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The determinants of reputational risk in the banking sector

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ABSTRACT

What determines reputational loss following operational losses in banking? The purpose of this paper is to empirically address this question. We estimate the reputational risk for a large sample of banks in Europe and the US between 2003 and 2008. We have two main results. First, we provide evidence that there is the probability that reputational damage increases as profits and size increase. Second, we show that a higher level of capital invested and intangible assets reduce the probability of reputational damage.

1. Introduction

Reputational risk is the "risk arising from negative perception on the part of customers, counterparties, shareholders, investors, debtholders, market analysts, other relevant parties or regulators that can adversely affect a bank's ability to maintain existing, or establish new, business relationships and continued access to sources of funding" (Basel Committee on Banking Supervision, 2009, p. 19). Reputation assumes special importance in banking because asymmetric information, the qualitative-asset-transformation made by banks, and the supply of payment and risk management services create a systemic risk (Allen and Santomero, 1997, 2001).

Interest in reputational risk in the financial sector has grown over the past two decades after the occurrence of some prominent examples of operating losses due to internal frauds (Dyck et al., 2010) (e.g. fraudulent trading in the Allied Irish Bank, Barings and Daiwa Bank Ltd generating operational losses of $691 million, $1 billion, and $1.4 billion, respectively), external fraud (e.g. the $611 million operational losses at the Republic New York Corp. for fraud committed by custodial clients), damage to physical assets (e.g. Bank of New York suffered $140 million operational losses to damage to facilities related to September 11, 2001), business disruption and system failures (e.g. Salomon Brothers suffered $303 million operational losses because of a change in computer technology that resulted in unreconciled balances). The credit turmoil from 2007 onwards has definitively increased the attention of academics, regulators and practitioners on bank reputation.

Despite its importance, few studies (De Fontnouvelle and Perry, 2005; Cummins et al., 2006; Gillet et al., 2010; Lin and Paravisini, 2011; Fiordelisi et al., accepted for publication) provide empirical evidence about reputational risk in financial services. Most of these studies focus on estimating the extent of reputational losses as market reaction to the operational loss announcement[1] running an event study: overall, operational loss announcements are usually found to generate statistically significant reputational damage. As far as we are aware, there is only one paper (Gillet et al., 2010) going beyond the measurement of reputational risk assessing the role of various determinants. Generally, the understanding that drives reputational losses in the banking industry is unknown and the need for empirical studies is noticeable.

What determines reputational damage in banking after operational losses? The purpose of this paper is to empirically address these questions. We show that the probability of reputational damage is influenced by bank risks, profits, size, capital invested, the level of intangibles and the business area experiencing the operational loss. In summary, we have two main results: first,

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[1] There are also some papers (Dahen and Dionne, 2010; Chernobai and Yildirim, 2008; Jarrow, 2008) dealing with operational risk in banking.

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the probability of reputational damage increases as there is an increase in bank profits and size. Second, we show that a higher level of capital invested and intangibles reduce the probability of reputational damage.

Our paper is one of the few estimating reputational risk using a large sample of operational losses. Specifically, we focus on listed banks in Europe and the US between 2003 and 2008. First, we run an event study to estimate the reputational damage following Gillet et al. (2010). Second, we estimate a multivariate model to assess the determinants of operational losses.

The remainder of the article is organized as follows: Section 2 presents the literature review and Section 3 outlines the research hypotheses. In Section 4, we provide an overview on the empirical research design, including a description of data, econometric approach and robustness tests. Our results are discussed in Section 5. Lastly, Section 6 offers concluding remarks.

2. Literature review

The literature dealing with reputational risk in non-financial industries is well developed, especially in the United States (De Fontnouvelle and Perry, 2005; Cummins et al., 2006; Gillet et al., 2010; Dyck et al., 2010; Fiordelisi et al., accepted for publication). Surprisingly, the number of studies related to the financial industry is still limited. All these studies estimate reputational losses using the event study method focusing on an event window of 1 day (0; 1). Overall, these papers consistently find the existence of statistically significant reputational losses, especially in the case of operational losses due to internal frauds (De Fontnouvelle and Perry, 2005; Gillet et al., 2010; Fiordelisi et al., accepted for publication). Gillet et al. (2010) also take into account various factors (e.g. firm size, price-to-book ratio, level of liabilities, ROA, the number of employees, and the type of loss) that have an influence on reputational damages. Our paper advances prior studies by considering a large number of potential determinants of reputational risk at both bank and country levels. Specifically, we posit that reputational damage can be influenced by bank riskiness, profitability, level of intangible assets, equity capitalization, bank size and business area that suffered the operational loss. We also show that the determinants of reputational damage are influenced by the time period selected to measure them, while previous studies (Merchant and Schendel, 2000; Gleason et al., 2003, 2006; Chiou and White, 2005; Marciukaityte et al., 2009) focus on the event window (0; 1).

Regarding the amount of operational losses, most of these studies (Cummins et al., 2006; Gillet et al., 2010) take into account operational losses greater than $10 million. The decision to focus on large operational losses increases the quality of data (since one can assume that operational losses are carefully recorded), but also reduces the number of operational losses by omitting consideration of medium and smaller operational losses that are the most likely to occur. Following Fiordelisi et al. (accepted for publication), we examine operational losses greater than $1 million: this enables us to consider medium operational losses and select a large sample of data (i.e. 215 operational loss cases for 163 banks), without reducing the quality of data collected.

Concerning the period under investigation, all prior studies deal with operational losses over the last two decades: e.g. De Fontnouvelle and Perry (2005) analyze operational loss announcements of 115 worldwide banks between 1974 and 2004; Cummins et al. (2006) analyze operational losses for both banks and insurance companies between 1978 and 2003; and Gillet et al. (2010) analyzed both European and US financial companies between 1990 and 2004. Consistently with Fiordelisi et al. (accepted for publication), we analyze banks in Europe and the US by using an updated sample of operational losses (between 2003 and 2008).

Since we analyze the impact of various factors on reputational damage that has not been analyzed in previous studies, we cannot develop our hypothesis based on these studies. As such, we build in the next section six new hypotheses (and also a competing hypothesis) for each factor that may affect reputational damage following an operational loss.

3. Research hypotheses

We identify the following six factors that may affect reputational damage following an operational loss: bank riskiness, profitability, level of intangible assets, capitalization, size, the entity of the operational loss and the business units that suffered the operational loss. First, we assume a positive relationship between riskiness and reputational damage: reputational damage suffered by risky banks is larger than that suffered by safe banks that could absorb the loss better than a riskier bank.

Hypothesis I (H_1). In the case of an operational loss, bank reputational damage increases as risk increases.

Second, we assume a positive relationship between profits and reputational damage: in the case of an operational loss, investors penalize a profitable bank more than a non-profitable bank since investors did not expect it and bank stock price may not have captured the operational losses.

Hypothesis II (H_2). In the case of an operational loss, bank reputational damage increases as profits increases.

Third, we assume a negative relationship between the level of bank intangible assets and reputational damage: in the case of an operational loss, investors penalize banks with a higher level of intangible assets less than banks with low intangible assets, *ceteris paribus*, since investors trust that intangible assets are related to future bank profitability (e.g. brand, licenses, high management quality, etc.) to cover the loss.

Hypothesis III (H_3). In the case of an operational loss, bank reputational damage decreases as the level of intangible assets increases.

Fourth, we assume a negative relationship between the capital invested in the bank and reputational damage: in the case of an operational loss, investors penalize poorly capitalized banks more than well capitalized banks, *ceteris paribus*, by punishing moral hazard behavior. Bank managers have incentives to take on more risk particularly when the level of bank capital is low. The moral hazard could arise in the presence of informational frictions and the existence of 'agency problems' between bank managers and owners, for example, when managers take on risks that are borne entirely by the shareholders. Better capitalized banks, in contrast, may have less moral hazard incentives and be more likely to adopt cost reducing practices.

Hypothesis IV (H_4). In the case of an operational loss, bank reputational damage decreases as the level of equity capital increases.

Fifth, we assume a positive relationship between bank size and reputational damage: investors penalize large banks more than small banks, *ceteris paribus*, after an operational loss. In such a case, the reputational damage suffered by a large bank is larger than that suffered by a small bank since investors panic and the market reaction is larger than in case of small banks.

Hypothesis V (H_5). In the case of an operational loss, bank reputational damage increases as bank size increases.

We assume that the business areas suffering the operational loss, *ceteris paribus*, influence reputational damage. We posit that two operational losses of equal entity generated in two different bank business areas (e.g. "commercial banking" and "payment and settlement") will result in reputational damage of different entities.

Hypothesis VI (H_6). In the case of an operational loss, the entity of the bank reputational damage differs according to the business area suffering the loss.

4. Empirical design

This section describes our data, the variable definitions and our econometric approach to test our research hypotheses.

4.1. Data

We collect a data set from various sources. Operational losses data are obtained from the ALGO OpData™ database according to the following criteria: (1) the parent company was a bank publicly quoted in the US and Europe; (2) price and market capitalization data were available at the time of the loss announcement; (3) the loss was operational and must have been known to be so at the time of the announcement; (4) there had been no prior announcement of the loss; (5) the operational loss was announced between 01/01/2003 and 01/08/2008; (6) a precise loss amount or exposure was announced on the day of the first announcement or shortly thereafter; and 7) there were no obvious confounding events. Market data for financial companies suffering operational losses are obtained from the Datastream database. At the end of the selection procedure, our sample comprises 215 operational losses referring to listed companies for 163 banks in Europe and the US.

Following Fiordelisi et al. (accepted for publication), operational losses have been classified according to two criteria: the event type of the loss (specifically, internal fraud, external fraud, employment practices and workplace safety, clients, products and business practices, damage to physical assets, business disruption and systems failures, execution, delivery and process management) and the business area that experienced the loss (specifically, corporate finance, trading and sales, retail banking, commercial banking, payments and settlement, agency services, asset management, retail brokerage, other areas).

As shown in Fig. 1 Panels A and B, the most common event type of operational losses are related to clients, products and business practices (148 cases) with a mean value of about \$100 millions. "Internal frauds" is the event type with the highest mean value and standard deviations. The number of other types of operational losses is quite limited (overall 41 observations) with small mean losses. Regarding the business lines suffering the operational loss, the "trading and sales" unit is the one with the highest mean value and standard deviation (35 observations). All the other business units have a substantial number of observations and the mean amount of operational losses is smaller than that of "trading ad sales". Focusing on the number of operational losses over the sample period (Fig. 1, Panel C), these are on average 40 per year with the exception of 2008 when we stopped collection at the 1 August.

We also collected stock market information (specifically, stock returns, Beta indicator, market financial leverages, price to book ratios, and market capitalization) from Bloomberg and accounting items (specifically, the net operating income before depreciation and amortization, and the total equity at the end of the year in which the bank occurred the loss) from the Bankscope database. Panel D in Fig. 1 reports the descriptive statistics for the variables used in the empirical analysis. We observe that bank asset size ranges between \$18 millions and \$1.1 billions, the mean value of the market financial leverage is 3.1 and banks analyzed are systemically important in the stock market.

4.2. Event study

Following previous studies (De Fontnouvelle and Perry, 2005; Gillet et al., 2010), we run an event study to measure reputational loss. First, we estimate abnormal returns, that is the forecast errors of a specific normal return-generating mode. We estimated daily AR using the Sharpe (1963) market model by applying OLS-regression methodology for time series of one full trading year (250 trading days) prior to the event window and regressing the daily returns for stock j on day t ($R_{j,t}$) on returns on market index on day t ($R_{m,t}$). Following Gillet et al. (2010), we adjust stock returns by adding the ratio between the operational loss (OL) and the market capitalization (MC) of the company: the negative return as a result of the operational loss event, is added to the abnormal return at time 0 before computing the average abnormal return of each day t ($AR_{j,0}$) to isolate the reputational effect. Specifically, the abnormal return ($AR_{j,t}$) following the operational loss of financial company i for day t is measured as follows:

$$AR_{j,0}(\text{Rep}) = R_{j,t} - \mu_j - \beta_j R_{m,t} + \left|\frac{OL_{j,t}}{MC_{j,t}}\right| \tag{1}$$

where μ_j is the idiosincratic risk component of share j and β_j is the beta coefficient of share j.

Following a standard approach, we consider various event windows both prior and after operational loss announcement (the widest extends from 20 days before the announcement day to 20 days after). Specifically, we focus on the following short event windows: $(-1;1)$. As a robustness check, we take into account the possibility that the event may have been forecast by investors or that stock price reaction may take more days (e.g. the operational loss amount may not have been precisely estimated until a few days after its first announcement): as such, we also estimate CAR using event windows with different length: $(-20;20)$, $(-10;10)$, $(-5;5)$ and $(-3;3)$.

We test the statistical significance of mean ARs using the Boehmer et al. (1991) test statistic Z to capture the event-induced increase in return volatility as follows[2]:

$$Z = \frac{\frac{1}{N}\sum_{j=1}^{N} SR_{j,t}}{\sqrt{\frac{1}{N(N-1)}\sum_{j=1}^{N}\left(SR_{j,t} - \sum_{j=1}^{N}\frac{SR_{j,t}}{N}\right)^2}} \tag{2}$$

where N is the number of stocks in the sample and $SR_{j,t}$ is the standardized abnormal return on stock j at day t obtained following the Mikkelson and Partch (1988) approach as follows:

$$SR_{j,t} = \frac{\text{CAR}_{j,e1-e2}}{\widehat{S}_j\sqrt{T_{s+1} + \frac{T_{s+1}^2}{T} + \frac{\sum_{j=e1}^{e2}(r_{m,t} - T_{s+1})\bar{r}_m))^2}{\sum_{j=1}^{T}(r_{m,t} - \bar{r}_m)^2}}} \tag{3}$$

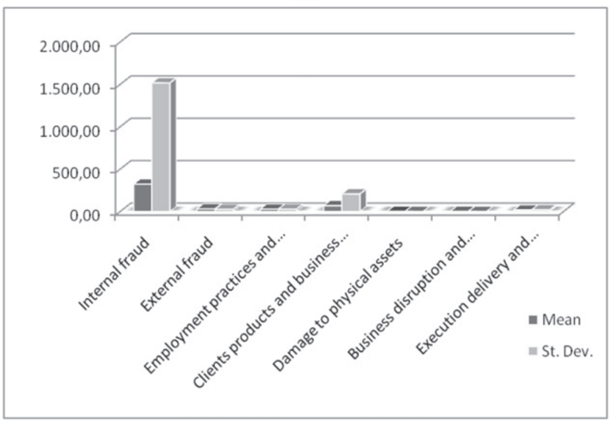
where e_1 and e_2 are the first and last days in the event window, $\text{CAR}_{j,e1-e2}$ is the cumulated abnormal return of stock j in the event window $(e_1;e_2)$, $r_{m,t}$ is the return on market index on day t (event period), $\overline{r_m}$ is the average return on market index in the estimation period, $\widehat{S}_j$ is the estimated standard deviation of abnormal return on stock j, T is the number of days in the estimation period and T_{s+1} is the number of days in the event window. The Z test statistic in (3) has a t-distribution with $T-2$ degrees of freedom and converges to a unit normal.

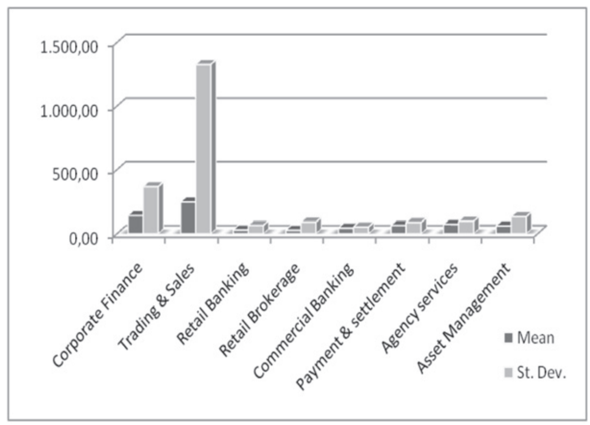
[2] Harrington and Shrider (2007) show that the use of the popular test statistic to assess the significance of CARs in short-horizon event studies is biased.

Panel A: number of operational losses by event type and business lines*

	Corporate Finance	Trading & Sales	Retail Banking	Retail Brokerage	Commercial Banking	Payment & settlement	Agency services	Asset Management	Total
Internal frauds	6	4	8	3	2	0	1	2	26
External frauds	0	0	5	1	1	1	1	0	9
Employment practices and workplace safety	0	2	2	7	1	0	0	0	12
Clients products and business practices	27	25	23	29	6	6	4	28	148
Damage to physical assets	0	0	0	0	1	0	0	0	1
Business disruption and system failures	0	0	0	0	0	1	0	0	1
Execution delivery and process management	4	4	3	4	2	1	0	0	18
Total	37	35	41	44	13	9	6	30	215

Panel B: The mean value of operational losses by event type and business line*





Panel C: number of operational losses by year

Year	Number of cases	Mean*	St. Dev.*	Sum*
2003	22	27.39	34.06	602.67
2004	43	45.32	77.44	1948.61
2005	46	106.91	332.10	4917.73
2006	37	48.31	116.49	1.787.44
2007	50	41.49	104.92	2074.29
2008	17	485.47	1875.56	8253.03
Total	215	91.09	553.56	19583.77

Panel D: Descriptive statistics of variables used in the empirical analysis[#]

	Obs	Mean	St. Dev.	Min	Max
St.Dev.Ret	215	22.66%	9.14%	1.23%	43.50%
Beta	215	1.34	0.34	0.12	2.57
M(D/E)	215	3.07	2.74	0.23	8.21
*NOI**	215	19.06	43.51	0.00	589.32
PBV	215	2.10	0.94	0.30	4.76
*EQ**	215	179.84	183.19	11.14	1,084.22
*SIZE**	215	215.91	192.82	18.08	1,136.02

Fig. 1. Operational losses in US and European banking between 2003 and 2008. Panel A reports the number of operational losses in our sample classified according to the event type and the business line that suffered the loss. Panel B reports the mean value and standard deviation of operational losses classified according to the event type and the business line that suffered the loss. Panel C reports the number of operational losses in our sample by year. Panel D reports the descriptive statistics of variables used in the analysis. *Denotes that data are in USD millions. # denotes that variable definitions are reported in Table 1. Data were collected from the ALGO OpData™ database.

4.3. The determinants of reputational damage and control variables

We consider a large number of potential determinants of reputational risk at both bank and country levels. We identify the following six factors that may affect the reputational damage following an operational loss: bank riskiness, profitability, level of intangible assets, firm capitalization, firm size, the entity of the operational loss and the business units that suffers the operational loss.

Specifically, we measure bank riskiness using three indicators: beta index, stock return standard deviation and market leverage.

Table 1
Variables definition. This table defines the variables used in the paper.

Variables	Symbol	Definition and calculation method
Beta indicator[a]	*Beta*	This expresses bank systematic risk, i.e. the risk associated with aggregate market returns and measured by the covariance of bank stock returns to stock market return
Standard deviation of stock returns[a]	*St.Dev.Ret*	This expresses the overall risk (both the systematic and idiosyncratic risk components) undertaken by a shareholder
Market financial leverage[a]	*M(D/E)*	This is calculated as the ratio between the market value of bank debts and the equity capital
Net Operating Income before Depreciation and Amortization[a]	*NOI*	This is estimated by adding depreciation and amortization back to operating income
Price-book value ratio[a]	*PBV*	This is calculated as the ratio between the stock market price and the book value of bank equity
Equity capital[b]	*EQ*	This is measured by the overall equity capital invested in the bank
Bank size[a]	*SIZE*	This is calculated as the sum of market value of equity and market value of debt, less the Cash
Large size[c]	*LS*	This is a dummy variable, i.e. LS = 1 if the loss size is the second half of the operational loss distribution (i.e. loss of largest amount); LS = 0 otherwise.
US deal[c]	*US*	US is a dummy variable, i.e. US = 1 if both the bank has headquarters in the US; CCH = 0 otherwise
Large bank	*LB*	This is a dummy variable, i.e. LB = 1 if the bank market capitalization is in the second half of the market capitalization distribution (i.e. banks of largest market capitalization); LB = 0 otherwise
Business area 1: corporate finance[c]	*BU_CF*	This is a dummy variable, i.e. BU_CF = 1 if the operational loss was in the corporate finance business unit; BU_CF = 0 otherwise
Business area 2: trading and sales[c]	*BU_TS*	This is a dummy variable, i.e. BU_TS = 1 if the operational loss was in the trading and sale business unit; BU_TS = 0 otherwise.
Business area 3: retail banking[c]	*BU_RBA*	This is a dummy variable, i.e. BU_RBA = 1 if the operational loss was in the retail banking business unit; BU_RBA = 0 otherwise
Business area 4: retail brokerage[c]	*BU_RBR*	This is a dummy variable, i.e. RBR_CG = 1 if the operational loss was in the retail brokerage business unit; BU_RBR = 0 otherwise.
Business area 5: commercial banking[c]	*BU_CB*	This is a dummy variable, i.e. BU_CB = 1 if the operational loss was in the commercial banking business unit; BU_CB = 0 otherwise
Business area 6: payment and settlement[c]	*BU_PS*	This is a dummy variable, i.e. BU_PS = 1 if the operational loss was in the payment and system business unit; BU_PS = 0 otherwise
Business area 7: agency services[c]	*BU_AS*	This is a dummy variable, i.e. BU_AS = 1 if the operational loss was in the agency service business unit; BU_AS = 0 otherwise
GDP per-capita[d]	GDP	This is the domestic GDP (in Euro) of the country where the operational losses was suffered divided by the number of inhabitants
Inflation[d]	*INF*	This is the consumer price index change over two consecutive years for the country where the operational losses was suffered

[a] Denotes that data source is Bloomberg.
[b] Denotes that data source is Bankscope.
[c] Denotes that data source is ALGO OpData™ database.
[d] Denotes that the source of data is the United Nations.

The beta indicator expresses bank systematic risk, i.e. the risk associated with aggregate market returns and measured by the covariance of bank stock returns to stock market return. The stock return standard deviation expresses the overall risk (both the systematic and idiosyncratic risk components) undertaken by a shareholder. The bank market leverage is calculated as the ratio between the market value of bank debts and the equity capital: this measure provides an indication of the bank exposure to insolvency risks.

We measure bank profitability by focusing on the Net Operating Income before Depreciation and Amortization, estimated by adding depreciation and amortization back to operating income. As proxy of the level of intangible assets held by the bank, we focus (in accordance with Gillet et al., 2010) on the price-book value ratio (*PBV*): *PBV* compares the market evaluation of bank equity (price) to the account evaluation of bank equity (BV) so a *PBV* greater than one implies that investors *expect* management to create more value from a given set of assets, all else equal (and/or that the market value of the firm's assets is significantly higher than their accounting value). As such, higher value of *PBV* signals a higher level of intangible assets (e.g. brand value, good management, etc.) in the bank. Bank equity capitalization is measured by the overall equity capital invested in the bank. We measure bank size by the enterprise value that is calculated as the sum of market value of equity and Market value of debt, less Cash. Also Gillet et al. (2010) takes into account bank size, measured by the market value and total assets, respectively.

Finally, we account for the business area that suffered operational losses (specifically, corporate finance, trading and sales, retail banking, retail brokerage, commercial banking, payment and settlement, agency services and asset management) by using dummy variables.

Table 1 summarizes all variables used in the empirical analysis.

Various factors may also influence the link between reputational losses and its determinants, such as the size of the operational losses and the bank's nationality. As such, we include two dummy variables to control for these factors: one dummy refers to bank nationality (1 = US, 0 otherwise), the second captures the size of the operational losses (1 = operational losses in the first half of the operational loss distribution; 0 = operational losses in the second half of the operational loss distribution). We also include several macroeconomic variables commonly used in the banking literature (e.g. Salas and Saurina, 2003; Yildirim and Philippatos, 2007; Demirgüç-Kunt and Huizinga, 2010; Fiordelisi and Molyneux, 2010; Fiordelisi et al., 2011). These include real GDP per capita (GDP_P) to capture differences in income levels, and money market interest rates (IR) to capture the stance of monetary policy.

4.4. Econometric approach

To investigate how reputational damage is influenced by bank risk, profitability, intangible assets, capitalization, size and business area, a straightforward approach would be to use ordinary least squares regressions (OLS). Following Gillet et al. (2010), we estimate the following multivariate linear model:

$$\mathrm{CAR}(-1,1) = \alpha + \sum_{j=1}^{7}\beta_j Det_j + \sum_{j=1}^{7}\gamma_j BA_j + \sum_{j=1}^{4}\delta_j Cont_j + \varepsilon \quad (4)$$

Table 2
Reputational loss in US and European banking between 2003 and 2008.

	No. obs.	CAR (−1; 1)	CAR (−3; 3)	CAR (−5; 5)	CAR (−10; 10)	CAR (−20; 20)
Overall sample	215	0.0003	0.0006	−0.0006	−0.0014*	−0.0041**
By event type						
– Internal frauds	26	−0.0105**	−0.0036	−0.0063	0.0018	0.0017
– External frauds	9	0.0053	0.0081	0.0154	0.0154	−0.0149
– Employment practices and workplace safety	12	−0.0006	−0.0066	−0.0093	−0.0103	0.0020
– Clients products and business practices	148	0.0025	0.0014	−0.0005	−0.0027**	−0.0048**
– Damage to physical assets	1	0.0153	0.0100	0.0275	0.0647	0.0899
– Business disruption and system failures	1	−0.0015	0.0152	0.0141	0.0020	−0.0062
– Execution delivery and process management	18	−0.0044**	−0.0004	0.0028	−0.0019	−0.0108
By business lines						
– Corporate finance	37	0.0004*	−0.0001	0.0011	0.0021	0.0017
– Trading and sales	35	−0.0062*	−0.0098**	−0.0085	−0.0209**	−0.0323***
– Retail banking	41	0.0042	0.0043	−0.0032***	−0.0030**	0.0025
– Retail brokerage	44	0.0044**	0.0061	0.0028	0.0031	0.0024
– Commercial banking	13	−0.0122	−0.0110	−0.0081	−0.0071	−0.0159
– Payment and settlement	9	0.0020	0.0104	0.0005	−0.0020	−0.0298*
– Agency services	6	−0.0048*	−0.0010	0.0052	0.0073	0.0062
– Asset management	30	0.0025	0.0030	0.0072	0.0136	0.0135

This table presents the mean cumulative abnormal return (CAR) estimated over various event windows. We estimated daily AR using the Sharpe (1963) market model by applying OLS-regression methodology for time series of one full trading year (250 trading days) prior to the event window and regressing the daily returns for stock j on day t ($R_{j,t}$) on returns on market index on day t ($R_{m,t}$). Following Gillet et al. (2010), we adjust stock returns by adding the ratio between the operational loss (OL) and the market capitalization (MC) of the company: the negative return as a result of the operational loss event, is added to the abnormal return at time 0 before computing the average abnormal return of each day t ($AR_{j,0}$) to isolate the reputational effect. The residuals (e_t) provide the estimates of ARs. The test of the statistical significance of mean CARs follows the Boehmer et al. (1991) test statistic z to capture the event-induced increase in return volatility.
*** Significance at 1%.
** Significance at 5%.
* Significance at 10%.

where CAR (−1, 1) are the cumulative abnormal returns calculated for the event windows (−1, 1), *Det* are the determinants of reputational risk analyzed[3] (specifically, (1) bank riskiness measures, i.e. *Beta* and *St.Dev.Ret*; (2) profitability measure, i.e. *NOI*; (3) the level of intangible assets, i.e. *PBV*; (4) bank capitalization, i.e. *EQ*; (5) bank size, i.e. *SIZE*; and (6) bank financial structure, i.e. *M*(*D*/*E*)), *BA* are the business units suffering the operational loss (specifically, corporate finance, trading and sales, retail banking, commercial banking, payments and settlement, agency services, asset management, retail brokerage, other areas, i.e. respectively, *BU_CF*, *BU_TS*, *BU_RBA*, *BU_RBR*, *BU_CB*, *BU_PS*, *BU_AS*); *Cont* are control variables at the bank level (specifically, the entity of the operational loss, i.e. LS; and the bank nationality, i.e. US) and country level (namely, GDP per capita, and interest rate, respectively GDP and INF).

Hypothesis H1 predicts a positive coefficient for risk variables (*Beta*, *St.Dev.Ret* and *M(D/E)*), H2 a negative coefficient for bank profits (*NOI*), H3 a positive coefficient for the profit-book value ratio (*PBV*), H4 a positive coefficient for invested capital (*EQ*), H5 a negative coefficient for bank size (*SIZE*), H6 non-null coefficients for business area dummy variables (*BA*).

In the second step, we aim to measure the probability of observing a reputational loss. Various studies (Efendi et al., 2007; Warusawitharana, 2008; Roberts and Sufi, 2009; Lucey and Šević, 2010, among others) apply multinomial and ordered logit models in finance. The choice of categories is governed by several considerations. First, more refined categories reveal more information and, all else equal, will lead to more efficient estimates. However, more categories also increase the number of parameters multiplicatively and reduce statistical power. These considerations, as well as the focus of our study, lead us to examine three mutually exclusive categories defined above: reputational gain, no reputational impact, and reputational damage. Specifically, our dependent variable takes on the value of 1 (labeled as "reputational gain") if the bank experienced a CAR that is in the top third of the CAR distribution. It takes on the value 2 (labeled as "no reputational damage") if the CAR is in the middle third of the CAR distribution; and it takes on the value 3 (labeled as "reputational damage") if the CAR is in the lowest third of the CAR distribution.

Our first model is an ordered logit model expressing the probability of observing reputational damage, respectively, being in a class greater than j as:

$$P(Y_i > j) = g(\alpha_j, \beta_j X_i) = \frac{\exp(\alpha_j + \beta_j X_i)}{1 + \exp(\alpha_j + \beta_j X_j)}, \quad \text{for } j = 1, 2, \ldots M - 1 \tag{5}$$

where M is the number of classes, X_i is the vector of independent variables for bank i, and α and β are the parameters of interest. The parameters α_i are the cut-off parameters for the different nodes of the dependent variable, i.e., α_1 is the intercept for a CAR classified as "reputational gain", α_2 is the intercept for a CAR classified as "no reputational damage", α_3 is the intercept for a CAR classified as "reputational damage"; β_j are the slope coefficients for the explanatory variables (i.e., risk measures, profit measure, etc.).

The ordered logit model makes an important "parallel odds" assumption. It assumes that only the cut-off parameters α_i are different across the changes in reputational damage, whereas the slope coefficients of the link function for the parameters of interest remain identical. In the context of our study, this means that factors influencing reputational damage are assumed to have an equi-proportionate effect on the probabilities of observing either a reputational gain or loss. There are reasons why this "parallel odds" assumption may be inappropriate when studying the determinants of reputational damage. For example, take a given operational loss in two banks with symmetric level of profits (e.g. bank A has net income of $1 million and bank B has net losses of $1 million): it is difficult to assume that the reputational damage will be symmetric for these banks (e.g. 1% reputational gain for bank A and −1% for bank B). It is therefore important to also test our hypotheses using a more flexible approach that does not make such strong assumptions.

[3] The variable definitions and notations are reported in Table 1.

In our third stage, we apply the so-called partial proportional odds model (Williams, 2006). This is a more flexible model allowing for varying intercepts as well as for different slope coefficients so that:

$$P(Y_i > j) = h(\alpha_j, \beta_j X_i) = \frac{\exp(\alpha_i + \beta_j X_i)}{1 + \exp(\alpha_j + \beta_j X_i)}, \quad \text{for } j = 1, 2, \ldots M-1 \tag{6}$$

We can write the respective probabilities that Y_i takes on values $j = 1, 2, \ldots, M$ as:

$$P(Y_i = 1) = 1 - h(\alpha_j, \beta_1, X_i) \tag{7}$$

$$P(Y_i = j) = h(\alpha_{j-1} + \beta_{j-1} X_i) - h(\alpha_j + \beta_j X_i) \quad \text{for } J = 2, \ldots, M-1 \tag{8}$$

$$P(Y_i = M) = h(\alpha_{M-1} + \beta_{M-1} X_i) \tag{9}$$

The partial proportional odds model resembles a series of simple logit models that bunch several ordered dependent variable categories into one. Specifically, we use $M = 3$ in our paper. This means that for $J = 1$, category 1 (CAR classified as "reputational gain") is contrasted with categories 2 and 3 ("no reputational gain" and "reputational damage", respectively); for $J = 2$, the contrast is between categories 1 and 2 vs. category 3.

5. Results

This section presents our findings. First, we present the event study results. Second, we discuss our econometric model result to investigate the link between reputational damage and its determinants.

5.1. Reputational damage measurement

Table 2 reports our results for the event study using the symmetric event windows of different length[4] (namely, the (−20; 20), (−10; 10), (−5; 5), (−3; 3), and (−1, 1)). By estimating CAR over various event windows, we take into account the possibility that investors may either forecast operational losses before its announcement or stock prices reaction may take more days. Overall, we find that operational losses mostly generate reputational damage measured by the Cumulative Adjusted Returns (Table 2).

On average, CARs are found to be negative and statistically significant (at the 5% confidence level) for operational losses related to clients, products and business practices, for operational losses in the "Trading and Sales" and in the "Retail banking" business units. Mean CAR for other event types and business lines are not found to be statistically significant, but this is not surprising considering the small number of observation available in these subsamples. It is interesting to note that in the cases of operational losses suffered in some business units, we find positive mean CAR. This shows that, on average, market reactions to the operational loss announcements were lower than the normal stock return and, especially, to the amount of the operational loss.

5.2. The determinants of reputational damage

Our results reported in Table 3 refer to the OLS multivariate regression linking the CAR (−1, 1) and the various determinants under investigation. Since CAR (1, 1) measure the reputational return, a positive regression coefficient for a given covariate implies a negative relation between that covariate and the reputational damage;

Table 3
The determinants of reputational damage in European and US banking.

	(1)	(2)	(3)	(4)
Beta	0.093	0.140	0.140	0.061
	(0.950)	(0.990)	(0.940)	(0.430)
St.Dev.Ret	−0.074	−0.331	0.078	−0.165
	(−0.750)	(−1.390)	(0.650)	(−1.170)
M(D/E)	0.154	0.102	0.296	0.403
	(1.160)	(0.340)	(1.190)	(1.450)
NOI	−0.092*	0.298	0.200	0.341
	(−1.920)	(0.920)	(0.700)	(1.030)
PBV	0.162**	0.302	0.227*	0.205
	(2.180)	(1.570)	(1.940)	(1.420)
EQ	0.613*	1.053**	0.279*	0.355*
	(1.890)	(2.120)	(1.910)	(2.150)
SIZE	−0.624**	−1.072**	−0.345*	−0.491*
	(−2.160)	(−2.330)	(−1.800)	(−1.740)
US	0.291	0.370	−0.281*	0.168
	(1.210)	(1.410)	(−1.830)	(0.940)
LS	−0.115	−0.058	−0.098	0.158
	(−0.850)	(−0.310)	(−0.640)	(0.920)
Z ∗ Beta		0.141	−0.277	−0.552*
		(0.360)	(−0.970)	(−1.670)
Z ∗ St.Dev.Ret		−0.329	−0.277	−0.530*
		(−0.910)	(−0.950)	(−1.750)
Z ∗ M(D/E)		−0.225	−0.148	−0.084
		(−1.150)	(−0.960)	(−0.490)
Z ∗ NOI		−1.198	0.746	0.700
		(−1.590)	(1.340)	(0.640)
Z ∗ PBV		1.047*	−0.659	−0.212
		(1.750)	(−1.330)	(−0.220)
Z ∗ EQ		0.143	0.295	0.298
		(0.490)	(1.260)	(1.130)
Z ∗ SIZE		−0.081	−0.144	−0.100
		(−0.640)	(−1.060)	(−0.740)
BU_CF	−0.044	0.052	−0.083	0.007
	(−0.170)	(0.200)	(−0.300)	(0.020)
BU_TS	−0.329	−0.197	−0.372	−0.300
	(−1.220)	(−0.750)	(−1.380)	(−1.070)
BU_RBA	−0.219	−0.045	−0.249	−0.157
	(−0.780)	(−0.150)	(−0.890)	(−0.600)
BU_RBR	−0.151	−0.075	−0.265	−0.083
	(−0.560)	(−0.280)	(−0.990)	(−0.320)
BU_CB	−0.521	−0.397	−0.604	−0.449
	(−1.190)	(−1.090)	(−1.410)	(−1.120)
BU_PS	−0.087	−0.080	−0.097	−0.034
	(−0.180)	(−0.160)	(−0.200)	(−0.070)
BU_AS	−0.455*	−0.343	−0.454*	−0.429
	(−1.890)	(−1.300)	(−1.660)	(−1.630)
GDP	0.167	0.149	0.149	0.186
	(1.130)	(1.100)	(1.010)	(1.250)
INF	0.066	0.093	0.075	0.038
	(0.880)	(1.110)	(1.020)	(0.400)
CONST$_1$	0.019	0.052	0.115	−0.105
	(0.080)	(0.170)	(0.500)	(−0.380)
R-squared	0.133	0.185	0.178	0.169

In this table, we estimate a OLS multivariate model in which our dependent variable is the CAR (−1, 1). Column (1) reports results for our base model, as described in the Eq. (4). Column (2) reports results for a model where we used the same covariates of the base model, plus variables obtained interacting the various determinants analyzed (i.e. risk, profits, intangible assets, capital, equity) with a dummy variable capturing bank nationality (1 = US, 0 = otherwise). Column (3) reports results for a model where we used the same covariates of the base model, plus variables obtained interacting the various determinants analyzed with a dummy variable capturing the size of operational losses (1 = large losses, 0 = otherwise). Column (4) reports results for a model where we used the same covariates of the base model, plus variables obtained interacting the various determinants analyzed with a dummy variable capturing bank size (1 = large banks, 0 = otherwise). As such, Z is equal to 0 in column (1), Z = US in the column (2), Z = LS in the column (3), and Z = LB in the column (4). Table 1 defines all variables used. We present robust z-statistics in brackets.

*** Significance at 1%.
** Significance at 5%.
* Significance at 10%.

[4] We also run the event study for asymmetric windows [specifically, the (−20; 0), (−10; 0), (−5; 0), (−3; 0), (0; 20), (0; 10), (0; 5) and (0; 3)], as a robustness check to account for the potential stock market inefficiency. Results are available on request from authors.

Table 4
The probability of reputational damage in European and US banking.

	(1) Order logit	(2) Partial proportional odds model	(3)
		Reputational gains vs. no gains	No reputational damage vs. reputational damage
Beta	0.944	0.784	1.110
	(−0.360)	(−0.980)	(0.480)
St.Dev.Ret	1.075	1.169	1.016
	(0.380)	(0.590)	(0.070)
M(D/E)	0.934	1.092	1.117
	(−0.300)	(0.260)	(0.400)
NOI	1.387**	2.037	2.152***
	(2.380)	(1.150)	(3.440)
PBV	0.810	1.073	0.619**
	(−1.360)	(0.300)	(−2.340)
EQ	0.310**	0.077**	0.245**
	(−2.470)	(−2.370)	(−2.100)
SIZE	2.558**	3.596**	1.438
	(2.060)	(2.400)	(0.640)
LS	1.357	1.176	1.534
	(1.040)	(0.430)	(1.220)
US	0.559*	0.412*	0.641
	(−1.720)	(−1.720)	(−0.940)
BU_CF	1.057	1.784	0.634
	(0.100)	(0.860)	(−0.760)
BU_TS	1.012	0.818	1.195
	(0.020)	(−0.300)	(0.290)
BU_RBA	1.759	5.493**	0.750
	(1.060)	(2.040)	(−0.430)
BU_RBR	1.108	1.267	0.971
	(0.180)	(0.370)	(−0.050)
BU_CB	1.590	2.211	1.252
	(0.620)	(0.890)	(0.280)
BU_PS	1.489	1.025	3.610*
	(0.400)	(0.030)	(1.800)
BU_AS	2.787	4.402	3.773
	(1.340)	(1.350)	(1.490)
GDP	1.124	1.238	1.412*
	(0.830)	(0.830)	(1.860)
INF	0.829	0.558**	1.188
	(−1.130)	(−2.160)	(0.660)
$CONST_1$	0.439*	2.661	0.520
	(−1.694)	(1.610)	(−1.200)
$CONST_2$	1.943		
	(1.360)		
Wald χ^2	23.64	53.75	
Pseudo R^2	0.0396	0.1577	

In this table, we estimate ordered logit and partial proportional odds models to estimate the probability of suffering operational damage. Our dependent variable takes on the value of 1 (labeled as "reputational gain") if the bank experienced a CAR that is in the top third of the CAR distribution. It takes on the value 2 (labeled as "no reputational damage") if the CAR is in the middle third of the CAR distribution; and it takes on the value 3 (labeled as "reputational damage") if the CAR is in the lowest third of the CAR distribution. Column (1) reports results for the ordered logit model (see Eq. (4)). Columns (2) and (3) report results for the partial proportional odds model that allows for varying intercepts as well as for different slope coefficients (see Eq. (5)). For ease of interpretation, we report odds ratios that are obtained by exponentiating the original coefficient. As such, an odds ratio of 1 indicates that the probabilities of observing reputational damage or gain are equally likely if there is a change in the covariate. An odds ratio below 1 indicates that an increase in the covariate is associated with a lower probability of reputational damage. Conversely, an odds ratio greater than 1 suggests that a covariate increase is associated with a greater probability of reputational damage. We present robust z-statistics in brackets. The Wald χ^2 tests the partial proportional odds assumption. Table 1 defines all variables used.
*** Significance at 1%.
** Significance at 5%.
* Significance at 10%.

conversely, a negative regression coefficient for a given covariate implies a positive link between the covariate and reputational loss. We report results for four models: column (1) refers to our base model, as described in Eq. (4). The other three columns reports results for a model including all covariates used in the base model, plus variables obtained interacting the various determinants analyzed (i.e. risk, profits, intangible assets, capital, equity) with a dummy variable capturing bank nationality (column 2), a dummy variable capturing the size of operational losses (column 3), and a dummy variable capturing bank size (column 4). The interacting variables enable us to assess the marginal contribution of each determinant of reputational losses according to the size of the loss and the bank nationality and size.

Our results show that reputational damage increases as bank profits and size increase, as the estimated coefficients are negative, supporting the Hypotheses 2 and 5. In the case of an operational loss, stock market losses are larger for profitable banks than those for non-profitable banks. This is probably due to investors' surprise at the (unexpected) operational loss suffered by profitable banks making the stock price reaction larger than that for non-profitable banks. Similarly, we show that investors penalize large banks more than small banks, *ceteris paribus*, after an operational loss. This suggests that, in the case of operational losses, investor panic and the market reaction for larger banks is greater than that for small banks.

We also observe that reputational damage decreases as capital invested in the bank increases, as the estimated coefficient is positive, supporting Hypothesis 4. In the case of an operational loss, investors seem to penalize poorly capitalized banks more than well-capitalized banks, *ceteris paribus*, by punishing moral hazard behavior. Since better-capitalized banks have less moral hazard incentives than poorly capitalized banks, stock return losses generated by an operational loss is smaller for well-capitalized banks.

Gillet et al. (2010) show that bank nationality, the relative size of the loss and the event type of loss play a role in determining reputational damage by comparing the entity of mean CAR for various sub-samples (e.g. large vs. small operational losses; losses in European banks vs. losses in US banks, etc.). In our paper, we propose a parametric approach to test the influence of these three factors on the determinants of reputational damage by interacting the various determinants analyzed (i.e. risk, profits, intangible assets, capital, equity and business areas) with each of these three factors (bank nationality, size of operational loss and bank size). As shown in Table 3, the incremental effect related to bank nationality, size of the loss, and size of the bank do not affect substantially the relationship between reputational damage and the various factors investigated. Our results (in columns 2, 3, and 4 of Table 3) are consistent with those presented for the base model in column 1: specifically, reputational damages decrease as equity increases and bank size decreases. Looking at the marginal contribution of various factors, we show that reputational damage decreases as the level of intangible assets of US banks increases (Table 3, column 2). We also observe that reputational damage is positively related to the systematic risk and financial leverage of large banks, but not to other factors (Table 3, column 4).

5.3. Estimating the probability of reputational damage

In order to estimate the probability of suffering reputational damage after an operational loss, we estimate the order logit (Table 4, column 1) and the less restrictive proportional odds models (Table 4, columns 2 and 3). Namely, we measure reputational damage as "reputational gain" if the bank experienced a CAR $(-1,1)$ that is in the bottom third of the CAR $(-1,1)$ distribution (i.e. the largest CAR); "no reputational damage" if the CAR $(-1,1)$ is in the middle third of the CAR $(-1,1)$ distribution; and "reputational damage" if the CAR $(-1,1)$ is in the top third of the CAR $(-1,1)$ distribution (i.e. smallest CAR).

We first report coefficients obtained by the order logit regressions (reported in column (1)), which considers reputational damage and gains in a symmetric way and yields only one coefficient for each variable. For ease of interpretation, we report odds ratios that are obtained by exponentiating the original coefficient. As such, an odds ratio of 1 indicates that the probabilities of observing reputational damage or gain are equally likely if there is a change in the covariate. An odds ratio below 1 indicates that an increase in the covariate (e.g. bank profits) is associated with a lower probability of reputational damage. Conversely, an odds ratio greater than 1 suggests that a covariate (e.g. bank profits) increase is associated with a greater probability of reputational damage.

Our results (Table 4) are consistent with those previously discussed. The probability of reputational damage increases as bank profits and size increase, as the odds ratio for these variables are greater than 1, by supporting Hypotheses 2 and 5. We also observe that the probability of reputational damage decreases as capital invested in the bank increases, supporting Hypothesis 4. In order to assess whether the slope coefficients differ, we turn to the partial proportional odds model: column (2) in Table 4 expresses the effect of the regressors on the probability of observing a "reputational gains" vs. "no reputational gains" (i.e. damage or no gains)". The coefficients in column (3) capture the effect of the regressors on the probability of "reputational damage" vs. "no damage" (i.e. reputational gains or no damage). Similar to the ordered logit model results, we report odds ratios that are obtained by exponentiating the original coefficient for ease of interpretation. The results of the partial proportional odds models are similar to those obtained in order logit regressions. We also show that the probability of reputational damage decreases as the bank price-to-book value ratio increases, as the odds ratio for this variable is smaller than 1. This result supports the investigated Hypothesis 3 and we can reject the competing hypothesis (H_3'). This suggests that, in the case of an operational loss, investors penalize banks with a higher level of intangible assets less than banks with low intangible assets, *ceteris paribus*, since investors trust that intangible assets are related to future bank profitability.

Similarly to our analysis made for the OLS model, we also test the incremental effect of bank nationality, loss size and bank size on the determinants of reputational damage by interacting the various determinants analyzed (i.e. risk, profits, intangible assets, capital, equity and business areas) with each of these three factors. We report results for both the order logit (column 1 Table 5) and the less restrictive proportional odds models (columns 2 and 3 Table 5). In the case of different results, we view the results based on the proportional model as more accurate.

We consistently find in all models that the probability of reputational damages decreases as equity increases and asset size decreases by confirming previous results in Table 4. We also find that an increase in the standard deviation of bank stock returns increases the probability of non-achieving reputational gains, but not the probability of obtaining reputational damage. As shown in Table 5, the incremental effect related to bank nationality, size of the loss, and size of the bank do not affect substantially the relationship between reputational damage and the various factors investigated.

5.4. Robustness check

Following various studies (Gleason et al., 2003, 2006; Marciukaityte et al., 2009), we analyzed the determinants of reputational loss focusing on the event window $(1;1)$. The length of the event window used to measure reputational damage is a critical decision. A short event window around the announcement date (as we used) is likely to be the most accurate measurement of reputational damage since the measured stock market reaction reflects "only" the event under investigation. However, this measurement relies on the assumption that stock markets are efficient (at least in a semi-strong form).

Consistently with Gillet et al. (2010) that measure CAR over longer time periods, we conduct a robustness check to confirm the validity of the empirical results reported in Tables 3 and 4. Specifically, we measure reputational damage using two longer windows capturing the effect after a week [CAR $(-5,5)$] and after a month [CAR $(-20,20)$] of the announcement date. By considering longer time periods than $(-1;1)$, we are aware that CAR may be generated by other factors than the operational loss announcement (especially, the CAR $(-20,20)$), but nevertheless their assessment is a useful robustness check by enabling us to account for possible market inefficiency and assessing reputational damage over a longer time period. Similarly to Table 5, we report results in Table 6 for both the order logit (column 1) and the less restrictive proportional odds models (columns 2 and 3). In the case of different results, we view the results based on the proportional model as more accurate.

Focusing on event window $(-5,5)$, our results show that the probability of reputational damage increases as there is an increase in the banks' market financial leverage, profits and size, as the odds ratio for these variables are greater than 1 (Table 6, Panel A). These results are strongly consistent with those reported in Table 4:

Table 5
The probability of reputational damage in European and US banking: the role of operational loss size, bank nationality and size.

Dependent variable	Panel A (Z = US)			Panel B (Z = LS)			Panel C (Z = LB)		
	(1) Order logit	(2) Partial proportional odds model	(3)	(1) Order logit	(2) Partial proportional odds model	(3)	(1) Order logit	(2) Partial proportional odds model	(3)
	CAR (0; 1)	Reputational gains vs. no gains	No reputational damage vs. reputational damage	CAR (0; 1)	Reputational gains vs. no gains	No reputational damage vs. reputational damage	CAR (0; 1)	Reputational gains vs. no gains	No reputational damage vs. reputational damage
Beta	0.883	0.879	1.253	0.833	0.746	0.899	0.928	0.635	1.254
	(−0.520)	(−0.340)	(0.760)	(−0.870)	(−1.100)	(−0.390)	(−0.320)	(−1.330)	(0.820)
St.Dev.Ret	1.452	5.237**	0.661	0.967	1.150	0.853	1.674*	5.586***	0.804
	(1.050)	(2.420)	(−0.590)	(−0.130)	(0.470)	(−0.480)	(1.830)	(2.930)	(−0.620)
M(D/E)	0.903	0.434	2.347	1.317	1.350	1.742*	0.848	0.427*	1.044
	(−0.230)	(−1.160)	(0.950)	(0.880)	(0.690)	(1.730)	(−0.400)	(−1.790)	(0.110)
NOI	0.441	0.283	1.016	1.617	1.727	2.455	0.481	0.128	1.611
	(−1.160)	(−0.800)	(0.010)	(0.840)	(0.640)	(1.200)	(−0.860)	(−1.150)	(0.370)
PBV	0.600	0.307*	0.741	0.825	1.050	0.624*	0.727	0.376**	0.789
	(−1.500)	(−1.750)	(−0.590)	(−0.870)	(0.160)	(−1.740)	(−1.050)	(−2.450)	(−0.890)
EQ	0.123***	0.118*	0.006*	0.257**	0.043**	0.198*	0.028*	0.000**	0.026*
	(−2.960)	(−1.720)	(−1.930)	(−2.170)	(−1.990)	(−1.840)	(−1.750)	(−2.290)	(−1.720)
SIZE	1.911***	2.637*	3.337*	2.859*	3.076*	1.626	3.842*	1.239***	2.746*
	(2.810)	(1.790)	(1.880)	(1.750)	(1.870)	(0.500)	(1.730)	(2.760)	(1.920)
Z ∗ Beta	1.074	1.081	0.705	1.451	1.156	1.853	0.843	0.595	0.726
	(0.210)	(0.150)	(−0.660)	(1.240)	(0.270)	(1.360)	(−0.610)	(−0.850)	(−0.650)
Z ∗ St.Dev.Ret	0.672	1.147**	2.064	1.251	0.799	1.550	0.483*	1.066***	1.602
	(−0.880)	(−2.350)	(0.870)	(0.630)	(−0.490)	(0.950)	(−1.910)	(−2.870)	(0.940)
Z ∗ M(D/E)	0.953	2.637	0.411	0.591	0.659	1.402*	1.719	0.983	1.367
	(−0.080)	(1.220)	(−0.910)	(−1.170)	(−0.670)	(−1.750)	(1.060)	(−0.010)	(0.500)
Z ∗ NOI	2.823	8.047	1.495	0.754	0.786	0.778	3.339*	4.163*	1.495
	(1.360)	(1.220)	(0.270)	(−0.480)	(−0.220)	(−0.310)	(1.820)	(1.730)	(0.310)
Z ∗ PBV	1.494	3.844	0.963*	1.010	0.832	1.031	1.081	3.372	0.681*
	(1.020)	(0.910)	(−1.910)	(0.030)	(−0.390)	(0.070)	(0.220)	(1.170)	(−1.890)
Z ∗ EQ	7.490*	1.682	5.963	1.758	4.986	1.858	9.798	10.181**	0.009*
	(1.730)	(0.250)	(1.920)	(0.620)	(0.740)	(0.440)	(0.920)	(2.010)	(−1.820)
Z ∗ SIZE	0.190	0.418	0.013*	0.770	0.397	0.736	0.050	0.000**	4.564*
	(−1.520)	(−0.430)	(−1.710)	(−0.300)	(−0.420)	(−0.250)	(−1.220)	(−2.480)	(1.760)
BU_CF	0.951	2.003	0.471	0.903	1.287	0.485	0.741	1.236	0.646
	(−0.100)	(0.980)	(−1.230)	(−0.200)	(0.390)	(−1.160)	(−0.590)	(0.290)	(−0.720)
BU_TS	0.858	0.711	1.192	0.801	0.599	0.894	0.735	0.456	1.180
	(−0.250)	(−0.530)	(0.280)	(−0.380)	(−0.840)	(−0.190)	(−0.510)	(−1.080)	(0.280)
BU_RBA	1.543	5.725	0.480	1.616	5.312**	0.528	1.175	9.674**	0.617
	(0.780)	(1.990)	(−0.960)	(0.890)	(1.980)	(−0.850)	(0.300)	(2.110)	(−0.680)
BU_RBR	0.886	1.168	0.601	0.827	0.912	0.605	0.716	0.624	0.840
	(−0.210)	(0.250)	(−0.780)	(−0.340)	(−0.150)	(−0.780)	(−0.630)	(−0.700)	(−0.280)
BU_CB	1.405	1.771	2.132	1.632	1.862	1.288	1.272	1.585	1.087
	(0.470)	(0.680)	(0.920)	(0.670)	(0.680)	(0.320)	(0.310)	(0.400)	(0.110)
BU_PS	1.480	0.789	3.573	1.468	1.028	2.879	1.100	0.068	9.205**
	(0.370)	(−0.280)	(1.540)	(0.370)	(0.030)	(1.140)	(0.090)	(−1.610)	(2.040)
BU_AS	2.622	2.995	3.493	2.211	3.539	2.957	2.533	8.272***	3.665
	(1.160)	(0.990)	(1.380)	(0.970)	(1.230)	(1.130)	(1.120)	(2.600)	(1.160)
GDP	1.162	1.023	1.631	1.102	1.154	1.488*	1.061	1.061	1.372
	(0.960)	(0.080)	(1.580)	(0.670)	(0.540)	(1.850)	(0.460)	(0.180)	(1.360)
INF	0.729	0.564	0.703	0.797	0.861	0.595	0.821	0.371**	1.408
	(−1.480)	(−1.230)	(−0.910)	(−1.230)	(−0.540)	(−1.550)	(−1.040)	(−2.240)	(1.130)
$CONST_1$	0.542	1.386	0.595	0.507	1.657	0.568	0.352**	4.226**	0.464
	(−1.339)	(0.640)	(−1.040)	(−1.506)	(1.020)	(−1.250)	(−2.288)	(1.960)	(−1.370)
$CONST_2$	2.431*			2.256*			1.613		

	(1.940)		(1.814)		(1.048)	
Wald χ^2	32.95***	79.13***	33.68***	73.90*** *	46.54***	71.32***
Pseudo R^2	0.0839	0.3631	0.0885	0.2809	0.1164	0.2752

In this table, we estimate ordered logit and partial proportional odds models in which our dependent variable takes on the value of 1 (labeled as "reputational gain") if the bank experienced a CAR that is in the top third of the CAR distribution. It takes on the value 2 (labeled as "no reputational damage") if the CAR is in the middle third of the CAR distribution; and it takes on the value 3 (labeled as "reputational damage") if the CAR is in the lowest third of the CAR distribution. Column (1) reports results for the ordered logit model (Eq. (5)). Columns (2) and (3) report results for the partial proportional odds model that allows for varying intercepts as well as for different slope coefficients (see Eq. (6)). For ease of interpretation, we report odds ratios that are obtained by exponentiating the original coefficient. As such, an odds ratio of 1 indicates that the probabilities of observing reputational damage or gain are equally likely if there is a change in the covariate. An odds ratio below 1 indicates that an increase in the covariate is associated with a lower probability of reputational damage. Conversely, an odds ratio greater than 1 suggests that a covariate (e.g. bank profits) increase is associated with a greater probability of reputational damage. We present robust z-statistics in brackets. The Wald χ^2 tests the partial proportional odds assumption. In Panel A, we interact various covariates with US, i.e. a dummy variable that equals one if the bank has headquarters in the US, and 0 otherwise. Table 1 defines all variables used.

*** Significance at 1%.

** Significance at 5%.

* Significance at 10%.

overall, these support the investigated Hypotheses 1, 2 and 5 and enable us to reject the competing hypotheses (respectively, H_1', H_2', and H_5'). We also find that the probability of reputational damage decreases as the level of intangible assets, the capital invested in the bank and the size of the loss increases, as the odds ratio for these variables is smaller than one. These results support the investigated Hypotheses 3 and 4 (this is consistent with our main results in Table 3). We also find that the probability of reputational damage increases if the operational loss is suffered in the following business units: "trading & sales", "retail banking" and "commercial banking". We interpret this result as a signal that, if the operational loss refers to traditional banking business areas, investors may take some time (i.e. a week) to realize the impact of the loss so that the stock price reaction will take a week.

Looking at the results for the event window (−20,20), our results show that the probability of reputational damage increases as bank beta and profits increase, as the odds ratio for these variables are greater than 1 (Table 6, Panel B). These results are strongly consistent with those obtained for the event windows (−1,1) and (−5,5): overall, these support the investigated Hypotheses 1, 2 and enable us to reject the competing hypotheses (H_2' and H_5'). We also find that the probability of reputational damage decreases as the level of intangible assets, the capital invested in the bank and the size of the loss increases, as the odds ratio for these variables is smaller than 1. These results are strongly consistent with those obtained for the event windows (−1,1) and (−5,5) supporting the investigated Hypotheses 3 and 4. We also find that the probability of reputational damage increases if the operational loss is suffered in the "trading & sales" business unit.

6. Conclusions

What determines reputational damage in banking after operational losses? Our paper is the first to empirically address this question. First, we have identified the six factors that may affect reputational damage following an operational loss: bank riskiness, profitability, level of intangible assets, capitalization, size, the entity of the operational loss and the business units that suffered the operational loss. For each of these factors, we posit a specific research hypothesis.

By selecting a large sample of European and US listed banks suffering operational losses between 01/01/2003 and 01/08/2008, we are the first study to provide empirical evidence of how the probability of experiencing a reputational loss is influenced by the selected factors that we investigated.

We show that the probability of reputational damage increases as bank profits and size increase. In the case of an operational loss, stock market losses are larger for profitable banks than that for non-profitable banks: this is probably due to investors' surprise at the (unexpected) operational loss suffered by profitable banks so that the stock price reaction is larger than that for non-profitable banks. Similarly, investors penalize large banks more than smaller banks, *ceteris paribus*, after an operational loss: this suggests that, in the case of operational losses, investors panic and the market reaction for a larger bank is greater than for a small bank. We also show that the probability of reputational damage decreases as capital invested in the bank increases. In the case of an operational loss, investors penalize poorly capitalized banks more than well-capitalized banks, *ceteris paribus*, by punishing moral hazard behavior. Since better capitalized banks have less moral hazard incentives than poorly capitalized banks, stock return losses generated by an operational loss is smaller than for well capitalized banks. Our results are found to be robust to various robustness checks. Specifically, we tested the influence of bank nationality, size of operational loss and bank size on the

Table 6
The probability of reputational damage in European and US banking: the role of time.

Dependent variable	Panel A CAR(−5,5)			Panel B CAR (20,20)		
	(1) Order logit	(2) Partial proportional odds model	(3)	(1) Order logit	(2) Partial proportional odds model	(3)
	CAR (−5; 5)	Reputational gains vs. no gains	No reputational damage vs. reputational damage	CAR (−10; 10)	Reputational gains vs. no gains	No reputational damage vs. reputational damage
Beta	0.997	0.986	0.802	0.938	0.561**	1.436*
	−0.010)	(−0.060)	(−0.890)	(−0.400)	(−2.320)	(1.770)
St.Dev.Ret	1.044	0.688	1.695**	0.989	1.124	0.791
	0.230)	(−1.520)	(1.970)	(−0.060)	(0.500)	(−1.040)
M(D/E)	1.125	0.684	2.298***	0.879	0.847	1.115
	0.530)	(−1.400)	(3.050)	(−0.560)	(−0.440)	(0.340)
NOI	1.891**	1.986*	2.674***	1.339*	0.406	3.557**
	2.130)	(1.880)	(2.950)	(1.820)	(−1.500)	(2.030)
PBV	0.724**	0.760*	0.524***	0.631***	0.682**	0.489***
	−2.040)	(−1.730)	(−2.930)	(−2.920)	(−2.010)	(−3.200)
EQ	0.851	2.660	0.063***	0.471*	0.232	0.276**
	−0.280)	(1.550)	(−2.990)	(−1.710)	(−1.460)	(−1.990)
SIZE	0.913	0.488	5.324**	1.841*	7.884**	1.194
	−0.170)	(−1.340)	(2.040)	(1.710)	(2.530)	(0.310)
LS	0.553**	0.816	0.364***	0.578*	0.762	0.477**
	−2.130)	(−0.600)	(−2.760)	(−1.840)	(−0.700)	(−2.080)
US	0.892	0.876	1.637	1.372	2.167	1.257
	−0.300)	(−0.270)	(1.000)	(0.730)	(1.420)	(0.400)
BU_CF	1.786	1.704	1.600	1.923	2.515*	1.714
	1.160)	(0.910)	(0.630)	(1.180)	(1.710)	(0.840)
BU_TS	3.734**	1.994	5.991***	3.563**	3.572*	3.273**
	2.570)	(1.110)	(2.800)	(2.190)	(1.850)	(1.940)
BU_RBA	3.650**	2.925*	4.264**	2.228	2.474	2.139
	2.530)	(1.840)	(2.250)	(1.430)	(1.500)	(1.240)
BU_RBR	1.844	3.059*	1.586	1.259	3.643**	0.691
	1.230)	(1.890)	(0.720)	(0.420)	(2.190)	(−0.580)
BU_CB	1.893	0.936	4.187*	1.474	1.976	0.918
	0.900)	(−0.080)	(1.870)	(0.580)	(0.920)	(−0.110)
BU_PS	1.770	2.328	0.717	3.161	4.120*	1.900
	0.750)	(0.790)	(−0.290)	(1.540)	(1.770)	(0.770)
BU_AS	1.434	0.839	2.223	2.716	9.991*	1.099
	0.410)	(−0.180)	(0.600)	(1.650)	(2.110)	(0.070)
GDP	0.940	0.820	1.059	0.776*	0.583**	0.774
	−0.320)	(−0.730)	(0.230)	(−1.910)	(−2.530)	(−1.260)
INF	1.067	0.910	1.087	0.772	0.628	0.907
	0.340)	(−0.380)	(0.260)	(−1.240)	(−1.290)	(−0.340)
$CONST_1$	0.630	1.260	0.213**	0.805	0.513	0.381*
	−0.988)	(0.390)	(−2.320)	(−0.419)	(−1.080)	(−1.690)
$CONST_2$	3.013***			3.801**		
	(2.343)			(2.533)		
Wald χ^2	33.68***	73.90*** *		46.54***	71.32***	
Pseudo R^2	0.0885	0.2809		0.1164	0.2752	

In this table, we estimate ordered logit and partial proportional odds models in which our dependent variable takes on the value of 1 (labeled as "reputational gain") if the bank experienced a CAR that is in the top third of the CAR distribution. It takes on the value 2 (labeled as "no reputational damage") if the CAR is in the middle third of the CAR distribution; and it takes on the value 3 (labeled as "reputational damage") if the CAR is in the lowest third of the CAR distribution. Column (1) reports results for the ordered logit model (see Eq. (5)). Columns (2) and (3) report results for the partial proportional odds model that allows for varying intercepts as well as for different slope coefficients (see Eq. (6)). For ease of interpretation, we report odds ratios that are obtained by exponentiating the original coefficient. As such, an odds ratio of 1 indicates that the probabilities of observing reputational damage or gain are equally likely if there is a change in the covariate. An odds ratio below 1 indicates that an increase in the covariate is associated with a lower probability of reputational damage. Conversely, an odds ratio greater than 1 suggests that a covariate (e.g. bank profits) increase is associated with a greater probability of reputational damage. We present robust z-statistics in brackets. The Wald χ^2 tests the partial proportional odds assumption. Table 1 defines all variables used.

*** Significance at 1%.
** Significance at 5%.
* Significance at 10%.

determinants of reputational damage. Furthermore, we measured reputational damage over various time periods. In all cases, results are strongly consistent.

We believe that our paper provides a useful first step in exploring in some depth what determines reputational damage in the banking industry, an often discussed but little-researched topic. Future research may fruitfully examine the impact of other factors on reputational damage, such as corporate governance and other managerial information.

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