KIER DISCUSSION PAPER SERIES

KYOTO INSTITUTE
OF
ECONOMIC RESEARCH

Discussion Paper No. 1024

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March 2020

KYOTO UNIVERSITY

KYOTO, JAPAN

Mortgage-related bank penalties and systemic risk among U.S. banks

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Abstract

We analyze link between mortgage-related regulatory penalties levied on banks and the level of systemic risk in the U.S. banking industry. We employ a frequency decomposition of volatility spillovers to draw conclusions about system-wide risk transmission with short-, medium-, and long-term dynamics. We find that after the possibility of a penalty is first announced to the public, long-term systemic risk among banks tends to increase. Short- and medium-term risk marginally declines. In contrast, a settlement with regulatory authorities leads to a decrease in the long-term systemic risk. Our analysis is robust with respect to several criteria.

Keywords: bank, financial stability, global financial crisis, mortgage, penalty, systemic risk.

JEL Classification: C14, C58, G14, G21, G28, K41

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We benefited from helpful comments from Jozef Baruník, Laure de Batz, Robert DeYoung, Zuzana Fungáčová, Martin Hodula, Martina Jašová, Tomáš Nidetzký, and Matthias Pelster. The following research support is acknowledged: SVV 260 463 project of the Charles University and GAUK project no. 1250218 (Brož), GAČR grant no. 20-17044S (Kočenda). The views presented in this paper do not represent the official views of the Czech National Bank. The usual disclaimer applies.

1. Introduction and motivation

In this study, we analyze the link between mortgage-related regulatory penalties levied on banks in the United States and the level of systemic risk in the U.S. banking industry. In recent years, oversight and enforcement bodies in the U.S. have levied substantial penalties on banks in connection to their (mis)conduct during the pre-crisis years (Koester and Pelster, 2018; Flore et al., 2018). This pertains especially to global banks and their managements that are perceived by many as prime suspects responsible for the global financial crisis (Kalemli-Ozcan et al., 2013; McConnell and Blacker, 2013).[1] Beginning of the crisis was marked by significant losses of mortgage-backed securities resulting from increased mortgage delinquencies (Schelkle, 2018). In this regard, it is not surprising that a sizable share of the penalties levied by U.S. authorities has been linked to how banks behaved with respect to mortgages and foreclosures (European Systemic Risk Board, 2015). We focus on this type of mortgage-related penalties and show how it contributes to the propagation of risk in the U.S. banking industry.[2]

While bank penalties aim to establish a corrective to the inflicted social harm and to serve as a deterrent for other banks, it is likely that such actions might create systemic risk in the banking sector (European Systemic Risk Board, 2015). First, negative publicity surrounding the policy actions can destabilize the offender's business operations, jeopardizing its stock price as well as investors' and clients' trust (Murphy et al., 2009). Second, the troubles of one market player may spill over to the operations of its competitors as the banking sector is highly interconnected (Morgan, 2002; Anginer et al., 2014). As a result, the penalties imposed on banks might ultimately create various negative externalities in the financial markets as well as in the real economy.

In our analysis, we focus on publicly-traded banks operating in the United States that have been subject to financial penalties regarding their (mis)conduct related to mortgages and foreclosures from U.S. authorities.[3] Based on the publicly available data from the Financial

[1] One can also consider the role of CEOs of large financial companies in the build-up of the global financial crisis. In this regard, Boyallian and Ruiz-Verdú (2017) show that the risk-taking behavior of CEOs of large U.S. financial companies was influenced in the period preceding the crisis by their exposure to stock returns of their firms. However, DeYoung and Huang (2016) establish that setting rules that should limit risk-taking incentives of bank management – and potentially also banks' contribution to systemic risk – can paradoxically lead to lower liquidity creation in the banking system.

[2] Typically, banks received penalties for the handling of subprime mortgages, misleading investors over mortgage backed securities, unlawful mortgage securitization, improper foreclosure processing allegations, securities law violations in connection with mortgage-backed securities sales to Fannie Mae and Freddie Mac, or misleading investors about collateralized debt obligations tied to mortgage securities. A special case was the so-called National Mortgage Settlement in February 2012, when several banks agreed to pay more than 25 billion USD to address their "mortgage servicing, foreclosure, and bankruptcy abuses" (National Mortgage Settlement, 2017).

[3] We do not consider potential effect of positive news in a form of various awards acknowledging the best banks etc. The reason is that (i) this type of news is not comparable to our data as it originates from different sources

Times and the Wall Street Journal, we construct a unique hand-crafted dataset on bank penalties that covers the period from 2010 to 2016. Most notably, our dataset includes information on two types of events related to a penalty: the announcement date, when the possibility of a penalty is first publicly released, and the settlement date, when an agreement about the penalty is reached between the bank and the relevant U.S. authority. Further, our interest in mortgage-related penalties is grounded also in the fact that they constitute an overwhelming majority of penalties levied on banks operating in the U.S. during the post-crisis period. Specifically, based on the Financial Times dataset and its extension that we describe in the data section (Section 3), mortgage-related penalties account for about 72% of all penalties levied on banks.[4]

Following Diebold and Yilmaz (2014), we model systemic risk as system-wide connectedness and we analyze and employ volatility spillovers derived in the spirit of Diebold and Yilmaz (2009, 2012). The connection between the above approach based on volatility spillovers and systemic risk is straightforward. Diebold and Yilmaz (2014) argue that the spillovers capturing the contribution of an individual network element to the system-wide connectedness (*to*-spillovers) can be seen as an analogy to the conditional value at risk (CoVaR) approach towards measuring systemic risk, as introduced in Adrian and Brunnermeier (2016). Similarly, the measure of the spillovers, expressing the extent to which individual network elements are exposed to system-wide events (*from*-spillovers) can be related to the marginal expected shortfall (MES) approach towards measuring systemic risk pioneered in Acharya et al. (2010).

In terms of our working hypotheses, we examine the extent of risk that banks discharge and receive (in the form of high volatility spillovers) in response to an announcement of potential penalty or to a settlement. Further, we hypothesize that the interaction between bank penalties and systemic risk might differ with respect to the short-, medium- and long-term. The potential differences in the interaction stem from the fact that agents operate on different investment horizons—these are associated with various types of investors, trading tools, and strategies that correspond to different trading frequencies (Gençay et al., 2010; Conlon et al., 2016). Shorter or longer frequencies are the result of the frequency-dependent formation of investors' preferences, as shown in the modeling strategies of Bandi et al. (2019), Cogley

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than from official oversight and enforcement authorities, and (ii)) it is well established that volatility tends to react disproportionally more to bad news (Koutmos and Booth, 1995; Braun et al., 1995). This avenue is left for further research.

[4] Other types of penalties are represented in small or marginal proportions (indicated in parentheses) and are related to Sanctions/Money Laundering/Tax Evasion (14 %), Market manipulation (10 %), Lending/Consumer Practices (3 %), M&A (1 %).

(2001), or Ortu et al. (2013). For our assessment we employ the frequency decomposition introduced by Baruník and Křehlík (2018) that extends the Diebold and Yilmaz (2009, 2012) index to analyzing volatility spillovers at various frequencies. Since we frequency-decompose the systemic risk from the stock prices of banks, the short-, medium, and long-term investment horizons are actually reflected in volatility spillovers at short-, medium- and long-term frequencies as shown in Baruník and Křehlík (2018). This allows us to distinguish system-wide risk transmission with short-, medium-, and long-term persistence. In other words, we are also able to assess whether the effect of bank penalties is persistent or short-lived.

Despite of importance of the systemic risk propagation among banks, research on the link between penalties and systemic risk is negligible. So far, and to the best of our knowledge, it is represented by Koester and Pelster (2018) and Flore et al. (2018); we review both expertly conducted analyses in more detail in the next section. Our analysis makes a new contribution to the literature as it provides assessment of the specific link between mortgage-related regulatory penalties levied on banks and the level of systemic risk in the U.S. banking industry. By employing a frequency decomposition of volatility spillovers, we are able to deliver evidence about system-wide risk transmission with short-, medium-, and long-term dynamics. Our key result is robust evidence on the differences between the penalty announcement and penalty settlement effects. We show that after the possibility of a penalty is first announced to the public, long-term systemic risk in the U.S. banking sector tends to increase. In contrast, a settlement with regulatory authorities leads to a decrease of the long-term risk. Further, since penalties are reflected in the behavior of investors with longer investment horizons, our results carry also implications for portfolio selection and investment strategies on financial markets as Dew-Becker and Giglio (2016) demonstrate importance of asset pricing in the frequency domain. Finally, our analysis is relevant to authorities imposing the penalties as well as those in charge of financial stability. While penalties are likely to affect both the performance and valuation of the receiving bank, they might also influence other (innocent) banks. The outcome casts some hesitation on the corrective effect of the penalties.[5] Hence, our results also have direct policy implications for financial stability.

The paper is structured as follows. Section 2 offers a review of the previous research on bank penalties and their connection to systemic risk. In Section 3, we describe the

[5] Moreover, in the post-crisis period banks have had to adapt to new rules and regulations that might potentially restrict certain business activities of banks and thus impact their financial performance; in this sense new rules and regulations can be, to a certain extent, considered somewhat similar to penalties (Wilmarth Jr., 2012; Pridgen, 2013). However, assessment of such a hypothetical impact is beyond the scope of our analysis.

methodological approach based on volatility spillovers. Section 4 presents the data, variables, and testable hypotheses. We display our results and inferences in Section 5. The last section concludes.

2. Literature review

The impact of bank penalties on stock prices and/or profitability is a focus of much research in the field and recent applications include Koester and Pelster (2017), Tilley et al. (2017), and De Batz (2020a, 2020b). On the other hand, the link between penalties imposed on banks and systemic risk has been so far analyzed only by Koester and Pelster (2018) and indirectly also by Flore et al. (2018).

Koester and Pelster (2018) focus on the link between penalties to internationally listed banks and two measures of systemic risk: dynamic MES and daily ΔCoVaR. The authors collect a large dataset on penalties (almost 700 cases) from 2007 to 2014 and employ panel estimation with time and fixed effects. In terms of results, it is shown that there is a positive statistical association between financial penalties and the level of systemic risk exposure of banks (captured by the MES measure) but not between financial penalties and the level of systemic risk contribution of banks (proxied by the daily ΔCoVaR). In other words, financial penalties make banks more vulnerable to market downturns but there is no evidence of the transmission of shocks between banks. In our approach, we focus on system-wide risk transmission with short-, medium-, and long-term dynamics as we assume a frequency decomposition of volatility spillovers.[6]

Flore et al. (2018) focus on market reactions (stock, bond, credit default spreads) to both the announcements of penalties and settlements of banks and interpret their results in terms of systemic risk. Using a dataset covering the cases of large global banks, they find that uncertainty decreases following the settlement. This event is perceived by the market as good news. This is also reflected in a positive market reaction (valuation effect) for banks under investigation with the same regulatory authority. Thus, the authors conclude that settlements do not contribute to a build-up of systemic risk in the economy.

In terms of the literature related to the methodological approach, we draw inspiration from seminal papers on systemic risk by Adrian and Brunnermeier (2016), Acharya et al.

[6] In this respect, we also do not find evidence for transmission of shocks on short- and medium frequencies but we provide evidence at long-term horizon. Adoption of the frequency decomposition approach is potentially reason behind the partial difference in the evidence.

(2010), and Diebold and Yilmaz (2014), along with recent papers on volatility spillovers by Baruník et al. (2016) and Baruník and Křehlík (2018).

Specifically, Baruník et al. (2016) introduce a method that allows disentangling asymmetries in volatility spillovers (good and bad volatility spillovers, i.e. spillovers due to positive and negative returns). The authors examine the connectedness in the U.S. stock market using data on liquid stocks in several sectors and show asymmetric spillovers of stocks in different sectors that vary over time. One of the studied sectors is the financial sector, represented by three major U.S. banks (Bank of America, Citigroup, Wells Fargo). In terms of bank-specific results, Baruník et al. (2016; p. 63). note that "positive spillovers flowing from individual banks to the rest of the sector diminished with the coming signs of the sub-prime mortgage crisis in 2007". Indeed, there is some evidence for the transmission of bad volatility spillovers from banks to other stocks in the crisis and the post-crisis years; at the same time, there is some evidence, although not overwhelming, that banks also received bad volatility from the system consisting of all other stocks.

Further, Baruník and Křehlík (2018) derive a general frequency-based method to decompose a measure of connectedness and apply it to the U.S. banking sector. Specifically, this method allows distinguishing the evolution of systemic risk at short-term, medium-term, and long-term horizons. The authors argue that such a distinction is useful as shocks might create linkages with different levels of persistence. Their empirical findings show that connectedness at high frequencies points to calm periods in markets while connectedness at low frequencies is especially pronounced during the global financial crisis and the European sovereign debt crisis. These distinct results underscore the usefulness of the frequency-based approach towards analyzing systemic risk.

We aim to build on the surveyed literature by incorporating the motivation of Koester and Pelster (2018) and Flore et al. (2018) into a framework designed by Baruník and Křehlík (2018). In doing so, we aim to provide a comprehensive assessment of the propagation of risk in the U.S. banking industry in connection to the announcement of mortgage-related penalties and their settlements.

3. Methodology

We use a methodology based on the concept of volatility spillovers introduced in Diebold and Yilmaz (2009, 2012, 2014). Further, we assume the frequency decomposition of volatility spillovers as in Baruník and Křehlík (2018). In the end, we work with time series of bank-specific spillovers at various frequencies capturing to what extent a bank contributes to the system-wide connectedness/systemic risk (*to*-spillovers) and to what extent a bank receives shocks from the banking industry (*from*-spillovers).

A starting point of the analysis are time series of daily total volatility measures derived from banks' stock prices. Because we do not work with high-frequency data, we compute the daily volatility of stock prices by following the approach introduced by Parkinson (1980) and used by Diebold and Yilmaz (2012).[7] We compute daily variance based on the deviation between high and low stock prices as:

$$\widehat{PV}^2 = \frac{1}{4ln2}(h-l)^2, \tag{1}$$

where h and l stand for high and low prices, respectively, and $\widehat{PV}^2$ is the estimator of daily variance. To obtain the annualized daily percentage volatility, we further compute:

$$PV \ = \ 100 \times \sqrt{252 \times \widehat{PV}^2}, \tag{2}$$

where 252 represents the number of trading days in a year as in Shu and Zhang (2003) and Taylor et al. (2010).

The spillover measures by Diebold and Yilmaz (2009) rely on variance decomposition from vector autoregressions (VARs) that captures how much of the future error variance of a variable j is due to innovations in another variable k. For N assets, we consider an N-dimensional vector of daily volatilities, $\mathrm{PV_t} = (\mathrm{PV_{1t}}, \dots, \mathrm{PV_{Nt}})'$, to measure total volatility spillovers.

Let us model the N-dimensional vector PV_t by a weakly stationary VAR(p) as $PV_t = \sum_{\mathrm{l}=1}^{p} \mathbf{\Phi}_\mathbf{l} \boldsymbol{PV}_{\boldsymbol{t}-\mathbf{l}} + \epsilon_t$, where $\boldsymbol{\epsilon_t} \sim N(0, \mathbf{\Sigma}_{\boldsymbol{\epsilon}})$ is a vector of iid disturbances and $\mathbf{\Phi}_\mathbf{l}$ denotes p coefficient matrices. For the invertible VAR process, the moving average representation has the following form:

$$PV_t = \sum_{\mathrm{l}=0}^{\infty} \mathbf{\Psi}_\mathrm{l} \boldsymbol{\epsilon}_{\boldsymbol{t}-\mathbf{l}}. \tag{3}$$

The $N \times N$ matrices holding coefficients $\mathbf{\Psi}_\mathbf{l}$ are obtained from the recursion $\mathbf{\Psi}_\mathrm{l} = \sum_{j=1}^{p} \mathbf{\Phi}_j \mathbf{\Psi}_{\mathrm{l}-j}$, where $\mathbf{\Psi}_0 = I_N$ and $\mathbf{\Psi}_\mathrm{l} = 0$ for $\mathrm{l} < 0$. The moving average representation is useful for describing the dynamics of the VAR system as it allows isolating the forecast errors that can be used for the computation of the connectedness of the system. Diebold and Yilmaz (2012) further assume the generalized VAR of Koop et al. (1996) and Pesaran and Shin (1998) to obtain

[7] The other possibility, suitable primarily for very high-frequency data, is to quantify volatility in terms of the realized variance (*RV*) introduced by Andersen et al. (2001) and Barndorff-Nielsen (2002) and used in Diebold and Yilmaz (2014).

forecast error variance decompositions that are invariant to variable ordering in the VAR model, and it also explicitly accommodates the possibility of measuring directional volatility spillovers.[8]

In order to define the total spillovers index of Diebold and Yilmaz (2012), we consider the H-step-ahead generalized forecast error variance decomposition matrix having the following elements for $\mathrm{H} = 1,2,\ldots$:

$$\theta_{jk}^{H} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H-1}\left(e_j'\boldsymbol{\Psi}_h\boldsymbol{\Sigma}_\epsilon e_k\right)^2}{\sum_{h=0}^{H-1}\left(e_j'\boldsymbol{\Psi}_h\boldsymbol{\Sigma}_\epsilon\boldsymbol{\Psi}_h' e_k\right)}, \qquad j,k = 1,\ldots,N, \tag{4}$$

where $\boldsymbol{\Psi_h}$ are moving average coefficients from the forecast at time t, $\boldsymbol{\Sigma_\epsilon}$ denotes the variance matrix for the error vector $\boldsymbol{\epsilon_t}$, σ_{kk} is the kth diagonal element of $\boldsymbol{\Sigma_\epsilon}$, and e_j and e_k are the selection vectors, with one as the jth or kth element and zero otherwise. Normalizing elements by the row sum as $\tilde{\theta}_{jk}^{H} = \theta_{jk}^{H}/\sum_{k=1}^{N}\theta_{jk}^{H}$, Diebold and Yilmaz (2012) then define the total connectedness as the contribution of connectedness from volatility shocks across variables in the system to the total forecast error variance:

$$S^H = 100 \times \frac{1}{N}\sum_{\substack{j,k=1\\ j\neq k}}^{N}\tilde{\theta}_{jk}^{H}. \tag{5}$$

Note that $\sum_{k=1}^{N}\widetilde{\theta_{jk}^{H}} = 1$ and $\sum_{j,k=1}^{N}\widetilde{\theta_{jk}^{H}} = N$, hence, the contributions of connectedness from volatility shocks are normalized by the total forecast error variance. To capture the spillover dynamics, we use a 300-day rolling window running from point $t-299$ to point t. Further, we assume a forecast horizon $H = 10$ and a VAR lag length of 2 based on the AIC.

The total connectedness indicates how shocks to volatility spill over throughout the system. Further, directional spillovers allow us to decompose the total spillovers to those coming from, or to, a particular asset in the network. Diebold and Yilmaz (2012) propose to measure the directional spillovers received by asset j from all other assets k (*from*-spillovers) as:

$$S_{N,j\leftarrow\bullet}^{H} = 100 \times \frac{1}{N}\sum_{\substack{k=1\\ j\neq k}}^{N}\tilde{\theta}_{jk}^{H}, \tag{6}$$

i.e., we sum all numbers in rows j, except the terms on the diagonal that corresponds to the impact of asset j on itself. The N in the subscript denotes the use of an N-dimensional VAR.

[8] The generalized VAR allows for correlated shocks; hence, the shocks to each variable are not orthogonalized.

In a similar fashion, the directional spillovers transmitted by asset j to all other assets k (*to*-spillovers) can be measured as:

$$S^{H}_{N,j\to\bullet} = 100 \times \frac{1}{N}\sum_{\substack{k=1\\ j\neq k}}^{N} \tilde{\theta}^{H}_{kj}. \tag{7}$$

Having introduced the directional spillovers that constitute a crucial dimension of our analysis, we further assume frequency decompositions of *to*- and *from*-volatility spillovers into those that reflect short-term (up to 5 days), medium-term (up to 20 days), and long-term (up to 300 days) dynamics. Importantly, these intervals correspond to connectedness within a business week, a business month, and a business year, respectively.

A natural way to describe the frequency dynamics (whether long, medium, or short term) of connectedness is to consider the spectral representation of variance decompositions based on frequency responses to shocks instead of impulse responses to shocks. As a building block, Baruník and Křehlík (2018) consider a frequency response function, $\left(\mathrm{e}^{-\mathrm{i}\,\omega}\right) = \sum_{h} \mathrm{e}^{-\mathrm{i}\omega\mathrm{h}}\, \mathbf{\Psi}_{h}$, which can be obtained as a Fourier transform of coefficients $\mathbf{\Psi}_{h}$ with $i = \sqrt{-1}$. The spectral density of $\mathrm{RV_t}$ at frequency ω can then be conveniently defined as a Fourier transform of the $MA(\infty)$ filtered series:

$$\mathrm{S_{RV}}(\omega) = \sum_{\mathrm{h}=-\infty}^{\infty} \mathrm{E}(\mathbf{RV_t}\mathbf{RV'_{t-h}})\mathrm{e}^{-\mathrm{i}\omega\mathrm{h}} = \mathbf{\Psi}\left(\mathrm{e}^{-\mathrm{i}\omega}\right)\mathbf{\Sigma}\mathbf{\Psi}'\left(\mathrm{e}^{+\mathrm{i}\omega}\right). \tag{8}$$

The power spectrum $\boldsymbol{S_{RV}}(\omega)$ is a key quantity for understanding frequency dynamics since it describes how the variance of $\mathbf{RV_t}$ is distributed over frequency components ω. Using the spectral representation for covariance, i.e., $E(\mathbf{RV_t}\mathbf{RV'_{t-h}}) = \int_{-\pi}^{\pi} \boldsymbol{S}_{x}\,(\omega)e^{i\omega h}d\omega$, Baruník and Křehlík (2018) naturally define the frequency domain counterparts of variance decomposition.

The spectral quantities are estimated using standard discrete Fourier transforms. The cross-spectral density on the interval $\mathrm{d} = (\mathrm{a},\mathrm{b})\colon \mathrm{a},\mathrm{b} \in (-\pi,\pi), \mathrm{a} < \mathrm{b}$ is estimated as $\sum_{\omega} \widehat{\mathbf{\Psi}}(\omega)\widehat{\mathbf{\Sigma}}\,\widehat{\mathbf{\Psi}}'(\omega)$ for $\omega \in \left\{\left\lfloor\frac{\mathrm{aH}}{2\pi}\right\rfloor, \ldots, \left\lfloor\frac{\mathrm{bH}}{2\pi}\right\rfloor\right\}$, where $\widehat{\mathbf{\Psi}}(\omega) = \sum_{\mathrm{h}=0}^{\mathrm{H}-1} \widehat{\mathbf{\Psi}}_{\mathrm{h}}\, \mathrm{e}^{-2\mathrm{i}\pi\omega/\mathrm{H}}$, and $\widehat{\mathbf{\Sigma}} = \hat{\boldsymbol{\epsilon}}'\hat{\boldsymbol{\epsilon}}/(\mathrm{T}-\mathrm{z})$, where z is a correction for a loss of degrees of freedom and depends on the VAR specification.

The decomposition of the impulse response function at the given frequency band can be estimated as $\widehat{\mathbf{\Psi}}(\mathrm{d}) = \sum_{\omega} \widehat{\mathbf{\Psi}}(\omega)$. Finally, the generalized variance decompositions at a desired frequency band are estimated as:

$$\widehat{\boldsymbol{\theta}}_{j,k}(d) = \sum_{\omega} \widehat{\Gamma}_j(\omega) \frac{\widehat{\sigma}_{kk}^{-1}\left(e_j'\widehat{\boldsymbol{\Psi}}(\omega)\widehat{\Sigma}e_k\right)^2}{e_j'\widehat{\boldsymbol{\Psi}}(\omega)\widehat{\boldsymbol{\Sigma}}\widehat{\boldsymbol{\Psi}'}(\omega)e_j}, \tag{9}$$

where $\widehat{\Gamma}_j(\omega) = \frac{e_j'\widehat{\Psi}(\omega)\widehat{\boldsymbol{\Sigma}}\widehat{\boldsymbol{\Psi}'}(\omega)e_j}{e_j'\Omega e_j}$ is an estimate of the weighting function, where $\Omega = \sum_{\omega} \widehat{\boldsymbol{\Psi}}(\omega)\widehat{\boldsymbol{\Sigma}}\widehat{\boldsymbol{\Psi}'}(\omega)$.

Then, the connectedness measure at a given frequency band of interest can be readily derived by substituting the $\widehat{\boldsymbol{\theta}}_{j,k}(d)$ estimate into the traditional measures outlined above.[9]

4. Data, variables, and hypotheses

4.1 Sample of banks and bank penalties

In this paper, we compute volatility spillovers based on the stock prices of 17 key banks operating in the United States. The analyzed network is comprised of publicly-traded banks that were given a penalty for their (mis)conduct related to mortgages and foreclosures by various U.S. oversight and enforcement authorities.[10] The sample of banks includes: the largest U.S. banks operating nationwide (Bank of America, JPMorgan Chase, Citigroup, Wells Fargo, Goldman Sachs, and Morgan Stanley), U.S.-domiciled banks with a more regional focus (SunTrust, PNC, U.S. Bancorp, Flagstar Bank, and Fifth Third Bancorp), and several major non-U.S. banks operating in the United States (Deutsche Bank, Credit Suisse, Royal Bank of Scotland, HSBC, UBS, and Barclays). The inclusion of non-U.S. banks is warranted by the fact that many of them received very large (volumes of) penalties when compared to some U.S. banks with a more regional focus, as we later present in Figure 1. Daily stock price data were downloaded from Yahoo Finance and stock price volatility is estimated using the ranged-based estimator in Parkinson (1980). Descriptive statistics of the volatility data are shown in Table A1.

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[9] The entire estimation is done using the package *frequencyConnectedness* in *R* software. The package is available on CRAN or at https://github.com/tomaskrehlik/frequencyConnectedness. So far, frequency connectedness has been empirically assessed by Baruník and Křehlík (2018), Baruník and Kočenda (2019), and Tiwari et al. (2018).

[10] The authorities that reached a settlement with banks include the Department of Housing and Urban Development, the Department of Justice, the Federal Deposit Insurance Corporation, the Federal Housing Finance Agency, the Federal Reserve, the National Credit Union Administration, the Office of the Comptroller of the Currency, the Securities and Exchange Commission, several state attorneys, and the Attorney General. For an overview of major U.S. law enforcers and regulators, see Flore et al. (2018) whose methodology related to misconduct results we follow and correspondingly, we do not distinguish between settlement or verdict as means of a case closure as the vast majority of cases is resolved through settlements. However, we do not assess potentially different impact of penalties on systemic risk with respect to the type of enforcement authority as we would be forced to work with number of fragmented subsamples; with a single exception (Office of the Comptroller of the Currency), Flore et al. (2018) report statistically insignificant results linked to the type of enforcement authority. This option might be explored in the future should the sample sizes become of statistical relevance.

Our analysis covers the years from 2010 to 2016 as we examine regulatory action taken *after* the global financial crisis based on the banks' behavior before the crisis. For our analysis, we construct a unique handcrafted dataset of the mortgage-related penalties imposed on banks operating in the United States that are listed in Table A2. Our accent on the mortgage-related penalties stems also from the fact that they represent about 72% of all penalties imposed on the banks operating in the U.S. during the post-crisis period. The core of the dataset was collected by Financial Times reporters.[11] However, the core of the dataset does not contain any data after July 2015 and, more importantly, it does not provide any information about when the possibility of a penalty was first publicly announced. Thus, we use the Factiva database to cross-check the accuracy of the dataset and we further extend it until the end of 2016. Most importantly, for each penalty we further add a date when the possibility of a penalty (that eventually materialized) was first publicly announced in the Wall Street Journal.[12] It needs to be stressed that the announcement date is, in fact, the very first public announcement related to the penalty as during our news search we did not find any previous indication about a penalty. Thus, the first announcement of a possibility of a penalty should be indeed unanticipated by the general public. As for the settlement, there might be available (but not necessarily) some news about the development in the case before the settlement itself. However, as we have identified only handful of unresolved cases, the settlement is not a question of "whether it happens" but rather "when it happens". This makes it quite distinct from the first announcement of the possibility of a penalty.

Figure 1 shows the gross volumes of penalties related to mortgage and foreclosure misconduct that several banks in the United States had to pay in the period from 2010 to 2016. The total amount stands at almost 140 billion USD.[13] The outlay of the single largest receiver – Bank of America – constitutes around 40% of the total volume; the results are robust with respect to this large penalty receiver as we show via a robustness check in Section 5.4. In general, the U.S. banks paid in penalties significantly more than their European counterparts. In terms of the yearly dispersion of penalties, Figure 2 illustrates that a decisive share of the penalties was levied between 2012 and 2014 (around 110 billion USD). After a quiet 2015, U.S.

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[11] The data can be downloaded at http://ig-legacy.ft.com/content/e7fe9f25-542b-369f-83b2-5e67c8fa3dbf.

[12] In our analysis we consider cases of penalties that eventually materialized. We do not consider cases when banks were acquitted after an announcement of an investigation related to mortgages or foreclosures. We admit that such an analysis could yield insights about if markets can foresee whether a case is relevant (i.e. leads to a penalty). However, our search in the Wall Street Journal shows that the number of such cases is negligible and immaterial with respect to the analysis.

[13] This amounts to almost 1% of the 2016 U.S. GDP.

authorities collected almost 24 billion USD in 2016.[14] A detailed overview of the penalties is presented in Tables A2a and A2b, which contain precise information on the announcement date, the settlement date, the name of the bank that received a penalty, the name of the regulator who imposed the penalty, and the value of the penalty (in million USD).[15] Interestingly, the same announcement date applies for several cases that were, however, settled at various dates. The size of the penalties typically ranges between 0.1 and 0.5 billion USD, as Figure 3 shows; still, there are several cases of very large penalties over 5 billion USD. Further, Figure 4 reveals that the enforcement process (i.e. the time span from the announcement date to the settlement date) takes in most cases more than 2 years.

4.2 The link between bank penalties and systemic risk

Our working hypotheses are focused on system-wide connectedness after the announcement date and the settlement date. Indeed, such events have a potential to create systemic risk in the banking sector (European Systemic Risk Board, 2015) as investors' trust might evaporate quickly (Murphy et al., 2009) and the troubles of a specific bank might swiftly transfer to its competitors (Morgan, 2002; Anginer et al., 2014). However, in terms of empirical evidence, Koester and Pelster (2018) do not find that a bank's contribution to a build-up of systemic risk is higher after a penalty is imposed. Also, Flore et al. (2018) conclude that the settlement has a rather calming effect on markets. Thus, in our working (null) hypotheses, we ask if a bank's contribution/exposure to systemic risk is higher after the announcement/settlement date or not:

Hypothesis #1: A bank's contribution to systemic risk does not increase after the announcement date or settlement date.

Hypothesis #2: A bank's exposure to systemic risk does not increase after the announcement date or settlement date.

We expect that the announcement date might lead to a build-up of systemic risk due to its unexpected nature. By construction, the announcement date is the first time when the possibility of a penalty (which was eventually imposed) was announced publicly. On the other hand, the settlement date might come as a relief for markets after a protracted period of uncertainty.

[14] The heat wave of penalties has not receded after that, as the Trump administration levied penalties on Barclays and the Royal Bank of Scotland in 2017 and 2018.

[15] There are a few cases when the announcement dates are unavailable. This means that the announcement of the settlement was also the first time when the possibility of the penalty was first announced. We classify these cases as settlement dates (and not announcement dates). A similar approach is used in Tilley et al. (2017).

Moreover, prior to the settlement, banks might disclose that they created provisions for legal matters, giving markets some indication that the penalty was already internally accounted for (Flore et al., 2018).[16] In terms of the three measures of connectedness, the long-term measure in particular might be affected by penalty-related events, as it represents shifts in investors' preferences and beliefs considered by Murphy et al. (2009). On the other hand, short-term and medium-term connectedness might also appear relevant if penalties were perceived by markets as one-time events. Finally, it might be insightful to assess Hypotheses #1 and #2 from two angles: to distinguish if there is any difference in a specific bank's contribution/exposure to systemic risk depending on whether the specific bank was the target of the penalty or one of its competitors was the target.

To assess both hypotheses empirically, we develop a testing strategy in the spirit of Doners and Vorst (1996), Clayton et al. (2005), and Uhde and Michalak (2010). As a tool we use the test of Wilcoxon (1945) to examine if two (paired) samples share the same distribution. The Wilcoxon test is quite effective for our purpose as it is especially suited to assess non-normal data (Gibbons and Chakraborti, 2011). As an alternative we also use a non-parametric paired sign test to check robustness of our results with respect to the choice of our testing strategy tool.

Initially, for each bank in our sample, we form two types of vectors of penalties for both the announcement and the settlement date. The first two vectors capture all the dates when a bank has its own penalty announced or settled; the two vectors are labelled as "own penalties". The other two vectors capture all the dates when all the other banks have their penalties announced or settled; these two vectors are labelled as "other banks' penalties". Note that all four vectors contain mutually exclusive information.

Second, for each bank in our sample, we collect median values of *to*- and *from*-spillovers with the short-, medium-, and long-term dynamics around the announcement date and the settlement date with the intervals indicated in Figure 5.[17] Note that the length of the intervals corresponds to how all three connectedness measures are defined: the short-term measure

[16] Such behavior would be also consistent with the requirements grounded in the International Financial Reporting Standards (IFRS) that banks are obliged to follow and that are enforced by the IAS 39.

[17] For the short term connectedness measure, we assume the time intervals [-5 days, 0 days] and [0 days, 5 days] before and after the announcement or settlement dates. For the medium term we consider the intervals [-20 days, 0 days] and [0 days, 20 days], and for the long term we work with the intervals [-300 days, 0 days] and [0 days, 300 days]. Since the systemic risk measures are computed for three different intervals on corresponding time-windows, the approach resembles an event-study analysis. As such, it benefits from the fact that an unwanted impact of general development in economy on specific time-bounded events is to a large extent eliminated by focusing on the time-windows and not on the entire time span.

captures spillovers of up to 5 days (one business week), the medium-term measure up to 20 days (one business month), and the long-term measure up to 300 days, which is the length of the rolling window (one business year), similar to the approach of Baruník and Křehlík (2018).

Third, we obtain tables of median values of *to*- and *from*-spillovers across banks with the short-, medium-, and long-term dynamics before and after the announcement or settlement date. The median values are obtained for each of the type of vectors of penalties ("own penalties" or "other banks' penalties"). Consequently, we employ the Wilcoxon test to determine if the distribution of penalties before and after the announcement/settlement date is the same or not. Specifically, we examine if the median difference between the values of spillovers before and after the announcement/settlement is statistically different from 0. Finally, we use boxplots to illustrate in a graphical way the relationship between pairs of values of spillovers before and after the announcement/settlement date.

Finally, for the sake of easier interpretation, in quadrants Q1 – Q4 of Table 1 we discuss four types of results we can obtain from the perspective of a specific bank. First, we obtain two types of results that seem of primary interest: Q2 – the extent of the contribution of a specific bank after it has its own penalty announced/settled (while nothing happens to its competitors), and Q4 – the extent to which a specific bank is exposed to systemic risk after one of its competitors has its own penalty announced/settled. The above two options are captured in bold in Table 1. However, the other two options that might be equally interesting – a specific bank's contribution to systemic risk after its competitors are targeted (Q1) and a specific bank's exposure to systemic risk after it is targeted but its competitors are not (Q3).

Specifically, if we find that the results for a specific bank are similar regardless of whether it was targeted or its competitor was, we can argue that *any* penalty affects the entire banking system. Thus, rather than having a desired corrective impact on a particular financial institution, a penalty increases the systemic risk, potentially making the banking sector less stable and more vulnerable.

5. Results

5.1 Total and frequency connectedness

As a preliminary step, we briefly comment on the total and frequency connectedness of our network of 17 banks. Corresponding spillovers are shown in Figure 6. Total connectedness stands at more than 80% throughout the entire sample period (2009–2017), except for the period after mid-2012 when it temporarily recedes after the "whatever it takes" speech by ECB

President Mario Draghi (2012).[18] In terms of frequency connectedness, the dynamics of short- and long-term components differs substantially. First, the long-term component prevails in the aftermath of the subprime mortgage crisis in 2009 and then briefly from mid-2011 to mid-2012. The result for our sample of banks exhibits a very similar pattern as that shown by Baruník and Křehlík (2018; Figure 1) for long-term frequency connectedness among eleven major financial firms representing the financial sector of the U.S. economy. The starting point of the latter period is likely associated with the downgrading of U.S. bonds on August 5, 2011, while the end point can be again related to the "whatever it takes" speech by ECB President Mario Draghi. After that, the long-term connectedness recedes and short- and medium-term connectedness become relatively more influential. As shown in Figure 6, the short- and long-term connectedness are almost perfectly negatively correlated. This is in line with the argument of Baruník and Křehlík (2018) that short-term connectedness characterizes periods of calm markets while long-term connectedness dominates in times of heightened investor uncertainty.

5.2 Contribution to systemic risk

In Hypothesis #1, we ask if a contribution of a bank to systemic risk (expressed by *to*-spillovers) is higher after the announcement/settlement date and if so, at which frequencies. Figure 7 reveals the detailed results; aggregated results are presented in Table 2, panel (a). First, we assess reaction in cases when a specific bank receives its own penalty (Figure 7a). It seems that the first public announcement of the possibility of a penalty leads to a realignment of the relative importance of the three frequency connectedness measures. The levels of the short-term and medium-term risk measures decline. However, after a penalty is announced, the receiving bank's contribution to long-term systemic risk rises. In other words, a penalty-receiving bank begins to make the system more interconnected with respect to a long period of time.

Our results at short- and medium-terms are in line with those of Koester and Pelster (2018) in that we also do not find evidence for transmission of shocks between banks. Our evidence at long-term differs but it can be explained from the perspective of the frequency decomposition approach that offers finer distinction of the penalties' impact with respect to investment horizons. Specifically, from a theoretical point of view (Gençay et al., 2010; Conlon et al., 2016; Bandi et al., 2019; Cogley, 2001; Ortu et al., 2013) as well as the fact that investors

[18] The end of the EU sovereign debt crisis coincides with a remarkable statement by the ECB President Mario Draghi (2012) at the Global Investment Conference in London on July 26, 2012: "Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough". Fiordelisi and Ricci (2016) show that the European financial markets started to rally immediately after this statement and that the economic situation began to improve.

focus on different investment horizons when forming their investment decisions, the degree of connectedness differs at different frequencies (Baruník and Křehlík, 2018). In practice, since a long-term represents a long investment horizon, the results might reflect worries of investors who do not know how long a penalty-to-settlement process might take. On the other hand, from the short and medium investment perspective, once a penalty is announced, portfolio adjustments can be swiftly made. The results and interpretation are also in line with the evidence that long-term spillovers dominate in times of heightened investor uncertainty in case of the U.S. financial institutions (Baruník and Křehlík, 2018) and that uncertainty substantially increases volatility spillovers at long-term in case of interactions between oil and forex markets (Baruník and Kočenda, 2019) or that long-term risk is more pronounced on forex market (Tiwari et al., 2018).

The opposite evidence is presented after a settlement between a receiving bank and a U.S. authority is reached. In these circumstances, the long-term systemic risk decreases while the two measures capturing the effects at shorter frequencies do not record any statistically significant change. This pattern might be interpreted as a relief experienced by financial markets once the enforcement process is over; such finding and interpretation are in line with Flore et al. (2018).

Interestingly, similar findings are also obtained when we work with the "other banks' penalties" vector of announcement/settlement dates (Figure 7b). This means that a specific bank – which is not mentioned in the announcement – radiates higher long-term spillovers after some other bank has a possible penalty announced. In other words, an event that occurred to a competitor induces a comparable reaction as if the penalty was granted to the specific bank. Similarly, after another bank settles its penalty, the contribution of a bank not receiving a penalty to long-term systemic risk decreases. The effects for short- and medium-term systemic risk vary but are generally smaller than that for the long-term counterpart.

5.3 Exposure to systemic risk

In the previous subsection, we established that a bank's contribution to long-term systemic risk is higher (lower) after the announcement (settlement) date, regardless of if the bank received its own penalty or if a competitor was targeted. Now, we are interested in whether for a specific bank, *from*-spillovers differ after other banks have a penalty announced/settled, as outlined in Hypothesis #2. Figure 8b then reveals that a specific bank – which does not have a penalty announced – receives higher long-term systemic risk from the banking sector after a penalty is announced for a competitor. Similarly, after a penalty is settled for the competitor of the specific bank (that does not face the need of its own the settlement), the specific bank faces lower systemic risk exposure with long-term persistence.

Next, the specific bank is also exposed to higher long-term systemic risk after it has its own penalty announced (Figure 8a). This signals that other banks in the system react even if they do not face the possibility of their own penalties. As a result, the system becomes more interconnected over a long period of time. However, after a settlement is reached the specific bank begins to receive less long-term systemic risk from its competitors.

Overall, it can be concluded that systemic risk is higher after the announcement of a penalty and systemic risk is lower after the settlement (Figures 7 and 8; aggregated results are presented in Table 2, panel (a)). Interestingly, this result is related to the long-term connectedness measure: the transmission of shocks through the system with higher persistence reflects high uncertainty on the market, which affects the beliefs of investors (Baruník and Křehlík, 2018; Baruník and Kočenda, 2019). After the announcement of a penalty, both long-term *from*- and *to*-spillovers increase, indicating an elevated level of long-term connectedness of the system. On the contrary, we see the opposite development after a settlement – both types of spillovers tend to decrease. Thus, the increased level of connectedness after the announcement of a penalty is not permanent.

Finally, some banks were affected by penalties simultaneously. However, from Table A2, it can be observed that such events constitute a minority of cases as the parallel events relate solely to the National Settlement in early 2012 or the settlement of several banks in January 2013. Nevertheless, parallel events are included in aggregate results when considering the vector of own penalties (and employing both *from*- and *to*-spillovers). On the other hand, parallel events are not included when considering the vector of other banks' penalties (for both *from*- and *to*-spillovers) as the vectors are mutually exclusive. The key observation is that the results based on both types of vectors are very similar, which indicates that occurrence of few parallel events does not compromise the results.

5.4 Robustness checks

We perform several types of robustness checks to consider: (i) a restricted set of penalties, (ii) different interval bounds for long-term spillovers, and (iii) an extended control sample of financial institutions. Finally, we also employ an alternative test – the sign test – to check the robustness of all reported results derived from using the Wilcoxon test.

First, we revisit the baseline estimation but restrict the set of penalties to include only larger penalties over 325 million USD (the median penalty value in the sample). As we show in panel (b) of Table 2, the key findings remain intact. The finding means that our baseline results are invariant to the penalty size and are not driven by relatively small penalties. In order to account for the single largest penalty receiver (Bank of America; about 40% of the total volume of penalties), we perform estimation on a group of banks without this particular bank. The results are reported in panel (c) of Table 2 and follow the same pattern as those for the full sample of banks. We conclude that our results are robust with respect to the inclusion of the largest penalty receiver.

We further assess whether the results substantially differ if we assume larger relative penalties instead of absolute ones; larger relative penalties are defined with respect to the total assets of a given bank in the quarter preceding the penalty. In this case, the median value is 0.04% (the absolute value of the penalty divided by the total assets of the bank). The results are very similar to those presented for absolute penalties in panel (b) of Table 2; these are not reported but are available upon request. Hence, we conclude that our results are invariant to whether a penalty is measured in absolute or relative terms.

Second, we test the robustness of our results in terms of long-term spillovers, which constitute a vital part of our analysis. 300 days is the boundary for long-term spillovers used in related studies (e.g. Baruník and Křehlík, 2018; Baruník and Kočenda, 2019). Still, it could be argued that over such a period of time, the distribution of the median values of long-term spillovers can change due to other factors than penalties, for example due to earnings announcements. Therefore, we lower the interval boundary to 80 days, which represents approximately one third of a business year and thus sufficiently accounts for quarterly earnings announcements. Further, the 80-days boundary is proportionally as much more than the medium-term spillovers interval (20 days) as the medium-term spillovers boundary is to the short-term spillovers boundary (5 days). The results are presented in panel (d) of Table 2. The magnitude of the coefficients with respect to the baseline case presented in panel (a) of Table 2 somewhat decreased as one might expect due to decrease of the long-term boundary from 300 to 80 days. However, the coefficients associated with both 80-days long-term *to*-spillovers and *from*-spillovers are statistically significant and their signs are same as in the baseline case of 300-days long-term spillovers (Table 2, panel (a)). Finally, the results for both 300-days and 80-days boundaries do not materially change with respect to employment of the Wilcoxon or an alternative signe test. Based on the detailed robustness check, we conclude that the reduction of the length of the long-term spillovers boundary does not affect our baseline results, and as such penalties represent key factors affecting risk propagation among banks.

Third, we extend our sample of 17 banks with additional 17 other publicly-traded financial firms operating in the U.S. that are not involved in the mortgage business with data available for the period 2008–2017.[19] These financial firms could not have received a penalty related to mortgage or foreclosure and constitute a suitable control group. We consider all the dates when one of the 17 banks from our baseline sample exhibits a penalty announced or settled. Then we inspect *from*- and *to*-spillovers after the announcement and settlement dates only for the control group of financial institutions. Our prior is that *to*-spillovers might not materialize as the additional financial institutions are not engaged in the mortgage business. The results are presented in panel (e) of Table 2 and provide a rather clear picture. The control group of financial firms unrelated to mortgages receives more long-term spillovers from the system of financial institutions (*from*-spillovers) that contains also 17 banks from our baseline sample that did receive mortgage-related penalties; long-term coefficients associated with *from*-spillovers are statistically significant. However, non-mortgage-related financial firms do not increase long-term systemic risk (*to*-spillovers) after an announcement of a mortgage-related penalty; the long-term coefficients associated with *to*-spillovers are small and statistically insignificant. On the other hand, the contribution of the non-mortgage-related financial firms to long-term systemic risk is somewhat lower after a settlement is announced for a bank that received a penalty related to mortgages or foreclosures. The finding points to an asymmetric reaction of non-mortgage-related financial firms to the announcement and settlement of mortgage-related penalties. Specifically, non-mortgage-related financial firms do not react to original shocks (penalty announcements) but take part in the systemic risk drop once the cases are closed. Overall, the findings can be summarized in a way that (i) non-mortgage financial institutions are indeed affected by the turmoil of financial institutions active in the mortgage business caused by mortgage-related penalties but (ii) non-mortgage financial institutions do not contribute to the amplification of the original shock on their own, although they might play some role in the lowering of systemic risk after settlements.

[19] The extended sample includes following companies: American Express Company (AXP), The Bank of New York Mellon Corporation (BK), MetLife, Inc. (MET), Mizuho Financial Group, Inc. (MFG), Capital One Financial Corporation (COF), State Street Corporation (STT), Sun Life Financial Inc. (SLF), Northern Trust Corporation (NTRS), KB Financial Group Inc. (KB), Torchmark Corporation (TMK), Western Alliance Bancorporation (WAL), Sterling Bancorp (STL), American Equity Investment Life Holding Company (AEL), Hilltop Holdings Inc. (HTH), Berkshire Hills Bancorp, Inc. (BHLB), Banco Latinoamericano de Comercio Exterior, S.A (BLX), and Citizens, Inc. (CIA). The extended sample includes not only banks but also other financial institutions because there were not enough banks that are not engaged in the mortgage business with data available for the entire period 2008–2017. In other words, limited availability of the relevant stock price data on banks operating in the U.S. precludes an analysis when one could compare how the announcement of mortgage-related regulatory penalties on a specific bank generates spillovers on other banks that are likely to be subject to similar penalties due to their past mortgage-related lending practices compared to other banks that are not likely to face such penalties.

Finally, when we compare results based on the sign test (right part of panels in Table 2) and those based on the Wilcoxon test (left part of panels in Table 2) we detect that a few results based on the sign test exhibit lower statistical significance. However, the sign-test results are in now way materially different from those based on the Wilcoxon test.

6. Conclusions

In this study, we analyze the link between mortgage-related regulatory penalties levied on banks and the level of systemic risk in the U.S. banking industry. It is generally acknowledged that the subprime mortgage crisis evolved into a global financial crisis. While the main objective of any penalty is arguably to correct the harm caused by a bank's behavior, it can be argued that such action by oversight and enforcement authorities can also destabilize the banking sector if the impact of the penalty travels across the sector and also affects innocent banks.

In this sense, our paper contributes to the recent wave of interest in how banks respond to penalties within the industry. Originally, a detailed assessment was prevented by the lack of adequate techniques. However, recent advances in the econometric literature enable a quantitatively new level of assessment. Thus, we build on seminal papers on systemic risk such as Diebold and Yilmaz (2009, 2012, 2014), Adrian and Brunnermeier (2016), and Acharya et al. (2010). Moreover, we assume the frequency decomposition of volatility spillovers – recently introduced by Baruník and Křehlík (2018) – which allows us to draw conclusions about the propagation of penalties in terms of volatility with short-, medium- and long-term dynamics within the U.S. banking sector. We develop a testing procedure based on Wilcoxon (1945) and in the spirit of Doners and Vorst (1996), Clayton et al. (2005), and Uhde and Michalak (2010) that suitably considers the construction of the frequency measures of connectedness. Finally, we use a hand-crafted dataset on mortgage-related penalties imposed on banks operating in the United States that includes both the date when the possibility of a penalty is first announced and the date when the bank reached a settlement with the relevant U.S. authority. We hypothesize that systemic risk might evolve in a different way after each type of event.

We find that after the possibility of a penalty is first publicly announced, long-term systemic risk in the U.S. banking sector tends to increase, indicating high uncertainty among investors with respect to longer investment horizons. Short- and medium-term systemic risk does not play a major role, which is in line with Koester and Pelster (2018) who show that penalties do not significantly affect banks' contribution to systemic risk. We believ that the difference is driven by the frequency-decomposition approach that allows to account for differences in investment horizons. In contrast, a settlement with regulatory authorities leads to a decrease in the long-term connectedness in the system. This latter pattern is in line with Flore et al. (2018) and might be interpreted as a relief that financial markets experience once the enforcement process is over. Interestingly, we show the same pattern in terms of the contribution/exposure of a given bank to systemic risk regardless if this bank had a penalty announced/settled or one of its competitors did. Thus, rather than having the desired corrective impact on a particular financial institution, the penalty can lead to bank contagion that increases systemic risk, potentially making the banking sector less stable and more vulnerable In this sense, our results can be compared to those of Pino and Sharma (2019) who study the contagion effect in the U.S. banking sector in the period from 2001 to 2012 and uncover bank contagion since 2003; the contagion became more pronounced before the onset of the global financial crisis and remained present until the end of the sample period.

In terms of robustness checks, we find that our baseline results are not driven by relatively smaller penalties or interval boundaries for the long-term spillovers. We also perform a robustness exercise that demonstrates that financial institutions that are not engaged in the mortgage business do not emanate higher (lower) long-term spillovers after an announcement (settlement) related to a mortgage or a foreclosure penalty of their competitors. Our results are also robust with respect to testing procedures used.

As any propagation of risk affects investment decisions, the impact at low frequencies hints that penalties are reflected in the behavior of investors with longer investment horizons. Thus, our results offer implications for portfolio selection and investment strategies on financial markets since asset pricing in the frequency domain allows to capture the price of risk at different frequencies, e.g. different investment horizons. Further, our analysis is relevant to authorities imposing the penalties as well as those in charge of financial stability. Based on the experience from the period after the global financial crisis, banks have faced several legal settlements that have frequently resulted in sizable penalties. Our results show that while these penalties might especially affect both performance and valuation of the receiving bank, they might also influence other banks. Without doubt the original objective of the penalties – to correct the social harm inflicted by banks – the potential ramifications related to the stability of the banking sector can give oversight and enforcement authorities a second thought on the effects of imposed penalties.

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Table 1: Interpretation of results from the perspective of a specific bank

Vector of penalties\Type of spillovers	***To*-spillovers**	***From*-spillovers**
Own penalties	**Q2: To what extent does a specific bank contribute to systemic risk after it has its own penalty announced/settled (while nothing happens its competitors)?**	Q1: To what extent is a specific bank exposed to systemic risk after it has its own penalty announced/settled (while nothing happens to its competitors)?
Other banks' penalties	Q3: To what extent does a specific bank contribute to systemic risk after its competitors (and not a specific bank) have their own penalty announced/settled?	**Q4: To what extent is a specific bank exposed to systemic risk after its competitors (and not a specific bank) have their own penalty announced/settled?**

Note: The vectors of own penalties and other banks' penalties are mutually exclusive.

Table 2: Aggregated results – baseline and robustness checks

(a) Baseline results

Vector of penalties	Type of a date	Wilcoxon test						Sign test					
		To-spillovers			*From*-spillovers			*To*-spillovers			*From*-spillovers		
		Short-term	Medium-term	Long-term	Short-term	Medium-term	Long-term	Short-term	Medium-term	Long-term	Short-term	Medium-term	Long-term
Own penalties	Announcement	-0.02***	-0.05***	0.50***	-0.02**	-0.02***	0.81***	-0.02**	-0.05***	0.43***	-0.02***	-0.02**	1.12***
	Settlement	0.00	0.00	-0.29***	-0.00	0.00	-0.27***	0.00	0.01	-0.29***	-0.00	0.01	-0.23*
Other banks' penalties	Announcement	0.01*	-0.02***	0.12***	0.00	-0.02***	0.24***	0.00	-0.01***	0.06	0.00	-0.02***	0.08*
	Settlement	0.00	-0.01**	-0.17***	0.00	-0.01***	-0.18***	0.00	-0.00	-0.16***	0.00	-0.01***	-0.16***

Note: The numbers in the table show the median difference between the value of the spillover before and after the announcement/settlement based on the Wilcoxon / sign test. The null hypothesis of both tests is that the median difference is equal to some value (0 in our case). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(b) Large penalties (absolute)

Vector of penalties	Type of a date	Wilcoxon test						Sign test					
		To-spillovers			*From*-spillovers			*To*-spillovers			*From*-spillovers		
		Short-term	Medium-term	Long-term	Short-term	Medium-term	Long-term	Short-term	Medium-term	Long-term	Short-term	Medium-term	Long-term
Own penalties	Announcement	-0.01**	-0.05*	0.51***	0.01	-0.02***	0.79***	-0.01	-0.05*	0.46***	-0.01**	-0.02*	1.12***
	Settlement	-0.01	-0.02	-0.26*	-0.01	0.00	-0.16	-0.01	-0.03	-0.29	-0.01	0.00	-0.07
Other banks' penalties	Announcement	0.01	-0.01	0.16***	0.01*	-0.01**	0.26***	-0.00	-0.01	0.10	-0.00	-0.02**	0.08
	Settlement	-0.01	-0.01*	-0.13***	-0.00	-0.02***	-0.14***	-0.00	-0.01	-0.10***	-0.00	-0.01***	-0.12***

Note: The numbers in the table show the median difference between the value of the spillover before and after the announcement/settlement based on the Wilcoxon / sign test. The null hypothesis of both tests is that the median difference is equal to some value (0 in our case). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Continued

(c) Sample of banks without Bank of America

Vector of penalties	Type of a date	Wilcoxon test						Sign test					
		***To*-spillovers**			***From*-spillovers**			***To*-spillovers**			***From*-spillovers**		
		Short-term	**Medium-term**	**Long-term**	**Short-term**	**Medium-term**	**Long-term**	**Short-term**	**Medium-term**	**Long-term**	**Short-term**	**Medium-term**	**Long-term**
Own penalties	**Announcement**	-0.01**	-0.04**	0.60***	-0.02**	-0.03***	0.84***	-0.02	-0.04**	0.41***	-0.02**	-0.02**	1.12***
	Settlement	-0.01	0.00	-0.25***	-0.01	0.00	-0.27**	-0.00	0.01	-0.17***	-0.01	0.01	-0.23*
Other banks' penalties	**Announcement**	0.00	-0.02**	0.22***	0.00	-0.01***	0.37***	0.00	-0.01**	0.12*	0.00	-0.02**	0.27***
	Settlement	-0.00	-0.01**	-0.17***	-0.00	-0.01***	-0.18***	-0.00	-0.00	-0.16***	-0.00	-0.01*	-0.16***

Note: The numbers in the table show the median difference between the value of the spillover before and after the announcement/settlement based on the Wilcoxon / sign test. The null hypothesis of both tests is that the median difference is equal to some value (0 in our case). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(d) 80-days boundary for long-term spillovers

Vector of penalties	Type of a date	Wilcoxon test		Sign test	
		***To*-spillovers**	***From*-spillovers**	***To*-spillovers**	***From*-spillovers**
		Long-term			
Own penalties	**Announcement**	0.18***	0.25***	0.11***	0.21***
	Settlement	-0.11***	-0.12***	-0.11***	-0.07**
Other banks' penalties	**Announcement**	0.04**	0.05***	0.04***	0.04**
	Settlement	-0.03***	-0.04***	-0.02	-0.01

Note: The numbers in the table show the median difference between the value of the spillover before and after the announcement/settlement based on the Wilcoxon / sign test. The null hypothesis of both tests is that the median difference is equal to some value (0 in our case). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Continued

(e) Financial firms unrelated to mortgages and foreclosures (control group)

Vector of penalties	Type of a date	Wilcoxon test						Sign test					
		***To*-spillovers**			***From*-spillovers**			***To*-spillovers**			***From*-spillovers**		
		Short-term	**Medium-term**	**Long-term**	**Short-term**	**Medium-term**	**Long-term**	**Short-term**	**Medium-term**	**Long-term**	**Short-term**	**Medium-term**	**Long-term**
All mortgage- and foreclosure-related penalties	**Announcement**	0.00	-0.01	0.02	-0.00	-0.02*	0.07**	0.00	-0.00***	0.00	-0.00	-0.02***	0.04***
	Settlement	-0.00	-0.00	-0.02*	-0.00	-0.01	-0.04***	0.00	-0.00***	-0.02***	0.00*	-0.00***	-0.02***

Note: The numbers in the table show the median difference between the value of the spillover before and after the announcement/settlement based on the Wilcoxon / sign test. The null hypothesis of both tests is that the median difference is equal to some value (0 in our case). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 1: Gross volumes of penalties to banks in the United States (2010–2016)

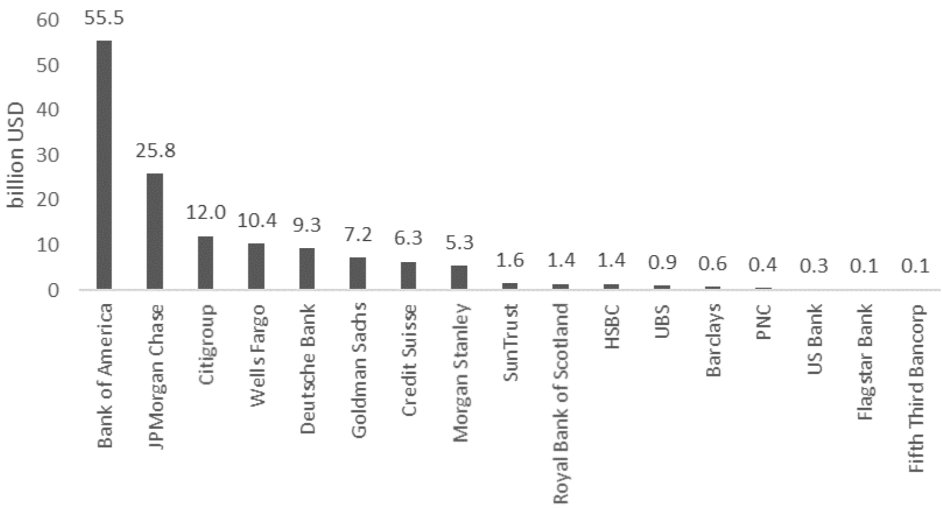


Figure 2: Yearly distribution of penalties to banks in the United States (2010–2016)

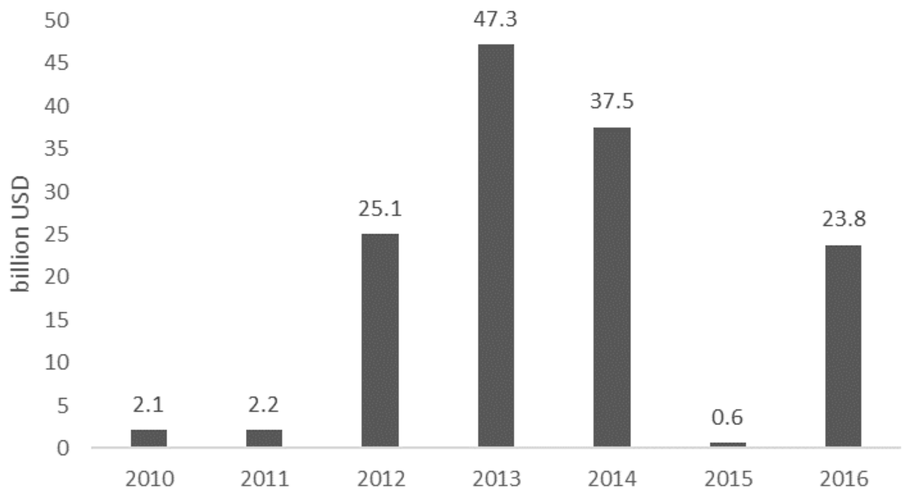


Figure 3: Size of penalties (2010–2016)

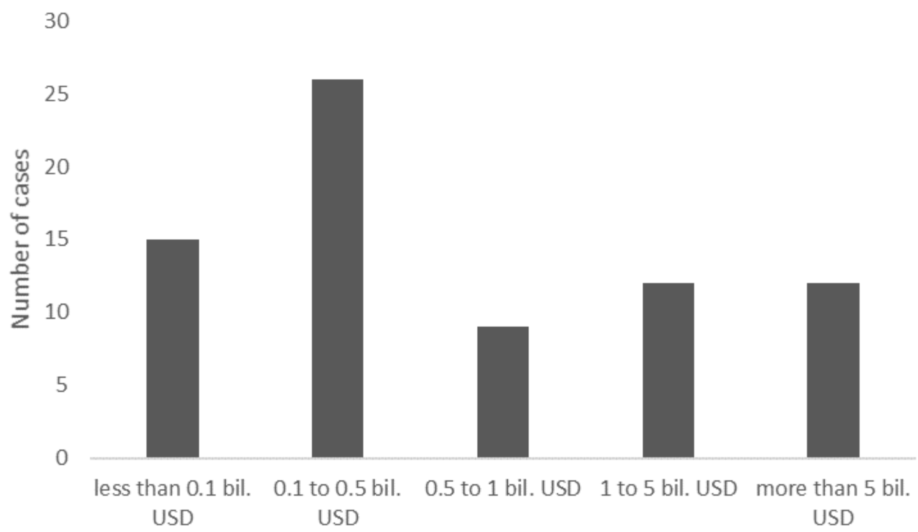


Figure 4: Length of the enforcement process (2010–2016)

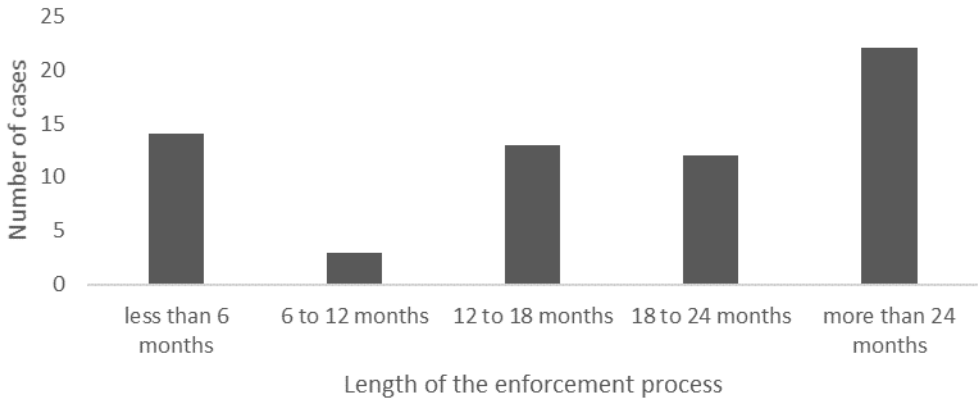


Figure 5: Test for the effect of penalties (in days)

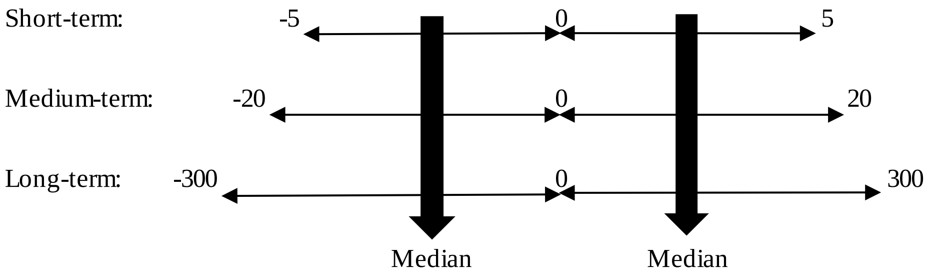


Figure 6: Total and frequency connectedness (2009–2017)

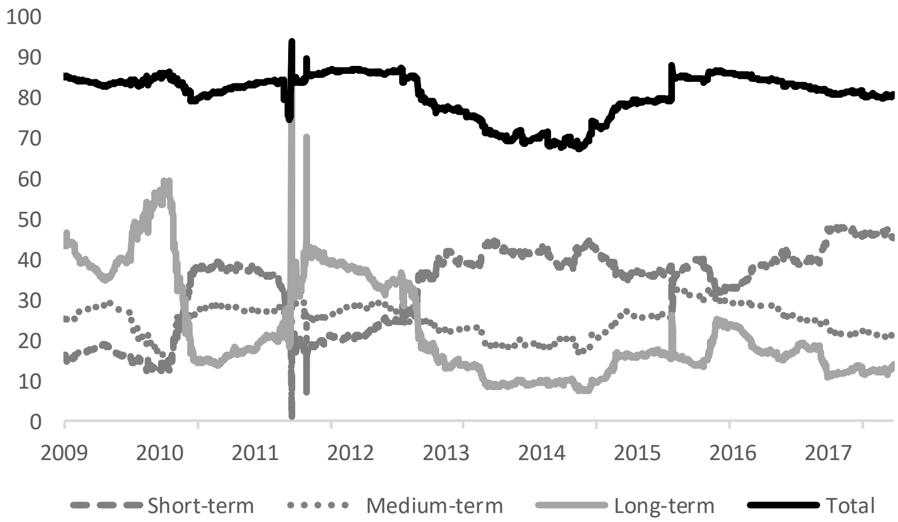
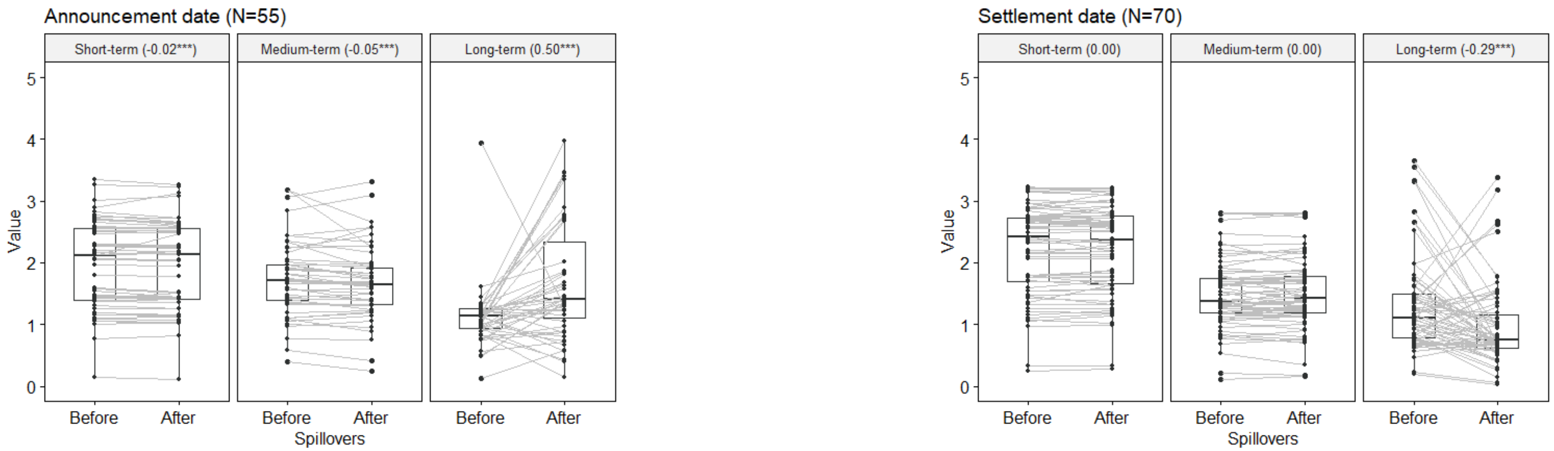
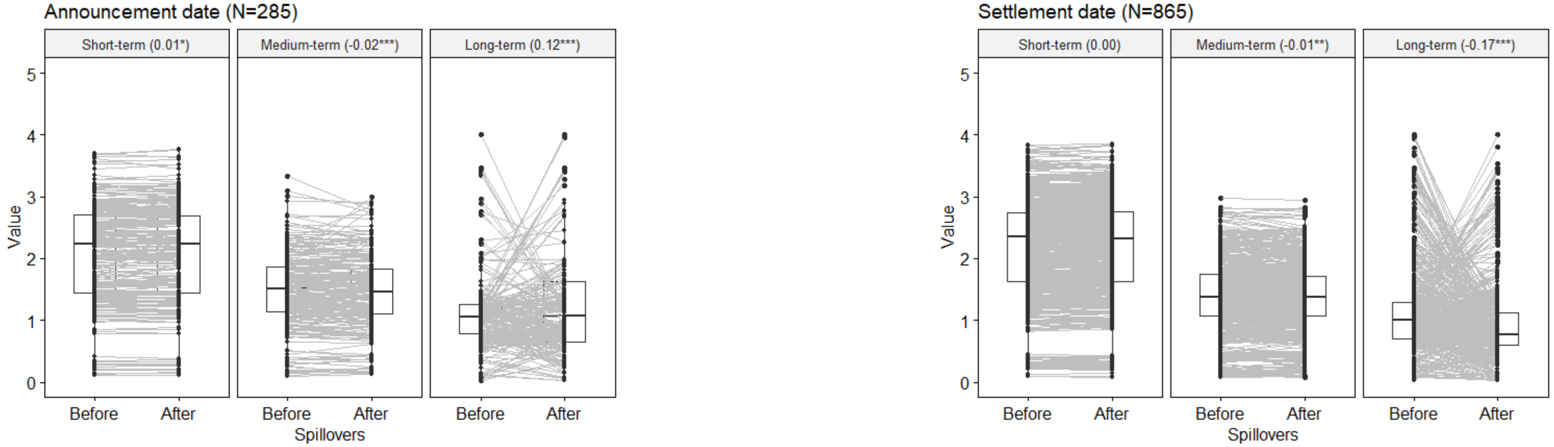


Figure 7: Contribution to systemic risk (*to*-spillovers)

(a) Own penalties



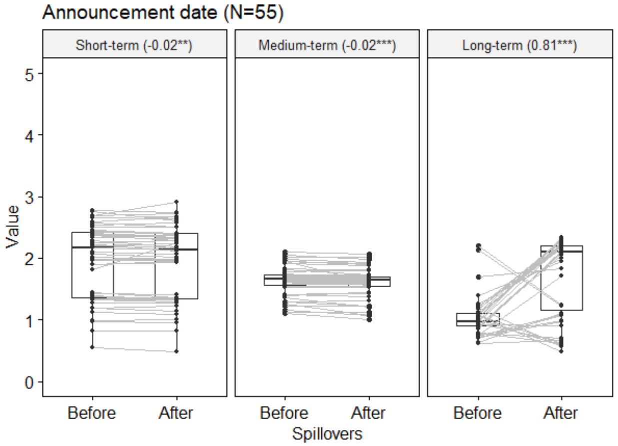
(b) Other banks' penalties

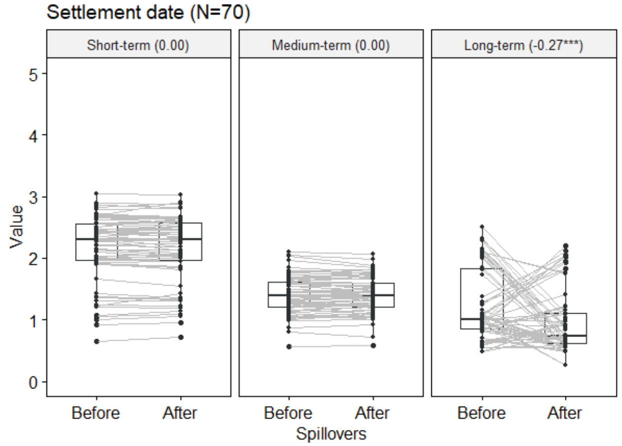


Note: The number in the brackets above each boxplot shows the median difference between the value of the spillover before and after the announcement/settlement based on the Wilcoxon test. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

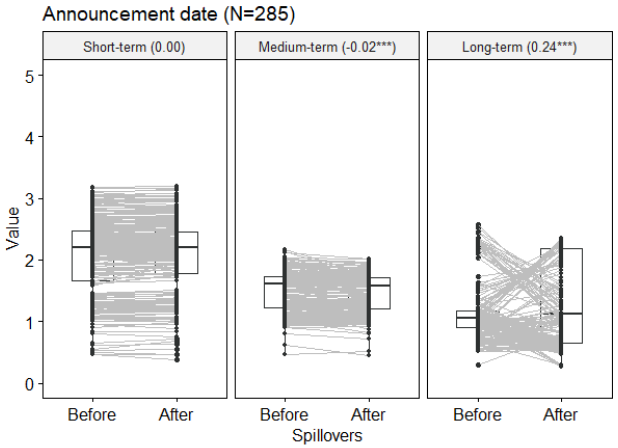
Figure 8: Exposure to systemic risk (*from*-spillovers)

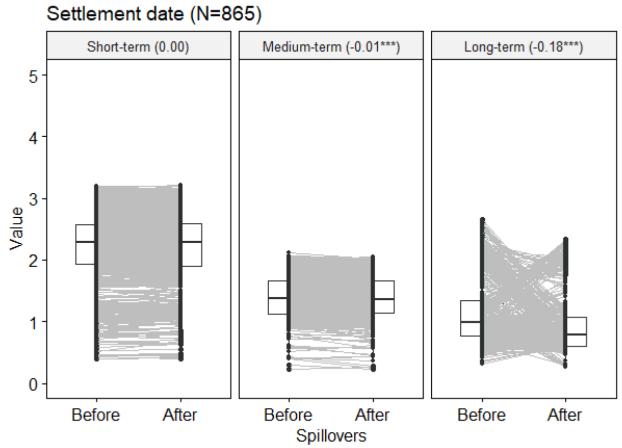
(a) Own penalties





(b) Other banks' penalties





Note: The number in the brackets above each boxplot shows the median difference between the value of the spillover before and after the announcement/settlement based on the Wilcoxon test. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1: Summary statistics of the daily volatility data

Bank	Ticker	Mean	Median	St. dev.	Skewness	Kurtosis
Bank of America	BAC	0.314	0.216	0.322	4.044	25.210
Barclays	BCS	0.251	0.175	0.261	4.737	35.700
Citigroup	C	0.321	0.209	0.373	4.912	37.321
Credit Suisse	CS	0.208	0.155	0.184	3.802	21.657
Deutsche Bank	DB	0.231	0.177	0.186	3.211	15.612
Fifth Third Bancorp	FITB	0.351	0.220	0.432	5.007	38.245
Flagstar Bank	FBC	0.531	0.340	0.565	3.931	27.998
Goldman Sachs	GS	0.247	0.183	0.229	4.747	35.093
HSBC	HSBC	0.140	0.106	0.117	3.419	17.612
JPMorgan Chase	JPM	0.253	0.180	0.238	3.495	16.786
Morgan Stanley	MS	0.330	0.233	0.373	7.163	85.800
PNC	PNC	0.256	0.174	0.272	5.419	56.983
Royal Bank of Scotland	RBS	0.260	0.184	0.285	7.035	90.872
SunTrust	STI	0.326	0.220	0.333	3.784	20.847
UBS	UBS	0.213	0.153	0.196	3.418	16.745
U.S. Bancorp	USB	0.233	0.159	0.242	4.075	24.704
Wells Fargo	WFC	0.262	0.172	0.277	3.426	14.886

Table A2a: List of penalties (2010–2016)

Announcement	Settlement	Bank	Regulator	Value (mil. USD)	Announcement	Settlement	Bank
n/a	2010-06-25	Morgan Stanley	SA/AG	102.7	2011-04-05	2013-01-07	JPMorgan Chase
2010-04-16	2010-07-15	Goldman Sachs	SEC	550	2011-04-05	2013-01-07	PNC
2009-05-28	2010-07-29	Citigroup	SEC	75	2011-04-05	2013-01-07	US Bancorp
2010-12-15	2010-12-31	Bank of America	FMCC	1350	2011-04-05	2013-01-07	Wells Fargo
2010-12-15	2011-01-03	Bank of America	FNMA	1520	2011-09-02	2013-01-07	Bank of America
2011-04-04	2011-04-05	Wells Fargo	SEC	11	2011-04-05	2013-01-16	Goldman Sachs
2011-04-14	2011-06-21	JPMorgan Chase	SEC	153.6	2011-04-05	2013-01-16	Morgan Stanley
2011-09-15	2011-10-19	Citigroup	SEC	285	2011-04-05	2013-01-18	HSBC
2011-03-23	2011-11-15	Citigroup	NCUA	20.5	2011-03-23	2013-03-29	Bank of America
2011-03-23	2011-11-15	Deutsche Bank	NCUA	145	2011-09-02	2013-05-28	Citigroup
n/a	2011-11-28	Royal Bank of Scotland	SA/AG	52	2011-09-02	2013-07-01	Citigroup
2011-04-13	2012-02-09	Wells Fargo	HUD	5350	2011-07-28	2013-07-23	UBS
2011-04-13	2012-02-09	Citigroup	HUD	2205	2011-03-23	2013-07-31	UBS
2011-04-13	2012-02-09	JPMorgan Chase	HUD	5290	n/a	2013-09-10	Barclays
2011-04-13	2012-02-09	Bank of America	HUD	11820	2011-09-02	2013-09-25	Citigroup
2012-02-29	2012-08-14	Wells Fargo	SEC	6.5	2011-09-02	2013-09-27	Wells Fargo
2012-02-29	2012-11-16	Credit Suisse	SEC	120	2011-04-13	2013-10-10	SunTrust
2012-02-29	2012-11-16	JPMorgan Chase	SEC	296.9	2012-06-07	2013-10-10	SunTrust
2011-04-05	2013-01-07	SunTrust	FED	163	2012-06-07	2013-10-10	SunTrust
2011-04-05	2013-01-07	Bank of America	COMP	2886	2011-09-02	2013-10-25	JPMorgan Chase
2011-04-05	2013-01-07	Citigroup	COMP	794	2011-09-02	2013-10-25	JPMorgan Chase

Source: Financial Times, Wall Street Journal, Factiva; SA/AG = state attorney / attorney general, SEC = Securities and Exchange Commission, FMCC = Federal Home Loan Mortgage Corp. (Freddie Mac), FNMA = Federal National Mortgage Association (Fannie Mae), NCUA = National Credit Union Administration, HUD = Department of Housing and Urban Development, FED = Federal Reserve, COMP = Office of the Comptroller of the Currency, FHFA = Federal Housing Finance Agency; DofJ = Department of Justice, FDIC = Federal Deposit Insurance Corporation.

Table A2b: List of penalties (2010–2016)

Announcement	Settlement	Bank	Regulator	Value (mil. USD)	Announcement	Settlement	Bank
2011-09-02	2013-10-25	JPMorgan Chase	FMCC	480	2011-09-02	2014-03-21	Credit Suisse
2011-09-02	2013-11-06	Flagstar Bank	FNMA	121.5	2011-09-02	2014-03-26	Bank of America
2011-09-02	2013-11-06	Wells Fargo	FHFA	335.23	2011-09-02	2014-04-24	Barclays
2013-09-23	2013-11-19	JPMorgan Chase	SA/AG	298.9	2011-09-02	2014-06-19	Royal Bank of Scotland
2013-09-23	2013-11-19	JPMorgan Chase	SA/AG	19.7	2011-09-02	2014-06-30	HSBC
2013-09-23	2013-11-19	JPMorgan Chase	DofJ	6000	2014-04-25	2014-07-14	Citigroup
2013-09-23	2013-11-19	JPMorgan Chase	FDIC	515.4	2014-02-25	2014-07-24	Morgan Stanley
2013-09-23	2013-11-19	JPMorgan Chase	FHFA	4000	2014-02-25	2014-08-20	Bank of America
2013-09-23	2013-11-19	JPMorgan Chase	SA/AG	100	2011-09-02	2014-08-21	Goldman Sachs
2013-09-23	2013-11-19	JPMorgan Chase	SA/AG	34.4	2011-09-02	2014-09-12	HSBC
2013-09-23	2013-11-19	JPMorgan Chase	NCUA	1400	n/a	2015-10-06	Fifth Third Bancorp
2013-09-23	2013-11-19	JPMorgan Chase	SA/AG	613.8	n/a	2015-10-19	Barclays
2013-11-06	2013-11-22	Fifth Third Bancorp	FMCC	26	n/a	2015-12-10	Morgan Stanley
n/a	2013-12-10	US Bancorp	FMCC	56	2015-06-05	2016-01-15	Goldman Sachs
2013-08-01	2013-12-12	Bank of America	SEC	131	n/a	2016-02-02	Morgan Stanley
n/a	2013-12-12	PNC	FMCC	89	2015-06-05	2016-02-04	Wells Fargo
2011-09-02	2013-12-20	Deutsche Bank	FHFA	1925	2015-06-05	2016-02-05	HSBC
2011-09-02	2013-12-27	Flagstar Bank	FMCC	10.75	2015-06-05	2016-02-11	Morgan Stanley
2011-09-02	2013-12-30	PNC	FNMA	140	n/a	2016-09-28	Royal Bank of Scotland
2011-09-02	2013-12-30	HSBC	FNMA	83	n/a	2016-10-03	Royal Bank of Scotland
2011-09-02	2013-12-30	Wells Fargo	FNMA	591	2015-06-05	2016-12-23	Credit Suisse
2011-09-02	2014-02-04	Morgan Stanley	FHFA	1250	2016-09-16	2016-12-23	Deutsche Bank

Source: Financial Times, Wall Street Journal, Factiva; SA/AG = state attorney / attorney general, SEC = Securities and Exchange Commission, FMCC = Federal Home Loan Mortgage Corp. (Freddie Mac), FNMA = Federal National Mortgage Association (Fannie Mae), NCUA = National Credit Union Administration, HUD = Department of Housing and Urban Development, FED = Federal Reserve, COMP = Office of the Comptroller of the Currency, FHFA = Federal Housing Finance Agency; DofJ = Department of Justice, FDIC = Federal Deposit Insurance Corporation