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OPERATIONAL AND CYBER RISKS IN THE FINANCIAL SECTOR

Abstract

We use a unique cross-country dataset at the loss event level to document the evolution and characteristics of banks' operational risk. After a spike following the great financial crisis, operational losses have declined in recent years. The spike is largely accounted for by losses due to improper business practices in large banks that occurred in the run-up to the crisis but were recognised only later. Operational value-at-risk can vary substantially – from 6% to 12% of total gross income – depending on the method used. It takes, on average, more than a year for operational losses to be discovered and recognised in the books. However, there is significant heterogeneity across regions and event types. For instance, improper business practices and internal fraud events take longer to be discovered. Operational losses are not independent of macroeconomic conditions and regulatory characteristics. In particular, we show that credit booms and periods of excessively accommodative monetary policy are followed by larger operational losses. Better supervision, on the other hand, is associated with lower operational losses. We provide an estimate of losses due to cyber events, a subset of operational loss events. Cyber losses are a small fraction of total operational losses, but can account for a significant share of total operational value-at-risk.

JEL Classification: D5, D62, D82, G2, H41

Keywords: Operational risks, financial institutions, cyber risks, time to discovery, Value-At-Risk

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and do not necessarily represent those of the Bank for International Settlements or ORX.

I. Introduction

Operational risk gained notoriety as a distinct risk category in the mid to late 1990s, following events such as the case of Nicholas Leeson, the “rogue” trader often credited with the undoing of Barings bank. Not long after, the Basel II standards introduced operational risk capital requirements, with operational risk defined as “the risk of losses resulting from inadequate or failed internal processes, people, systems or from external events” (Basel Committee on Banking Supervision (2003)).[1]

Measuring and understanding operational risk is critical for both banks and public authorities. Operational risk currently represents a significant portion of banks' risk-weighted assets, second only to credit risk.[2] Regulators, central banks and international organisations, in turn, place the understanding and mitigation of operational risk – and subcomponents such as cyber risk – high in their agendas. Despite this focus, the paucity of data and analysis on operational risk means that discussions on the topic lack a proper empirical grounding.

In this paper, we contribute to filling this gap by analysing a unique cross-country dataset of operational losses. We present stylised facts on the evolution of operational losses since 2002; compute operational value-at-risk (VaR) through different methods; use proportional hazards models to study the lag between occurrence, discovery and recognition of operational loss events; and link losses to the macroeconomic environment. Finally, we construct a proxy for cyber losses using the event type categorisation of Basel II, document their evolution and compute a cyber VaR.

We use data at the loss event level from ORX, a consortium of financial institutions. The consortium was founded by banks with the aim of sharing operational loss risk data in an anonymised fashion in order to benchmark operational risk models. The sample we use contains over 700,000 operational loss events from 2002 until end-2017 for a group of 74 large banks from North and Latin America, Asia/Pacific, Europe and Africa. This makes our paper the most comprehensive in terms of its time series and, especially, cross-country coverage.

We document that, after a notable increase post-Great Financial Crisis (GFC), operational risk losses in banks have been declining strongly since 2015. Digging deeper in to the type of event behind this aggregate trend shows that one category in particular is responsible for the pattern in cost, namely “Clients, Products & Business Practices”. This category includes improper business practices like fiduciary breaches, aggressive sales, breaches of privacy, account churning and misuse of confidential information. These are the type of operational risks that characterise periods of financial excess, with mis-selling of mortgage-backed securities in the mid-2000s being a prime example. Towards the peak of the GFC there is a significant increase in the occurrence of this type of event (especially in North America), which were then recognised in the books of banks a few years later. Importantly, this pattern is observed only in terms of loss amounts and not in terms of frequency of occurrence.

[1]Before Basel II, losses stemming from operational risks were to be covered by capital provisions set aside from credit and market risk.

[2]Up to 40% of risk-weighted assets can be attributed to operational risk in some jurisdictions (Liao et al. (2018)).

Operational losses are characterised by a fat-tailed distribution.[3] Accordingly, VaR estimates can lead to quite different results depending on the method used and how well it captures what happens at extreme values of the distribution of operational losses. Indeed, our estimates for operational VaR using methodologies from the Advanced Measurement Approach (AMA) range from 6% to 12% of gross income, against the 15% benchmark of the Basic Indicator Approach. This finding provides some support for the new regulatory framework that proposes the adoption of the Standardised Measurement Approach (SMA) for all banks. This has two practical effects. First, it reduces heterogeneity in the application of different AMAs and the need for regulators to validate these models. Second, it simplifies the regulation, while at the same time preserving capital adequacy to cover operational risks.

We find that, on average for all banks over the sample, it takes 251 days between occurrence and discovery of operational loss events, and 184 days between discovery and recognition. Taken together, this puts the average time between occurrence and recognition of losses at 435 days. The time between occurrence, discovery and recognition, however, varies across several dimensions. Using a proportional hazards approach, our results show that loss events associated with internal fraud and improper business practices are less likely to be discovered than other events. This result could be explained by two facts. First, perpetrators of internal fraud do their best to cover their tracks such that the event goes unnoticed for longer. Second, "business practices" events are often settled through lengthy legal proceedings that delay loss recognition in banks' books. Small banks, in turn, tend to be slower in discovering and recognising operational losses in their books. Finally, we also find substantial heterogeneity across jurisdictions when it comes to discovering and recognising losses: banks in North America are the quickest to discover losses, whereas those in Eastern Europe are the slowest. Different approaches to regulation and supervision across jurisdictions may play a role in these results. Our findings on duration can inform policy discussions regarding the principles for executive compensation packages.

The stylised facts we present point to the existence of a link between operational losses and macroeconomic conditions. Abdymomunov et al. (2017) use data for US banks to document a contemporaneous correlation between macroeconomic conditions and operational risk losses, e.g. operational losses rise during economic downturns. We build on this idea and use a cross-country panel analysis to argue that the ultimate cause of the rising losses during economic downturns is to be found in the excesses characterising the run-up to the downturn. In other words, favourable conditions during periods of macroeconomic expansion and financial exuberance lead to the occurrence of events that are only discovered when the economic tide starts to turn, and recognised in the books of banks even later.

We show that credit booms are followed by an increase in operational losses. This is driven by the frequency rather than the severity of events. Periods of excessively accommodative monetary policy can lead to increased risk-taking by banks, which can boost the type of improper business practices that account for the lion's share of operational losses. We use deviations of policy rates from an implied Taylor rule

[3] In other words, there are a large number of inconsequential events from a cost perspective and a limited number of very large cost events. The latter group in particular complicates the quantification of operational risks, as such low frequency/high severity events are often cited as being "one-in-a-hundred years" events.

benchmark to document that indeed periods of accommodative monetary policy are also followed by larger operational losses. Finally, in line with the literature that associates increased competition with financial stability, we find that periods of intense bank competition are also associated with lower operational losses.

The time pattern of losses stemming from internal fraud and improper business practices suggests that the quality of regulation and supervision can also be related to operational losses in the cross-section of countries. Indeed, we find that better regulation and supervision – as captured by the financial reform index by Abiad et al. (2010) and Denk and Gomes (2017) – is associated with lower operational losses.

The fallout of the financial crisis attracted attention to operational losses caused by people. However, as society moves to a digital age, retail banks are moving from the high street to the world wide web, intensifying interconnectedness through technology. This has led to a growing focus and concerns regarding cyber and IT-related risks. We use the data to construct a proxy range of cyber losses (which are a subset of operational losses). We document that cyber losses, to date, represent a relatively small share of operational losses. In recent years, however, losses from cyber events saw a spike which aligns with the growing attention cyber risk has been receiving. Despite representing a relatively small share of operational losses, cyber value-at-risk can account for up to a third of total operational value-at-risk.

The paper is organised as follows. The next section reviews the related literature. Section III describes the data. Section IV uses the analytic and loss distribution approaches to estimate operational value-at-risk. Section V, in turn, documents the duration between occurrence, discovery and recognition of loss events. The link between operational losses and the macroeconomic environment is the focus of Section VI, whereas Section VII presents our estimate of cyber risks, a very important class of emerging risks in the financial sector. Finally, Section VIII presents the main conclusions.

II. Related literature

Research on operational risk intensified after 2001, when the BCBS introduced an amendment to the Basel Capital Accord to support operational risk with regulatory capital. Early work on the subject focused on issues related to how to conceptualise and quantify the risks (Power (2005), Cornalba and Giudici (2004), Chavez-Demoulin et al. (2006), Antonini et al. (2009), Jarrow (2008)).

The literature has found links between characteristics of financial institutions and operational risk. Shih et al. (2000) and Curti et al. (2019) find a positive relationship between the size of financial institutions and the size of operational losses incurred. Chernobai et al. (2011) uses data for US financial institutions and finds that most operational losses can be traced to a breakdown of internal controls. Firms suffering from these losses tend to be younger and more complex, and have higher credit risk, more antitakeover provisions, and CEOs with higher stock option holdings and bonuses relative to salary. Operational losses can also pose risks for the financial system at large (i.e. systemic risks). Berger et al. (2018) find that operational risk at large US bank-holding companies is statistically and economically positively linked to standard measures of bank systemic risk.

Operational losses can also have an impact on bank returns (Sturm (2013), Gillet et al. (2010) and Cummins et al. (2006)). Biell and Muller (2013) also look at the timing of market responses to operational loss announcements, finding heterogeneity across different loss categories. Allen and Bali (2007) find cyclical components in both catastrophic and operational risk measures, and show that 18% of financial institutions returns represent compensation for operational risk. However, depository institutions are exposed to operational risk levels that average 39% of their overall equity risk premium. Byrne et al. (2017) examine the stock market reactions to the announcement of fines on systemically important financial institutions and find negative abnormal returns at the announcement of an investigation. Köster and Pelster (2017) analyse the impact of financial penalties on the profitability and stock performance of banks, finding a negative relation between financial penalties and pre-tax profitability but no relation to after-tax profitability.

Fraud and employee misconduct have contributed to operational losses and have come under scrutiny from regulators, often resulting in sizeable financial penalties. Altunbaş et al. (2018) find that banks are more likely to engage in misconduct when their CEOs have a long tenure. Eshraghi et al. (2015) study regulatory enforcement actions issued against US banks to show that both board monitoring and advising are effective in preventing misconduct by banks. Fich and Shivdasani (2007) study whether external directors suffer reputational penalties if the firms they serve on were accused of financial fraud. Schnittker et al. (2017) employ provisions for misconduct costs as an instrumental variable to identify the causal effect of a bank capital shock on risk-taking, finding that a negative bank capital shock causes an increase in risk-taking in the UK mortgage market.

Operational risk could also be intertwined with business and financial cycles. Carrivick and Cope (2013) and Hess (2011) look at the consequences of the GFC on operational risk losses in the financial sector. Abdymomunov et al. (2017) provide additional evidence of a relationship between operational losses in US banks and macroeconomic conditions. We build on this literature and investigate why such relationships are observed. Sakalauskaite (2018) shows that banks' misconduct has been relevant over our sample period and that its intensity correlates with the business cycle. Interestingly, the study finds that misconduct initiation is related to bank remuneration schemes, increasing with CEO bonuses in periods of high economic growth and when bank leverage is high.

Growing concerns around the economic and social impact of cyber risk in financial institutions have drawn attention to a lack of literature in this domain. Data on cyber incidents are scarce and thus quantitative analyses on the impacts of cyber events is challenging. The absence of common agreed standards to record such events further complicates the analysis. We devise a proxy for cyber-related incidents from the categorisation of different event types. Kaffenberger et al. (2017) examines the current regulatory framework and supervisory approaches, and identifies information asymmetries and other inefficiencies that hamper the detection and management of systemic cyber risk. Kashyap and Wetherilt (2019) outline some principles for regulators to consider when regulating cyber risk in the financial sector. From a perspective of the wider economy, Romanosky (2016) analyse the characteristics of cyber incidents across different sectors. Bouveret (2018) provides an estimate for the total cost of cyber events to the global financial sector. In the baseline case, average losses due to cyber-attacks in the sample amount to USD 97 billion or 9 percent of banks net income. Duffie and Younger (2019) analyse a sample of 12 systemically important U.S. financial institutions and suggest that these firms have sufficient stocks of high quality liquid assets to cover wholesale funding run-offs in a relatively extreme cyber event. Facchinetti et al. (2019) propose ordinal measures to evaluate cyber risk in the presence of a lack of data regarding the severity of such events.

III. Data

A. *Operational loss data*

Our analysis is based on a database that collects operational losses reported by financial firms from across the globe. The data are owned and managed by ORX, the largest operational risk association in the financial services sector. The association, established in 2002, is primarily a platform for the secure and anonymised exchange of high-quality operational risk loss data, with the objective of improving the management and measurement of operational risk.[4]

Firms report their losses voluntarily based on the operational risk reporting standards established by ORX. These standards follow the event type and business line classification defined in the operational risk framework of the BCBS.[5] To be included in the dataset, operational events need to have an associated monetary cost reflected in the books of the banks, and be above a minimum of EUR 20,000.

Data are reported at the operational loss event level and include a number of characteristics associated with the event. Table I provides an example on how the data are structured.

RefID	Region	Business Line	Event Type	Gross Loss Amount	…	Loss Occurrence	Loss Discovery
123XYZ	Asia/Pacific	BL0101	EL0101	20000	…	ddmmyyyy	ddmmyyyy
⋮	⋮	⋮	⋮	⋮	…	⋮	⋮

Table I
Example of the data structure

Each loss event is associated with an *event type* category. In line with Basel II definitions, there are seven event type (level 1) loss categories. Table II provides an overview of these categories and their definition. They include a wide array of potential causes of operational losses, such as internal/external fraud, disasters, improper business practices related to either clients or products, IT related, etc.

Most of our analysis will be done at the level 1 category. However, the data also include a subdivision of each loss into level 2 event types, allowing for even more granular analysis. We will use the level 2 event type information to proxy for cyber-related events in Section VII.

[4]For details on the ORX consortium, see: https://managingrisktogether.orx.org/about.

[5]For details on the ORX reporting standards, see: https://managingrisktogether.orx.org/standards. For the BCBS classification, see: https://www.bis.org/basel_framework/chapter/OPE/30.htm.

Event Type	Description
ET01 - Internal Fraud	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.
ET02 - External Fraud	Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third-party
ET03 - Employee Related	Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events
ET04 - Clients, products & business practices	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.
ET05 - Disasters	Losses arising from disruption of business or system failures.
ET06 - Technology and Infrastructure	System failures (hardware or software), disruption in telecommunication, and power failure can all result in interrupted business and financial loss.
ET07 - Transactions and Processing	Losses from failed transaction processing or process management, from relations with trade counterparties and vendors.

Table II

Overview of event types based on the operational risk reporting standards of ORX

Each loss event is also associated with a particular business line. The business line classification, which again follows pre-specified standards, comprises nine business lines, including inter alia asset management, clearing, retail banking and trading & sales. Table A.1 in the Appendix provides a detailed description of the business lines. The business line classification is used in conjunction with the event type classification in order to evaluate the value-at-risk for the financial institutions in the database (see Section IV).

The data are also partitioned into macro-regions. The regions included are North America, Latin America & Caribbean, Eastern Europe, Western Europe, Asia/Pacific and Africa. For some of the regions that are more densely populated in terms of bank coverage, a further division into sub-regions is possible (see Table A.2 in the Appendix for details).

While data are collected so as to preserve bank anonymity, each loss event has a tag for bank size. This indicator variable divides financial institutions based on income into large, medium and small. It is important to bear in mind, however, that we cannot associate a given loss event to any specific financial institution.

Finally, each loss event has three dates associated with it. The *date of occurrence* captures the date at which the event that caused the loss was deemed to have taken place. The *date of discovery* captures the point in time at which staff became aware of the event the lead to the operational loss. Finally, the *date of recognition* represents the date at which the loss was recorded in the accounts of the bank

Figure 1 shows these dates through the timeline of a loss. These dates play a crucial part in the analysis in Section V. Consistent with the literature, when constructing a panel, the data are aggregated over the *date of recognition* (Abdymomunov et al. (2017)).

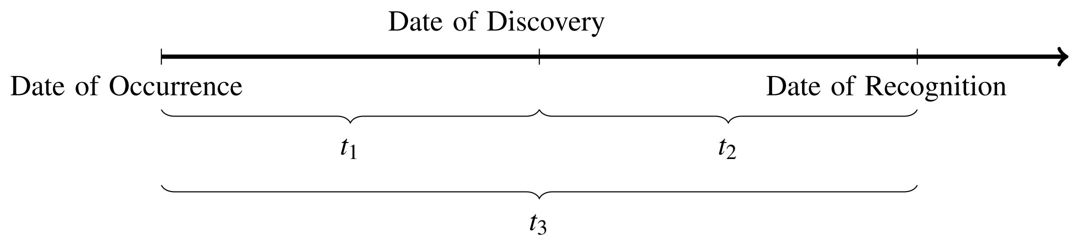

Figure 1
Loss timeline and key dates

B. Additional data

For the analysis of the link between operational losses, macroeconomic conditions and regulatory characteristics, we complement the operational risk data with data from a variety of sources.

To proxy for the build-up of financial imbalances, we rely on credit-to-GDP gap data from the Bank for International Settlements.[6]

To capture competition in the banking sector, we use the Boone (2008) indicator, retrieved from the World Bank.[7] This measure proxies bank competition by the elasticity of profits to marginal costs. The elasticity is calculated by regressing the logarithm of profits on the logarithm of marginal costs.[8] The indicator is based on the premise that higher profits are achieved by more efficient banks, thus a more negative Boone indicator implies a higher degree of competition. This is in line with Boyd and De Nicolò (2005) and De Nicolò and Lucchetta (2013) who find that banks in a higher competition environment increase monitoring efforts and reduce risks.

Excessively accommodative monetary policy can be conducive to more risk-taking (Altunbaş et al. (2014)). In order to measure the stance of monetary policy we use deviations of monetary policy rates from implied rates based on country-specific Taylor rules. The measure is constructed by subtracting the implied policy rate by the Taylor rule from the actual policy rate:

$$\tilde{\phi}_t = i_t - \phi_t \tag{1}$$

where i_t is the observed policy rate, ϕ_t denotes the rate implied by the Taylor rule, and $\tilde{\phi}$ denotes the deviation of the actual rate from the implied one. Central bank policy rates are sourced from the Bank for

[6] See https://www.bis.org/statistics/c_gaps.htm.
[7] See https://datacatalog.worldbank.org/boone-indicator.
[8] The estimates of the Boone indicator in this database are based on the approach used by Čihák and Schaeck (2010) but use marginal costs rather than average costs.

International Settlements and the implied Taylor rule rates are computed following Bogdanova and Hofmann (2012):

$$\phi = r^* + \pi^* + 1.5(\pi - \pi^*) + 0.5y \tag{2}$$

where, π denotes inflation, y captures the output gap, π^* is the inflation target and r^* is the long-run level of the real interest rate.

Finally, to assess regulation and supervision in the cross-section of countries, we use an index of regulation and bank supervision, originally presented in Abiad et al. (2010) and extended in Denk and Gomes (2017). The full dataset is used to construct a measure of financial reforms across countries. To do so various indicators are aggregated into a single index calculated as the simple average of the following seven dimensions: credit controls, interest rate controls, banking sector entry barriers, capital account controls, state ownership of banks, regulation of securities markets, and prudential regulation and bank supervision. The main variable of interest in our work is the measure of regulation and supervision. This variable takes into account the following four factors, i) Has a country adopted a capital adequacy ratio based on the latest Basel standard?; ii) Is the banking supervisory agency independent from executives' influence?; iii) Does the banking supervisory agency conduct effective supervision through on-site and off-site examinations? ; and, iv) Does a country's banking supervisory agency cover all financial institutions without exception? We use these questions to calculate an index at the regional level to be matched with the ORX data (an example of how this is done can be found in Section VI). The index runs from 0 to 1, whereby, a score of 0 indicates a repressed regulatory and supervisory framework and a score of 1 a well-developed and liberalised framework. The series is provided annually from 2002 up to 2015. For further details on these data, we refer the reader to Denk and Gomes (2017).

C. *Stylised facts*

Against the background of limited data to underpin discussions of operational risk in the financial sector, we present initially some useful stylised facts. The full sample comprises over 700,000 observations of operational loss events occurring between 2002 and early 2019. This is considerably larger than many other available datasets on operational risk and has the added appeal – relative to detailed datasets at the country level such as the one available to U.S. regulators – that it includes a cross-section of countries over a large period.[9]

Figure 2 reports the evolution of the ORX consortium, in terms of participating banks (left plot) and frequency of the reported losses (right plot). The number of banks in the consortium has grown over time, which may bias assessments of the evolution of operational losses when aggregating them over time.

To account for this trend, we first adjust the gross losses and income to be in 2017 prices, using a

[9] Algo FIRST, SAS OpRisk Global Data are typically used for analysis in the literature on operational risk, as well as the ORX database. Cope et al. (2012) also use the ORX Global Loss Data Database, which at the time had approximately 180,000 loss events.

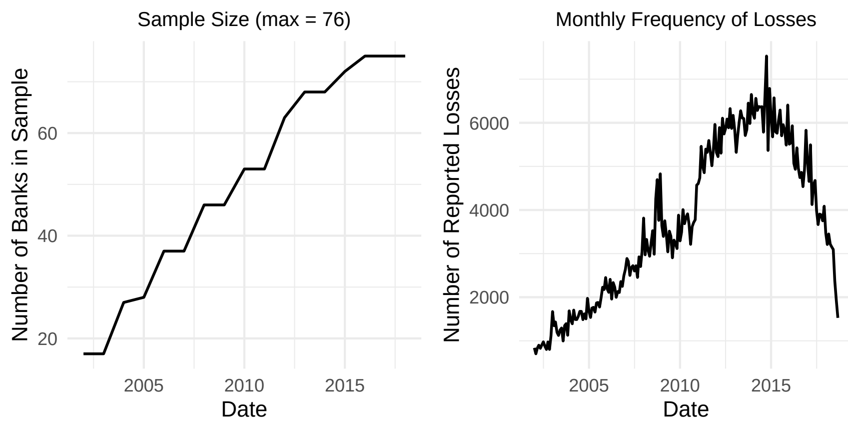

Figure 2
Sample size and frequency of events

composite of OECD countries as a proxy for global inflation. We then divide the inflation-adjusted gross losses and the frequency by the total income of the banks in the consortium at any given period. This adjusts for the growing number of banks in the sample, but also for their size. This second point is important, as simply dividing by the number of banks in the sample would fail to capture the heterogeneity in bank sizes. In addition, any residual gross losses below EUR 20,000 are not included and the data are truncated at the end of 2017. This is due to a bias in underreporting towards the end of the sample: as losses take time to be discovered and recognised in the books of banks, observations for the last few quarters may under-represent to true extent of operational losses which are currently occurring (we explore this issue in detail in Section V).[10] Figure 3 shows the frequency of losses after the data have been adjusted. The rising trend up until 2014 is still prevalent in the data before a decline in more recent periods, indicating that the trend observed in Figure 2 may not only be driven by the growing size of the consortium.

Figure 4 shows the evolution of the value and frequency of losses as a fraction of income. In the upper panel, they are aggregated by Date of Discovery and in the lower panel by Date of Recognition.

There is a visible lag in the accumulation of losses. In the upper left panel, the peak comes in 2009, whereas in the lower left panel the peak is in 2011. This lag is indicative of the fact that many losses in the business practices/negligence failure category face protracted legal proceedings before they are eventually settled and incorporated into the accounts of the bank. The bars are partitioned by event type, with business practices clearly dominating the loss amounts. The event types that dominate in terms of frequency are transactions and process management. This is consistent with the former being a high severity item, largely attributable to fines and regulatory actions, and the latter a high-frequency item, arising from thousands of daily operations that take place in banks.

The breakdown by region (see Figure A.2 in the Appendix) shows that North America and Western Europe dominate in terms of the value of the losses. This is where the majority of the worlds' largest banks

[10]Carrivick and Cope (2013) make use of transformations based on survival analysis to adjust for this bias.

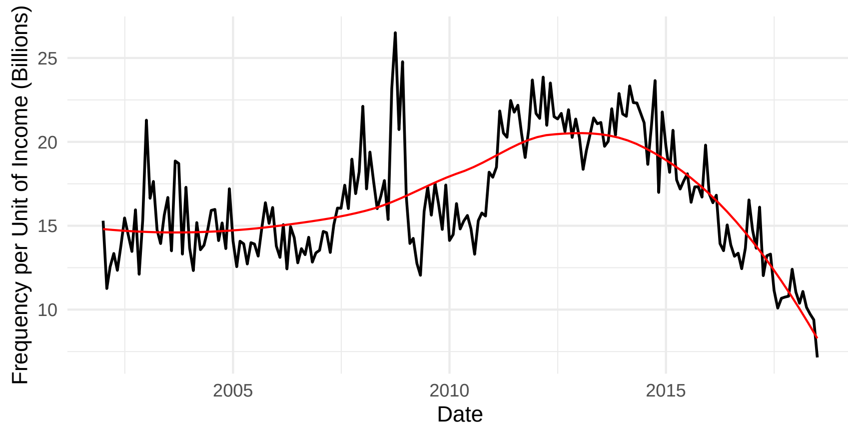

Figure 3
Monthly frequency of losses per billion units of income

are headquartered, which were particularly affected by the events leading up to the crisis.

Figure A.3 in the appendix shows the losses and frequency but normalised by the income level of the bank. For each year, we divide the banks by size (large, medium and small) and show by means of bars the sum of losses (frequency). The frequency of events tends to be quite stable across bank sizes. In terms of gross losses, there is much more variability, in particular in larger banks. Moreover, a large proportion of the losses that were realised around the crisis period can be attributed to large banks. This is line with the increased scrutiny of large banks (including domestic and global systemically important banks – DSIBs and GSIBs respectively) for their role in events alleged to have taken place in the run-up to the crisis, such as the LIBOR scandal and the selling of mortgage-backed securities.

IV. Operational value-at-risk

The Basel II accord allows three methods for calculating the capital charge assigned to operational risk: i) the Basic Indicator Approach (BIA); ii) the Standardised Approach (SA); and iii) the Advanced Measurement Approach (AMA). These methods vary with increasing sophistication and risk sensitivity. Under the BIA, banks have simply to keep in the form of capital at least 15% of their revenues, while in the SMA calculation this percentage is not fixed at 15% but varies according to the different business lines. The AMA applies external and internal data to value-at-risk methods that have to be validated by the supervisory authority. The new Basel III accord streamlines the operational risk framework, by replacing the AMA and the existing three standardised approaches with a single risk-sensitive standardised measurement approach (SMA) to be used by all banks. Capital requirements to cover operational risk for different business lines under the SMA amount to a fixed percentage of a banks total gross income. In this section, we quantify operational risks by using VaR methods and compare the results against the more conservative BIA benchmark.

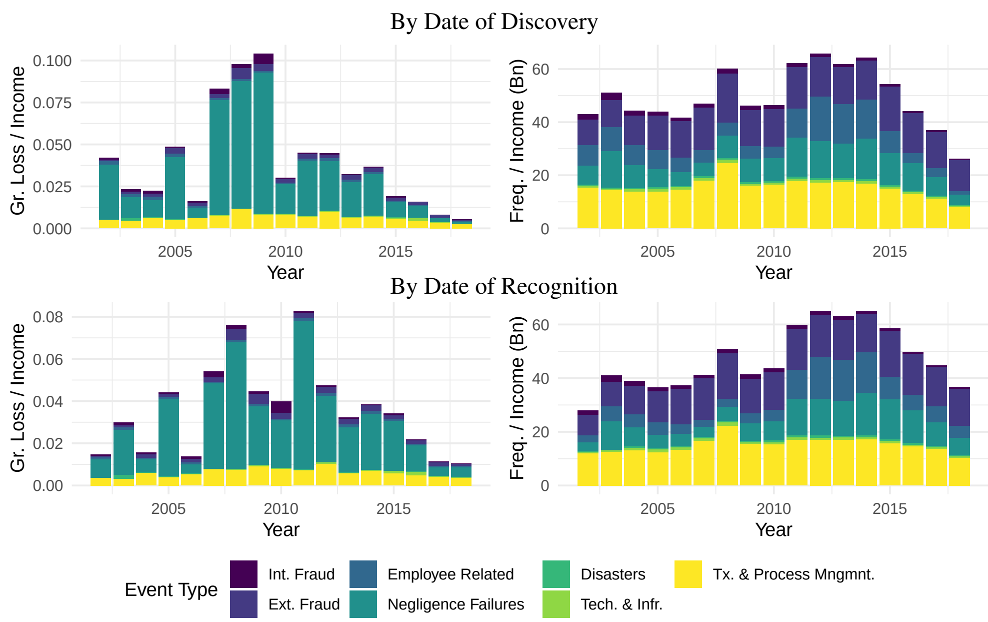

Figure 4

Loss and frequency of operational losses by event type

The VaR indicates the level of risk to which a firm, a portfolio or a single position may be exposed to over a given time period. This metric has been largely adopted by banks under the Basel II revision to measure market risk (see Dowd (1998), Jorion (1997)) and operational risk using the AMA approach (Esterhuysen et al. (2008)).

There are multiple methodologies that can be used to construct VaR measures. We estimate the VaR based on two widely used approaches: an analytical approach and the loss distribution approach. Both approaches allow us to characterise the distribution of annual total losses, from which we draw three measures of interest:

- **Expected losses**. Losses below this value should be covered by general provisions. This measure is simply calculated by taking the sample mean of historical loss observations.
- **99.9$^{\text{th}}$ percentile losses**. This value corresponding to a year with exceedingly high losses, in an extreme scenario. This scenario could lead to bankruptcies and should be covered by an adequate level of capital.
- **Unexpected losses**. This value corresponds to the capital to cover losses in between the expected loss and 99.9$^{\text{th}}$ percentile.

Basel II rules require banks to calculate their regulatory capital requirement as the sum of expected and unexpected losses. However, if a bank can demonstrate that it is adequately capturing expected losses in its internal business practices, it may base the minimum regulatory capital requirement on unexpected losses alone.

A. *The analytical method*

The analytical method is based on the internal measurement of losses and used for the AMA approach. The analytical method is used to determine the Basel "gamma" factors, in order to derive more tractable ways to compute the unexpected losses (Alexander (2008)). In particular, the unexpected losses are simply calculated as the difference between the 99.9$^{\text{th}}$ percentile losses minus the expected loss (see above).

The calculation of unexpected losses is based on the following formula:

$$\text{Unexpected Loss} = \phi \times \mu_L \times \sqrt{\lambda} \times \sqrt{1 + \left(\frac{\sigma_L}{\mu_L}\right)^2} \tag{3}$$

where, ϕ is a parameter that corresponds to the Basel 'gamma', σ_L is the standard deviation of annual losses, μ_L is the mean of annual losses and λ is the mean frequency of losses under the assumption they follow a Poisson distribution. From this equation, one can derive an analytical equation for ϕ,

$$\phi = (99.9^{\text{th}}\text{percentile} - \lambda \mu_L)/\sqrt{\lambda(\mu_L^2 + \sigma_L^2)} \tag{4}$$

Note that the unexpected losses increase with the variation in loss severity (σ_L). To calculate the VaR based on this approach, we have to first obtain the mean, μ_L, and standard deviation, σ_L, of annual losses from the ORX database. For each intersection of business line and event type, i, we use maximum-likelihood estimation to fit $\hat{\lambda}_i$ and then compute the estimate of $\hat{\phi}_i$ from equation 4.

B. *The loss distribution approach*

The analytical method gives a quick but potentially inaccurate estimate of unexpected losses. A more precise method, suggested in the literature and employed in risk management practice, is the loss distribution approach. In this framework, the frequency and severity of losses are each independently assumed to follow a statistical distribution, whose parameters are estimated directly from the data. The convolution of these two distributions is used to compute the distribution of losses. To estimate the parameters either a maximum likelihood approach or a Bayesian approach can be followed. Here we choose a Bayesian approach, which is more flexible and avoids estimation problems typically encountered when working with extreme value distributions. In any case, we will consider non-informative priors for which Bayesian estimates converge to maximum likelihood ones. We follow the approach used by Figini et al. (2015) to estimate the annual loss distribution. We consider a convolution between a Generalised Pareto distribution for the mean loss (severity), with a Poisson distribution for the number of loss events (frequency).

The annual losses can be written as a product of Frequency (the number of loss events during a certain time period) and Severity (the mean impact of the event, in terms of financial losses, in the same period). In particular,

$$L_{it} = s_{it} \times n_{it} \tag{5}$$

where, for the business line/event type intersection i and for t time periods available, L_{it} denotes the annual operational loss, s_{it} denotes the severity and n_{it} the frequency. Following the operational risk literature, we consider the following three general assumptions: i) within each intersection i, and each time period t, the distribution of the frequency n_{it} is independent of the distribution of the severity s_{it}; ii) for any given time period t, the losses, occurring in different intersections, i, are independent of each other; iii) for any given intersection, i, losses occurring in different time periods, t, are independent of each other.

Let $f(s_t|\theta)$ and $f(n_t|\lambda)$, denote the likelihood functions of the severity and frequency respectively, where θ denotes the parameter vector of the severity distribution and λ denotes the parameter vector of the frequency distribution, we have that, according to assumptions i)-iii):

$$L(s,n|\theta,\lambda) = \prod_{t=1}^{T} f(n_t|\lambda) f(s_t|\theta) \tag{6}$$

Within the AMA approach in the Basel II framework, the functional forms for the frequency and severity distributions for each ET/BL intersection can be specified uniquely. Here we consider a Poisson distribution for the frequency and a Generalised Pareto distribution for the severity, across all intersections as in Chavez-Demoulin et al. (2006).

Whilst expert input can be useful to construct informative priors, we use uninformative priors with high variance, as in Dalla Valle and Giudici (2008). For the frequency, we use the conjugate gamma distribution.

$$\lambda_i \sim \Gamma(\alpha,\beta) \tag{7}$$

We choose $\alpha = 0.01$ and $\beta = 0.01$. The severity is assumed to follow a general Pareto distribution:

$$F_i \sim GPD(\mu,\xi,\sigma) \tag{8}$$

First, we assume the location parameter, $\mu = 0$. We then follow Cabras and Castellanos (2007) and use an uninformative prior for ξ and σ of the severity distribution.

$$\pi(\xi,\sigma) \propto \sigma^{-1}(1+\xi)^{-1}(1+2\xi)^{-1/2}, \quad \xi > -0.5, \sigma > 0 \tag{9}$$

Since there are no analytical solutions to this problem, we use the Metropolis-Hastings algorithm to estimate the posterior distributions of the annual frequency and severity. We then take the convolution of the two distributions to obtain the annual loss distribution. From the estimation of the annual loss distribution, we derive the expected losses, unexpected losses and VaR. The results of the two approaches are shown in Table III.

The two approaches lead to very different results. For the analytical approach, the VaR is equal to 56 billion EUR for the whole ORX consortium of banks, of which about 32 billion EUR are accounted for by unexpected losses and 24 billion EUR are classified as expected losses. To put these figures into perspective, we also report them as a proportion of total annual gross income for 2017. The corresponding percentages

	Expected Loss	Unexpected Loss	value-at-risk
Analytical (EUR millions)	23,802	32,902	56,704
LDA (EUR millions)	44,823	72,644	117,467
Analytical % of Income (2017)	2.4	3.3	5.7
LDA % of Income (2017)	4.5	7.3	11.8

Table III
Operational value-at-risk

are: 5.7% (VaR) 3.3% (unexpected losses); 2.4% (expected losses).

By contrast, based on the loss distribution approach we find that the VaR for the whole consortium is more than double and equal to 117 billion EUR, while the unexpected losses amount to 73 billion EUR and expected losses to 45 billion EUR. These figures represent, respectively, 11.8%; 7.3% and 2.3% of total gross income.

As discussed above, the capital charge can be based on solely unexpected losses or the value-at-risk at the discretion of the supervisor. Therefore, the lower bound of our estimates would yield a capital charge of 3.3% (unexpected losses for the analytical method) and an upper bound of 11.8% (VaR using the loss distribution approach). It is worth noting that these estimates are lower than the suggested 15% of gross income used by the Basic Indicator Approach. These results confirm that the BIA is quite conservative with respect to alternative measures that use more complex models (such as the AMA). This heterogeneity across estimates seems to be consistent with the shift towards the Basel III SMA.

Potential capital charges can be broken down by business line and event type. Table A.3 in the appendix reports the distribution of unexpected losses across business lines and event types calculated based on the analytical approach. Similar distribution patterns are obtained in terms of VaR (not reported for the sake of brevity). From the table it is evident that Process Management (transaction execution and maintenance, monitoring and reporting) and Business Practices represent the majority of unexpected losses, consistent with the number of events described in Figure 4. Within Business Practices, the majority of losses arise from the Agency and Trading business lines. Within Process Management, the majority of losses arises from the Corporate finance and Agency business lines.

V. How long does it take for discovery and recognition of losses?

As discussed in Section III, the time it takes for a loss to be discovered, reported and finally accounted for in the books can reveal important differences regarding operational risks. Carrivick and Cope (2013) acknowledge that some of the losses are not discovered or reported to the consortium until well after the event occurs because of fraudulent activities that were well hidden by the perpetrator. In other cases, legal proceedings can take some time to reach a settlement.

We study the durations of the three intervals defined in Figure 1, namely $t_1 = discovery - occurrence$, $t_2 = recognition - discovery$, and $t_3 = t_1 + t_2 = recognition - occurrence$.

Table IV, provides a breakdown of the average duration of events by different categories. The average duration of the three time intervals vary across different dimensions. By region and size of bank, this could be due to various approaches to regulation, whereby supervisors across regions implement different strategies to tackle operational risk, in particular in Pillar II of the Basel regulation. In addition, banks of different size could face varying degrees of attention and scrutiny from regulators due to their different contribution to systemic risk. By event type, Business Practices have considerably longer duration times: the average duration between occurrence and recognition is approximately two and a half years. This provides further evidence that certain losses take longer to materialise than others, in particular those that go through legal proceedings. The quantification of these lags is particularly relevant for CEO compensation and provides support for the introduction of the FSB's Principles and Standards on Sound Compensation (Cerasi et al., 2020). We will follow up on this aspect below.

	$t_1 = time\ to$ discovery	$t_2 = time\ to$ recognition	$t_3 = t_1 + t_2$
Panel A - By region			
Africa	194	126	320
Asia/Pacific	236	81	317
East Europe	486	189	674
Latin America & Caribbean	163	437	600
North America	146	150	296
West Europe	403	110	513
Panel B - By event type			
Internal fraud	299	149	448
External fraud	117	81	199
Employee-related	165	448	613
Business Practices	566	261	827
Disasters	60	132	192
Technology & infrastructure	77	63	139
Transactions & process management	254	143	397
All	251	184	435

Table IV

Average durations by region and event type (in days)

We can further model the duration of each t_i, accounting for the variation across these multiple dimensions, by employing a proportional hazards model as in Cox (1972). In a proportional hazards regression model, the measure of effect is the hazard rate, which is generally interpreted as the risk or probability of incurring the event of interest, conditional on the individual/entity of interest not having incurred the event up to a certain time. In our application, the hazard rate of each of the intervals can be interpreted as follows

- $\lambda(t_1)$: conditional probability of the loss being discovered at time t conditional on being undiscovered until time $t_1 - 1$.
- $\lambda(t_2)$: conditional probability of the loss being recognised in the books at time t, conditional on being discovered but not accounted for until time $t_2 - 1$.

- $\lambda(t_3)$: conditional probability of the loss being recognised in the books at time t conditional on being undiscovered and unaccounted for until time $t_3 - 1$.

For each of the intervals defined above, we estimate the following equation,

$$\lambda(t_i|X_i) = \lambda_0(t)\exp(X_i\beta + FE) \tag{10}$$

where $\lambda_0(t)$ denotes the baseline hazard function, X_i is a vector of explanatory variables whose effect on the hazard is captured by the β coefficients. The explanatory variables in the vector X include, *event type, region, bank size*. We include a yearly fixed effect in the equation, denoted by FE.

Following Cox (1972), the β parameters could be estimated via a partial likelihood in order to remove the need to estimate the baseline hazard function, $\lambda_0(t)$. From the partial likelihood, we obtain simply the estimates of the log of the hazard ratios. Taking the exponent, $\exp(\hat{\beta})$, we get the hazard ratio, which can be loosely interpreted as the ratio between the conditional probabilities of a financial firm having the event in the future, provided that the financial firm has not incurred the event up until t and given the corresponding probability for the baseline hazard.

As the regressors are all categorical variables, in each of the explanatory variables one category is dropped to maintain full rank of the covariate matrix. Table A.4 in the appendix reports the results of the three regressions for t_1, t_2 and t_3. For these regressions the baseline hazard ratio is that for an internal fraud event at a large bank based in Africa, such that the coefficients reported are all relative to this baseline. We report the estimated coefficient and for interpretability the exponent (the ratio). To compare hazard ratios with the baseline it is best to use the exponent minus one ($\exp(\hat{\beta}) - 1$), i.e. an external fraud event at a large African bank is 40% more likely to be discovered, given it is undiscovered until time t, than an internal fraud event at a large African bank (the baseline).

Internal fraud events and failures as a result of negligence or improper business practices are less likely to be discovered than other events. This result is intuitive, as inside actors would likely take steps to cover their misdeeds and illegal acts, which may be unearthed only when pressure from management and regulators intensifies. Small banks are found to be slower in discovering events. This could be due to the fact that they typically have less resources and personnel dedicated to managing risk in comparison to the larger banks. There is heterogeneity across jurisdictions between the date of the discovery of the event and the date of recognition. Regional differences could be driven by different regulatory approaches towards operational risk. This is more likely to manifest itself through Pillar II of the Basel capital framework, which leaves more to the discretion of supervisors (i.e. how frequent are on-site inspections conducted, how efficiently is the supervisor communicating with banks). Moreover, different legal systems also affect the time to the booking of the loss into the bank's balance sheet. For example, other things being equal, losses in North America are discovered more quickly than in Western Europe, possibly due to more pressure from supervisors and more direct supervision on operational loss problems after the GFC. However, the time from discovery to recognition is longer in North America than Western Europe, which may be an indication that the legal proceedings in North America are more protracted than those in Western Europe.

A. The effect of supervision

Differences in the implementation of the Basel framework across regions could explain partly why we observe the heterogeneity in duration times in Panel A of Table IV. To investigate this, we look at the cross-regional impact of regulation and supervision of banks on duration times using an index of prudential regulation and bank supervision described in Section III.

We assign a score from the index to each observation given the year and the region in which it occurred. We re-estimate the proportional hazards model of equation 10 but with the inclusion of the supervisory index as a regressor. We present the results in Table V.

	I (t_1)		II (t_2)		III (t_3)	
	$\hat{\beta}$	$exp(\hat{\beta})$	$\hat{\beta}$	$exp(\hat{\beta})$	$\hat{\beta}$	$exp(\hat{\beta})$
Supervisory Index	8.6*** (0.11)	5200	4.9*** (0.1)	130	10*** (0.11)	24000
Year FE	Y		Y		Y	
Region FE	Y		Y		Y	
Event Type FE	Y		Y		Y	

Table V
Proportional Hazard Models with Supervisory Index

The results imply that increases in the supervisory index can be associated with a rise in the likelihood of discovery and recognition of the event. This supports the guidance issued in Financial Stability Board (2014) regarding supervisors' interactions with financial institutions on the subject of risk culture. The report notes that since the GFC, supervisory approaches are tending towards a more direct and more intense approach to instil resilience of the financial system. Our result supports the notion that this shift in approach should ensure that ex-post emerging risks are recognised, assessed, and addressed in a timely manner. This effect takes place not only through time, but also across the regional dimension. Financial institutions in regions with more effective supervisory frameworks are more likely to recognise and address operational risks in a timely manner.

VI. Operational losses and macroeconomic conditions

The descriptive statistics presented in Section III point to operational losses varying over time. In particular, the risk-taking associated with upswings in the financial cycle could be associated with operational losses surfacing down the line. In addition, during these periods the operating environment and control structure of financial institutions could be weaker, and the implementation of controls could be viewed as restrictions to growth and entrepreneurship (European Systemic Risk Board (2015)).

Abdymomunov et al. (2017) find evidence that operational losses for US banks are contemporaneously correlated with domestic macroeconomic conditions (i.e. operational losses increase in recessions). They argue that during economic downturns banks are subject to certain pressures that translate into an increased likelihood of discovering losses that occurred in the past. Our findings provide support for this argument in a cross-country setting. We argue further that it is in fact the excesses that take place during the upswing that lead to the occurrence of operational risk events with large associated costs, which only materialise in the books of banks a few years later.

We use the lags of three different financial indicators to look at whether prior economic and financial conditions are correlated with future losses. This approach also echoes Liao et al. (2018) and Migueis (2018) in their critiques of the backward-looking nature of operational risk capital requirements. While the approach used in this paper is by no means a solution to this problem, it does offer some insight and support to measures, such as the countercyclical capital buffer (CCyB), that can be used to absorb losses in a high-risk environment after periods that are more prone to risk-taking behaviour (Drehmann and Gambacorta (2012)).

As discussed above, we use the credit-to-GDP gap as measure of the build-up of financial imbalances.[11] In particular, for the different regions in our data, we construct a composite credit-to-GDP gap by weighting the each region by weighting the credit gaps of the countries that contain banks in our sample.[12] For example and to fix ideas, if the region Western Europe were made up of two UK banks, three German banks and four French banks, we would compute the statistic for the region ($creditToGDP_{WE}$) as follows:

$$CreditGap_{WE} = \frac{2 \times CreditGap_{UK} + 3 \times CreditGap_{DE} + 4 \times CreditGap_{FR}}{9}$$

There has been a notable debate in the banking literature on the impact of bank competition on financial stability (Allen and Gale (2004)). While the dominant view sees a detrimental impact of competition on the stability of banks, especially in the securitization market,[13] this view has been challenged by Boyd and De Nicolò (2005), De Nicolò and Lucchetta (2013) and Kim (2018), who see the reverse effect. We test this relationship by looking at whether periods of higher competitiveness in the banking sector are followed by periods of less/more frequent or severe operational losses. To this end, we use the Boone indicator – discussed in Section III – as the dependent variable.

Low interest rate environments may also influence bank risk-taking via two channels. First, low interest rates affect banks measures of risk through valuations, incomes and cash flows. Second, low yields on risk-free assets may increase financial institutions' appetite for taking on more risk. Altunbaş et al. (2014) show that low levels of short-term interest rates over an extended period of time lead to an increase in bank risk. Against this backdrop we evaluate to what extent monetary policy stance may lead to a build-up of

[11] The credit-to-GDP gap is calculated as the difference between the credit-to-GDP ratio and a long-run trend derived from a one-sided HP filter which takes into account only the data available up to that point in time, and a high smoothing parameter λ (400,000 for quarterly data). More details are provided in Basel Committee on Banking Supervision (2010).

[12] While we cannot associate a specific loss with any given bank, we know which banks comprise the sample

[13] Periods of high competition may encourage banks to take on more risk in order to boost profits. Altunbas et al. (2014) show how securitisation can exacerbate the negative effect of competition on banks' appetite to take risks. Banks in more competitive markets that have high levels of securitisation activity are likely to contain riskier loan portfolios, and in turn may have fewer incentives to monitor their loan book (Ahn and Breton (2014)).

operational risk losses. To do so we use the deviations of policy rates from implied Taylor rule rates as a proxy for periods in which monetary policy has been too accommodative.[14]

Bank supervision and regulation is an integral part of the Basel framework, which ultimately aims to minimise risk in the financial sector, one aspect being operational risk. We look at the cross-regional impact of regulation and supervision of banks on operational risk using an index of prudential regulation and bank supervision. This index is described in Section III. We use lags of this index in the regression since we anticipate that the effect of reforms to regulatory and bank supervision are not observed immediately as there is a period of adjustment for banks to comply with new standards.

Our panel regressions, which are run at the quarterly frequency for the financial indicators and at yearly frequency for the regulatory and supervisory index, take the following form:

$$\ln(Y_{it}) = \sum_k \beta_k X_{i,t-k} + \alpha_i + \gamma_t + \sum_k \varepsilon_{i,t-k} \tag{11}$$

where, Y_{it}, indicates the dependent variable in region i at time t, X_{it} denotes our main independent variable (either the credit-to-GDP gap, Boone indicator, deviations from the Taylor rule, or financial and supervisory index), α_i is a regional fixed effect and γ_t is a time fixed effect. We look at three dependent variables: namely the gross loss amount, the frequency of losses, and the severity of losses (which results from dividing gross losses by frequency), all normalised by gross income.

The results of the four panel regressions are contained in Table VI. Note that the coefficients are the cumulative effect of the lagged dependent variables i.e. we are interested in the medium (four lags) to longer term effects (eight lags). The standard errors reported in parentheses are hence the standard error of the sum of the coefficients.

Gross losses and the frequencies are both positively correlated with the credit-to-GDP gap (panel A). Periods in which financial imbalances build up are followed by larger operational losses recognised in the books of banks and a higher frequency of operational loss events. A one standard deviation increase in the credit gap leads to a respective 8% and 9% increase in operational losses per unit of income after one year and two years.

The results in Panel B suggest that more intense bank competition is associated with lower operational losses in subsequent periods. This result is in line with the work of De Nicolò and Lucchetta (2013), who find that banks in a higher competition environment increase monitoring efforts and reduce risks, and with Kim (2018) who finds that banks with lower market power (i.e. operating in more competitive environments) take less liquidity risk, implying that increased competition leads to financial stability. Recall that the more negative the Boone indicator the higher the competition in the banking sector, therefore a one standard deviation decrease in the Boone indicator (indicative of a more competitive market) leads to a 34% decrease in operational losses as a fraction of income.

In Panel C, we see the results from the regressions including the deviations from the Taylor rule. The

[14]The aggregation by region for both the Boone indicator and deviations from implied Taylor rules is done in the same way as for credit-to-GDP gaps.

	I Log(GrossLoss/Income)	II Log(Freq/Income)	III Log(Severity/Income)	N Obs
Panel A				
Credit-GDP-Gap - 4 Lags	0.007* (0.004)	0.0067*** (0.002)	0.0002 (0.003)	580
Credit-GDP-Gap - 8 Lags	0.008** (0.004)	0.0056** (0.002)	0.0027 (0.003)	540
Panel B				
Boone Ind. - 4 Lags	2.1*** (0.54)	1.6*** (0.33)	0.41 (0.45)	446
Boone Ind. - 8 Lags	2.1*** (0.69)	1.3*** (0.43)	0.82 (0.59)	406
Panel C				
Taylor Rule Dev. - 4 Lags	-0.059*** (0.018)	-0.07*** (0.011)	0.011 (0.015)	606
Taylor Rule Dev. - 8 Lags	-0.084*** (0.021)	-0.11*** (0.012)	0.023 (0.018)	566
Panel D				
Supervision Index - 1 Lag	-5.2** (2.5)	-4.6** (1.8)	-0.67 (1.9)	130
Supervision Index - 2 Lags	-7.1** (3.2)	-5.8** (2.3)	-1.3 (2.6)	120
Regional Fixed Effects	Y	Y	Y	
Time Fixed Effects	Y	Y	Y	

Notes: The table is divided into four panels summarising the results from 24 panel regressions. Each column denotes the different dependent variables used. Each panel distinguishes between the dependent variables used. The coefficients shown are the sum of the lagged regressors i.e. the cumulative effect, for example at 4 lags the coefficient reported is, $\sum_{i=1}^{4} \hat{\beta}_i$. Robust standard error of the sum of the coefficients is reported in parenthesis. The asterisks denote the significance as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions are two way fixed effects models, including a regional and time effect. In Panels A-C the time unit is quarters, in Panel D the time unit is years.

Table VI

Operational losses, macroeconomic conditions and the regulatory environment

results suggest that following periods of overly accommodative monetary policy, operational losses increase in frequency and value. This supports the idea that risk-taking in low-yield environments leads to a build-up of operational losses. A one standard deviation decrease in the Taylor gap leads to a 16% increase of operational losses in the following four quarters and 21% in the following 8 quarters.

Panel D contains the results of the panel with the financial and supervisory index. The sign suggest that higher scores on the index are associated with lower gross amounts and frequency of operational losses per unit of income. The index ranges in the sample between 0.56 and 1 and it is very sluggish because it depends on institutional characteristics. Operational losses are very sensitive to change in the index. A simple 0.1 increase in the supervisory score is associated with a decrease in the gross loss (frequency) per unit of income of around 67% (51%) one period after. The cumulative effect of a 0.1 increase in two subsequent periods rises in excess of 200% (78%) for gross loss (frequency) per unit of income. The insignificance on results regarding severity points to stronger supervisory frameworks helping offset operational risks by reducing the frequency of their occurrence, as presumably they lead banks to implement better risk management strategies.

VII. Cyber risks in the financial sector

Cyber and IT-related risks can be seen as a subset of operational risks and are frequently cited as a prominent threat to the financial system (see Kaffenberger et al. (2017); Kashyap and Wetherilt (2019). This threat extends well beyond finance as the interest in cyber has gradually increased over time, as shown for example by web search queries (see Figure A.1 in the appendix). In March 2017, the G20 Finance Ministers and Central Bank Governors noted that "the malicious use of information and communication technologies (ICT) could disrupt financial services crucial to both national and international financial systems, undermine security and confidence, and endanger financial stability". In December 2018 the Basel Committee on Banking Supervision published a report on the range of cyber-resilience practices (Basel Committee on Banking Supervision (2018)).

An accurate quantification of cyber risks using the ORX database is challenging, as there is no precise definition of cyber events. We thus need to rely on a number of assumptions. In particular, we make use of event type definitions and consider as cyber events a subclass of operational risks events. Table VII describes the event categories that are most likely to be associated with cyber events. As discussed above, we use the level 2 event type classification in order to compute a proxy range for cyber events. Given the nature of the classification, we are not able to accurately capture all the events. Other categories not included could in principle have some cyber events within them. Similarly, some events included in the categories we consider might not be cyber-related, especially for the upper bound estimate. We highlight in bold the event types we consider as a lower bound to approximate cyber events, after discussions with risk management experts acquainted with the event type categorisation. The full list presented in Table VII (i.e. bold plus non-bold) constitutes our upper bound estimate for cyber events.

In total, there are almost 14,000 observations of cyber events within the database according to our lower bound definition. We depict the estimated cyber loss range as a share of total operational risk losses through time in Figure 5, both in terms of gross losses (left-hand panel) as well as frequency of events (right-hand panel).

Cyber losses so defined represent a small fraction of total losses in terms of gross amount and frequency. More recently, however, the share of cyber losses in terms of amounts has been increasing, with a strong spike in particular around 2016. The effect of the financial crisis is not as evident as it was for the larger operational risk class, indicating that cyber costs are less correlated with macroeconomic conditions. Indeed, in unreported results we find that the stance of monetary policy and the credit-to-GDP gap are not associated with higher cyber losses in the future. On the contrary, as shown in Table VIII, stronger supervision can influence the incidence of cyber losses at least to the same extent as it does broader operational risk losses,

Event Type	Description
ET0101	Unauthorised Activity e.g. Rogue trading, unreported transaction, mis-marking positions
ET0102	Internal Theft - Forgery e.g. theft, extortion, embezzlement, bribes/kickbacks
ET0103	System Security Internal - Intentional damage to systems by internal staff
ET0201	External Theft and Fraud e.g. Robbery, Forger, Cheque Kiting
ET0202	System Security External - Wilful Damage e.g. Hardware/Software, Hacking Damage, Theft of Data
ET0601	Technology & Infrastructure - Losses arising from disruption of business or system failures

Table VII

Summary of cyber-relevant event types

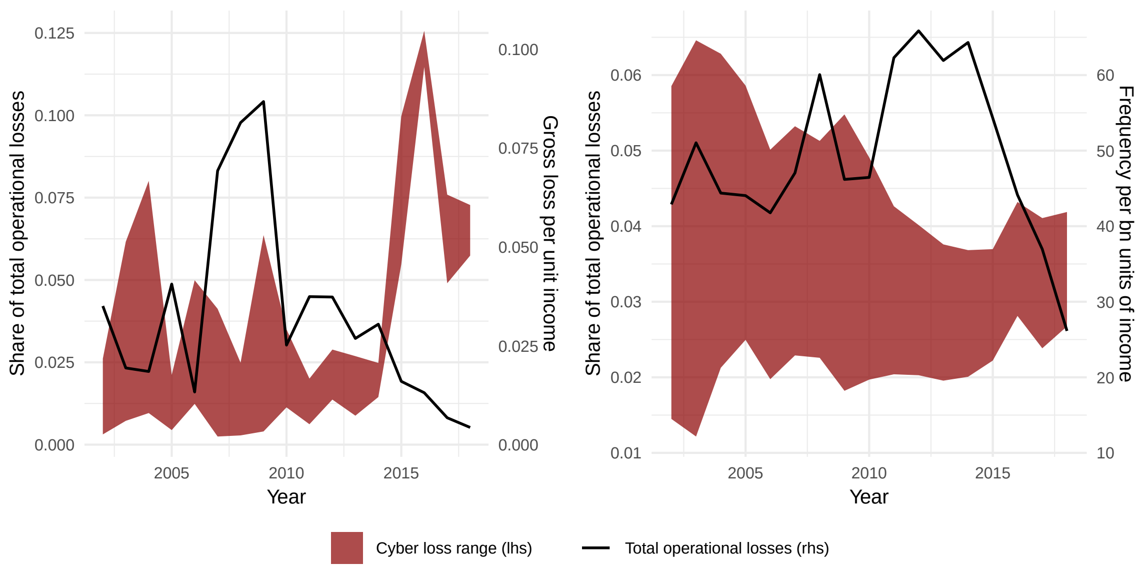

Figure 5

Gross losses and frequency of operational and cyber events

and especially for the lower bound estimate of cyber losses.

We report the breakdown of losses and frequency by region, "cyber" event types and by bank size, in Figures A.4-A.6 in the appendix with supplementary material.[15] In Figure A.4 it appears the dominating event type is Technology & Infrastructure. Since category ET0202 tends to account for damage from hacking, we assume that these are typically non-malicious or failures that are out of the control of the firm, a

[15]For the sake of space, we report these only for the lower bound estimate of cyber losses.

	I Log(GrossLoss/Income)	II Log(Freq/Income)	III Log(Severity/Income)	N Obs
Panel A - Lower bound of cyber losses				
Supervision Index - 1 Lag	-7.5** (3.5)	-3.5* (2.0)	-4.0 (2.9)	126
Supervision Index - 2 Lags	-10.0** (4.8)	-5.1* (2.7)	-4.9 (4.2)	116
Panel B - Upper bound of cyber losses				
Supervision Index - 1 Lag	-5.2* (2.8)	-3.6* (1.9)	-1.6 (2.0)	129
Supervision Index - 2 Lags	-5.5 (3.4)	-2.5 (2.3)	-3.0 (2.7)	119
Regional Fixed Effects	Y	Y	Y	
Time Fixed Effects	Y	Y	Y	

Notes: The table is divided into two panels summarising the results from 12 panel regressions. Each column denotes the different dependent variables used. Each panel distinguishes between the dependent variables used. The coefficients shown are the sum of the lagged regressors i.e. the cumulative effect, for example at 4 lags the coefficient reported is, $\sum_{i=1}^{4} \hat{\beta}_i$. Robust standard error of the sum of the coefficients is reported in parenthesis. The asterisks denote the significance as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions are two way fixed effects models, including a regional and time effect. The time unit is years.

Table VIII

Cyber losses and the regulatory environment

contrived example being a power outage. Damages from hacking appear to be low. In a companion paper, we show, using a different dataset which focuses only on cyber events, that the financial sector is relatively more resilient than other sectors in riding out attacks with malicious intent, most likely thanks to investments in security practices done by banks also under the auspices of regulators (Aldasoro et al. (2020)).

In terms of regions, Western Europe suffers more cyber losses than other regions, with the exception of 2016, when considerable cyber losses were suffered in the U.S. When doing the split by bank size, in turn, the share across banks appears to be relatively stable. The peak in 2016, however, can be largely attributed to small and medium-sized banks. This could be an indicator that larger budgets and thus more investment in security pays dividends for larger banks.

A. *Cyber value-at-risk*

To complement the analysis in Section IV, we also compute an estimate for VaR for cyber-related losses. To do so we use the two methodologies described in Section IV refining the event types to be those defined as cyber-related, considering both the lower and upper bound. The results are summarised in Figure 6. The figure includes the estimates for total operational risk in red bars as a benchmark. The cyber loss range is captured by the black whiskers.

Cyber VaR is a fraction of the total operational VaR if based the calculation on the analytical approach. The value ranges from 0.25-0.65% of the gross income of the consortium, which corresponds to around 2.45 EUR billions and 6.46 EUR billions, respectively. These figures reflect that cyber risk is a small fraction of

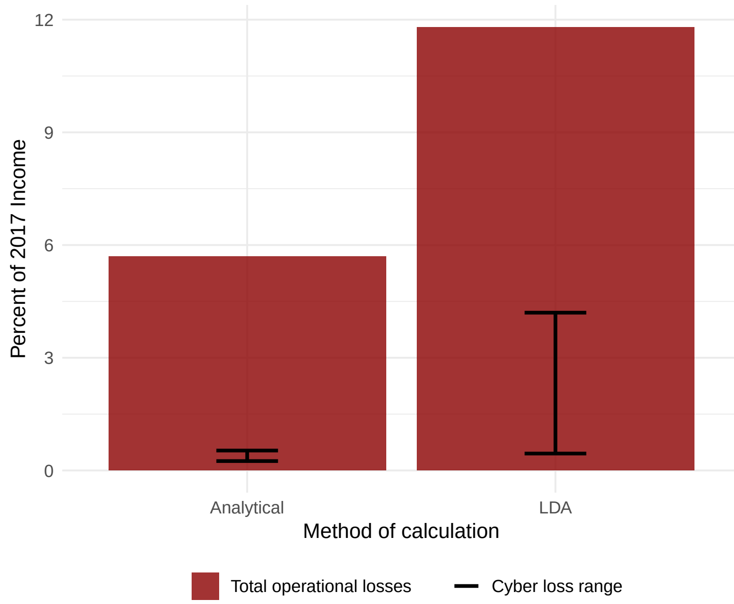

Figure 6
Operational and cyber value-at-risk

total operational risks, as discussed above. However, this result should be taken cautiously for two reasons. First, if the method to calculate cyber VaR changes to one that more appropriately captures the fat-tailed nature of cyber losses, the VaR can jump to around 4.2% of gross income, around a third of operational losses under the same methodology. This finding is quite remarkable when placed against the relatively minor share of operational losses that cyber losses can represent, as shown in Figure 5. Second, cyber is an emerging risk and reporting cyber-related losses is not always mandatory. Accordingly, not all the costs of cyber may be covered in our approximation. Moreover, cyber is an evolving risk and we may not have seen the full extent of damage that can be inflicted by a "tail-event".

VIII. Conclusions

The recent financial crisis has drawn the attention of regulators and academics towards operational risk. Moreover, the shift to the new Standardised Approach in Basel III and imminent threat of cyber events are talking points in the debate around policy towards operational risk. We contribute to the debate by using a unique cross-country data at the operational loss event level for the last 16 years for over 70 large banks.

We provide some stylised facts as a basis for discussions of operational risk in the financial sector. After a spike in operational losses in the immediate aftermath of the GFC, operational losses have declined. Informed by our analysis on the average duration between occurrence and recognition of operational risk events, we truncate the data at end-2017 (despite having data up to early 2019) in order to account for potential underreporting bias. We are thus confident that, despite this bias, there has been a general decrease in the severity of operational losses since 2014. The post-crisis spike is to a large extent accounted for by the severity of losses related to improper business practices that occurred in large banks in the run-up to the crisis, which materialised only later. An example of such event is the mis-selling of mortgage-backed securities which took place around 2005/2006 but was crystallised as a loss in the books of banks only a few years later, when heavy fines were imposed.

We compute operational value-at-risk and show it can vary substantially depending on the methodology. The average VaR for the financial institutions in the sample ranges from 6% to 12% of total gross income, depending on whether the method used is better able to capture the heavy-tailed nature of the data. These numbers are consistent with actual capital requirements, but notably smaller than the basic indicator approach. Our results provide some support for the shift to the standardised approach in Basel III. First, the heterogeneity of estimates is reduced. Moreover, the simplified approach could also free up resources at banks and supervisory authorities.

We document a substantial lag between the dates of discovery and recognition of loss events. On average, it exceeds one year, but it varies across regions, business lines, event types, and bank size. Internal fraud events and failures due to improper business practices are less likely to be discovered than other events, especially when the size of the financial firm is small. These findings can inform policy discussions on compensation practices.

We show that operational losses are higher after credit booms and after periods of excessively accommodative monetary policy. In other words, the link between monetary policy, credit booms and bank risk-taking found in the literature also extends to operational risk-taking. A higher quality of financial regulation and supervision is associated with lower operational risk losses. We also find that periods of increased bank competition lead a reduction in operational losses.

Finally, we use the categorisation of operational loss events to compute a proxy range of cyber events, a subset of operational events. Cyber losses represent a relatively small portion of overall operational risk losses, especially in terms of frequency. That said, recent years saw a notable increase in losses due to cyber events, with a strong peak in 2016 and a decline afterwards, which could be explained by increased efforts and resources spent by banks to tame cyber risks. We note that a higher quality of financial regulation and supervision is also associated with lower cyber losses. Despite representing a relatively minor share of operational losses, cyber losses can account for up to a third of total operational value-at-risk.

References

Abdymomunov A, Curti F, Mihov A. 2017. US banking sector operational losses and the macroeconomic environment. Technical report, Available at SSRN 2738485.

Abiad A, Detragiache E, Tressel T. 2010. A New Database of Financial Reforms. *IMF Staff Papers* **57**: 281–302.

Ahn JH, Breton R. 2014. Securitization, competition and monitoring. *Journal of Banking & Finance* **40**: 195–210.

Aldasoro I, Gambacorta L, Giudici P, Leach T. 2020. The drivers of cyber risk. BIS Working Papers, Forthcoming, Bank for International Settlements.

Alexander C. 2008. *Statistical Models of Operational Loss*, chapter 11. Handbook of Finance.

Allen F, Gale D. 2004. Competition and Financial Stability. *Journal of Money, Credit and Banking* **36**: 453–480.

Allen L, Bali TG. 2007. Cyclicality in catastrophic and operational risk measurements. *Journal of Banking & Finance* **31**: 1191–1235.

Altunbaş Y, Gambacorta L, Marques-Ibanez D. 2014. Does monetary policy affect bank risk-taking? *International Journal of Central Banking* **10**: 95–135.

Altunbas Y, Leuvensteijn Mv, Marques-Ibanez D. 2014. Competition and bank risk: the effect of securitization and bank capital. Working Paper Series 1678, European Central Bank.

Altunbaş Y, Thornton J, Uymaz Y. 2018. CEO tenure and corporate misconduct: Evidence from US banks. *Finance Research Letters* **26**: 1–8.

Antonini G, Cope EW, Mignola R Giulioand Ugoccioni. 2009. Challenges in measuring operational risk from loss data. *Journal of Operational Risk* **4**: 3–27.

Basel Committee on Banking Supervision. 2003. Basel II: The new Basel capital accord. Consultation, Basel, Switzerland.

Basel Committee on Banking Supervision. 2010. Guidance for national authorities operating the countercyclical capital buffer. Guidelines, Basel, Switzerland.

Basel Committee on Banking Supervision. 2018. Cyber-resilience: range of practices. Other, Basel, Switzerland.

Berger AN, Curti F, Mihov A, Sedunov J. 2018. Operational risk is more systemic than you think: Evidence from US bank holding companies. *Available at SSRN 3210808* .

Biell L, Muller A. 2013. Sudden crash or long torture: the timing of market reactions to operational loss events. *Journal of Banking & Finance* **37**: 2628–2638.

Bogdanova B, Hofmann B. 2012. Taylor rules and monetary policy: a global 'great deviation'? *BIS quarterly review, September* .

Boone J. 2008. A new way to measure competition. *The Economic Journal* **118**: 1245–1261.

Bouveret A. 2018. Cyber risk for the financial sector: A framework for quantitative assessment. IMF Working Paper 18/143, International Monetary Fund.

Boyd JH, De Nicolò G. 2005. The theory of bank risk taking and competition revisited. *The Journal of Finance* **60**: 1329–1343.

Byrne B, Coughlan J, Tilley SV. 2017. An empirical analysis of the impact of fines on bank reputation in the US and UK. *Available at SSRN 2980352* .

Cabras S, Castellanos ME. 2007. A default bayesian procedure for the generalized pareto distribution. *Journal of Statistical Planning and Inference* **137**: 473–483.

Carrivick L, Cope EW. 2013. Effects of the financial crisis on banking operational losses. *The Journal of Operational Risk* **8**: 3.

Cerasi V, Deininger S, Gambacorta L, Oliviero T. 2020. How post-crisis regulation has affected bank ceo compensation. *Journal of International Money and Finance,* Forthcoming.

Chavez-Demoulin V, Embrechts P, Nešlehová J. 2006. Quantitative models for operational risk: extremes, dependence and aggregation. *Journal of Banking & Finance* **30**: 2635–2658.

Chernobai A, Jorion P, Yu F. 2011. The determinants of operational risk in US financial institutions. *Journal of Financial and Quantitative Analysis* **46**: 1683–1725.

Čihák M, Schaeck K. 2010. Competition, efficiency, and soundness in banking: An industrial organization perspective. *European Banking Centre Discussion Paper* .

Cope EW, Piche MT, Walter JS. 2012. Macroenvironmental determinants of operational loss severity. *Journal of Banking & Finance* **36**: 1362–1380.

Cornalba C, Giudici P. 2004. Statistical models for operational risk management. *Physica A: Statistical Mechanics and its applications* **338**: 166–172.

Cox DR. 1972. Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)* **34**: 187–202.

Cummins JD, Lewis CM, Wei R. 2006. The market value impact of operational loss events for US banks and insurers. *Journal of Banking & Finance* **30**: 2605–2634.

Curti F, Frame WS, Mihov A. 2019. Are the largest banking organizations operationally more risky? *Available at SSRN 3210206* .

Dalla Valle L, Giudici P. 2008. A bayesian approach to estimate the marginal loss distributions in operational risk management. *Computational Statistics & Data Analysis* **52**: 3107–3127.

De Nicolò G, Lucchetta M. 2013. Bank Competition and Financial Stability: A General Equilibrium Exposition. CESifo Working Paper Series 4123, CESifo Group Munich.

Denk O, Gomes G. 2017. Financial re-regulation since the global crisis? OECD Economics Department Working Papers 1396, Organisation for Economic Co-operation and Development.

Dowd K. 1998. *Beyond value at risk: the new science of risk management*. John Wiley & Sons.

Drehmann M, Gambacorta L. 2012. The effects of countercyclical capital buffers on bank lending. *Applied Economics Letters* **19**: 603–608.

Duffie D, Younger J. 2019. Cyber runs. Hutchins Center Working Paper 51, Brookings institution.

Eshraghi A, Hagendorff J, Nguyen DD. 2015. Can bank boards prevent misconduct? *Review of Finance* **20**: 1–36.

Esterhuysen J, Styger P, Van Vuuren G. 2008. Calculating operational value-at-risk (opvar) in a retail bank. *South African Journal of Economic and Management Sciences* **11**: 1–16.

European Systemic Risk Board. 2015. Report on misconduct risk in the banking sector. Esrb reports, European Systemic Risk Board.

Facchinetti S, Giudici P, Osmetti SA. 2019. Cyber risk measurement with ordinal data. *Statistical Methods & Applications* : 1–13.

Fich EM, Shivdasani A. 2007. Financial fraud, director reputation, and shareholder wealth. *Journal of Financial Economics* **86**: 306–336.

Figini S, Gao L, Giudici P. 2015. Bayesian operational risk models. *Journal of Operational Risk* **10**.

Financial Stability Board. 2014. Guidance on supervisory interaction with financial institutions on risk culture: a framework for assessing risk culture. Compendium of standards, Financial Stability Board.

Gillet R, Hübner G, Plunus S. 2010. Operational risk and reputation in the financial industry. *Journal of Banking & Finance* **34**: 224–235.

Hess C. 2011. The impact of the financial crisis on operational risk in the financial services industry: empirical evidence. *The Journal of Operational Risk* **6**: 23.

Jarrow RA. 2008. Operational risk. *Journal of Banking & Finance* **32**: 870–879.

Jorion P. 1997. *Value at risk: the new benchmark for controlling market risk*. Irwin Professional Pub.

Kaffenberger L, Kopp E, Wilson C. 2017. *Cyber risk, market failures, and financial stability*. 17-185. International Monetary Fund.

Kashyap AK, Wetherilt A. 2019. Some principles for regulating cyber risk. In *AEA Papers and Proceedings*, volume 109. 482–87.

Kim J. 2018. Bank competition and financial stability: Liquidity risk perspective. *Contemporary Economic Policy* **36**: 337–362.

Köster H, Pelster M. 2017. Financial penalties and bank performance. *Journal of Banking & Finance* **79**: 57–73.

Liao G, Ma Y, Sands P. 2018. Rethinking operational risk capital requirements. *Journal of Financial Regulation* **4**: 1–34.

Migueis M. 2018. Forward-looking and incentive-compatible operational risk capital framework. *Journal of Operational Risk* **13**.

Power M. 2005. The invention of operational risk. *Review of International Political Economy* **12**: 577–599.

Romanosky S. 2016. Examining the costs and causes of cyber incidents. *Journal of Cybersecurity* **2**: 121–135.

Sakalauskaite I. 2018. Bank risk-taking and misconduct. *University of Amsterdam and the Tinbergen Institute Working Paper* .

Schnittker C, Sowerbutts R, Tracey B. 2017. Bank capital and risk-taking: evidence from misconduct provisions. Bank of England working papers 671, Bank of England.

Shih J, Samad-Khan A, Medapa P. 2000. Is the size of an operational loss related to firm size. *Operational Risk* **2**: 21–22.

Sturm P. 2013. Operational and reputational risk in the european banking industry: The market reaction to operational risk events. *Journal of Economic Behavior & Organization* **85**: 191–206.

Appendix A. Supplementary material

Event Type	Description
BL01 - Corporate finance	Structuring, issuance or placement of securities and similar instruments, not just for capital raising
BL02 - Trading & sales	Products / Positions held in the Trading Book of the firm and Corporate Investments.
BL03 - Retail banking	Retail Loans, Retail Deposits, Banking Services, Trusts & Estates, Investment Advice, Cards - Credit & Debit
BL04 - Commercial banking	Project Finance, Real Estate Finance, Export Finance, Trade Finance, Factoring, Leasing, Loans Guarantees, Bills of Exchange
BL05 - Clearing	Financing and related services
BL06 - Agency services	Bank account, deposit services, plain vanilla investment products
BL07 - Asset Management	Management of individual assets invested in financial instruments on behalf of others (i.e. not in the bank's own name for its own account) in which the bank has the power to make investment decisions. This includes activities where each customer's assets are held in a separate portfolio, as well as those where the assets of different customers are pooled in one portfolio.
BL08 - Retail Brokerage	Various services related to administration and management of estates, trusts, assets, portfolios etc.
BL09 - Private Banking	Limited category for items than can only be categorised at corporate level

Table A.1
Overview of business lines based on the operational risk reporting standards of ORX

Region	Sub-regions
North America	US, Canada
Latin America & Caribbean	-
Eastern Europe	-
Western Europe	Southern Europe, Northern Europe, United Kingdom, Western Europe
Asia / Pacific	-
Africa	-

Table A.2
Overview of regions and sub-regions

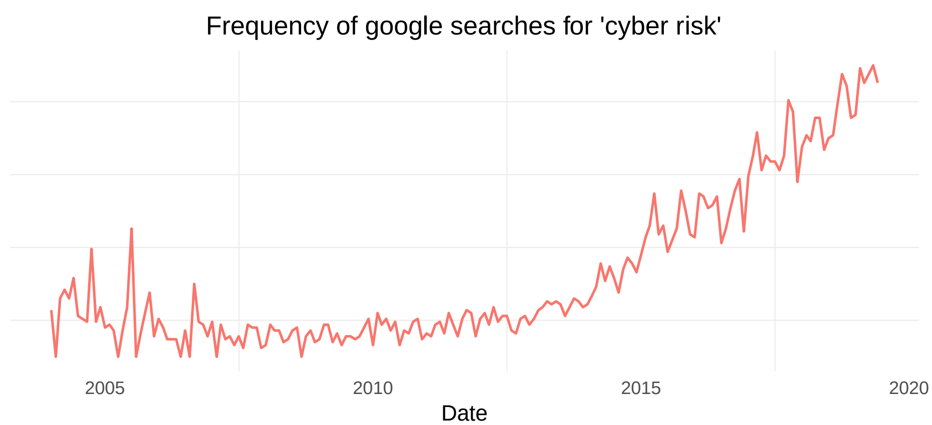

Figure A.1
Source: Google trends

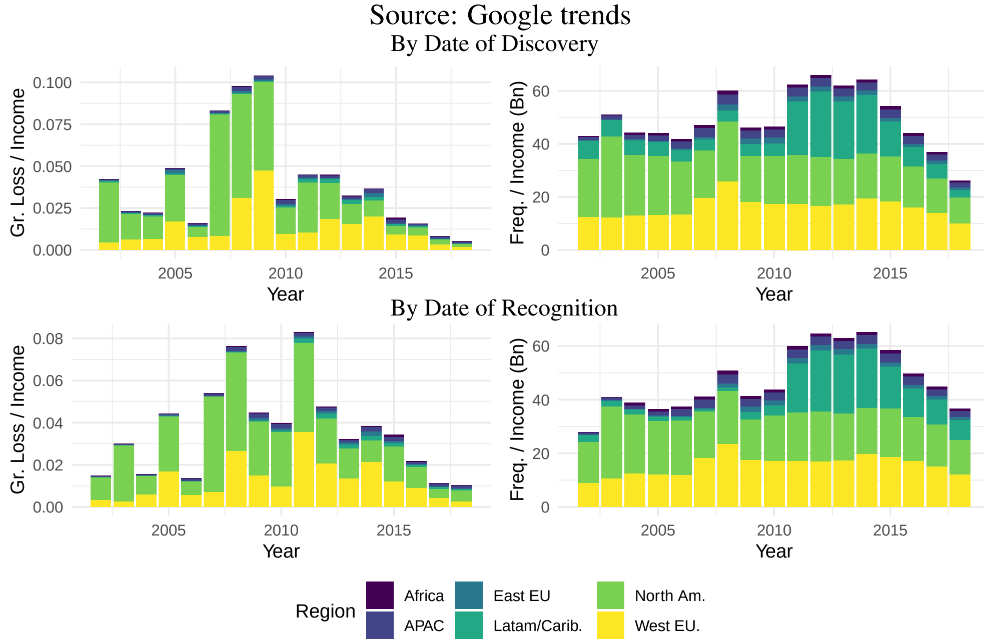

Figure A.2
Loss and frequency over time partitioned by region

	Internal Fraud	External Fraud	Employee Related	Negligence Failures	Disasters	Technology and Infrastructure	Transaction and Process Management
Corporate Finance	60	112	23	1,896	24	23	184
Trading	3,636	1,080	35	12,858	27	2,075	1,751
Retail Banking	140	500	449	25,947	80	285	2,045
Commercial Banking	254	577	28	6,919	9	180	814
Clearing	38	17	11	180	1	434	613
Agency	11	26	7	2,022	5	41	161
Asset Management	177	13	41	512	22	15	393
Retail Brokerage	72	19	137	242	13	36	93
Private Banking	93	82	67	422	2	5	121
Corporate Items	113	186	271	16,264	78	184	1,046
Total	4,596	2,612	1,070	67,263	260	3,277	7,221

Notes This table contains a breakdown of the unexpected losses across business lines and event types for the analytical method. The figures are quoted in millions of euros. Note that the value for unexpected loss for all business lines is obtained by taking the square root of the sum of squares of the intersections. This is due to the assumption that losses are independent across intersections.

Table A.3

Breakdown of the unexpected loss by intersection of business line and event type

	I (t_1)		II (t_2)		III (t_3)	
	$\hat{\beta}$	$\exp(\hat{\beta})$	$\hat{\beta}$	$\exp(\hat{\beta})$	$\hat{\beta}$	$\exp(\hat{\beta})$
Asia / Pacific	-0.06*** (0.012)	0.94	0.17*** (0.012)	1.2	0.05*** (0.012)	1.1
East Europe	-0.46*** (0.013)	0.63	-0.13*** (0.013)	0.88	-0.49*** (0.013)	0.61
Latin America & Caribbean	0.27*** (0.011)	1.3	-0.14*** (0.011)	0.87	-0.018 (0.011)	0.98
North America	0.24*** (0.011)	1.3	-0.079*** (0.011)	0.92	0.088*** (0.011)	1.1
West Europe	-0.21*** (0.011)	0.81	0.13*** (0.011)	1.1	-0.13*** (0.011)	0.88
Medium	0.0046 (0.004)	1	0.02*** (0.004)	1	0.001 (0.004)	1
Small	-0.039*** (0.005)	0.96	-0.04*** (0.005)	0.96	-0.022*** (0.005)	0.98
External fraud	0.36*** (0.009)	1.4	0.28*** (0.009)	1.3	0.44*** (0.009)	1.5
Employee-related	0.16*** (0.009)	1.2	-0.28*** (0.009)	0.76	-0.12*** (0.009)	0.89
Business practices	-0.1*** (0.009)	0.9	-0.18*** (0.009)	0.83	-0.29*** (0.009)	0.75
Disasters	0.6*** (0.014)	1.8	0.02 (0.014)	1	0.34*** (0.014)	1.4
Technology & infrastructure	0.57*** (0.013)	1.8	0.25*** (0.013)	1.3	0.61*** (0.013)	1.8
Transactions & process management	0.13*** (0.009)	1.1	0.077*** (0.009)	1.1	0.13*** (0.009)	1.1
Year FE	Y		Y		Y	

Notes This table presents the estimates and their exponents from the cox regressions with three different dependent variables, t_1, t_2, t_3. The standard errors are reported in parentheses. The asterisks denote the significance as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.The exponent of the coefficients are the hazard ratios with respect to the baseline hazard. The baseline hazard is an event that occurred in Africa, at a large bank and was an Internal Fraud. Standard errors are reported in parentheses.

Table A.4

Results from proportional hazards models

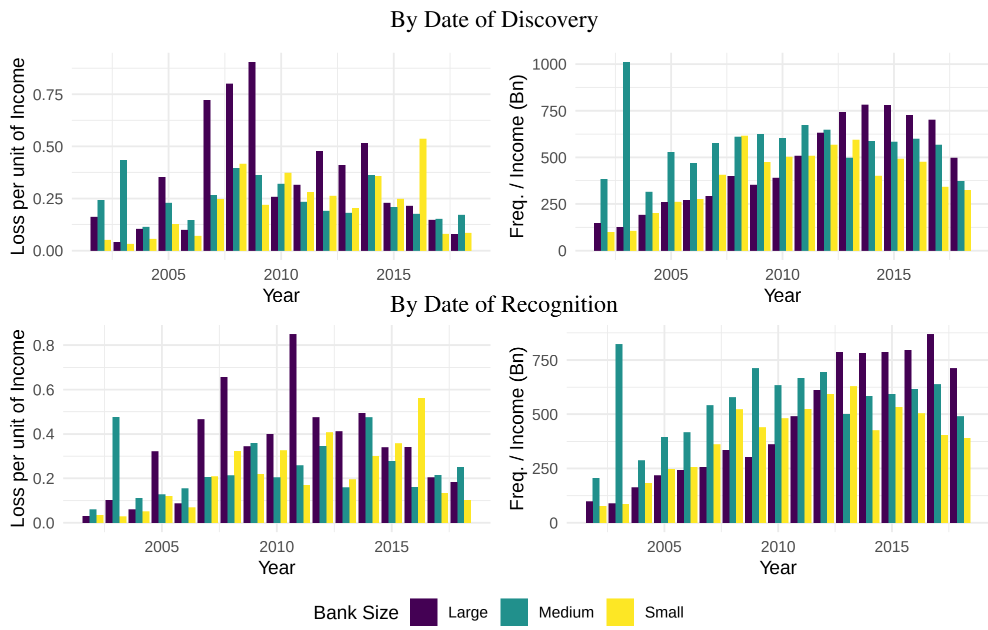

Figure A.3
Loss and frequency over time partitioned by bank size

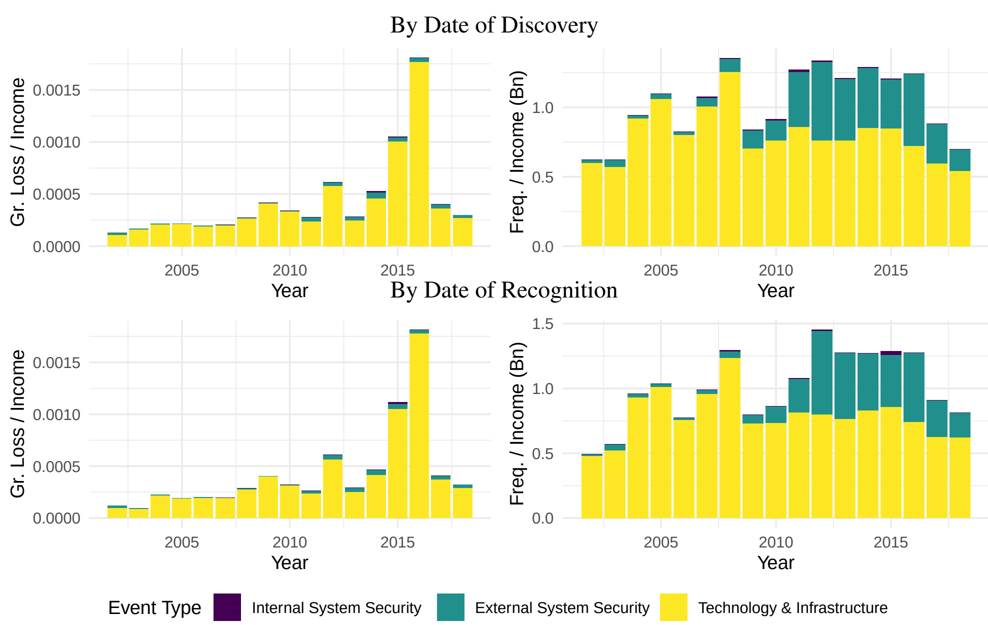

Figure A.4
Cyber loss and frequency by event type

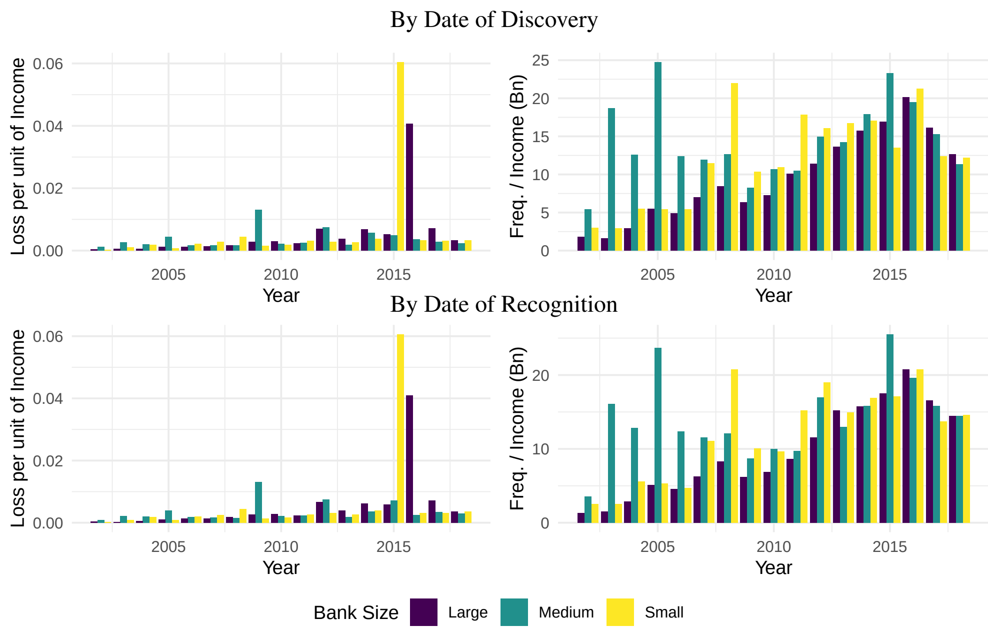

Figure A.5
Cyber loss and frequency by bank size

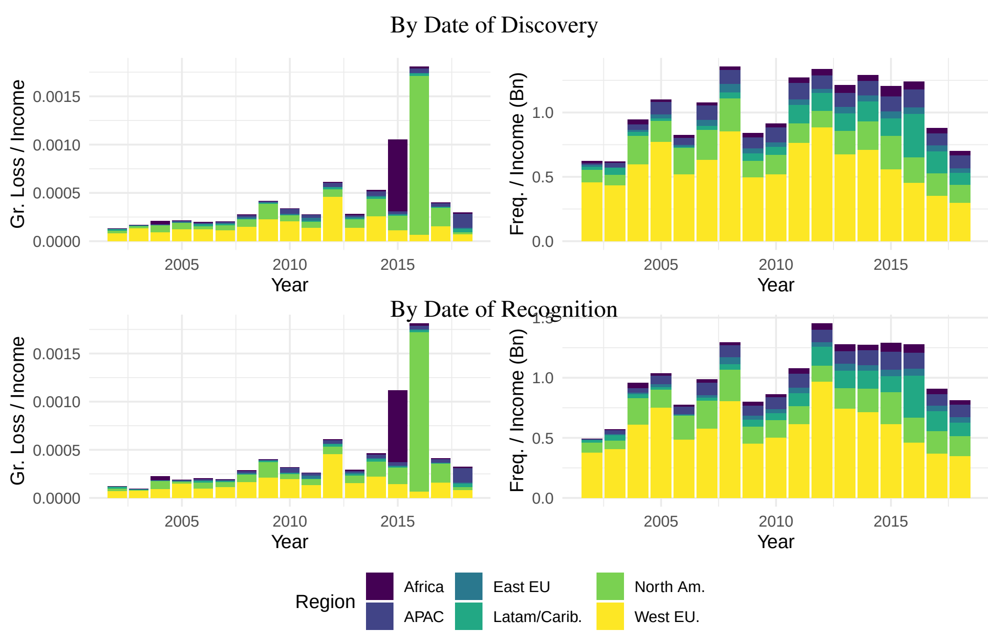

Figure A.6
Cyber loss and frequency by region