	(0.063)
Net chargeoffs	-11.491	(-0.079)
Noninterest income	5.355**	(2.182)
Return on equity	-8.607*	(-1.821)
ΔTotal assets	-3.092	(-1.297)
ln(GDP per capita)	-48.269	(-1.473)
ΔGDP per capita	1.092**	(2.352)
Constant	456.451	(1.312)
Year FE	Yes	
Country FE	Yes	
Cluster level	Bank	
N	7,211	
R^2	0.086	
Sample	Zero+Nonzero	
Model	Tobit	

Table 4: Descriptive Statistics of Unbalanced and Entropy-Balanced Samples

This table reports descriptive statistics of unbalanced and entropy-balanced samples. The balancing is based on year 2006, uses the first two moments of the distribution of matching covariates, and a tolerance level of 0.015.

	Treated		Control	
Unbalanced	Mean	Variance	Mean	Variance
ln(Total assets)	14.480	3.812	13.850	1.481
Noninterest income	0.356	0.042	0.234	0.020
Return on equity	0.109	0.008	0.161	0.007

	Treated		Control	
Entropy-balanced	Mean	Variance	Mean	Variance
ln(Total assets)	14.480	3.812	14.480	3.806
Noninterest income	0.356	0.042	0.355	0.042
Return on equity	0.109	0.008	0.110	0.008

Table 5: The Effect of the Basel II Operational Risk Regulation on Operational Losses

This table presents estimates of the treatment effect from the Basel II operational risk regulation using the diff-in-diff model detailed in Equation (1). The dependent variable is the natural logarithm of aggregated bank-year operational losses. Treated×Post is an interaction term between the treatment group dummy and post-treatment dummy. Columns (1)-(3) employ a Tobit model for a sample that contains all bank-year observations (i.e., ln(OpLoss) is set to 0 when a bank does not report operational losses in a given year). Columns (4)-(6) use a truncated regression to estimate the treatment effect for a sample of banks with reported operational losses. Robust t-statistics and z-statistics are reported in parentheses for tobit model and truncated model, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) ln(OpLoss)	(2) ln(OpLoss)	(3) ln(OpLoss)	(4) ln(OpLoss)	(5) ln(OpLoss)	(6) ln(OpLoss)
Treated×Post	-2.696***	-3.151***	-3.151***	-2.980***	-3.211***	-3.211***
	(-3.202)	(-3.826)	(-4.779)	(-3.548)	(-3.844)	(-5.837)
Post	1.526**			1.505**		
	(2.435)			(1.988)		
ln(Total assets)	1.376***	1.437**	1.437***	1.108*	1.250**	1.250***
	(2.861)	(2.556)	(13.654)	(1.783)	(2.150)	(13.280)
Deposit ratio	-5.353***	-4.789**	-4.789***	-1.281	-0.582	-0.582
	(-2.626)	(-2.322)	(-3.891)	(-0.518)	(-0.226)	(-1.330)
Equity ratio	-2.244	-0.411	-0.411	-3.537	-2.720	-2.720
	(-0.501)	(-0.111)	(-0.163)	(-0.679)	(-0.419)	(-1.262)
Mortgage exposure	1.091	1.040	1.040**	1.440	1.462	1.462***
	(1.016)	(1.000)	(2.017)	(1.051)	(1.025)	(3.024)
Net chargeoffs	-12.476	-19.411	-19.411**	13.994	14.569	14.569
	(-0.851)	(-1.341)	(-2.164)	(0.998)	(0.916)	(1.020)
Noninterest income	1.218	1.043	1.043**	-1.851	-1.829	-1.829***
	(1.029)	(0.834)	(1.999)	(-1.258)	(-1.293)	(-3.294)
Return on equity	0.360	-0.194	-0.194	2.363**	2.285*	2.285***
	(0.282)	(-0.138)	(-0.337)	(2.182)	(1.958)	(6.248)
ΔTotal assets	-0.581	-1.120	-1.120***	-0.019*	-0.021**	-0.021***
	(-0.499)	(-0.925)	(-5.434)	(-1.891)	(-2.410)	(-3.760)
ln(GDP per capita)	9.762*	7.099	7.099	-2.952	1.880	1.880
	(1.924)	(0.731)	(0.528)	(-0.678)	(0.356)	(0.351)
ΔGDP per capita	-0.041	0.598***	0.598***	-0.018	0.123	0.123
	(-0.603)	(3.312)	(2.711)	(-0.232)	(1.004)	(1.067)
Constant	-146.707***	-122.673	-122.673	29.376	-26.073	-26.073
	(-2.874)	(-1.229)	(-0.898)	(0.653)	(-0.469)	(-0.456)
Year FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Bank	Country	Bank	Bank	Country
N	18,567	18,567	18,567	766	766	766
R^2	0.174	0.170	0.170	0.310	0.329	0.329
Sample	Zero+Nonzero	Zero+Nonzero	Zero+Nonzero	Nonzero	Nonzero	Nonzero
Model	Tobit	Tobit	Tobit	Truncated	Truncated	Truncated

Table 6: The Effect of the Basel II Operational Risk Regulation on Operational Losses Across Measurement Approaches

This table examines the role of the measurement approach used to calibrate operational risk regulation using a diff-in-diff model detailed in Equation (1). The dependent variable is the natural logarithm of aggregated bank-year operational losses. Dummy variables for the measurement approach, Basic Indicator Approach (BIA), The Standardized Approach (TSA), and Advanced Measurement Approach (AMA), are interacted with the Post dummy variable. Columns (1) and (2) employ a Tobit model for a sample containing all bank-year observations (i.e., ln(OpLoss) is set to 0 when a bank does not report operational losses in a given year). Columns (3) and (4) use a truncated regression to estimate the treatment effect for a sample of banks with reported operational losses. Robust t-statistics and z-statistics are reported in parentheses for tobit model and truncated model, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) ln(OpLoss)	(2) ln(OpLoss)	(3) ln(OpLoss)	(4) ln(OpLoss)
BIA×Post	1.702	1.702	-0.931	-0.931
	(1.121)	(0.740)	(-0.971)	(-0.872)
TSA×Post	-3.517***	-3.517***	-1.648**	-1.648**
	(-3.535)	(-3.357)	(-2.131)	(-1.990)
AMA×Post	-4.080***	-4.080***	-2.060**	-2.060***
	(-3.741)	(-3.921)	(-2.191)	(-3.113)
ln(Total assets)	1.340**	1.340***	1.171*	1.171***
	(2.306)	(10.283)	(1.865)	(10.861)
Deposit ratio	-5.034**	-5.034***	-0.465	-0.465
	(-2.403)	(-4.382)	(-0.170)	(-0.861)
Equity ratio	-1.215	-1.215	-3.142	-3.142*
	(-0.321)	(-0.613)	(-0.468)	(-1.708)
Mortgage exposure	1.165	1.165***	1.381	1.381***
	(1.092)	(2.629)	(0.904)	(2.785)
Net chargeoffs	-23.140	-23.140***	15.208	15.208
	(-1.526)	(-2.997)	(0.901)	(0.957)
Noninterest income	0.885	0.885**	-1.998	-1.998***
	(0.701)	(2.278)	(-1.386)	(-3.989)
Return on equity	-0.609	-0.609	2.442**	2.442***
	(-0.423)	(-1.606)	(2.003)	(9.722)
ΔTotal assets	-1.128	-1.128***	-0.021**	-0.021***
	(-0.900)	(-5.259)	(-2.397)	(-3.267)
ln(GDP per capita)	23.525**	23.525**	1.630	1.630
	(2.364)	(2.306)	(0.274)	(0.288)
ΔGDP per capita	0.392**	0.392*	0.077	0.077
	(2.023)	(1.896)	(0.588)	(0.630)
Constant	-262.010**	-262.010**	-23.824	-23.824
	(-2.455)	(-2.429)	(-0.377)	(-0.395)
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country
N	7,797	7,797	718	718
R^2	0.161	0.161	0.318	0.318
Sample	Zero+Nonzero	Zero+Nonzero	Nonzero	Nonzero
Model	Tobit	Tobit	Truncated	Truncated

Table 7: The Effect of the Basel II Operational Risk Regulation on Operational Losses Across Event Categories

This table examines the treatment effect for different types of operational losses according to the Basel II classification (Appendix B). Columns (1) and (2) report results for internal losses, columns (3) and (4) report results for external losses, columns (5) and (6) report results for event type "Clients, Products, and Business Practices (CPBP)", columns (7) and (8) report results for event type "Execution, Delivery, and Process Management (EDPM)", and columns (9) and (10) report results for event type "Internal Fraud (IF)". The treatment effect from the introduction of operational risk regulation is estimated using the diff-in-diff model detailed in Equation (1). The dependent variable is the natural logarithm of aggregated bank-year operational losses. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) ln(OpLoss)	(2) ln(OpLoss)	(3) ln(OpLoss)	(4) ln(OpLoss)	(5) ln(OpLoss)	(6) ln(OpLoss)	(7) ln(OpLoss)	(8) ln(OpLoss)	(9) ln(OpLoss)	(10) ln(OpLoss)
Treated×Post	-4.260***	-4.260***	-0.074	-0.074	-3.992***	-3.992***	0.971	0.971	-2.429	-2.429**
	(-3.630)	(-7.526)	(-0.066)	(-0.083)	(-2.854)	(-6.498)	(0.492)	(0.521)	(-1.547)	(-2.356)
ln(Total assets)	0.923	0.923***	0.571	0.571	-0.637	-0.637***	6.412***	6.412**	0.408	0.408
	(1.134)	(7.801)	(0.378)	(1.435)	(-0.651)	(-5.167)	(3.671)	(2.404)	(0.262)	(0.331)
Deposit ratio	0.625	0.625	-2.123	-2.123*	3.081	3.081***	0.136	0.136	4.764	4.764
	(0.171)	(1.013)	(-0.547)	(-1.657)	(0.842)	(2.799)	(0.028)	(0.023)	(1.113)	(1.008)
Equity ratio	9.753	9.753***	-32.827***	-32.827***	1.249	1.249	46.318*	46.318***	11.383	11.383
	(1.259)	(2.928)	(-2.638)	(-6.310)	(0.128)	(0.532)	(1.746)	(2.665)	(0.452)	(1.129)
Mortgage exposure	2.759	2.759***	7.099***	7.099***	3.121	3.121	-1.006	-1.006	7.742***	7.742***
	(1.520)	(2.768)	(4.210)	(14.579)	(1.088)	(1.373)	(-0.278)	(-0.239)	(3.297)	(4.475)
Net chargeoffs	0.688	0.688	37.376	37.376*	42.955**	42.955***	-117.017*	-117.017	6.567	6.567
	(0.036)	(0.040)	(1.404)	(1.873)	(2.027)	(5.448)	(-1.844)	(-1.137)	(0.153)	(0.273)
Noninterest income	-3.770	-3.770***	3.154***	3.154***	-2.979	-2.979***	4.499**	4.499	-7.829**	-7.829
	(-1.632)	(-2.892)	(2.689)	(6.562)	(-1.167)	(-4.042)	(2.294)	(1.460)	(-1.963)	(-1.141)
Return on equity	1.988	1.988***	2.332	2.332***	1.645	1.645***	-10.528**	-10.528	1.691	1.691
	(1.183)	(6.206)	(1.510)	(3.880)	(0.750)	(3.654)	(-2.027)	(-1.216)	(0.645)	(1.197)
ΔTotal assets	-0.028**	-0.028***	0.030	0.030**	-0.014*	-0.014***	-0.022	-0.022	-0.023	-0.023*
	(-2.565)	(-3.395)	(1.471)	(2.284)	(-1.874)	(-3.994)	(-1.172)	(-1.531)	(-1.271)	(-1.712)
ln(GDP per capita)	2.116	2.116	2.619	2.619	0.274	0.274	-21.286	-21.286	10.868	10.868
	(0.356)	(0.374)	(0.234)	(0.197)	(0.039)	(0.041)	(-1.092)	(-1.216)	(0.909)	(0.877)
ΔGDP per capita	-0.023	-0.023	0.303	0.303	-0.099	-0.099	-0.155	-0.155	-0.149	-0.149
	(-0.144)	(-0.173)	(1.112)	(1.114)	(-0.495)	(-0.640)	(-0.529)	(-0.518)	(-0.582)	(-0.648)
Constant	-22.190	-22.190	-24.903	-24.903	23.528	23.528	125.664	125.664	-105.522	-105.522
	(-0.354)	(-0.373)	(-0.204)	(-0.177)	(0.304)	(0.334)	(0.586)	(0.594)	(-0.782)	(-0.816)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country	Bank	Country	Bank	Country	Bank	Country
N	616	616	354	354	424	424	115	115	284	284
R^2	0.279	0.279	0.469	0.469	0.531	0.531	0.491	0.491	0.272	0.272
Sample	Internal	Internal	External	External	CPBP	CPBP	EDPM	EDPM	IF	IF
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated

Table 8: Test of Identifying Assumptions

This table reports results for the counterfactual treatment effects based on the model detailed in Equation (3). The dependent variable is the natural logarithm of aggregated bank-year operational losses. The dummy variable *Treated* is interacted with individual years. The year before the treatment year (2006) is used as the benchmark (i.e., coefficient constrained to equal zero). Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Coefficient	z-statistic
Dependent variable: ln(OpLoss)		
Treated×Year_2000	-0.719	(-0.694)
Treated×Year_2001	1.489	(1.080)
Treated×Year_2002	0.080	(0.063)
Treated×Year_2003	2.259**	(1.978)
Treated×Year_2004	-1.909	(-0.821)
Treated×Year_2005	-1.203	(-0.767)
Treated×Year_2006	0.000	
Treated×Year_2007	-1.443	(-1.149)
Treated×Year_2008	-2.273**	(-2.185)
Treated×Year_2009	-3.397***	(-2.738)
Treated×Year_2010	-4.202***	(-3.218)
Treated×Year_2011	-4.317***	(-3.479)
Treated×Year_2012	-4.081***	(-3.531)
Treated×Year_2013	-3.840***	(-2.615)
Treated×Year_2014	-2.611**	(-2.010)
Treated×Year_2015	-2.524*	(-1.920)
ln(Total assets)	1.415***	(2.754)
Deposit ratio	-0.572	(-0.258)
Equity ratio	-5.388	(-0.640)
Mortgage exposure	1.279	(0.810)
Net chargeoffs	-2.959	(-0.153)
Noninterest income	-2.215	(-1.465)
Return on equity	1.764	(1.246)
ΔTotal assets	-0.023***	(-2.649)
ln(GDP per capita)	5.984	(1.043)
ΔGDP per capita	-0.091	(-0.966)
Constant	-71.393	(-1.171)
Year FE	Yes	
Bank FE	Yes	
Cluster level	Bank	
N	766	
R^2	0.348	
Sample	Nonzero	
Model	Truncated	

Table 9: Shorter Event Windows

This table examines the effect of limiting the event window to a period one (columns 1 and 2), two (columns 3 and 4) and three (columns 5 and 6) years pre- and post-treatment. The dependent variable is the natural logarithm of aggregated bank-year operational losses. Treated×Post is an interaction term between the post-treatment dummy and treatment group dummy. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) ln(OpLoss)	(2) ln(OpLoss)	(3) ln(OpLoss)	(4) ln(OpLoss)	(5) ln(OpLoss)	(6) ln(OpLoss)
Treated×Post	-3.121***	-3.121***	-2.921**	-2.921***	-1.863	-1.863**
	(-2.824)	(-4.075)	(-2.450)	(-3.152)	(-1.375)	(-2.037)
ln(Total assets)	4.120***	4.120***	4.601**	4.601***	1.884	1.884
	(2.837)	(5.098)	(2.166)	(4.252)	(0.970)	(1.339)
Deposit ratio	-1.638	-1.638	-0.320	-0.320	-10.437	-10.437**
	(-0.549)	(-1.360)	(-0.054)	(-0.213)	(-0.886)	(-2.250)
Equity ratio	-7.133	-7.133*	-2.379	-2.379	22.810	22.810
	(-0.583)	(-1.810)	(-0.125)	(-0.537)	(0.592)	(1.280)
Mortgage exposure	1.553	1.553***	-0.050	-0.050	2.300	2.300
	(0.474)	(4.200)	(-0.011)	(-0.084)	(0.437)	(0.935)
Net chargeoffs	45.880	45.880***	14.767	14.767	314.994	314.994*
	(1.390)	(6.035)	(0.244)	(1.289)	(1.180)	(1.759)
Noninterest income	-3.495***	-3.495***	-2.049	-2.049**	2.571	2.571
	(-3.019)	(-4.310)	(-1.472)	(-2.420)	(0.352)	(0.829)
Return on equity	5.386***	5.386***	4.734**	4.734***	-2.780	-2.780
	(3.160)	(6.185)	(2.182)	(3.650)	(-0.400)	(-0.845)
ΔTotal assets	-0.034***	-0.034**	-0.028**	-0.028**	-0.003	-0.003
	(-3.688)	(-2.567)	(-2.009)	(-2.335)	(-0.153)	(-0.254)
ln(GDP per capita)	-15.590	-15.590	-11.502	-11.502	34.128	34.128
	(-1.006)	(-1.454)	(-0.448)	(-0.583)	(1.063)	(1.205)
ΔGDP per capita	0.447**	0.447**	0.289	0.289	-0.433	-0.433
	(2.409)	(2.363)	(1.064)	(0.939)	(-1.228)	(-1.355)
Constant	110.495	110.495	56.914	56.914	-376.271	-376.271
	(0.637)	(1.002)	(0.197)	(0.275)	(-1.066)	(-1.227)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country	Bank	Country
N	409	409	323	323	212	212
R^2	0.561	0.561	0.561	0.561	0.744	0.744
Sample	[-3, +3]	[-3, +3]	[-2, +2]	[-2, +2]	[-1, +1]	[-1, +1]
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated

Table 10: Placebo Tests

This table presents results from two placebo tests. In Panel A the treatment year is assumed to be 2004, while in Panel B the treatment is assumed to occur in 2012. The dependent variable is the natural logarithm of aggregated bank-year operational losses. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Panel A. Treatment in 2004			*Panel B. Treatment in 2012*		
	(A1) ln(OpLoss)	(A2) ln(OpLoss)	(A3) ln(OpLoss)	(B1) ln(OpLoss)	(B2) ln(OpLoss)	(B3) ln(OpLoss)
Treated×Post	-1.789	-2.007	-2.007	0.151	1.143	1.143*
	(-1.204)	(-1.103)	(-1.577)	(0.115)	(1.537)	(1.855)
Post	-1.877			-0.550		
	(-1.493)			(-0.560)		
ln(Total assets)	2.436	1.951	1.951***	-1.567*	-0.483	-0.483
	(1.384)	(0.957)	(3.123)	(-1.756)	(-0.407)	(-1.385)
Deposit ratio	6.130	-1.639	-1.639	-6.951**	-7.202***	-7.202***
	(0.905)	(-0.297)	(-0.633)	(-2.508)	(-4.722)	(-11.385)
Equity ratio	-22.763	-25.045	-25.045**	-10.115	-13.770**	-13.770***
	(-0.651)	(-0.871)	(-2.229)	(-1.054)	(-2.514)	(-6.655)
Mortgage exposure	-1.509	-3.395	-3.395***	2.114	2.374	2.374
	(-0.498)	(-1.126)	(-5.248)	(1.310)	(1.438)	(1.040)
Net chargeoffs	54.704	48.785	48.785	64.049	27.774	27.774**
	(0.415)	(0.362)	(0.474)	(1.228)	(1.610)	(2.472)
Noninterest income	1.967	0.773	0.773	-5.827***	-4.611***	-4.611***
	(0.313)	(0.118)	(0.189)	(-2.847)	(-4.332)	(-3.082)
Return on equity	8.875*	11.090***	11.090*	-2.369	0.620	0.620
	(1.874)	(2.658)	(1.792)	(-0.630)	(0.476)	(1.104)
ΔTotal assets	-0.009	-0.028*	-0.028	0.024	0.022	0.022***
	(-0.399)	(-1.681)	(-1.256)	(1.304)	(1.513)	(5.904)
ln(GDP per capita)	20.142	57.220	57.220*	-8.840	3.137	3.137
	(1.056)	(1.456)	(1.816)	(-1.101)	(0.506)	(0.420)
ΔGDP per capita	-0.084	-0.216	-0.216	0.555**	0.238	0.238
	(-0.216)	(-0.265)	(-0.330)	(2.302)	(1.294)	(1.189)
Constant	-245.929	-616.011	-616.011*	146.735	-3.978	-3.978
	(-1.332)	(-1.536)	(-1.853)	(1.592)	(-0.058)	(-0.049)
Year FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Bank	Country	Bank	Bank	Country
N	117	117	117	609	609	609
R^2	0.675	0.743	0.743	0.488	0.504	0.504
Sample	2000-2006	2000-2006	2000-2006	2008-2015	2008-2015	2008-2015
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated

Table 11: Falsification Tests

This table reports the falsification test results. Panel A compares the treatment effect on US complaint banks versus EU systemically important (SI) banks. Panel B compares the treatment effect on US complaint SI banks versus EU SI banks. The dependent variable is the natural logarithm of aggregated bank-year operational losses. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Panel A. US Compliant vs EU SI Banks		*Panel B. US SI Compliant vs EU SI Banks*	
	(A1)	(A2)	(B1)	(B2)
	ln(OpLoss)	ln(OpLoss)	ln(OpLoss)	ln(OpLoss)
Treated×Post	-1.582	-1.582	-1.389	-1.389
	(-1.021)	(-1.070)	(-0.871)	(-0.930)
ln(Total assets)	0.431	0.431***	0.715	0.715
	(1.021)	(2.644)	(1.066)	(1.182)
Deposit ratio	-1.777	-1.777	-3.598	-3.598
	(-0.678)	(-1.237)	(-1.080)	(-1.136)
Equity ratio	8.335	8.335	13.220	13.220
	(0.560)	(0.892)	(0.728)	(0.687)
Mortgage exposure	6.187**	6.187***	5.998*	5.998
	(2.187)	(2.604)	(1.665)	(1.588)
Net chargeoffs	42.341**	42.341***	41.514*	41.514***
	(2.240)	(4.344)	(1.958)	(3.420)
Noninterest income	0.218	0.218	0.458	0.458
	(0.136)	(0.212)	(0.257)	(0.317)
Return on equity	0.852	0.852	1.624	1.624*
	(0.584)	(1.151)	(0.992)	(1.762)
ΔTotal assets	0.007	0.007	0.017	0.017
	(0.842)	(0.750)	(1.416)	(1.422)
ln(GDP per capita)	7.043	7.043	6.119	6.119
	(0.589)	(0.572)	(0.555)	(0.524)
ΔGDP per capita	0.201	0.201	0.241	0.241
	(1.213)	(1.609)	(1.522)	(1.502)
Constant	-66.186	-66.186	-62.162	-62.162
	(-0.499)	(-0.482)	(-0.507)	(-0.466)
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country
N	266	266	198	198
R^2	0.520	0.520	0.487	0.487
Sample	Nonzero	Nonzero	Nonzero	Nonzero
Model	Truncated	Truncated	Truncated	Truncated

Table 12: Possible Confounding Events

This table examines the sensitivity of findings to various confounding factors. Columns (1) and (2) exclude all losses originating during the Global Finance Crisis period 2007-2009, columns (3) and (4) exclude losses realized during the 2007-2009 period, columns (5) and (6) deduct any legal liabilities from the operational loss amount to remove the impact of different litigation propensities, and columns (7) and (8) include a control variable for media attention. The dependent variable is the natural logarithm of aggregated bank-year operational losses. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) *ln*(OpLoss)	(2) *ln*(OpLoss)	(3) *ln*(OpLoss)	(4) *ln*(OpLoss)	(5) *ln*(OpLoss)	(6) *ln*(OpLoss)	(7) *ln*(OpLoss)	(8) *ln*(OpLoss)
Treated×Post	-2.622**	-2.622***	-4.000***	-4.000***	-3.259***	-3.259***	-3.182***	-3.182***
	(-2.565)	(-4.387)	(-3.892)	(-5.159)	(-3.835)	(-5.880)	(-3.748)	(-5.495)
ln(Total assets)	1.088	1.088***	1.340*	1.340***	1.032*	1.032***	1.306**	1.306***
	(1.603)	(6.405)	(1.740)	(5.498)	(1.719)	(8.808)	(2.239)	(11.586)
Deposit ratio	1.273	1.273**	-4.070	-4.070***	-1.134	-1.134**	-0.646	-0.646
	(0.459)	(2.162)	(-1.374)	(-3.840)	(-0.445)	(-2.358)	(-0.251)	(-1.382)
Equity ratio	6.559	6.559**	-12.631*	-12.631***	-2.777	-2.777	-2.991	-2.991
	(0.873)	(2.413)	(-1.946)	(-4.135)	(-0.382)	(-1.255)	(-0.453)	(-1.320)
Mortgage exposure	1.630	1.630***	2.935	2.935***	1.328	1.328***	1.351	1.351***
	(0.854)	(3.393)	(1.419)	(7.631)	(0.885)	(2.759)	(0.969)	(2.887)
Net chargeoffs	18.815	18.815**	-1.585	-1.585	15.041	15.041	11.145	11.145
	(0.950)	(2.176)	(-0.083)	(-0.118)	(0.948)	(1.127)	(0.705)	(0.811)
Noninterest income	-2.630**	-2.630***	-4.610***	-4.610***	-1.902	-1.902***	-1.892	-1.892***
	(-2.231)	(-3.752)	(-3.992)	(-10.953)	(-1.288)	(-2.997)	(-1.304)	(-3.186)
Return on equity	2.736	2.736***	3.680**	3.680***	2.313**	2.313***	2.244*	2.244***
	(1.642)	(2.720)	(2.256)	(5.840)	(1.978)	(6.067)	(1.910)	(5.741)
ΔTotal assets	-0.032**	-0.032***	-0.036**	-0.036***	-0.023***	-0.023***	-0.022**	-0.022***
	(-2.218)	(-3.504)	(-2.502)	(-3.105)	(-2.616)	(-3.698)	(-2.515)	(-3.868)
ln(GDP per capita)	2.795	2.795	-3.042	-3.042	1.885	1.885	1.051	1.051
	(0.384)	(0.387)	(-0.355)	(-0.369)	(0.353)	(0.354)	(0.197)	(0.204)
ΔGDP per capita	0.065	0.065	-0.021	-0.021	0.120	0.120	0.136	0.136
	(0.373)	(0.515)	(-0.141)	(-0.201)	(0.960)	(1.040)	(1.077)	(1.169)
Media attention							-0.002**	-0.002
							(-2.056)	(-1.588)
Constant	-34.087	-34.087	29.534	29.534	-22.206	-22.206	-18.192	-18.192
	(-0.452)	(-0.442)	(0.326)	(0.340)	(-0.395)	(-0.389)	(-0.322)	(-0.330)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country	Bank	Country	Bank	Country
N	539	539	513	513	759	759	677	677
R^2	0.364	0.364	0.341	0.341	0.351	0.351	0.508	0.508
Sample	Exclude losses originated 2007–2009	Exclude losses originated 2007–2009	Exclude losses realized 2007–2009	Exclude losses realized 2007–2009	Losses Net of legal liabilities	Losses Net of legal liabilities	Nonzero	Nonzero
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated

Table 13: Alternative Loss Measures

This table examines the treatment effect for different dependent variables. Columns (1) and (2) use the natural logarithm of operational losses scaled by gross income as the dependent variable, columns (3) and (4) employ the natural logarithm of operational losses scaled by total assets as the dependent variable, columns (5) and (6) use the natural logarithm of annual average loss per event as the dependent variable, and columns (7) and (8) employ the natural logaritm of annual average loss per employee as the dependent variable. Robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) $ln(\frac{OpLoss}{Gross\ income})$	(2) $ln(\frac{OpLoss}{Gross\ income})$	(3) $ln(\frac{OpLoss}{Total\ assets})$	(4) $ln(\frac{OpLoss}{Total\ assets})$	(5) $ln(\frac{OpLoss}{Loss\ count})$	(6) $ln(\frac{OpLoss}{Loss\ count})$	(7) $ln(\frac{OpLoss}{Capita})$	(8) $ln(\frac{OpLoss}{Capita})$
Treated×Post	-3.008***	-3.008***	-2.990***	-2.990***	-2.329***	-2.329***	-3.116***	-3.116***
	(-3.135)	(-4.936)	(-3.049)	(-4.806)	(-2.859)	(-4.115)	(-3.202)	(-5.330)
ln(Total assets)	0.207	0.207**	0.076	0.076	0.291	0.291***	0.045	0.045
	(0.343)	(2.209)	(0.130)	(0.983)	(0.542)	(3.970)	(0.072)	(0.474)
Deposit ratio	-1.200	-1.200***	-1.615	-1.615***	-0.932	-0.932*	-1.833	-1.833***
	(-0.437)	(-3.280)	(-0.579)	(-3.227)	(-0.335)	(-1.994)	(-0.687)	(-4.257)
Equity ratio	-3.930	-3.930	-4.643	-4.643*	-3.393	-3.393	-4.458	-4.458*
	(-0.653)	(-1.565)	(-0.672)	(-1.768)	(-0.544)	(-1.595)	(-0.718)	(-1.846)
Mortgage exposure	1.761	1.761***	1.313	1.313**	0.868	0.868**	1.230	1.230**
	(1.207)	(3.152)	(0.906)	(2.722)	(0.751)	(2.600)	(0.808)	(2.533)
Net chargeoffs	6.802	6.802	14.820	14.820	7.999	7.999	14.858	14.858
	(0.322)	(0.413)	(0.736)	(0.887)	(0.520)	(0.574)	(0.762)	(0.912)
Noninterest income	-1.570	-1.570**	-1.368	-1.368**	-1.201	-1.201**	-1.703	-1.703***
	(-1.166)	(-2.665)	(-0.890)	(-2.673)	(-0.783)	(-2.416)	(-1.169)	(-2.919)
Return on equity	2.037	2.037***	1.892	1.892***	1.723	1.723***	1.887	1.887***
	(1.426)	(4.676)	(1.364)	(5.166)	(1.323)	(4.207)	(1.332)	(4.615)
ΔTotal assets	-0.021**	-0.021***	-0.019*	-0.019***	-0.012	-0.012**	-0.019**	-0.019**
	(-2.034)	(-3.112)	(-1.865)	(-3.227)	(-1.127)	(-2.754)	(-1.987)	(-2.835)
ln(GDP per capita)	-0.327	-0.327	1.638	1.638	1.695	1.695	1.028	1.028
	(-0.058)	(-0.059)	(0.289)	(0.281)	(0.318)	(0.347)	(0.195)	(0.189)
ΔGDP per capita	0.101	0.101	0.088	0.088	0.027	0.027	0.070	0.070
	(0.752)	(0.801)	(0.657)	(0.687)	(0.214)	(0.238)	(0.526)	(0.577)
Constant	1.454	1.454	-19.783	-19.783	-6.550	-6.550	-3.223	-3.223
	(0.025)	(0.025)	(-0.333)	(-0.319)	(-0.117)	(-0.126)	(-0.058)	(-0.055)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country	Bank	Country	Bank	Country
N	765	765	766	766	766	766	762	762
R^2	0.428	0.428	0.477	0.477	0.430	0.430	0.458	0.458
Sample	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Table 14: Removing Potential Outliers

This table examines the treatment effect after removing potential outliers in the dependent variable and assessing the impact of bank size. Columns (1) and (2) correspond to a sample where observations corresponding to the largest 5% of operational losses over the full sample are removed, columns (3) and (4) remove observations corresponding to the largest 5% of losses each year, columns (5) and (6) remove the top 5% in the treated and control samples, while columns (7) and (8) examine whether findings hold when banks with total assets less than USD 10 billion are removed. The dependent variable is the natural logarithm of aggregated bank-year operational losses. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) ln(OpLoss)	(2) ln(OpLoss)	(3) ln(OpLoss)	(4) ln(OpLoss)	(5) ln(OpLoss)	(6) ln(OpLoss)	(7) ln(OpLoss)	(8) ln(OpLoss)
Treated×Post	-3.004***	-3.004***	-3.045***	-3.045***	-1.994***	-1.994***	-3.430***	-3.430***
	(-3.804)	(-5.516)	(-3.849)	(-5.015)	(-2.677)	(-3.904)	(-3.849)	(-5.524)
ln(Total assets)	1.228**	1.228***	1.376**	1.376***	1.841***	1.841***	0.976	0.976***
	(2.180)	(10.526)	(2.446)	(11.313)	(4.424)	(15.754)	(1.109)	(5.483)
Deposit ratio	0.927	0.927*	-2.038	-2.038**	0.167	0.167	0.588	0.588
	(0.402)	(1.921)	(-0.923)	(-2.329)	(0.112)	(0.265)	(0.225)	(0.749)
Equity ratio	-1.786	-1.786	-4.929	-4.929*	6.041	6.041***	9.466	9.466**
	(-0.300)	(-1.059)	(-0.811)	(-1.805)	(1.256)	(2.951)	(1.016)	(2.177)
Mortgage exposure	1.255	1.255***	1.290	1.290**	0.745	0.745*	1.753	1.753***
	(0.904)	(2.665)	(0.891)	(2.442)	(0.532)	(1.725)	(0.949)	(3.011)
Net chargeoffs	9.497	9.497	12.924	12.924	14.808	14.808	5.356	5.356
	(0.596)	(0.895)	(0.796)	(0.958)	(0.929)	(1.442)	(0.272)	(0.265)
Noninterest income	-1.995	-1.995***	-2.914**	-2.914***	-2.520**	-2.520***	-2.780**	-2.780**
	(-1.465)	(-3.332)	(-2.473)	(-3.453)	(-2.340)	(-3.232)	(-2.224)	(-2.548)
Return on equity	2.171*	2.171***	2.770**	2.770***	2.334**	2.334***	2.898**	2.898***
	(1.784)	(5.384)	(2.526)	(5.806)	(2.117)	(4.650)	(2.542)	(5.859)
ΔTotal assets	-0.028***	-0.028***	-0.023***	-0.023***	-0.027***	-0.027***	-0.032***	-0.032***
	(-3.907)	(-5.155)	(-2.795)	(-4.537)	(-3.701)	(-5.372)	(-3.796)	(-3.139)
ln(GDP per capita)	-1.635	-1.635	-2.385	-2.385	-1.489	-1.489	1.765	1.765
	(-0.349)	(-0.362)	(-0.419)	(-0.413)	(-0.298)	(-0.310)	(0.311)	(0.327)
ΔGDP per capita	0.232*	0.232*	0.211	0.211	0.151	0.151	0.110	0.110
	(1.914)	(1.911)	(1.559)	(1.521)	(1.236)	(1.291)	(0.871)	(0.919)
Constant	10.229	10.229	18.066	18.066	-1.885	-1.885	-20.856	-20.856
	(0.208)	(0.210)	(0.300)	(0.293)	(-0.036)	(-0.037)	(-0.350)	(-0.360)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country	Bank	Country	Bank	Country
N	727	727	734	734	729	729	571	571
R^2	0.295	0.295	0.298	0.298	0.355	0.355	0.472	0.472
Sample	Remove top 5% in full sample	Remove top 5% in full sample	Remove top 5% in each year	Remove top 5% in each year	Remove top 5% in treated/control	Remove top 5% in treated/control	Remove banks TA¡10bn	Remove banks TA¡10bn
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated

Appendix A. Variable Definition

Variable Label	**Definition**	**Source**
Dependent variables		
OpLoss	The present value of CPI-adjusted operational losses as of 2018	SAS OpRisk Global
ln(OpLoss)	Natural logarithm of OpLoss	SAS OpRisk Global
$ln(\frac{OpLoss}{Gross\ income})$	Natural logarithm of OpLoss scaled by gross income	SAS OpRisk Global
$ln(\frac{OpLoss}{Total\ assets})$	Natural logarithm of OpLoss scaled by total assets	SAS OpRisk Global
$ln(\frac{OpLoss}{Loss\ count})$	Natural logarithm of annual average OpLoss per event	SAS OpRisk Global
$ln(\frac{OpLoss}{Capita})$	Natural logarithm of OpLoss scaled by the number of employees	SAS OpRisk Global
Bank characteristics		
ln(Total assets)	Natural logarithm of a bank's total assets at fiscal year end	Bankscope
Deposit ratio	Deposits scaled by total assets	Bankscope
Equity ratio	Book value of equity divided by total assets	Bankscope
Dividend payout ratio	Dividends paid divided by net income	Bankscope
Media attention	The number of news articles for each bank in a given year	Financial Times
Mortgage exposure	Mortgage loans divided by total assets	Bankscope
Net chargeoffs	Net loan charge-offs divided by gross loans	Bankscope
Noninterest income	Noninterest income divided by the sum of net interest income and noninterest income	Bankscope
Return on equity	Pretax income scaled by total assets	Bankscope
ΔTotal assets	Annual growth rate of total assets	Bankscope
BIA	Dummy=1 if a bank's operational risk capital is calculated using Basic Indicator Approach	Annual Report; Pillar 3
TSA	Dummy=1 if a bank's operational risk capital is calculated using The Standardized Approach	Annual Report; Pillar 3
AMA	Dummy=1 if a bank's operational risk capital is calculated using Advanced Measurement Approach	Annual Report; Pillar 3
Country characteristics		
ln(GDP per capita)	Natural logarithm of annual GDP per capita	World Bank
ΔGDP per capita	Annual growth rate of GDP per capita	World Bank

Appendix B. Basel II Operational Risk Event Categories

Basel II describes seven operational risk event categories:

Business Disruption and System Failures (BDSF): Losses arising from disruption of business or system failures.

Clients, Products, and Business Practices (CPBP): Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product.

Employment Practices and Workplace Safety (EPWS): Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity/discrimination events.

Execution, Delivery, and Process Management (EDPM): Losses from failed transaction processing or process management, from relations with trade counterparties and vendors.

Internal Fraud (IF): Losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy, excluding diversity/ discrimination events, which involves at least one internal party.

Damage to Physical Assets (DPA): Losses arising from loss or damage to physical assets from natural disaster or other events.

External Fraud (EF): Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party.

Source: Bank for International Settlements (2001)

Appendix C1. Descriptive Statistics of Unbalanced and Entropy-Balanced Samples

This table reports descriptive statistics of unbalanced and entropy-balanced samples. The balancing is based on year 2006. Panel A reports the balancing property of the first three moments of the distribution of matching covariates, with a tolerance level of 0.1. Panel B presents the balancing based on the first three moments of the distribution of bank size, with a tolerance level of 0.001.

Panel A. 3rd Moment Entropy Balanced on 3 Matching Covariates

	Treated			Control		
Unbalanced	Mean	Variance	Skewness	Mean	Variance	Skewness
ln(Total assets)	14.480	3.812	0.935	13.850	1.481	1.457
Noninterest income	0.356	0.042	0.977	0.234	0.020	1.864
Return on equity	0.109	0.008	2.175	0.161	0.007	0.176

	Treated			Control		
Entropy-balanced	Mean	Variance	Skewness	Mean	Variance	Skewness
ln(Total assets)	14.480	3.812	0.935	14.480	3.812	0.934
Noninterest income	0.356	0.042	0.977	0.355	0.421	0.966
Return on equity	0.109	0.008	2.175	0.109	0.008	2.143

Panel B. 3rd Moment Entropy Balanced on Bank Size

	Treated			Control		
Unbalanced	Mean	Variance	Skewness	Mean	Variance	Skewness
ln(Total assets)	14.480	3.804	0.932	13.850	1.481	1.457

	Treated			Control		
Entropy-balanced	Mean	Variance	Skewness	Mean	Variance	Skewness
ln(Total assets)	14.480	3.804	0.932	14.480	3.804	0.932

Appendix C2. Diff-in-Diff Results: 3-Moment Entropy Balancing

This table uses a synthetic control sample resulting from 3-moment entropy balancing. Estimates of the treatment effect from the introduction of operational risk regulation are presented using the diff-in-diff model detailed in Equation (1). The dependent variable is the natural logarithm of aggregated bank-year operational losses. Treated×Post is an interaction term between the treatment group dummy and post-treatment dummy. Columns (A1)-(A3) employ an entropy-balanced sample created in Panel A of Appendix C1. Columns (B1)-(B3) use an entropy-balanced sample created in Panel B of Appendix C1. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Panel A. 3rd Moment; 3 Covariates			*Panel B. 3rd Moment; Bank Size*		
	(A1)	(A2)	(A3)	(B1)	(B2)	(B3)
	ln(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)
Treated×Post	-3.592***	-3.514***	-3.514***	-2.793***	-2.726***	-2.726***
	(-4.216)	(-4.329)	(-6.229)	(-3.384)	(-3.281)	(-4.841)
Post	2.072***			1.338*		
	(2.867)			(1.720)		
ln(Total assets)	1.377***	1.493***	1.493***	0.746	1.235*	1.235***
	(2.825)	(3.361)	(18.861)	(0.934)	(1.752)	(8.620)
Deposit ratio	-2.045	-1.369	-1.369**	-1.769	-0.498	-0.498
	(-0.850)	(-0.530)	(-2.349)	(-0.844)	(-0.208)	(-1.189)
Equity ratio	-3.681	-2.128	-2.128	-4.528	1.600	1.600
	(-0.636)	(-0.320)	(-0.998)	(-0.818)	(0.218)	(0.946)
Mortgage exposure	-0.141	0.693	0.693*	1.708	1.777	1.777***
	(-0.076)	(0.427)	(1.840)	(1.476)	(1.489)	(4.657)
Net chargeoffs	19.116	20.955	20.955	40.005**	48.570***	48.570***
	(1.615)	(1.639)	(1.556)	(2.373)	(2.692)	(6.817)
Noninterest income	-1.007	-1.177	-1.177**	-2.065*	-2.341*	-2.341***
	(-0.673)	(-0.714)	(-2.168)	(-1.658)	(-1.867)	(-3.670)
Return on equity	3.137***	2.705**	2.705***	3.672***	3.660***	3.660***
	(3.571)	(2.489)	(6.268)	(2.978)	(2.700)	(4.548)
ΔTotal assets	-0.025***	-0.024***	-0.024***	-0.018*	-0.021**	-0.021***
	(-2.836)	(-3.123)	(-5.127)	(-1.794)	(-2.489)	(-3.231)
ln(GDP per capita)	-3.853	1.275	1.275	0.894	1.209	1.209
	(-0.898)	(0.244)	(0.244)	(0.174)	(0.228)	(0.231)
ΔGDP per capita	-0.024	0.114	0.114	0.009	0.063	0.063
	(-0.265)	(0.973)	(1.097)	(0.124)	(0.511)	(0.670)
Constant	34.690	-23.549	-23.549	-5.104	-18.977	-18.977
	(0.764)	(-0.428)	(-0.423)	(-0.099)	(-0.328)	(-0.340)
Year FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Bank	Country	Bank	Bank	Country
N	749	749	749	749	749	749
R^2	0.401	0.424	0.424	0.385	0.400	0.400
Sample	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated

Appendix D1. Balancing Property of the Matching Covariates

This table details the sample balancing properties of the matching covariates. The balancing is based on year 2006. Panel A reports the balancing properties of the matching covariates using nearest neighbor matching. Panel B reports the balancing properties of the matching covariates using radius matching.

Panel A. Nearest Neighbor Matching

	Treated	Control	Difference	t-statistic	p-value
ln(Total assets)	17.029	16.735	0.294	0.66	0.515
Noninterest income	0.425	0.410	0.015	0.21	0.835
Return on equity	0.185	0.192	-0.006	-0.23	0.821

Panel B. Radius Matching

	Treated	Control	Difference	t-statistic	p-value
ln(Total assets)	18.098	17.769	0.329	0.90	0.369
Noninterest income	0.443	0.413	0.029	0.61	0.549
Return on equity	0.193	0.168	0.025	1.49	0.141

Appendix D2. Diff-in-Diff Results: Propensity Score Matching

This table presents estimates using a propensity score matched sample to isolate the treatment effect from the introduction of operational risk regulation using the diff-in-diff model detailed in Equation (1). The dependent variable is the natural logarithm of aggregated bank-year operational losses. Treated×Post is an interaction term between the treatment group dummy and post-treatment dummy. Columns (A1)-(A3) employ a control sample generated using nearest neighbor matching as shown in Panel A of Appendix D1. Columns (B1)-(B3) use a control sample created using radius matching as reported in Panel B of Appendix D1. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Panel A. Nearest Neighbor Matching			*Panel B. Radius Matching*		
	(A1)	(A2)	(A3)	(B1)	(B2)	(B3)
	ln(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)	*ln*(OpLoss)
Treated×Post	-3.319***	-4.044***	-4.044***	-1.718**	-1.880***	-1.880***
	(-3.307)	(-3.844)	(-4.376)	(-2.526)	(-2.847)	(-3.902)
Post	1.007			0.463		
	(1.388)			(0.833)		
ln(Total assets)	1.632*	2.549**	2.549***	0.754	1.518***	1.518***
	(1.806)	(2.324)	(3.389)	(1.644)	(3.140)	(4.635)
Deposit ratio	-0.587	0.982	0.982	-0.786	-0.015	-0.015
	(-0.193)	(0.287)	(0.293)	(-0.491)	(-0.009)	(-0.014)
Equity ratio	-12.714	-1.623	-1.623	-1.108	4.045	4.045
	(-1.083)	(-0.102)	(-0.125)	(-0.263)	(0.855)	(0.965)
Mortgage exposure	0.982	1.340	1.340	0.896	0.769	0.769
	(0.490)	(0.771)	(0.572)	(0.924)	(0.762)	(0.715)
Net chargeoffs	32.517	13.509	13.509	19.745	32.434**	32.434***
	(1.313)	(0.480)	(0.655)	(1.554)	(2.275)	(2.955)
Noninterest income	-5.644*	-7.526**	-7.526***	-0.560	-0.999	-0.999
	(-1.942)	(-2.333)	(-2.878)	(-0.501)	(-0.967)	(-1.124)
Return on equity	1.540	2.521*	2.521	0.960	0.568	0.568
	(1.001)	(1.683)	(1.338)	(1.066)	(0.609)	(0.867)
ΔTotal assets	-0.015	-0.022*	-0.022*	0.002	-0.000	-0.000
	(-1.036)	(-1.946)	(-1.660)	(0.320)	(-0.036)	(-0.039)
ln(GDP per capita)	3.728	4.611	4.611	2.728	4.681	4.681
	(0.833)	(1.190)	(1.528)	(0.838)	(0.966)	(0.905)
ΔGDP per capita	0.037	0.251	0.251	0.027	-0.005	-0.005
	(0.458)	(1.569)	(1.626)	(0.555)	(-0.045)	(-0.042)
Constant	-50.013	-77.834*	-77.834**	-26.742	-61.693	-61.693
	(-1.120)	(-1.733)	(-2.040)	(-0.793)	(-1.191)	(-1.110)
Year FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Bank	Country	Bank	Bank	Country
N	220	220	220	766	766	766
R^2	0.336	0.378	0.378	0.310	0.328	0.328
Sample	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated

Appendix E. Diff-in-Diff Results: No Matching

This tables uses the original unmatched sample to present estimates of the treatment effect from the introduction of operational risk regulation using the diff-in-diff model detailed in Equation (1). The dependent variable is the natural logarithm of aggregated bank-year operational losses. Treated×Post is an interaction term between the treatment group dummy and post-treatment dummy. No matching is performed to identify the group of control banks (i.e., all banks in our original sample that are not subject to the treatment are included in the control sample). Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) ln(OpLoss)	(2) ln(OpLoss)	(3) ln(OpLoss)
Treated×Post	-1.701**	-1.864***	-1.864***
	(-2.528)	(-2.848)	(-3.863)
Post	0.486		
	(0.888)		
ln(Total assets)	0.759*	1.468***	1.468***
	(1.711)	(3.115)	(4.647)
Deposit ratio	-0.885	-0.148	-0.148
	(-0.562)	(-0.090)	(-0.150)
Equity ratio	-0.415	4.508	4.508
	(-0.097)	(0.940)	(1.057)
Mortgage exposure	0.830	0.757	0.757
	(0.881)	(0.772)	(0.727)
Net chargeoffs	20.461*	30.939**	30.939**
	(1.662)	(2.207)	(2.568)
Noninterest income	-0.511	-0.911	-0.911
	(-0.461)	(-0.889)	(-1.068)
Return on equity	0.954	0.509	0.509
	(1.073)	(0.552)	(0.848)
ΔTotal assets	0.002	-0.000	-0.000
	(0.347)	(-0.009)	(-0.009)
ln(GDP per capita)	2.138	4.411	4.411
	(0.668)	(0.913)	(0.854)
ΔGDP per capita	0.035	0.001	0.001
	(0.724)	(0.014)	(0.013)
Constant	-20.517	-57.878	-57.878
	(-0.617)	(-1.122)	(-1.043)
Year FE	No	Yes	Yes
Bank FE	Yes	Yes	Yes
Cluster Level	Bank	Bank	Country
N	850	850	850
R^2	0.335	0.353	0.353
Sample	Nonzero	Nonzero	Nonzero
Model	Truncated	Truncated	Truncated

Appendix F. Other Robustness Tests

This table reports additional robustness test results. Columns (1) and (2) exclude 2007 and employ a balanced pre (2000–2006) versus post period (2008–2014). Columns (3) and (4) remove the last three years in the sample period. Columns (5) and (6) average all variables in the pre- and post-treatment periods to perform entropy balancing and the subsequent regressions. Robust z-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	(1) ln(OpLoss)	(2) ln(OpLoss)	(3) ln(OpLoss)	(4) ln(OpLoss)	(5) ln(OpLoss)	(6) ln(OpLoss)
Treated×Post	-3.455***	-3.455***	-3.478***	-3.478***	-2.211***	-2.211***
	(-3.686)	(-4.881)	(-4.306)	(-4.966)	(-4.638)	(-4.149)
ln(Total assets)	1.355**	1.355***	2.231***	2.231***	0.527	0.527
	(2.096)	(9.781)	(2.951)	(13.325)	(0.521)	(1.163)
Deposit ratio	-2.380	-2.380***	-0.901	-0.901	1.742	1.742
	(-0.747)	(-7.273)	(-0.322)	(-1.582)	(0.571)	(0.790)
Equity ratio	-6.444	-6.444	-0.423	-0.423	26.967	26.967*
	(-0.559)	(-1.619)	(-0.040)	(-0.133)	(1.406)	(1.848)
Mortgage exposure	1.872	1.872***	1.877	1.877***	1.413	1.413**
	(1.629)	(3.356)	(1.069)	(5.180)	(0.888)	(2.009)
Net chargeoffs	15.916	15.916*	13.833	13.833	-46.250***	-46.250***
	(0.833)	(1.750)	(0.846)	(0.737)	(-3.434)	(-2.940)
Noninterest income	-1.568	-1.568***	-1.588	-1.588***	-0.024	-0.024
	(-0.957)	(-5.533)	(-1.132)	(-3.704)	(-0.035)	(-0.095)
Return on equity	3.090**	3.090***	2.828**	2.828***	0.450	0.450
	(2.479)	(4.244)	(2.442)	(4.786)	(1.231)	(1.107)
ΔTotal assets	-0.023	-0.023***	-0.021**	-0.021***	-0.026	-0.026
	(-1.571)	(-2.830)	(-2.205)	(-3.683)	(-0.788)	(-0.605)
ln(GDP per capita)	12.106	12.106	8.839	8.839	5.613	5.613
	(1.035)	(0.974)	(0.987)	(0.683)	(0.852)	(0.902)
ΔGDP per capita	0.070	0.070	0.148	0.148	-0.607**	-0.607**
	(0.375)	(0.477)	(1.053)	(0.858)	(-2.045)	(-2.449)
Constant	-135.110	-135.110	-117.237	-117.237	-56.487	-56.487
	(-1.092)	(-1.021)	(-1.252)	(-0.849)	(-0.887)	(-0.865)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Bank	Country	Bank	Country	Bank	Country
N	571	571	600	600	293	293
R^2	0.408	0.408	0.431	0.431	0.815	0.815
Sample	Balanced	Balanced	2000-2012	2000-2012	Averaged	Averaged
Model	Truncated	Truncated	Truncated	Truncated	Truncated	Truncated