Financial penalties and the systemic risk of banks*

Hannes Köster†

Matthias Pelster‡

Leuphana University of Lueneburg

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Abstract

This study analyzes the impact of financial penalties on the stability of the banking sector. Using a unique database of 671 financial penalties imposed between 2007 and 2014 on 68 international listed banks, we study the impact of financial penalties on the systemic risk of banks. We obtain evidence for a significant negative relation between financial penalties and banks' systemic risk exposure but not between financial penalties and banks' systemic risk contribution. We also demonstrate that the characteristics of the regulatory and supervisory system of a given country affect the relation between financial penalties and banks' systemic risk exposure. Our results contribute to the ongoing debate on the appropriateness of financial penalties and address the question whether bank regulators limit or contribute to banks' systemic risk.

Keywords: systemic risk, bank regulation, financial penalty, bank fines, misconduct

JEL classification: G01, G21, G28

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† Scharnhorststr. 1, D-21335 Lueneburg, Germany, telephone: +49 4131 677 2166, e-mail: *hannes.koester@leuphana.de.*

‡ Scharnhorststr. 1, D-21335 Lueneburg, Germany, telephone: +49 4131 677 2188, e-mail: *matthias.pelster@leuphana.de.*

1. Introduction

Unresolved legal disputes have become a permanent burden for many banks today. In the aftermath of the financial crisis, the banking sector has faced significant financial penalties for a broad range of misconduct, e.g., for mortgage malpractices, market manipulations, and embargo breaches. These and other penalties have reached a dimension that caused the European Systemic Risk Board to issue warnings that the current and forecasted levels of financial penalties might pose systemic risks (European Systemic Risk Board, 2015).[1] The Board's report argued that the growing number and amount of financial penalties could increase public concerns with the regard to the business model and solvency of banks. In addition, banks may be encouraged to withdraw from specific financial markets, which could lead to adverse effects on the functioning of these markets (European Systemic Risk Board, 2015). Thus, regulators might prevent future misconduct by imposing financial penalties, though by doing so, they might also increase systemic fragility. If that were the case, imposing penalties would undermine their mission to protect the stability of the financial system.

Since the European Systemic Risk Board does not provide any empirical evidence for its claim, the effect of financial penalties on the stability of the financial system remains an unanswered and controversial issue. This study aims to contribute to this debate by addressing the following two questions: Do financial penalties affect the systemic risk of banks and, if so, to what extent? If there is an impact, how do regulatory and supervisory characteristics mitigate or exacerbate the impact of financial penalties on the banking sector's stability?

To the best of our knowledge, our paper is the first to examine these relations. Thus, we address a major gap in the literature. Our results will be helpful for banking supervisors and policymakers. Banking authorities have, in response to the financial crisis, changed their approach to a more sanction-based supervision, aligning their regulations more closely with banks' business behavior. The results of this study allow for a more nuanced perspective on this regulatory policy change. Furthermore, it examines whether financial penalties are an appropriate instrument to penalize banks' misconduct from a macro-prudential perspective. Because of the financial intermediation and transformation function of banks, a well-

[1] The European Banking Authority (EBA) also included "conduct risk" as a factor in its stress test for the first time in 2014 (European Banking Authority, 2014). By doing so, the EBA acknowledged that increasing fines and settlement costs could threaten the stability of the banking sector. In the 2016 stress test, the EBA predicted that in an adverse market scenario from 2016 to 2018, the 51 examined banks will bear additional costs for fines and settlements of approximately USD 71 billion (European Banking Authority, 2016).

functioning banking system with no serious impairments from excessive financial penalties is an important factor for the well-being of the entire economy.

To examine these issues, we created a unique database that comprises hand-collected information on the dates and amounts of financial penalties imposed on individual banks between 2007 and 2014. Our main sources are different datasets provided by regulatory authorities, newspaper archives, and investor briefs describing litigation and regulatory news compiled by business information providers. To measure the banks' systemic risk, we use the dynamic Marginal Expected Shortfall of Acharya et al. (2010) and Brownlees and Engle (2012) and the ΔCoVaR of Adrian and Brunnermeier (2016).

The results of our analyses and its implications contribute to several strands of literature. First, our empirical findings inform the debate on the design of a well-functioning regulatory environment, which enables banks to earn stable profits and thereby not harm the stability of the banking sector. Exemplary studies in this field are those by Barth et al. (2004), Anginer and Demirgüç-Kunt (2014b) and Hoque et al. (2015), who explore how regulatory and supervisory characteristics at the country level influence banking stability. Second, this study extends the literature on the determinants of systemic risk (e.g., López-Espinosa et al., 2013; Weiß et al., 2014b; Laeven et al., 2016). Third, our paper is related to the literature on corporate misconduct and its consequences. Several studies in this field analyze how corporate violations of regulations and laws affect short-term stock performance (e.g., Bhagat et al., 1994; Griffin et al., 2004; Karpoff et al., 2008; Köster and Pelster, 2017). We contribute to this literature stream by focusing on the dimension of risk.

The rest of the paper is organized as follows. In the following section, we develop our hypothesis and discuss related literature. In Section 3, we describe the data sources, empirical methods, applied systemic risk measures and explanatory variables used in the regression models. Section 4 discusses the results and the implications. The final section concludes.

2. Hypothesis development and related research

The common concern of national and international regulatory and supervisory authorities is to prevent deficiency in the financial system that may threaten the safety of the assets entrusted to banks or harm the stability of the banking sector and the economy. Thus, in recent years several studies analyzed the impact of bank regulation and supervision on systemic risk. Anginer et al. (2014a), Anginer and Demirgüç-Kunt (2014b), and De Jonghe et al. (2015) provide evidence that greater power of banking authorities leads to lower systemic fragility in the banking sector. In line with these results, the Basel Committee on Banking

Supervision recommend in their ‘Core principles for effective banking supervision’ that supervisors should have enough corrective and sanctioning power to be able to address unsound bank activities that can cause systemic fragility (Bank for International Settlements, 2012). One tool is to impose financial penalties on banks which infringe the rules or abuse the market. Unethical and illegal behavior can destroy the trust of the other market participants. A loss of trust has far-reaching consequences for the banking sector’s stability, as documented by the recent financial crisis. Origin of the crisis was banks’ misconduct, as they used unethical and illegal methods in the origination of mortgages and in the structuring and distribution of the resultant mortgage-backed securities (McConnell and Blacker, 2013).

Consequently, financial penalties may increase the stability in the banking sector due to three reasons: First, financial penalties demonstrate that the supervisory authority will not tolerate misconduct and that banking principles of fairness, honesty and integrity have to be honored strictly. As a result, financial penalties may restore the investors’ and customers’ confidence in the banking system, thus contributing to its stability. Second, financial penalties may have a deterrent and disciplinary effect. They may prevent repeated future offences of banks by indicating the significant and direct consequences of breaking the rules. Third, financial penalties may discourage banks to enter specific businesses that are associated with excessive risk-taking and thus are related with a higher systemic risk contribution and exposure.

On the other hand, bank practitioners warn that financial penalties may have the opposing effect. Contrary to expectations, systemic risk may increase due to greater crisis vulnerability of penalized and thus debilitated banks, the transmission of losses via direct and indirect linkages between banks, and the lack of readily available substitutes.

Banks are often subjected to multiple litigations that involve several authorities at the same time. The sum of the different financial penalties and the associated costs may have the power to debilitate a bank. The associated costs can be separated into direct and indirect costs. Direct costs include additional legal charges and expenses for lawyers, enlarged legal departments and external advisers (Murphey et al., 2009). Indirect costs result primarily due to reputational damages, which can have a considerable financial impact. For example, in their study on financial misrepresentation of companies of different sectors, Karpoff et al. (2008) observe that the estimated reputational losses are, on average, 7.5 times the sum of all financial penalties imposed by the U.S. Securities and Exchange Commission. Reputational damages can be reflected by increased funding costs or lower income, and as a result lower equity resources. Due to increased operational risk of sanctioned banks, external providers of equity and debt capital will demand higher rates of returns (European Systemic Risk Board, 2015). Similarly, private and corporate customers may be more conservative to do business with those banks (Bhagat et al, 1994; Murphy et al., 2009). A bad reputation is a serious motive for customers to change their banking connection, which is increasingly convenient due to the higher digitalization of the business. In line with those arguments, Köster and Pelster (2017) show that financial penalties decrease the current and future pre-tax profitability of banks. The authors find that a decline in income is responsible for lower future profitability. To sum up, financial penalties might debilitate banks to such extent that they are more vulnerable for global crises.

The lack of resistance also comprises that banks are less able to absorb global shocks and more likely to propagate those shocks through the system. In addition, due to the heavy financial burden banks might collapse and initiate a cascade of bank failures by passing financial distress on to their business partners. Indirect loss transmission can be caused by fire sales and information spillovers. Troubled banks might sell their assets at fire sale prices to obtain liquidity. In turn, the marked-to-market value of portfolios of other financial institutions will drop and induce a loss spiral (Tarullo, 2011; Brunnermeier and Oehmke, 2013; Bank for International Settlements, 2013). Information spillovers can cause an individual shock to trigger a systemic crisis. This mechanism describes that market participants perceive information of financial problems in one firm as a signal of possible problems in other firms (Tarullo, 2011; Anginer et al. 2014b). Information spillovers occur more often in banks, as their assets and businesses are more opaque for outsiders than those of other types of firms (Morgan, 2002). Thus, bank creditors, investors, and customers may assume unethical or illegal behavior of one bank is shared by other banks. Consequently, the announcement of financial penalties may increase the uncertainty about the business model and solvency of other banks that are not related to a specific misconduct case in the banking sector.

Financial penalties may also cause systemic fragility if specific financial services are discontinued and no substitutes are readily available. Bank managers may evaluate the returns on specific financial activities against the risk of violating rules and to be subjected to penalties. As a consequence, banks may fully withdraw from financial services that have become associated with financial penalties. When other banks lack the capacity or professional knowledge to supply similar financial services, the discontinuation of a critical function could have a negative influence on other banks and other industries. As consequence, the impaired functioning of a particular market could jeopardize the stability of the whole financial system (Tarullo, 2011; European Systemic Risk Board, 2015).

Overall, the mentioned arguments show that financial penalties can create risks to the financial stability in different ways and therefore justify the warnings of the European Systemic Risk Board. In the following empirical investigation we test the hypothesis that financial penalties have a significant positive effect on a bank's systemic risk.

3. Empirical Design

3.1 Data

We exploit a database that comprises hand-collected information from different sources on the dates and amounts of financial penalties imposed on individual banks. Sources include, e.g., Thomson Reuters, Financial Times, the public archives of different regulatory and supervisory authorities such as the United States Securities and Exchange Commission, the Financial Industry Regulatory Authority, the Financial Conduct Authority, and information regarding individual legal proceedings from banks' annual reports. We compiled the information from several sources as the institutions examined here do not disclose the aggregated sums of financial penalties in their annual reports. Oftentimes, these expenses are simply added to other cost positions without any explanations. Even if information on these costs are presented in an annual report, their itemization or definition may vary, or the amounts are only provided for a limited number of years. Therefore, the information in annual reports alone is not suitable for a multi-year analysis. Consequently, we compile information from multiples sources, so that the aggregated sums can be used as an approximation for the real amount of financial penalties paid by each bank in a given year. To reduce the possible approximation bias, we restrict our sample to banks that are included in the list of Global Systemically Important Banks (G-SIB) of the Financial Stability Board, or those that belong to the larger institutions of a given county. These institutions enjoy greater public attention; therefore, it is more likely that information providers report their financial penalties. We only focus on listed financial institutions, as we need stock price information to compute the systemic risk measures. In total, our database includes 68 banks from 20 countries and 671 cases of financial penalty payments from 2007 to 2014. In Appendix A.1, we provide a list of all the banks used in our empirical investigation.

The stock market information, e.g., the stock prices of the banks, market indices, and state variables, come from *Thomson Reuters Financial Datastream*. The stock prices are adjusted for dividends and splits. To calculate the independent variables, we use accounting data from *Thomson Worldscope*. We follow Anginer and Demirgüç-Kunt (2014b) and collect all stock market and accounting information in U.S. dollars to avoid possible distorted results due to different currencies. Information on the banks' regulatory environments are obtained from the *Bank Regulation and Supervisory Survey* database, which was developed by Barth et al. (2004) and is operated by the World Bank. Macroeconomic variables are retrieved from the *World Development Indicators* database of the World Bank and the *International Financial Statistics* database of the International Monetary Fund.

3.2 Methodology

To analyze the effect of financial penalties on the systemic risk of banks, we estimate a time-fixed and bank-fixed effect regression for panel data of the following form:

$$SYSTEMIC\ RISK_{it} = \alpha + \beta_1 PENALTY_{it-1} + \sum_{j=2}^{J+1} \beta_j X_{it-1}^{j} + \sum_{t=1}^{T} \gamma_t \, Year_t + \varepsilon_{it} \,. \qquad (1)$$

Here, the first subscript i is the specific financial institution being observed, while the second subscript t is the specific year in which it is observed. $SYSTEMIC\ RISK_{it}$ refers to the respective systemic risk measure. $PENALTY_{it}$ is the proxy for the financial penalties that an institution faces within a year. X_{it} refers to the control variables, and $Year_t$ is a time-specific dummy variable. α labels the constant, and ε_{it} is the disturbance variable that includes both the individual effect (μ_i) and the remaining disturbance ($\nu_{i,t}$). To determine, in a second step, how the regulatory environment of each country influences the relationship between financial penalties and systemic risk, we add regulation variables and their interactions with the financial penalty variable in Eq. (1). The standard errors are clustered at the bank level. To mitigate possible reverse causality problems, we lag all explanatory variables by one year. The applied systemic risk measures are explained in the following section (3.2.1), and the explanatory variables are described in Section 3.2.2.

3.2.1 Systemic risk measures

To measure the systemic risk of banks, we use the dynamic Marginal Expected Shortfall (MES) and the daily ΔCoVaR. We select these two measures as both of them have been substantially discussed in the recent literature and can be easily used by bank regulators and other bank practitioners for monitoring day-to-day financial stability.

In addition, the two approaches measure two separate dimensions of systemic risk. The MES proposed by Acharya et al. (2010) captures the marginal exposure to systemic risk of a bank and measures the average return of each bank during days when the market as a whole experiences enormous downward movements:

$$MES_t^i = \frac{1}{T}\sum_{t=1}^{T}(R_t^i \,|R_t^S < \Gamma). \tag{2}$$

R_t^i refers to the equity return of bank i in the specific year t, and R_t^S refers to the market index return. $R_t^S < \Gamma$ denotes the systemic event, i.e., an event when the market index falls under a threshold Γ. We follow Acharya et al. (2010) and define these events as the days in the bottom 5 percent of returns. We employ the World Datastream Bank Index as market index. To take nonlinear tail dependence, time-varying volatility, and correlation in the firms' and market's returns into account, we use the dynamic version of MES described in Brownlees and Engle (2012). For that reason, we apply the Dynamic Conditional Correlation (DCC) (see Engle, 2002) and TARCH (see Rabemananjara and Zakoïan, 1993) specifications for calculating daily MES values for each individual bank for all trading days within one year.

In contrast to the MES, the ΔCoVaR proposed by Adrian and Brunnermeier (2016) measures the contribution of a bank to systemic risk. This measure is based on the conditional downside risk co-movement between the returns of a financial institution and the returns of the entire financial system. More specifically, the CoVar considers the Value at Risk (VaR) of the financial system conditional on the VaR of an individual bank. CoVar, then, is defined as follows:

$$\Pr\left(R_t^S \le CoVaR_{q,t}^{S|i} \middle| R_t^i = VaR_{q,t}^i\right) = q. \tag{3}$$

R_t^S refers to the return of the financial system and R_t^i to the return of the specific bank. $VaR_{q,t}^i$ denotes the Value-at-Risk of the specific financial institution for a probability level q between 0 and 1. Adrian and Brunnermeier (2016) capture the individual bank's contribution to systemic risk by introducing ΔCoVaR. ΔCoVaR measures how the VaR of the system changes when a specific bank becomes financially distressed. It is defined as the difference between CoVaR conditional on the financial institution being in distress and the CoVaR conditional on the normal (median) state of the financial institution:

$$\Delta CoVaR_{q,t}^{S|i} = CoVaR_{q,t}^{S|R^i = VaR_{q,t}^i} - CoVaR_{q,t}^{S|R^i = Median^i}. \tag{4}$$

We compute the ΔCoVaR on the 5 percent quantile for each financial institution in our sample. Therefore, we use quantile regressions and a set of state variables as proposed by Adrian and Brunnermeier (2016) to capture the development of tail risk dependence over time. More specifically, we use the VIX index (implied equity market volatility), the difference between the three-month repo rate and the three-month Treasury bill rate ("liquidity spread"), the difference between the ten-year Treasury Bond and the three-month Treasury bill rate ("change in the slope of the yield curve"), the difference between the ten-year Moody's BAA-rated bond and the ten-year Treasury Bond ("change in the credit spread"), the change in the three-month Treasury bill rate, and the MSCI World Index return as state variables.[2] To capture the return of the entire financial system, we again employ the World Datastream Bank Index.

Finally, for the ongoing panel analyses, we use the annual means of the daily dynamic MES and ΔCoVaR estimates. We invert these amounts, so that higher values denote larger systemic risk.

3.2.2 Financial penalty and control variables

To analyze the relation between financial penalties and the systemic risk of banks, we add all financial penalties for each bank within one year to one aggregated value. By dividing the aggregated value by the total assets, we create our main explanatory variable PENALTY.

We control for a number of bank-specific variables. Following previous studies in the literature (e.g., Weiß et al., 2014b; Anginer et al., 2014a; Hoque et al., 2015), we consider the asset structure, funding structure, capitalization, size, income structure, liquidity, loan portfolio quality, and profitability of banks. The asset structure (ASSET) is measured by the ratio of loans to total assets. The funding structure (FUND) is proxied by the ratio of long-term funding to total funding. The income structure is defined as the ratio of non-interest income to total income (NONINC). This ratio reflects the extent to which a bank is engaged in non-core banking activities. The capitalization (CAP) is proxied by the ratio of equity to total assets. Size (SIZE) is measured by the natural logarithm of total assets. The quality of the loan portfolio (LOANLOSSPROV) is proxied by the provision for loan loss divided by total loans. The liquidity ratio (LIQUIDITY) is measured by cash and due from banks in relation to total deposit funding. This ratio shows the proportion of deposits that could be served if they were withdrawn abruptly. Profitability is represented by the return on total assets (ROA), for which we apply the pre-tax profit in the numerator.

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[2] Following López-Espinosa et al. (2013), Anginer et al. (2014a) and Bostandzic et al. (2014), we use the state variables mentioned here for non-US banks in our sample, too. According to López-Espinosa et al. (2013), this practice is unlikely to lead to distortions. They argue that the literature has provided empirical evidence for the following two insights. First, financial indicators are strongly correlated across different economies (e.g., King and Wadhwani, 1990; Longstaff et al., 2011). Second, financial indicators in the US economy significantly predict those in other developed countries (e.g., Rapach et al., 2013). Adrian and Brunnermeier (2016) also use the real estate sector stock return as a state variable. Because our sample does not include real estate companies, we do not use this state variable.

In addition, we use different regulatory variables developed by Barth et al. (2004) to analyze the interaction effects of these variables with the financial penalty variable in Section 4.2. To that end, we use the capital regulations' stringency, the supervisors' prompt corrective power and its power to declare insolvency, the degree of monitoring by external institutions, and the extent of the deposit insurance of individual countries. Capital stringency (CAP_STRING) quantifies the extent to which the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined. Higher values denote greater stringency. The supervisors prompt corrective power index (PROMPT_CORR) measures mainly two aspects. First, it considers the degree to which the authorities operate an early intervention framework that forces automatic action when certain regulatory thresholds are crossed. Second, it regards the availability of different supervisory tools to enforce specific corrective actions. Higher values of this combined score reflect greater readiness to respond to problems. The declaring insolvency power index (DECL_INS) measures the power of supervision to supersede bank shareholder rights, to declare a bank insolvent, or to suspend ownership rights of a problem bank. Again, higher values denote greater power. The external monitoring index (EXT_MONITOR) measures the degree of evaluations by external rating agencies and incentives for creditors to monitor bank performance. Higher values indicate more pronounced external monitoring. The extent of deposit insurance (DEPOSIT_INSUR) is captured by the proportion of a banking system's assets funded with insured deposits. Higher values denote more comprehensive deposit insurance.

In Appendix A.2, we include an overview of all variables used in our analyses and their data sources.

3.3 Summary statistics

The summary statistics on systemic risk measures, the financial penalty variable, and the various control variables employed in our examinations are provided in Table 1.

[Place Table 1 here]

The signs of the systemic risk measures are adjusted so that, for all measures, higher values indicate higher systemic risk. The mean dynamic MES is 4.56 percent for the full sample of 68 financial institutions over the 8-year time period. The maximum value for the dynamic MES is 28.74 percent, -42.03 percent for the minimum.[3] The standard deviation

[3] In unreported robustness tests, we set negative MES values to zero and re-run the regression models. Since the results do not differ noticeably, we follow De Jonghe et al. (2015), among others, and do not cap the MES.

amounts to 4.80 percent. The ΔCoVaR ranges from 0.25 to 7.45 percent for the sample period. The mean value of ΔCoVaR amounts to 1.02 percent, and the standard deviation is 0.72 percent.

With regard to financial penalties, we find that the highest ratio of financial penalty to total assets amounts to 3.862 percent. In this case, a financial institution received a total of USD 374.25 million in financial penalties in one year. The greatest amount that a bank paid was USD 27 billion. This number corresponds to a ratio of 1.285 percent. On average, financial institutions listed in our sample received penalties of 0.04 percent in relation to their total assets.

In Figure 1, we provide additional information about the means of the ratio of financial penalties to total assets broken down by the source region of the regulators.

[Place Figure 1 here]

Panel A considers financial penalties imposed by US regulators and Panel B by European regulators. The first bar of each panel includes all banks of our sample. US regulators imposed, on average, higher financial penalties proportional to the banks' assets than European regulators. The mean value of the financial penalty ratio paid to US regulators amounts to 0.0401 percent, whereas European regulators received, on average, penalties of 0.0013 percent in relation to the banks' assets. The second and third bars of both panels compare the imposed financial penalties by US and European regulators on US banks and European banks, respectively. US regulators impose, on average, financial penalties of 0.1000 percent in relation to the banks' assets to US banks, whereas the financial penalties imposed to European banks are lower with a ratio of 0.0171 percent. Similarly, European regulators impose, on average, larger financial penalties to domestic banks with a ratio of 0.0028 percent, while they impose on average financial penalties of 0.0003 percent in relation to the banks' assets to US banks. These numbers show that the presumption that domestic regulators punish foreign banks more severely cannot be supported.

4. Empirical Results

4.1. Financial penalties and systemic risk: Baseline regression

The results of our time-fixed and bank-fixed regression analyses of systemic risk are presented in Table (2). Model (1) employs the dynamic MES as the dependent variable, whereas Model (2) applies the ΔCoVaR as the dependent variable.

[Place Table 2 here]

The financial penalty variable exhibits a significant coefficient in Model (1). The dynamic MES measures the extent to which a single financial institution is affected by a system-wide collapse. The result shows that financial penalties are associated with a higher exposure towards systemic risk. A one standard deviation increase in the financial penalty variable yields an increase in systemic risk exposure of 0.41 percent. The coefficient indicates that financial penalties debilitate the corresponding bank to such an extent that it becomes more vulnerable to systemic events. Taking that into consideration, the financial penalties and the resulting costs should also decrease the distance of default of these banks. This relationship is confirmed by the regression results presented in Table 3. In the presented model, we run a time-fixed and bank-fixed effect regression model with the same explanatory variables as in Eq. (1) and use the log-transformed Z-Score (also termed as distance to default) as the dependent variable. The Z-Score represents the number of standard deviations that a firm's return on assets can fall before the firm becomes insolvent. The variable is constructed as the ratio of the return on assets plus the capital ratio divided by the standard deviation of the return on assets.[4] Since the Z-Score is highly skewed, we use its log-transformed values. The results given in Table 3 show a significant negative relationship between financial penalties and the log-transformed Z-Score. These results, then, confirm that financial penalties are associated with an increased default risk, which, in turn, raises the systemic risk exposure of a given bank.

[Place Table 3 here]

In Model (2) of Table 2, the financial penalty variable exhibits no significant coefficient. The ΔCoVaR measures the sensitivity of the financial system to a negative shock to a single financial institution (Adrian and Brunnermeier, 2016; see also Sedunov, 2016). Thus, the estimated coefficient shows that financial penalties have no significant impact on the contribution of a bank to systemic risk. That means that the level of banks' financial penalties do not represent an individual shock that would have a significant contagion effect on the entire banking system via direct and indirect linkages. Most market participants do not assume that the serious financial distress experienced by an individual bank due to financial penalties would necessarily be shared by financial institutions that follow similar business practices. The insignificant coefficient of the financial penalty variable also indicates that the negative mechanism of the discontinuation of specific financial services on the overall financial stability does not appear to play a significant role.

[4] The Z-Score is a widely-used default risk measure in the literature (e.g., Laeven and Levine, 2009; Houston et al., 2010; Beck et al., 2013).

Turning to the control variables, the regression results of Model (1) of Table 2 suggest that systemic risk exposure is further driven by capitalization, loan quality, liquidity, and asset structure. Lower loan quality and larger loan portfolios are associated with a higher exposure to systemic risk. In case of an economic shock, which may result in, for example, high bankruptcy and unemployment rates, these banks in particular will be affected. In contrast, the liquidity of a bank decreases the systemic risk exposure, as sufficient liquidity resources can be regarded as a cushion against deposit run-offs or dried-up inter-bank markets. The capitalization of a bank is also related to a lower systemic risk exposure, since well-capitalized banks are more resistant to any kind of shock (Anginer and Demirgüç-Kunt, 2014a). The regression results of Model (2) also show that capitalization has a significant negative impact on the contribution of a bank to systemic risk. Well-capitalized banks are more capable of coping with individual shocks and are therefore less likely to propagate a shock through the entire banking system (Anginer and Demirgüç-Kunt, 2014a).

4.2. Financial penalties, regulation, and systemic risk

We also examine the extent to which specific regulatory and supervisory configurations exacerbate or mitigate the positive relationship between financial penalties and the instability of the banking sector. The results of the analyses of the corresponding interaction effects on the banks' systemic risk exposure are presented in Table 4.

[Place Table 4 here]

Primarily in response to the recent financial crisis, national banking regulators have gradually adopted more stringent capital standards. Banking systems with sufficient quantitative and qualitative capital requirements seem to be more robust against external shocks. A bank experiencing financial difficulties in one of these systems would not be perceived as a major cause of concern. Therefore, we expect that the impact of financial penalties on systemic risk exposure will be less strong in systems characterized by more stringent regulatory capital requirements. Model (1) of Table 5 provides support for these assumptions, as the interaction term between the capital stringency variable and the financial penalty variable exhibits a negative coefficient.

In addition, a number of national supervisory authorities were given greater leeway in the aftermath of the recent financial crisis to intervene in difficult times. As a consequence, supervisory authorities can, to various extents, a) take prompt corrective actions and restructure banks and b) declare deeply troubled banks insolvent and suspend ownership rights of distressed banks. Model (2) of Table 5 indicates that greater prompt corrective power mitigates the positive effect of financial penalties on banks' systemic risk. Laws that grant authorities the discretionary power to take timely and precise actions increase their ability to correct undesirable developments.

In contrast, Model (3) of Table 5 shows that the opposite effect is observed if the power of supervisors to declare a bank insolvent is greater. The significant positive interaction term indicates that financial penalties have more serious consequences for the stability of a banking system in which the supervisory authorities are more likely to declare banks insolvent. If the probability of a bank's survival is lower because the supervisory authorities are more likely to declare the bank bankrupt, then its ability to raise capital is limited. Under these regulatory circumstances, other financial institutions and customers might be reluctant to do business with this bank. As a result, banks that already have do deal with high financial penalties are further harmed. Consequently, the systemic risk exposure of those banks is increased.

Next, we also expect that the external monitoring culture in a particular country has an increasing influence on the positive effect of financial penalties on the systemic risk. In general, external ratings by international and domestic rating agencies and incentives for creditors to monitor the banks' performance tend to encourage banks to reduce their risk taking. However, rating agencies and other institutions might downgrade the rating of banks that face large-scale financial penalties. As a consequence, obtaining money from the funding and capital markets becomes more difficult and expensive, which, in turn, leads to a weaker lending business (Karam et al., 2014). In extreme cases, the public questions the business model of the affected banks. As a result, this kind of uncertainty, along with the more difficult access to debt and equity capital, increases banks' vulnerability to systemic shocks. Consistent with these considerations, Model (4) of Table 4 shows that the external credit monitoring variable exacerbates the positive impact of financial penalties on the systemic risk exposure.

Finally, in Model (5) of Table 4, we consider the national deposit insurance schemes and their impact on the relationship between financial penalties and systemic risk. In general, studies have determined two directions how deposit insurance can influence the stability of the banking system. On the one hand, deposit insurance can lead to less monitoring of banks by depositors and an increased moral hazard. This could lead to disproportionate risk taking by banks, which, in turn, increases the likelihood of financial crises (Demirgüç-Kunt and Detragiache, 2002; Demirgüç-Kunt and Huizinga, 2004; Barth et al., 2004). On the other hand, deposit insurance is meant to strengthen the banking system stability in times of crisis, since it reinforces depositors' confidence in the financial safety net and prevents bank runs (Diamond and Dybvig, 1983). A study by Anginer et al. (2014b) provides corresponding empirical evidence; they found that, during the recent financial crisis, deposit insurance decreased the systemic risk exposure of banks. This line of argumentation suggests that the impact of financial penalties on the systemic risk will be less pronounced in the presence of more comprehensive deposit insurances. However, the estimation result of Model (6) shows an interaction term that is not significantly different from zero. Thus, we do not find evidence that the deposit insurance has a mitigating impact on the positive relationship between financial penalties and systemic risk.[5] The deposit insurance variable by itself shows a significant negative association to systemic risk, which is in line with the findings of Anginer et al. (2014b).

4.3. Additional tests

To verify the robustness of our empirical results, we perform a number of additional tests. First, we test whether the significant positive relation between financial penalties and systemic risk exposure holds when we use alternative measures of systemic risk exposure. In particular, we use the Systemic Risk Index (SRISK) approach proposed by Acharya et al. (2012) and the lower tail dependence (LTD) approach proposed by Weiß et al. (2014a).

The SRISK approach is an extension of the MES approach and reports the capital that a financial institution is assumed to need conditional on a systemic crisis, i.e., $SRISK_{i,t} = E_{t-1}\,(Capital\,Shortfall_i \mid Crisis)$. Accordingly, the SRISK approach provides complementary information, since it explicitly takes the leverage of a firm into account. More specifically, the SRISK for bank i at year t is calculated by $SRISK_{i,t} = k(Debt_{i,t-1}) - (1-k)\big(1 - LRMES_{i,t}\big)Equity_{i,t}$. $Debt_{i,t}$ is the financial institution's book value of debt. $Equity_{i,t}$ denotes the daily market value of the financial institution's equity. $LRMES_{i,t}$ is the daily estimated long-run Marginal Expected Shortfall defined as $1 - \exp(-18 * MES)$, where MES is the computed dynamic Marginal Expected Shortfall of Eq. (2). k is the prudential capital ratio, which is set to 8 percent.

The LTD approach captures the propensity of joint extreme adverse effects of a bank and the financial market. As already noticed by Adrian and Brunnermeier (2016), spillover

[5] We run the same model also with a dummy variable proposed by Barth et al. (2004) that takes the value 1 if a country possess an explicit deposit insurance scheme and depositors were fully compensated the last time a financial institution became insolvent. Nonetheless, the coefficient of the interaction term is not statistically significant different from zero.

effects with regard to systemic risk are not necessarily observable in equilibrium, as banking firms might take preventive actions in order to reduce the impact of externalities. Consequently, the LTD provides a suitable measure to estimate systemic risk. In general, the LTD between two random variables captures the probability that an observation of the random variables joint distribution will lie in the distribution's extreme lower tail. The lower tail dependence between two samples of financial returns measures the returns' propensity to crash simultaneously without respect to causality.[6] Mathematically, the LTD is defined as $LTD = \lim_{q \to 0^+} P_i(q)$, where $P_i(q) = PR\left[R_t^i < F_{R_t^i}^{-1}(q) \,\middle|\, R_t^S < F_{R_t^S}^{-1}(q)\right]$. As previously defined, R_t^i denotes the return of the specific bank and R_t^S the return of the financial system. $F_{R_t^i}^{-1}$ and $F_{R_t^S}^{-1}$ refer to the univariate distribution functions. To compute the LTD, we rely on the skewed t-copula estimated using the Dynamic Asymmetric Copula model proposed by Christoffersen et al. (2012) and subsequently applied by Christoffersen et al. (2014) and Meine et al. (2016).

The regression results with the SRISK and LTD as alternative systemic risk measures are reported in Model (1) and (2) in Table 5, respectively. The financial penalty variable exhibits in both models a significant positive coefficient. This outcome supports the robustness of our main result, i.e., that financial penalties increase the systemic risk exposure of banks.

[Place Table 5 here]

Second, we follow Weiß et al. (2014b) and test the robustness of our results by using two alternative specifications of the dynamic MES in our regression model. In Model (3) (Table 5), we re-calculate the MES by replacing the global bank index with the MSCI World Index. In doing so, we deal with reservations that the MES conditioning on a global bank index only estimates the sensitivity of a financial institution to a tail event in the banking industry and not to one in the global economy. However, the significant positive coefficient of the financial penalty variable in Model (3) indicates that the result is robust even if a different market index is used. Weiß et al. (2014b) also show that, by focusing on a bank's exposure to either regional or global systemic risk, a study can yield different results. In their study, some of the bank-specific factors lose their statistical significance when they analyze the regional systemic risk exposure instead of the global one. For this reason, we also compute the MES

[6] In the context of analyzing systemic risk determinants, the LTD approach is used in two studies by Weiß et al. (2014a, 2014b). Using the LTD to measure systemic risk is also conceptually related to the so-called Tail Betas, which are used in the studies by Straetmanns et al. (2008), De Jonghe (2010), and van Oordt and Zhou (2016).

conditional on regional bank indices and re-estimate the baseline regression. The obtained results in Model (4) confirm that the financial penalties also significantly affect the bank's regional systemic exposure in a positive way.

Third, we check the stability of the relationship between financial penalties and systemic risk by adding specific variables to the baseline regression. In direct response to the recent financial crisis, several financial institutions were bailed out by national governments. Financial institutions that were classified as too-big-to-fail or as too-interconnected-to-fail in particular were recapitalized. This is also true for the systemic important and larger institutions in our sample. Of these institutions, 52.94 percent benefited from direct capital injections or asset relief measures in the period between 2007 and 2014. To verify that the public recapitalizations of financial institutions do not distort our main finding, we add a recapitalization dummy (RECAP) in our baseline regression. The dummy takes the value one if a bank was recapitalized in a specific year and zero otherwise. We obtained the corresponding information on public recapitalization programs primarily from different press releases and websites of the corresponding banks and national authorities[7], from the findings report by the Financial Stability Board (2015), and from the list compiled by López-Espinosa et al. (2013). As shown in Table 5, the results of Model (5) indicate that the financial penalty variable maintains its significant positive impact on banks' systemic risk exposure. In contrast, the capitalization dummy shows no significant coefficient, which is in line with the study by López-Espinosa et al. (2013). Likewise, the interaction of the recapitalization dummy with the financial penalty variable exhibits no significance in Model (6). In Model (7) and (8) (Table 5), we control for the economic development of a country and analyze its influence on the effects of financial penalties on the systemic risk. We add the interest rate (INT) on the main refinancing operations of the national central banks and the annual growth rate of the real gross domestic product (GGDP) to the baseline equation. The outcome of Model (7) shows that the results are also robust with these additional specifications, as the financial penalty variable retains its sign and statistical significance. The GDP growth rate has a significant negative influence on the systemic risk exposure of banks, whereas the interest rate has no significant impact. In Model (8), we consider the interaction term of the GDP growth rate with the financial penalty variable. The results indicate that penalties have a

[7] For example, the U.S. Department of the Treasury compiled on its website a list of all banks that received capital injections under the Troubled Assets Relief Program (http://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/Pages/default.aspx). Recapitalization of European banks are documented primarily in the State Aid Register of the European Commission (http://ec.europa.eu/competition/state_aid/register/).

weaker positive impact on the systemic risk exposure of a bank in times of an economic upturn financial.

Next, we run robustness tests using different sample selection criteria. Model (9) (Table 5) excludes all investment banks and personal and business credit institutions based on the SIC Codes. Model (10) excludes all banks that were acquired in the sample period by another bank or were split up into two or more banks. The virtually unchanged significance of the financial penalty variable in both models shows that the sample is sufficiently homogenous and that the results are not driven by exiting banks.

Finally, in Model (11) and (12) (Table 5), we check the methodological robustness of the baseline result. In Model (11), we winsorize all financial variables at the 1st and 99th percentile level of their distributions to mitigate possible distorting effects of influential outliers. In Model (12), we implement the system generalized methods of moments estimator (system GMM estimator) with finite-sample corrected standard errors (Windmeijer, 2005), including both lagged differences and levels of the explanatory variables as instruments. The system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) is well-suited to deal with possible biases caused by the potential endogenous character of certain variables or by significant omitted variables. The regression results of Model (11) and (12) show that there are no significant distorting effects of the mentioned methodological concerns, as the financial penalty variable retains its statistical significance. The F-test, the Hansen-test of overidentifying restrictions, and the first-and second-order autocorrelation tests of Arellano and Bond (1991) are also satisfactory and confirm a reasonable specification of the system GMM model.

5. Conclusions

As a result of sub-prime-related instances of misconduct, market manipulations, violation of sanctions, and other unsound practices, banks across the globe have received heavy financial penalties. Since regulators continue to focus their activities on how banks behave, several bank analysts expect that the future costs of financial penalties will exceed the costs of penalties that have been incurred. Accordingly, there is a vigorous debate on the appropriateness of financial penalties and their consequences for the health of the financial system.

Contributing to this debate, our paper is the first to analyze the impact of financial penalties on the systemic risk of banks. To do so, we build on a unique database that comprises hand-collected information on the date and amounts of 671 financial penalties imposed on 68 international banks between 2007 and 2014. To examine the link between financial penalties and systemic risk, we capture the systemic risk with the dynamic MES and the ΔCoVaR estimates and run bank-fixed and time-fixed panel regressions.

The results of our regression analyses indicate that financial penalties increase the systemic risk exposure of banks, whereas they do not significantly affect banks' contribution to systemic risk. Financial penalties raise banks' default probability and makes them more vulnerable for systemic events. However, they neither promote nor prevent the possibility that individual shocks will propagate throughout the banking system. Our results also show that the design of the regulatory and supervisory framework of a country influences the effects of financial penalties on systemic risk exposure. The link between those two variables is weaker in countries with more stringent capital requirements and more prompt corrective power of national authorities. In contrast, the stronger power of supervisory authorities to declare insolvency and a greater external monitoring culture exacerbate the positive effects of financial penalties on systemic risk exposure.

Overall, our results have several policy implications. First, the positive effect of financial penalties on the systemic risk exposure suggests that authorities should take the macro-prudential perspective into consideration when they impose financial penalties on banks. In this context, they should also consider the interaction effects between financial penalties and specific institutional environments (such as capital requirements, intervention framework of the supervisory, and external monitoring culture). Second, our findings support the efforts by supervisory authorities to strictly monitor misconduct risk and the corresponding financial penalties of banks. The fact that financial penalties drive the systemic risk exposure of banks encourages, e.g., the decision of the European Banking Authority to include litigation costs in their EU-wide stress tests.

Finally, our findings indicate that authorities around the world should coordinate their efforts before imposing significant financial penalties on banks. By improving consultation and transparency among them, regulators could ensure that inappropriate financial penalties do not threaten the financial stability. Further research needs to investigate how other supervisory actions influence the systemic risk of banks and how alternative means of enforcement could be used to punish misconduct by banks without jeopardizing the stability of the banking sector.

Appendix

A.1 Sample banks

This table provide a list of all financial institutions in alphabetical order that are included in our empirical analysis.

Banks	
Agricultural Bank of China	Goldman Sachs
Allied Irish Banks	HSBC Holdings
Ally Financial	Industrial and Commercial Bank of China
American Express	ING Groep
Australia and New Zealand Banking Group	Intesa Sanpaolo
BBVA	Israel Discount Bank
Banco BPI	JPMorgan Chase & Co
Banco Comercial Português	Liechtensteinische Landesbank
Banco Espírito Santo	Lloyds Banking Group
Banco Santander	Mitsubishi UFJ Financial Group
Bank Hapoalim	Mizuho Financial Group
Bank Leumi	Morgan Stanley
Bank of America	Nordea
Bank of China	Pamrapo Bancorp
Bank of New York Mellon	PNC Financial Services Group
Barclays	Royal Bank of Canada
BB&T	Royal Bank of Scotland
BNP Paribas	Saehan Bancorp
Capital One	Société Générale
China Construction Bank	Standard Chartered
Citigroup	State Street Corporation
Citizens Financial Group	Sumitomo Mitsui Financial Group
Citizens Republic Bancorp	SunTrust Banks
Commerzbank	TCF Financial Corporation
Commonwealth Bank of Australia	Toronto-Dominion Bank
Crédit Agricole	TSB Banking Group
Credit Suisse Group	U.S. Bancorp
Danske Bank	UBS Group
Deutsche Bank	UniCredit
Dexia	UnionBanCal Corporation
DNB ASA	Wachovia Corporation
EverBank Financial Corp	Wells Fargo & Company
Fifth Third Bancorp	Westpac Banking Corporation
Flagstar Bancorp	Zions Bancorporation

A.2 Variable definitions and data sources.

This table provides definitions and data sources for all variables that are employed in our empirical analysis.

Variable name	Definition	Data source
Dyn. MES	Marginal Expected Shortfall (MES) as defined by Acharya et al. (2010) measures the average return of a particular firm during the days when a specific market index experiences enormous downward movements. The dynamic MES, as proposed by Brownless and Engle (2012), takes additional account for nonlinear tail dependency, time-varying volatility, and correlations in the firms' and market's returns. To compute the dynamic MES, we use the World Datastream Bank Index and its 5 percent worst outcomes.	Datastream, own calc.
ΔCoVaR	ΔCoVaR as defined by Adrian and Brunnermeier (2016) measures the difference between the Value-at-Risk (VaR) of a market index conditional on the distress of a particular firm and the VaR of the market index conditional on the median state of the firm. For the computation of ΔCoVaR, we use quantile regressions (5 percent quantile), the World Datastream Bank Index as market index, and the following state variables: VIX index, the difference between the three-month repo rate and the three-month Treasury bill rate, the difference between the ten-year Treasury Bond and the three-month Treasury bill rate, the difference between the ten-year Moody's BAA-rated bond and the ten-year Treasury Bond, the change in the three-month Treasury bill rate, and the MSCI World Index return.	Datastream, own calc.
ln Z-Score	Natural logarithm of the ratio of the return on assets plus the capital ratio divided by the standard deviation of return on assets.	Worldscope, own calc.
SRISK	SRISK as defined by Acharya et al. (2012) measures the capital that a financial institution is assumed to need conditional on a systemic crisis. For the computation of the SRISK, we use the dynamic MES estimates and set the prudential capital ratio to 8 percent.	Datastream, own calc.
LTD	Lower tail dependence (LTD) as defined by Weiß et al. (2014a) captures the joint crash probability of a banking firm and the market. For computation of the LTD, we rely on the skewed t-copula estimated using the Dynamic Asymmetric Copula model proposed by Christoffersen et al. (2012). We use the World Datastream Bank Index to proxy for the market index.	Datastream, own calc.
PENALTY	Sum of bank financial penalties to total assets (in %).	Own calc.
ASSET	Ratio of total loans to total assets (in %).	Worldscope
CAP	Ratio of equity to total assets (in %).	Worldscope
FUND	Ratio of long-term funding to total funding (in %).	Worldscope
GGDP	Annual growth rate of the real gross domestic product (in %).	World Development Indicators Database, World Bank
INT	Interest rate on the main refinancing operations of the national central banks (in %).	International Financial Statistics, International Monetary Fund
LIQUIDITY	Ratio of cash and due from banks to total deposits (in %).	Worldscope
LOANLOSSPROV	Ratio of provision for loan loss to total loans (in %).	Worldscope
NONINC	Ratio of non-interest income to total income (in %).	Worldscope
RECAP	Dummy variable taking on the value one if a bank were to be recapitalized in a specific year and zero otherwise.	Own calc.
ROA	Ratio of pre-tax profits to total assets (in %).	Worldscope

A.2 Variable definitions and data sources. (continued)

Variable name	Definition	Data source
SIZE	Natural logarithm of a bank's total assets.	Worldscope
CAP_STRING	This variable measures the extent to which the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined. The index ranges from 0 to 7. Higher values denote greater stringency.	Bank Regulation and Supervisory Survey Database, World Bank, Barth et al. (2006, 2013).
DECL_INSOLV	This variable measures the power of the supervision to supersede bank shareholder rights, to declare a bank insolvent, and to suspend ownership rights of a problem bank. The index ranges from 0 to 4. Higher values denote greater power.	Bank Regulation and Supervisory Survey Database, World Bank, Barth et al. (2006, 2013).
DEPOSIT_INSUR	This variable measures the proportion of banking system's assets funded with insured deposits. Higher values denote more comprehensive deposit insurance.	Bank Regulation and Supervisory Survey Database, World Bank, Barth et al. (2006, 2013).
EXT_MONITOR	This variable measures the degree of evaluations by external rating agencies and incentives for creditors to monitor bank performance. The index ranges from 0 to 5. Higher values indicate more pronounced external monitoring.	Bank Regulation and Supervisory Survey Database, World Bank, Barth et al. (2006, 2013).
PROMPT_CORR	This variable measures the degree to which supervisory authorities operate an early intervention framework that forces automatic action when certain regulatory thresholds are crossed and the availability of different tools to enforce specific corrective actions. The index ranges from 0 to 6. Higher values reflect greater readiness to respond to problems.	Bank Regulation and Supervisory Survey Database, World Bank, Barth et al. (2006, 2013).

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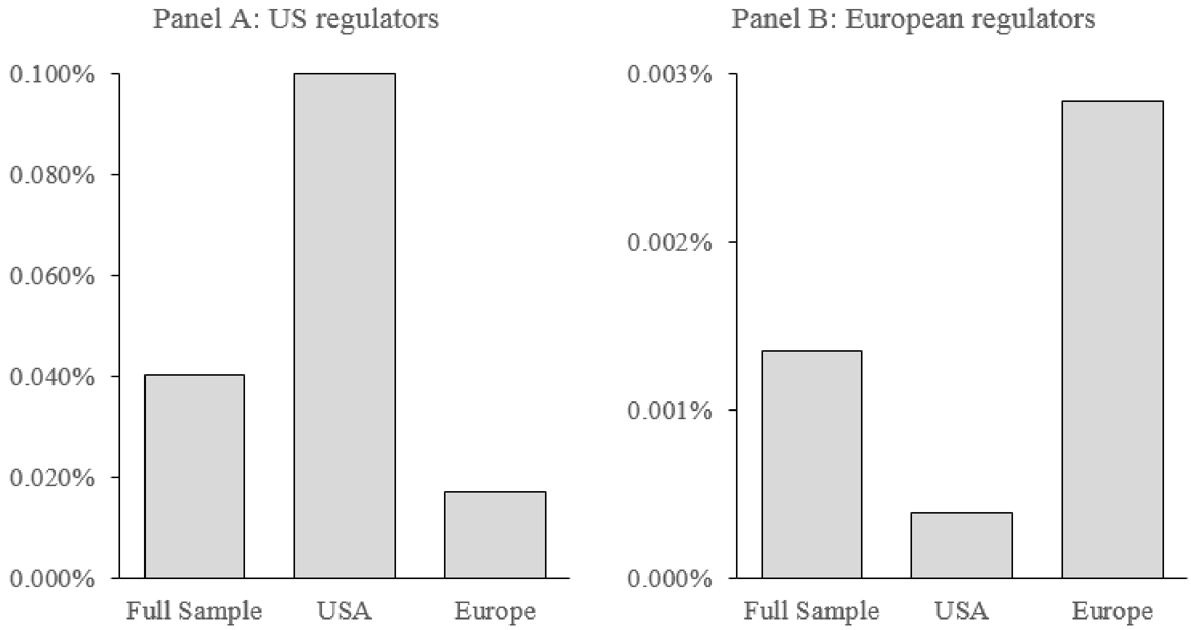
Figures and Tables

Figure 1

Financial penalty ratios categorized by the source region of the regulators.



The figure shows the ratio of financial penalties to total assets broken down by the origin of the regulators. Panel A considers financial penalties imposed by US regulators and Panel B considers financial penalties imposed by European regulators. The first bar of each Panel includes all banks of our sample, the second bar includes only US banks, and the third bar includes only European banks. For visual convenience, the ordinates of both panels were adjusted to different scales.

Table 1

Summary statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Dyn. MES	529	0.0463	0.0436	-0.0556	0.2874
ΔCoVaR	529	0.0102	0.0072	0.0025	0.0745
SRISK (US$ bn)	524	5.1732	9.7795	0.0000	53.5007
LTD	528	0.0106	0.0138	0.0000	0.0991
ln Z-Score	546	7.2346	0.9021	-0.0074	9.1582
PENALTY (%)	529	0.0418	0.2225	0.0000	3.8615
FUND (%)	529	15.2231	11.0385	0.0403	60.5709
ASSET (%)	529	55.4367	18.3187	4.6449	88.2116
CAP (%)	529	6.4167	2.9076	-0.4897	16.8528
SIZE (ln)	529	19.8041	1.6850	13.2649	22.0523
NONINC (%)	529	33.9425	16.5133	0.8501	85.8636
LIQUIDITY (%)	529	8.7751	11.4449	0.3166	177.0137
LOANLOSSPROV (%)	529	0.9694	1.4035	-0.6000	10.4700
ROA (%)	529	0.6855	1.1957	-8.5810	5.7270

This table shows the summary statistics of the main regression variables. We present the number of observations, the mean, standard deviation, and the minimum and maximum values. The signs of dynamic MES and ΔCoVaR are inverted such that higher values indicate higher systemic risk. All variables and data sources are defined in Appendix A.2.

Table 2

Financial penalties and systemic risk: baseline results.

	(1) Dyn. MES	(2) ΔCoVaR
PENALTY	0.0186**	-0.0011
	(0.008)	(0.001)
FUND	-0.0004	0.0002
	(0.000)	(0.000)
ASSET	0.0011*	0.0000
	(0.001)	(0.000)
CAP	-0.0064**	-0.0009**
	(0.003)	(0.000)
SIZE	0.0153	-0.0015
	(0.010)	(0.002)
NONINT	-0.0002	0.0000
	(0.000)	(0.000)
LIQUDITY	-0.0003*	-0.0000
	(0.000)	(0.000)
LOANLOSSPROV	0.0054**	0.0004
	(0.003)	(0.000)
ROA	0.0003	-0.0010*
	(0.003)	(0.001)
Constant	-0.2828	0.0387
	(0.215)	(0.040)
Bank-fixed effects	YES	YES
Time-fixed effects	YES	YES
Observations	529	529
Number of banks	68	68
F-test (p-value)	16.19	73.97
	(0.000)	(0.000)
adj. R^2	0.434	0.541

The table shows the results of the analysis of systemic risk measures. Model (1) employs the dynamic MES as systemic risk measure, whereas Model (2) uses the ΔCoVaR as systemic risk measure. All regressions are estimated with time-fixed and bank-fixed effects. We report heteroscedasticity-robust standard errors clustered at the bank level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables and data sources are defined in Appendix A.2.

Table 3

Financial penalties and distance to default

	(1) ln Z-Score
PENALTY	-0.2453**
	(0.114)
FUND	-0.0000
	(0.001)
ASSET	-0.0047
	(0.005)
CAP	0.1667***
	(0.026)
SIZE	-0.0751
	(0.057)
NONINC	0.0093***
	(0.003)
LIQUIDITY	0.0008
	(0.001)
LOANLOSSPROVISION	-0.0149
	(0.014)
ROA	0.1197***
	(0.024)
Constant	7.5043***
	(1.217)
Bank-fixed effects	Yes
Time-fixed effects	Yes
Observations	546
No. of banks	68
F-test (p-value)	18.47
	(0.000)
adj. R^2	0.475

The table shows the results of the distance to default (ln Z-Score) regression analysis. The regression is estimated with time-fixed and bank-fixed effects. We report heteroscedasticity-robust standard errors clustered at the bank level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables and data sources are defined in Appendix A.2.

Table 4

Financial penalties and systemic risk: regulation interactions.

	(1)	(2)	(3)	(4)	(5)
PENALTY	0.0710***	0.0304**	0.0393**	0.0187**	0.0301*
	(0.020)	(0.014)	(0.015)	(0.008)	(0.017)
CAP_STRING	-0.0008				
	(0.001)				
PENALTY x CAP_STRING	-0.0779***				
	(0.025)				
PROMPT_CORR		0.0005			
		(0.001)			
PENALTY x PROMPT_CORR		-0.0114*			
		(0.006)			
DECL_INSOLV			0.0116**		
			(0.005)		
PENALTY x DECL_INSOLV			0.0402**		
			(0.019)		
EXT_MONITOR				0.0017	
				(0.005)	
PENALTY x EXT_MONITOR				0.2699**	
				(0.131)	
DEPOSIT_INSUR					-0.0002**
					(0.000)
PENALTY x DEPOSIT_INSUR					-0.0008
					(0.001)
Other controls	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	529	529	529	529	529
No. of banks	68	68	68	68	68
F-test (p-value)	16.09	15.22	18.92	14.78	17.19
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
adj. R^2	0.443	0.435	0.448	0.438	0.442

The table shows the regression analyses of specific regulatory variables and their interactions with the financial penalty variable on the systemic risk exposure. The regulatory variables involve the overall capital stringency (Model 1), the supervisory prompt corrective power (Model 2), the supervisory declaring insolvency power (Model 3), the external monitoring index (Model 4), and the ratio of the banking system's assets to insured deposits (Model 5). All regressions are estimated with time-fixed and bank-fixed effects. We report heteroscedasticity-robust standard errors clustered at the bank level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables and data sources are defined in Appendix A.2.

Table 5

Financial penalties and systemic risk: additional tests.

	Alternative systemic risk measures		Alternative specification of dyn. MES	
	(1) SRISK	(2) LTD	(3) dyn. $MES_{MSCIWorld}$	(4) dyn. $MES_{regional}$
PENALTY	4.6121***	0.0039*	0.0156*	0.0133*
	(1.012)	(0.002)	(0.008)	(0.008)
Other controls	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Observations	524	528	529	529
No. of banks	68	68	68	68
F-test	6.887	6.826	18.84	2.870
(p-value)	(0.000)	(0.000)	(0.000)	(0.001)
adj. R^2	0.242	0.138	0.369	0.0609

	Additional control variables			
	(5) RECAP	(6) RECAP x PENALTY	(7) Macro-economic variables	(8) GGDP x PENALTY
PENALTY	0.0190**	0.0193**	0.0186**	0.0638***
	(0.009)	(0.009)	(0.008)	(0.019)
RECAP	0.0111	0.0124		
	(0.009)	(0.010)		
RECAP x PENALTY		-0.1528		
		(0.145)		
INT			-0.0030	-0.0026
			(0.003)	(0.003)
GGDP			-0.0030**	-0.0027*
			(0.001)	(0.001)
GGDP x PENALTY				-0.0276**
				(0.011)
Other controls	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Observations	529	529	524	529
No. of banks	68	68	68	68
F-test	17.45	17.32	15.45	15.87
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
adj. R^2	0.435	0.434	0.440	0.446

Table 5 (continued)

	Alternative sample selection criteria		Methodological robustness	
	(9) Excl. non-commercial banks	(10) Excl. exit banks	(11) Outlier	(12) system GMM
PENALTY	0.0199**	0.0135**	0.0184**	0.0220**
	(0.009)	(0.005)	(0.009)	(0.010)
Other controls	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Observations	514	502	529	529
No. of banks	64	62	68	68
F-test	17	22.23	16.61	16.85
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
adj. R^2	0.435	0.507	0.434	
Hansen				54.21
(p-value)				(1.000)
AR1				-4.931
(p-value)				(0.000)
AR2				-0.407
(p-value)				(0.684)

The table shows the results of additional panel regression to verify our main findings. Model (1) employs the SRISK as dependent variable in the baseline equation. Model (2) uses the LTD as an alternative systemic risk measure. Model (3) employs the dynamic MES conditional on the MSCI World Index and Model (4) the dynamic MES conditional on regional bank indices as the dependent variable. Model (5) adds a recapitalization dummy in the baseline equation, and Model (6) additionally includes the interaction between the financial penalty variable and the recapitalizations dummy in the regression. Model (7) comprises the interest rate and the growth rate of the real GDP as further control variables, and Model (8) adds the interaction between the financial penalty variable and the growth rate of the real GDP in the regression. Model (9) excludes all investment banks and personal and business credit institutions from the regression sample, whereas Model (10) excludes all exit banks. In Model (11), the variables are winsorized at the 1 percent level. Model (12) is estimated using the system-GMM estimator as proposed by Arellano and Bover (1995) and Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. Hansen is the test for over-identifying restrictions and AR1 and AR2 are the Arellano-Bond tests for first and second-order autocorrelation. All regressions are estimated with time-fixed and bank-fixed effects. We report heteroscedasticity-robust standard errors clustered at the bank level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables and data sources are defined in Appendix A.2.