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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Micro-prudential regulation and banks' systemic risk

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Abstract

This paper investigates how countries' micro-prudential regulatory regimes are related to banks' systemic risk. We use a bank-level systemic risk indicator that can be decomposed into a bank's individual risk and its systemic linkage. To proxy the strictness of a country's regulatory regime, we employ World Bank survey data. Our results suggest that entry regulations increased systemic risk before and after the crisis. Liquidity and entry regulations seem to reduce individual risk in the post-crisis era, with little impact on systemic linkage. Other regulation categories, including capital regulation, do not have a robust relationship with systemic risk or its subcomponents.

JEL Codes: G21; G28

Keywords: systemic risk, regulatory regime, micro-prudential regulation

1 Introduction

In response to the recent global financial crisis, micro-prudential regulations (notably capital requirements) have been tightened in most countries to strengthen the stability and resilience of the banking system (Aiyar et al. (2015)).[1] Micro-prudential regulation is intended to limit the riskiness of individual institutions. However, studies that have examined whether micro-prudential regulation is related to bank riskiness reach different conclusions. For example, Demirgüç-Kunt and Detragiache (2011) fail to find a significant relationship between countries' compliance with the Core Principles for Effective Bank Supervision as issued by the Basel Committee on Banking Supervision and banking risk as measured by the Z-score. In contrast, using measures of bank regulation drawn from a World Bank survey, Klomp and de Haan (2012) report that regulation has a highly significant effect on high-risk banks.

So far, the impact of micro-prudential regulation on systemic risk has received limited attention. Systemic risk refers to the risk of a breakdown of the entire financial system rather than the failure of individual financial institutions. Systemic risk not only depends on the risks taken by individual banks, but also on how these risks relate to other institutions in the system. For example, common exposures and interlinkages are of paramount importance for systemic risk (Borio (2003, 2014)).[2] That is why, conceptually, the systemic risk of a bank may be broken down into two components: the downside tail risk of a bank and its link to the rest of the system in the event of financial stress.

The goal of this paper is to investigate how countries' micro-prudential regulatory regimes are related to banks' systemic risk. We therefore do not focus on the time dimension of systemic risk, i.e. how systemic risks evolves over time, but focus on the cross-sectional dimension of systemic risk, i.e., the distribution of systemic risk across financial institutions.[3]

[1] In addition, macro-prudential policies have become more important (Cerutti et al. (2017); Blinder et al. (2017); Galati and Moessner (2018)). Under macro-prudential regulation, not only the risk or probability of the failure of individual banks is crucial, but also preventing simultaneous bank failures; in other words, limiting systemic risk is they key objective of macro-prudential policies.

[2] We refer to de De Bandt et al. (2010) for a general survey on systemic risk.

[3] Systemic risk has two dimensions depending on the risk dimension focused upon: a time-varying dimension, which captures financial imbalances (like asset price bubbles), and a structural dimension,

We employ a bank-level systemic risk indicator as developed by van Oordt and Zhou (2019) that measures banks' sensitivity to extremely adverse shocks in the economy. This systemic risk measure can be decomposed into two components: (1) the level of individual risk of a bank ("individual risk") and (2) the link between a bank's risk taking and severe shocks in the financial system ("systemic linkage"). We use their framework but apply it to examine the relationship between micro-prudential regulation and banks' systemic risk and its decomposition.

More specifically, we evaluate whether banks in countries with a tougher regulatory regime are less systemically risky. Following the methodology of Pasiouras et al. (2006), we measure the strictness of micro-prudential regulation in seven categories using the survey data collected by Barth et al. (2004a,b, 2008, 2013), namely activity restrictions, capital regulation, supervisory control, deposit insurance facilities, private sector monitoring, liquidity regulation, and entry regulation (see also Klomp and de Haan (2012)). For each category, we examine its relationship with banks' systemic risk. In addition, we examine whether this relationship is due to banks' individual risk or systemic linkage, using the decomposition of our systemic risk measure. Finally, we examine whether the relationship between our proxies for micro-prudential regulations and (the decomposition of) systemic risk differs before and after the global financial crisis.

To summarize, this paper aims at answering three research questions: First, to what extent do banks in countries with a tougher micro-prudential regulatory regime have a lower level of systemic risk? Second, via which component of systemic risk, i.e. individual risk or systemic linkage, does micro-prudential regulation affect systemic risk? Third, have these relationships changed after the global financial crisis?

This study contributes to the literature in at least three ways. Firstly, it fills a gap in the literature by providing a bank-level analysis of the relationship between micro-prudential regulation and systemic risk. To the best of our knowledge, there is no comprehensive empirical analysis of the impact of micro-prudential regulation on bank level

which focuses on the interconnectedness of individual financial institutions and markets, as well as their common exposure to economic risk factors. For an overview of the rich literature on the time dimension of systemic risk we refer to Galati and Moessner (2013).

systemic risks. The paper that comes closest to our work is Klomp and de Haan (2012) who analyze the relationship between regulation and banks' tail risks. However, this study focuses on banks' individual risk only. By contrast, we focus on banks' systemic risk. Alternatively, there is work investigating the effectiveness of regulation and supervision in mitigating system-wide risk (see, e.g. Barth et al. (2004a)). Here system-wide risk is measured at the system level, whereas our study focuses on bank level systemic risk. Several studies have examined banks' systemic risk using different measures for systemic risk. Nice examples include Laeven et al. (2016) and Black et al. (2016). However, these studies do not consider the relationship between the prudential regulatory regime and banks' systemic risk.

Secondly, this study investigates different dimensions of the regulatory regime as bank regulation is a multi-faceted concept. Despite its importance (see e.g. Delis et al. (2012)), we argue that capital regulation merely constitutes one category of bank regulation and supervision. By using the seven categories of micro-prudential regulation as suggested by Pasiouras et al. (2006), based on World Bank survey data reported in Barth et al. (2004a,b, 2008, 2013), we go beyond capital regulation and provide a broader view on the relationship between micro-prudential regulation and bank-level systemic risk.

Thirdly, by decomposing systemic risk into banks' individual risk and systemic linkage, we provide insight on the relationship between micro-prudential regulation and these two components of systemic risk. This is important, as the seven dimensions of the regulatory regime that we distinguish may not reduce a bank's individual risk and systemic linkage simultaneously. Micro-prudential regulations towards reducing bank-level risk taking might affect banks' systemic linkages and thereby lead to a higher level of systemic risk. Our analysis will provide a quantitative basis for evaluating such a tradeoff.

Our results suggest that activity restrictions increased systemic risk during and after the financial crisis via both individual risk and systemic linkage. Entry regulation leads to high systemic risk before the crisis, due to its impact via the systemic linkage channel. This impact is weakened after the crisis. Together with its impact on reducing individual risk, overall, it reduces systemic risk after the crisis. Liquidity regulations seem to reduce individual risk in the post-crisis era, with little impact on systemic linkage. Other regulation categories, including capital regulation, do not have a robust relationship with systemic risk or its subcomponents.

The remainder of the paper is structured as follows. The next section gives a brief literature review on banking sector regulation and systemic risk. Section 3 describes the data and methodology used. Section 4 presents the estimation results of the effect of micro-prudential regulation on bank-level systemic risk, while section 5 contains a robustness analysis. The final section concludes.

2 Theory

Most of the existing literature, both theoretical and empirical, focuses on the relationship between bank regulation and banks' risk taking behavior. In this section, we follow the categorization of regulation as suggested by Pasiouras et al. (2006), and examine the theoretical impact of each of these categories of regulation on banks' risk taking behavior.

We focus on systemic risk. For that reason, we discuss the impact of regulation on both individual risk and systemic linkage. The theoretical foundation of this discussion is based on Wagner (2010) and Ibragimov et al. (2011). Wagner (2010) argues that banks' diversification strategies can be undesirable. Diversification, a common strategy for mitigating individual bank risk, may lead to instability in the financial system. On the one hand, diversification reduces the likelihood of institutional failure and thus contributes to financial stability. On the other hand, diversification also increases the chance that banks may fail at the same time. Ibragimov et al. (2011) also find that with heavy-tailed risks, diversification of individual intermediaries may be suboptimal for society. Likewise, Zhou (2013) argues that regulations that reduce bank individual risk-taking may simultaneously enhance systemic linkage among banks, and therefore may have an ambiguous impact on overall systemic risk. Following this stream of theoretical literature, we examine the impact of the seven distinguished categories of bank regulation on individual risk and systemic linkage.

Activity restrictions

Theoretically, the impact of activity restrictions on banks' individual risk is mixed. On the one hand, fewer activity restrictions will lead to an increase in banks' individual risk. For example, due to moral hazard, banks will engage in risky behavior if they are allowed to engage in a broad range of activities (Boyd et al. (1998)). Furthermore, banks with a broad range of activities are harder to monitor, and they may become so powerful, both economically and politically, that they are "too big to discipline" (Barth et al. (2004a)). So, individual risks of banks can be reduced by restricting banks' activities. On the other hand, restricting banks' activities may make it more difficult for banks to diversify, which may make them more risky (Wagner (2010)).

The empirical evidence on the impact of activity restrictions is mixed as well. On the one hand, Demirgüç-Kunt and Detragiache (2011) point out that banking strategies that rely prominently on generating non-interest income or attracting non-deposit funding create financial instability. In other words, curtailing banks' activities may lead to more stable banks. On the other hand, Barth et al. (2004a) find that restricting banks' activities is negatively related to bank stability and increases the probability of financial crises.

The aforementioned discussion refers to bank level risk. For banks' interconnectedness, or in other words systemic linkage, differences in activity restrictions across countries reduce the potential that banks will be exposed to common shocks, thereby reducing interconnectedness. However, if within a given country banks are restricted to domestic investments, this will increase the potential that the domestic banking system will be exposed to common shocks, thereby increasing interconnectedness. As we evaluate systemic risk as the sensitivity to a domestic market crash, we expect a positive relationship between activity restrictions and systemic linkage. The overall effect of activity restrictions on systemic risk is ambiguous.

Capital regulation

Several studies focus on the impact of capital regulation on bank risk. On the one hand, the traditional view emphasizes that capital regulation reduces risk (Fernandez and González (2005); Dewatripont and Tirole (1994)). Stringent capital regulation may lead to lower bank risk for the following reasons. Firstly, capital serves as a buffer against losses and hence helps to prevent bank failure and crises. Secondly, with more capital at risk, banks' incentives to engage in risky activities are curtailed. Lastly, capital regulation plays a crucial role in aligning the incentives of bank owners with those of creditors (Barth et al. (2004a); Berger et al. (1995)). On the other hand, some theoretical studies come to different conclusions. For instance, Rochet (1992) shows that the relationship between bank capital and bank risk can be ambiguous, in particular, when the risk weights used in capital regulation deviate from actual market risks. Moreover, Perotti et al. (2011) argue that more equity funding may enable banks to take more tail risk. Consequently, more stringent capital regulations may not necessarily lead to lower individual risk. So theoretically, the relationship between capital regulation and banks' individual risk is ambiguous.

For the systemic linkage dimension, Zhou (2013) discusses the tradeoff between individual risks and systemic linkage under more stringent capital requirements. With more stringent capital requirements, banks have to reduce their individual risk by adopting a more diversified strategy. As a result, financial institutions tend to hold similar portfolios and hence systemic linkage increases. Therefore, we expect that stringent capital regulations will lead to high systemic linkage.

In sum, similar to activity restrictions, we do not make a theoretical prediction on the relationship between capital requirements and systemic risk, but leave this to the empirical analysis.

There are several empirical studies on the relationship between banks' actual capital ratios and systemic risk. Vallascas and Keasey (2012), Brunnermeier et al. (2012), López-Espinosa et al. (2012) and Girardi and Ergün (2013) find evidence that capital buffers and systemic risk are negatively related. Vallascas and Keasey (2012) and De Jonghe (2010) report a negative link between measures for co-exceedance and tail dependence. Such measures can be interpreted as a proxy for systemic linkage. In other words, these studies find a negative relationship between banks' actual capital buffers and systemic linkage. However, it is important here to distinguish between capital regulation and banks' actual capital buffers. The former is imposed by the regulator, while the latter reflects what banks actually do. Although banks cannot set their desired capital ratio ignoring the regulatory restrictions, how and how quickly they adjust to the required ratios can differ because of conflicting pressures from shareholders and regulators (see Bakkar et al. (2019) for a discussion and references to the literature on this issue).[4] Therefore, although de facto higher capital buffers lead to lower systemic linkage and systemic risk, there is no guarantee that this also holds for the de jure measure considered in this study.

Supervisory control

Supervisory control refers to the supervisor's power to take corrective actions like declaring insolvency and restructuring banks. Theoretical models predict that supervisory control will reduce bank risk for the following reasons. First, the high cost of monitoring banks usually leads to under-monitored banks, which implies sub-optimal performance and stability. Supervisory control can, to a certain extent, mitigate this problem. Second, supervisory control can prevent bank runs due to information asymmetries. Third, as the presence of deposit insurance provides banks incentives for engaging in risky behavior and reduces depositors' incentives for monitoring banks (see below), strong supervisory control can prevent banks from taking risky investments and hence improve stability (Barth et al. (2004a)). Therefore, theoretically, supervisory control may have a negative relationship with banks' individual risk. However, Barth et al. (2004a) do not find empirical support for this proposition. In contrast, Fernandez and González (2005) report that supervisory power can reduce risk in countries with low accounting and auditing requirements.

In addition, supervisory controls may also mitigate potential crisis contagion across banks. When a systemic crisis occurs, defaulting banks can be orderly liquidated if supervisors have the power to intervene at an early stage. This reduces both the direct contagion effects on other banks, as well as the information asymmetry in the market.

[4] For a sample of OECD banks, Bakkar et al. (2019) find that the speed of adjustment for the Tier 1 capital ratio is only 0.29.

Consequently, it prevents the potential contagion to the system.

To summarize, we conjecture that supervisory control has a negative relationship with both banks' individual risk and systemic linkage. Consequently, we expect it has a negative relationship with systemic risk.

Deposit insurance

The aim of a deposit insurance scheme is to prevent bank runs. According to Demirgüç-Kunt and Detragiache (2002), deposit insurance has a twofold effect on financial stability. On the one hand, insuring deposits lowers the probability of bank runs. On the other hand, with a deposit insurance program in place, banks have incentives to engage in risk-taking behavior. This may offset the stabilization benefits of deposit insurance. Therefore, we do not predict the relationship between deposit insurance and banks' individual risk and leave it for the empirical analysis. Empirically, Barth et al. (2004a) and Demirgüç-Kunt and Detragiache (2002) provide evidence that deposit insurance tends to increase the probability of a banking crisis.

Notice that deposit insurance primarily protects the deposit holders of the underlying bank only. It does not protect interbank lending. Therefore, there is no reason to expect a relationship between deposit insurance and crisis contagion via direct exposures. Nevertheless, Acharya and Yorulmazer (2007) argue that the poor performance of one bank will convey news to the depositors of other banks. So, a crisis in one bank may trigger a crisis in another bank even if the two banks have no direct exposures. Since the deposit insurance will prevent the likelihood of bank runs, it will mitigate the potential runs due to information contagion. Therefore, we predict a negative relationship between deposit insurance and banks' systemic linkage.

By combining the two dimensions of the systemic risk, we do not make a prediction on the relationship between deposit insurance and systemic risk.

Private sector monitoring

Regulations regarding private sector monitoring refer to the degree of information that is released to officials and others, in particular certified auditors and rating agencies. There is disagreement in the literature about the role of the private sector in monitoring banks. For instance, Fernandez and González (2005) conclude that regulations encouraging private sector monitoring improve financial soundness, because they reduce information asymmetries and moral hazard. However, according to Barth et al. (2004a), countries with less developed capital markets may not be able to rely on private sector monitoring. Therefore, excessive reliance on private sector monitoring may lead to underperforming banks. The relationship between regulation regarding private sector monitoring and bank risk taking is therefore ambiguous.

Although private sector monitoring may in general help to reduce information asymmetries and consequently enhance the stability of individual banks, it creates common risks for banks. If private sector monitoring fails to evaluate certain risks in a fair way, all banks may underestimate risks and therefore have from the same risk exposure. This is a channel of systemic linkage. Regulations encouraging private sector monitoring therefore can be associated with high systemic linkage.

Finally, because of the opposite effects on individual risk and systemic linkage, we do not make a prediction on the relationship between regulations on private sector monitoring and systemic risk.

Liquidity regulation

Literature on the impact of liquidity regulation is scarce.[5] Wagner (2010) finds that more homogeneous bank balance sheets may negatively affect financial stability. For instance, if banks have common exposures and suffer from liquidity problems, this may lead to fire sales. More stringent liquidity regulations may diminish this problem, thereby reducing banks' individual risk. However, liquidity regulations may also diminish banks' possibilities for diversification. Furthermore, liquidity regulations may force banks to

[5] There is some literature on the impact of banks' actual liquidity on financial stability (see, for instance, Vazquez and Federico (2015) and Chiaramonte and Casu (2017)), but here the same argument applies as for banks' actual capital position, namely that de facto higher liquidity buffers may lead to lower systemic risk, but there is no guarantee that this also holds for the de jure measure considered in this study.

increase their liquidity buffers (liquidity hoarding), which can have negative externality effects, leading to market illiquidity at the aggregate level (Hong et al. (2014)). So the impact on banks' individual risk is ambiguous.

Following similar arguments for individual risk, we can assess the potential impact of liquidity regulation on systemic linkage. If there is a moderate shock on part of the system, having liquid assets will help banks to absorb the shock and therefore mitigate crisis contagion. Nevertheless, if there is a severe shock to common liquid assets, the fact that banks hold such common assets may enhance systemic linkage. As a consequence, the impact on banks' systemic linkage is also ambiguous: it depends on the type of shocks to the system. Consequently, we do not make a prediction on the impact of liquidity regulation on systemic risk.

Regulations on bank entry

Successful screening of banks by regulators may promote stability even if it creates monopoly power. For example, Keeley (1990) argues that banks with monopolistic power possess greater franchise value, enhancing prudent risk-taking behavior. In addition, strict entry restrictions will limit bank mergers. Because consolidated banks usually become more similar, the entire financial system could become more vulnerable to idiosyncratic or macroeconomic shocks (see De Nicolo and Kwast (2002)). Using a sample of 440 international bank mergers between 1991 and 2009, Weiß et al. (2014) find that bank mergers coincide with statistically and economically significant increases in the contribution of acquirers, targets and their competitors to financial instability.

Alternatively, some empirical papers present results suggesting a negative link between (the consequences of) strict entry regulations and financial stability. For instance, Beck et al. (2006) find that banking systems with strict entry applications and restrictions on non-loan activities face a higher probability that a systemic crisis occurs. One potential explanation is the fact that entry restrictions may reduce competition. Recently, Silva-Buston (2019) has distinguished between the interbank commonality driven by banks' diversification activities, referred to as the systematic component, and the other sources

Table 1: Regulatory impact: summary

Variable	*Individual risk*	*Systemic linkage*	*Systemic risk*
Activity restrictions	$\pm$	$+$	$\pm$
Capital regulation	$\pm$	$+$	$\pm$
Supervisory control	$-$	$-$	$-$
Deposit insurance	$\pm$	$-$	$\pm$
Private sector monitoring	$\pm$	$+$	$\pm$
Liquidity regulation	$\pm$	$\pm$	$\pm$
Entry regulation	$\pm$	$+$	$\pm$

of commonality, referred to the excess component. Using European bank-level data, she finds a negative relationship between competition and the excess component of systemic risk, while she finds no significant relation between competition and the diversification component.

As to systemic linkage, it is notable that monopolistic banks, due to their excessive size, are usually widely diversified. Following the argument of diversification outlined above, a system consisting of such banks will then be more systemically linked. Consequently, stringent regulations towards bank entry may lead to a financial system consisting of monopolistic banks, and therefore leads to banks with high systemic linkage. Again, we do not predict the impact of regulation on bank entry on systemic risk due to its ambiguous impact on individual risk.

Finally, we summarize our predictions in Table 1. Note that most relations between micro-prudential regulation and individual risks are ambiguous, while previous literature generally comes up with a clear prediction of the relationship between regulation and systemic linkage. This may reflect that there is much more literature on individual risk than on systemic linkage.

3 Data and methodology

In this section we first discuss how we measure banks' systemic risk and decompose that into banks' tail risk and systemic linkage. Then we explain the data used for measuring regulation and supervision. Finally, we outline the empirical framework used to test the impact of regulation and supervision on systemic risk and its subcomponents.

3.1 Measuring and decomposing systemic risk

Following van Oordt and Zhou (2019), we measure banks' systemic risk by evaluating their sensitivity to shocks in the financial system. The essence of this approach is to consider a linear relationship between the equity returns of a financial institution and the financial system conditional upon extremely adverse shocks in the financial system. As shown in van Oordt and Zhou (2019), this systemic risk measure can be decomposed into two dimensions: the level of a bank's tail risk and the linkage between the bank's tail risk and the shocks in the financial system. Here, bank tail risk refers to risk at the individual bank level which can be attributed to both shocks in the system or idiosyncratic shocks. The second dimension measures the "fraction" of shocks stemming from the financial system, which is referred to as "systemic linkage". Given the level of systemic linkage, the bank that has more individual tail risk would make a higher loss under a systemic shock. Conversely, given the level of a bank's tail risk, a bank whose tail risk is more related to shocks in the financial system should be considered more systemically risky.

Specifically, the methodology of measuring and decomposing systemic risk is given as follows. Let R_i and R_s denote the stock return of bank i and the return on an equity investment in the financial system, respectively. Consider the following linear tail model

$$R_i = \beta_i^T R_s + \varepsilon_i \text{ for } R_s < -VaR_s(\bar{p}), \tag{3.1}$$

where $VaR_s(\bar{p})$ is the Value-at-Risk of an equity investment in the financial system, which is exceeded with the probability $\bar{p}$, and where ε_i is assumed to be independent of the shocks in the financial system represented by R_s. Note that we only assume a linear relationship between the bank and the financial system when the system suffers an extremely adverse loss, i.e., only if $R_s < -VaR_s(\bar{p})$. We do not require any assumptions about this relationship during tranquil periods.

We measure systemic risk by the coefficient β_i^T in (3.1). This reflects the conceptual setup for systemic risk in our framework: banks with a higher β_i^T are expected to suffer from larger capital losses in case of an extremely adverse shock in the financial system. van Oordt and Zhou (2019) show that there is a strong analogy between the coefficient β_i^T and the MES measure discussed by Acharya et al. (2009, 2012).

Empirically, the coefficient β_i^T is estimated with observations corresponding to extremely adverse shocks in the financial system. van Oordt and Zhou (2019) propose an estimator of β_i^T based on Extreme Value Theory (assuming heavy tails in the equity returns) and show that the EVT estimator of β_i^T performs better than OLS. [6] Following van Oordt and Zhou (2019), the estimator is constructed as follows. Let R_i and R_s follow heavy-tailed distributions with tail indices ζ_i and ζ_s, respectively.[7] Then β_i^T can be estimated as

$$\hat{\beta}_i^T := \hat{\tau}_i(k/n)^{1/\hat{\zeta}_s} \frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_s(k/n)}. \tag{3.2}$$

Here we use observations in the tail region corresponding to the k worst losses of the financial system. The tail index $\hat{\zeta}_s$ is estimated by the so–called Hill estimator proposed by Hill (1975). The two VaRs $\widehat{VaR}_i(k/n)$ and $\widehat{VaR}_s(k/n)$ are estimated by the $(k+1)$th worst return on the bank's stock and the financial index. Finally, the term $\hat{\tau}_i(k/n)$ is the non-parametric estimator of the tail dependence parameter in multivariate EVT; see Embrechts et al. (2000). The estimator $\hat{\beta}_i^T$ is consistent and asymptotically normal, even under temporal dependence such as volatility clustering provided that the sequence k is properly chosen; see van Oordt and Zhou (2017). Theoretically, the sequence k must satisfy that $k := k(n) \to \infty$ and $k(n)/n \to 0$ as $n \to +\infty$. In practice, samples are finite and k is fixed at a certain level. For all our estimations, we use an estimation window of four years of daily returns, i.e. $n \approx 1000$. For such a level n, van Oordt and Zhou (2019) take $k = 40$, i.e. $k/n \approx 4\%$. In this paper, we take $k \approx 50$, such that $k/n \approx 5\%$.

Following van van Oordt and Zhou (2019), we decompose the systemic risk measure

[6] van Oordt and Zhou (2016) apply the same methodology in an asset pricing framework and show that estimates are relatively persistent over time and that historical estimates help to predict which stocks suffer relatively large losses in market crashes.

[7] A distribution is called heavy-tailed if it decays at power-law speed in the tail. Formally, for R_i it means $\Pr(R_i < -u) = u^{-\zeta_i} l_i(u)$ with $\lim_{u\to\infty} \frac{l_i(tu)}{l_i(u)} = 1$ for all $t > 1$.

as follows.

$$SR_i := \log \hat{\beta}_i^T = \log \widehat{\tau}_i(k/n)^{1/\hat{\zeta}_s} + \log \frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_s(k/n)} =: SL_i + IR_i. \tag{3.3}$$

The subcomponent SL_i measures the systemic linkage of bank i to the system while the subcomponent IR_i measures the tail risk of bank i. In total, the log of the estimated systemic risk measure, $\hat{\beta}_i^T$, equals the sum of the two. The rationale behind this decomposition is as follows. The SL_i component builds on the tail dependence between an individual bank and adverse shocks in the financial system. The level of tail dependence is not related to the bank's tail risk, while containing information on the dependence of bank losses on severe financial system shocks only. This reflects the conceptual idea of systemic linkage. The IR_i component builds on the ratio of the tail risk of bank i and that of the financial system. Due to the homogeneous denominator $\widehat{VaR_s(k/n)}$ across all financial institutions, the cross-sectional variation in this component is solely attributed to the variation in bank tail risk.

The estimation procedure is applied to global banks that have been traded actively in the equity market from 2008 till 2015. We take this period for two reasons. Firstly, we intend to make an "out-of-sample" regression analysis between the systemic risk measure and the regulation variables (see section 3.3 below). Since the latest observation for the regulation data refers to 2011, our post-crisis systemic risk measures are estimated using equity returns in 2012-2015. Secondly, we intend to make a comparison between the "in-crisis" and "post-crisis" periods. To ensure that the estimation windows are non-overlapping, our in-crisis systemic risk measures are estimated using equity returns in 2008-2011. Consequently, we require that the banks chosen in this exercise must have been traded in the equity market throughout the period 2008-2015.

Based on the availability of the SR measure defined in (3.3), together with the data availability for the variables measuring regulation and supervision, we end up with 108 banks in the "in-crisis" period (2008-2011) and 96 banks in the "post-crisis" period (2012-2015).[8] The summary statistics of the systemic risk measure and its two subcomponents

[8]Notice that for some banks it is possible to have one of the two systemic risk components available,

Table 2: Summary statistics: systemic risk measure and its subcomponents

	Year	Variable	Number of obs.	Mean	Std. Dev.	Min	Max
Full sample	2008-2011	SR	108	0.016	0.860	-5.848	1.309
		SL	108	-0.487	0.288	-1.556	-0.080
		IR	108	0.503	0.751	-4.668	1.980
	2012-2015	SR	96	-0.180	0.831	-4.411	0.802
		SL	96	-0.476	0.320	-1.638	-0.122
		IR	96	0.296	0.613	-3.171	1.205
Subsample	2008-2011	SR	84	0.029	0.913	-5.848	0.968
		SL	84	-0.463	0.289	-1.556	-0.080
		IR	84	0.493	0.805	-4.668	1.980
	2012-2015	SR	62	-0.196	0.957	-4.411	0.802
		SL	62	-0.460	0.330	-1.638	-0.122
		IR	62	0.264	0.721	-3.171	1.150

are provided in the upper panel of Table 2. In our regression analysis, we will control for bank characteristics and macroeconomic variables. By taking the data availability of the control variables into consideration, we end up with 84 and 62 banks in the two periods, respectively. The corresponding summary statistics in this subsample are provided in the lower panel of Table 2. Due to the additive feature between the systemic risk measure and its subcomponents, we observe that the means of IR and SL variables always add up to that of the SR variable.

3.2 Measuring regulation

There are two potential information sources for constructing proxies for bank regulation and supervision discussed in the literature. Several IMF studies (e.g. Demirgüç-Kunt and Detragiache (2011)) use an index measuring the extent to which countries adhere to the Core Principles of Effective Bank Supervision, issued by the Basel Committee on Banking Supervision (BCBS). This information is not publicly available. An alternative is to use the World Bank survey data to compute proxies for bank regulation and supervision which is publicly available. More specifically, Barth et al. (2004a,b, 2008, 2013) collected detailed information on bank regulation and supervision for over 107 countries between

either SL or IR. In that case, the SR measure is not available and the bank is excluded in this sample. Nevertheless, we include such a bank in the panel regression analysis when only the available systemic risk component is considered as the dependent variable.

1999 and 2011. In this paper, we use the World Bank data and construct measures of bank regulation and supervision using the methodology in Pasiouras et al. (2006) and Klomp and de Haan (2012). The data is organized as follows.

First, we classify the survey question into seven categories: (1) regulations on activities restrictions (AR); (2) capital regulations (CR); (3) supervisory control (SC); (4) deposit insurer's power (DI); (5) regulations on private sector monitoring (PSM); (6) liquidity regulations (LR); and (7) market entry regulations (ER). Then, within each category, we adopt the principle component analysis (PCA) proposed by Klomp and de Haan (2012) to construct one common factor. This factor can be regarded as the score of the level of regulation in each category for each country. The cross-sectional mean and variance for each factor is standardized to mean zero and unit variance.

To minimize causality and endogeneity issues, we construct the regulation and supervision measures for 2007 and 2011 and relate them to the systemic risk measures in the period 2008-2011 and 2012-2015, respectively. The principle component analysis is constructed based on the data in 2007. To ensure that the seven constructed factors are comparable across the two years 2007 and 2011, we keep the loadings of the principle components to the actual scores of the sub questions in each category and the standardization constants (mean and standard deviation) obtained from the 2007 survey and apply them to the 2011 survey.[9]

3.3 Empirical model

To examine the relationship between systemic risk and bank regulation and the impact of the global financial crisis on this relation, we run a regression model including two time points, before and after the crisis. We use three variables as the dependent variable, the systemic risk measure and its two subcomponents reflecting bank's tail risk and systemic linkage. By including the decomposition of the systemic risk measures, we are able to identify the channel via which the relation between systemic risk and bank regulation is

[9]However, the sample mean and standard error are not exactly zero and one for the 2007 survey because the banks in our sample are a subset of all available banks in the original survey.

more pronounced. The baseline regression model is given as follows,

$$Y_i = \alpha_i + \theta_1 Reg_i + \theta_2 D_i + \theta_3 D_i * Reg_i + \theta_4 X_i + \varepsilon_i,$$

where Y_i is the systemic risk measure SR or its subcomponents IR and SL, Reg_i is one of the seven variables measuring regulation and supervision, D_i is a dummy variable that is equal to one for observations in the period 2012-2015, and X_i are other control variables.

We run the panel regression model by including one regulation variable at a time. In this model, we do not include control variables. Next, we include bank-specific and macroeconomic control variables. Given that our sample size is limited, we need to limit the number of control variables included in our model. For that purpose, we apply a general-to-specific method to eliminate the less relevant control variables. As a result, the bank level characteristics that we include are: return on equity, log assets, and the loans-to-assets ratio (the last two variables are also considered by Laeven et al. (2016) and Black et al. (2016) in their analysis of the determinants of systemic risk). Finally, the macroeconomic variables we use are: inflation, economic growth and the current account balance. These variables vary across countries, but remain the same for banks from the same country. We cluster the standard errors at the country level, since some countries in our sample have a lot more observations than others.

4 Results

4.1 Baseline results

Table 3 shows the results for the baseline model using the aggregate systemic risk measure as the dependent variable, without including any control variables. The regression results suggest that the coefficients on most measures of bank regulation are not significant. We also find that banks in a country with more activity restrictions and stricter liquidity regulations tend to be more systemically risky. These results hold both before and after the financial crisis. (However, below we will show that our findings for liquidity

Table 3: Baseline model: systemic risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SR	SR	SR	SR	SR	SR	SR
D	-0.159	-0.192	-0.192	-0.173	-0.618***	-0.108	-0.191
	(0.117)	(0.125)	(0.125)	(0.121)	(0.217)	(0.120)	(0.129)
AR	0.160**						
	(0.073)						
D*AR	-0.006						
	(0.096)						
CR		0.014					
		(0.057)					
D*CR		-0.160					
		(0.214)					
SC			-0.047				
			(0.067)				
D*SC			0.077				
			(0.136)				
DI				0.030			
				(0.097)			
D*DI				0.073			
				(0.142)			
PSM					0.052		
					(0.086)		
D*PSM					0.361*		
					(0.191)		
LR						0.155***	
						(0.051)	
D*LR						-0.106	
						(0.110)	
ER							0.097
							(0.085)
D*ER							-0.154
							(0.142)
Const	0.013	0.007	0.004	0.012	0.002	-0.067	0.036
	(0.080)	(0.090)	(0.084)	(0.083)	(0.084)	(0.084)	(0.083)
Obs	204	204	204	204	204	204	204
R-squared	0.064	0.016	0.016	0.019	0.043	0.059	0.021

Note: The dependent variable is the measure for systemic risk SR. The independent variables are (1) regulations on activities restrictions (AR); (2) capital regulations (CR); (3) supervisory control (SC); (4) deposit insurer's power (DI); (5) regulations on private sector monitoring (PSM); (6) liquidity regulations (LR); and (7) market entry regulations (ER). D indicates a time dummy that equals one for the period 2012-2015. The standard errors are clustered at the country level. Significance levels: *-0.05, **-0.01, ***-0.001.

regulations are not robust to the inclusion of control variables.)

In contrast, the relationship between private sector monitoring and systemic risk is different before and after crisis. The insignificant coefficient on the variable PSM shows that before the crisis private sector monitoring is not related to systemic risk, but the (weakly) significant coefficient on the variable D*PSM indicates that after the crisis, banks in a country with a higher level of private sector monitoring are more systemically risky.

Recall that systemic risk can be decomposed into two channels reflecting individual risk and systemic linkage. To further understand the relationship between different regulatory regimes and systemic risk, Tables 4 and 5 show the results when we estimate the base model using the two subcomponents of systemic risk, individual risk and systemic risk, as dependent variables, respectively. As in Table 3, controls are not included. The following conclusions can be drawn from these tables.

Firstly, the relationship between activity restrictions and high systemic risk that we identified in Table 3 seems to run via both channels. That is, within a country with many activity restrictions banks tend to be both individual risky and systemically linked. The positive relation via the individual risk subcomponent confirms the prediction that activity restrictions limit banks' possibilities to diversify their risks. The relationship with systemic linkage is also in line with the theoretical prediction in Table 1: banks that are limited to domestic investments will be exposed to common shocks and therefore tend be more interconnected. Our results also suggest that these relations hold both before and after the crisis.

Secondly, also our previous finding that stricter liquidity regulations correspond to higher systemic risk seems to run via both channels. For the individual risk channel, our findings confirm the theoretical argument that liquidity regulations tend to limit banks' diversification possibilities. For the systemic linkage channel, our results lend support to the argument that encouraging banks to hold liquid assets may lead to higher systemic linkage since common shocks on such liquid assets will affect more banks in the system. Again, we do not find evidence that these relations are different before and after the

Table 4: Baseline model: individual risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IR	IR	IR	IR	IR	IR	IR
D	-0.185*	-0.183*	-0.201**	-0.190*	-0.436**	-0.165*	-0.174*
	(0.096)	(0.101)	(0.101)	(0.099)	(0.177)	(0.098)	(0.105)
AR	0.106*						
	(0.060)						
D*AR	-0.021						
	(0.079)						
CR		0.037					
		(0.046)					
D*CR		-0.088					
		(0.174)					
SC			-0.009				
			(0.054)				
D*SC			-0.001				
			(0.110)				
DI				0.035			
				(0.079)			
D*DI				0.027			
				(0.116)			
PSM					0.070		
					(0.070)		
D*PSM					0.166		
					(0.156)		
LR						0.086**	
						(0.041)	
D*LR						-0.120	
						(0.091)	
ER							0.020
							(0.069)
D*ER							-0.105
							(0.116)
Const	0.500***	0.478***	0.500***	0.497***	0.483***	0.459***	0.506***
	(0.065)	(0.073)	(0.068)	(0.067)	(0.068)	(0.069)	(0.068)
Obs	205	205	205	205	205	205	205
R-squared	0.050	0.026	0.022	0.026	0.040	0.044	0.027

Note: The dependent variable is the measure for individual risk IR. The independent variables are the regulation and supervision variables as in Table 3. D indicates a time dummy that equals one for the period 2012-2015. No control variables included. The standard errors are clustered at country level. Significance levels: *-0.05, **-0.01, ***-0.001.

Table 5: Baseline model: systemic linkage

	(1) SL	(2) SL	(3) SL	(4) SL	(5) SL	(6) SL	(7) SL
D	0.008	-0.025	-0.011	-0.008	-0.146*	0.036	-0.042
	(0.043)	(0.047)	(0.046)	(0.045)	(0.081)	(0.044)	(0.047)
AR	0.054**						
	(0.027)						
D*AR	0.017						
	(0.036)						
CR		-0.024					
		(0.021)					
D*CR		0.011					
		(0.075)					
SC			-0.036				
			(0.025)				
D*SC			0.076				
			(0.051)				
DI				-0.006			
				(0.037)			
D*DI				0.015			
				(0.053)			
PSM					-0.020		
					(0.032)		
D*PSM					0.143**		
					(0.071)		
LR						0.067***	
						(0.019)	
D*LR						0.026	
						(0.040)	
ER							0.076**
							(0.031)
D*ER							-0.034
							(0.052)
Const	-0.488***	-0.471***	-0.496***	-0.486***	-0.481***	-0.523***	-0.471***
	(0.030)	(0.034)	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)
Obs	206	206	206	206	206	206	206
R-squared	0.061	0.006	0.015	0.001	0.020	0.090	0.034

Note: The dependent variable is the measure for systemic linkage SL. The independent variables are the regulation and supervision variables as in Table 3. D indicates a time dummy that equals one for the period 2012-2015. No control variables included. The standard errors are clustered at the country level. Significance levels: *-0.05, **-0.01, ***-0.001.

crisis.

Thirdly, our finding that after the crisis private sector monitoring variable is positively related to systemic risk seems to reflect a positive relationship with systemic linkage rather than individual risk. The coefficient on the D*PSM variable in Table 5 is significant, whereas the coefficient on this variable in Table 4 is insignificant. As we will show below, our findings for private sector monitoring are sensitive to the inclusion of control variables.

Finally, we find a significant positive relation between entry regulations and systemic linkage, but not individual risk. This finding is again in line with the theoretical prediction in Table 1.

4.2 Extension: bank level characteristics and macroeconomic variables

Next, we include the control variables, i.e. bank level characteristics and macroeconomic variables. While the bank characteristics vary across banks and may capture systemic risk differences due to banks' operational choices, the macroeconomic variables vary across countries and may capture systemic risk differences across countries. The regression results on regulatory and supervision variables thus explain the cross-section of systemic risk that cannot be explained by bank fundamentals and macroeconomic factors. The results are shown in Table 6.

The most important findings are as follows. Firstly, for most supervisory variables we obtain results that are qualitatively similar to those obtained in the baseline analysis reported in Table 3. Most variables that had insignificant coefficients remain insignificant (the exception is discussed below). Likewise, the coefficient on D remains negative, although it is now always significantly different from zero, suggesting that systemic risk has been reduced after the financial crisis. Furthermore, the relationship between activity restrictions and systemic risk remains significantly positive and holds before and after the crises. It means that on top of the difference in systemic risk explained by bank level characteristics and macroeconomic variables, the difference in systemic risks across countries is still related to differences in activity restrictions.

Secondly, two variables that were significant in Table 3, become insignificant in Table 6, namely liquidity regulations and private sector monitoring. Apparently, the significance of the coefficients on these variables in Table 3 was due to omitted variables.

Finally, in Table 6, entry regulation, which had an insignificant coefficient in Table 3, is positively associated with systemic risk before the crisis. And the relation is reverted after the crisis. The impact swaps from positive to negative with about the same absolute magnitude.Before the crisis the coefficient is positive (0.207), while the post crisis coefficient is $0.207 - 0.388 = -0.181$. This difference is statistically significant.

Tables 7 and 8 show the results for individual risk and systemic linkage, respectively, after controlling for both bank level characteristics and macroeconomic variables. We

Table 6: Extension with control variables: systemic risk

	(1) *SR*	(2) *SR*	(3) *SR*	(4) *SR*	(5) *SR*	(6) *SR*	(7) *SR*
D	-0.824***	-0.757***	-0.636**	-0.689***	-0.938***	-0.705***	-0.693**
	(0.251)	(0.252)	(0.259)	(0.261)	(0.354)	(0.259)	(0.266)
AR	0.248**						
	(0.110)						
D*AR	-0.144						
	(0.131)						
CR		0.054					
		(0.075)					
D*CR		-0.047					
		(0.303)					
SC			-0.090				
			(0.088)				
D*SC			-0.118				
			(0.220)				
DI				0.042			
				(0.134)			
D*DI				0.071			
				(0.189)			
PSM					0.155		
					(0.109)		
D*PSM					0.082		
					(0.293)		
LR						0.045	
						(0.078)	
D*LR						-0.237	
						(0.181)	
ER							0.207*
							(0.109)
D*ER							-0.388**
							(0.180)
Const	-0.846**	-0.812**	-0.713**	-0.676*	-0.655**	-0.668**	-0.715**
	(0.324)	(0.363)	(0.332)	(0.358)	(0.328)	(0.327)	(0.322)
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	146	146	146	146	146	146	146
R-squared	0.168	0.132	0.142	0.134	0.148	0.139	0.161

Note: The dependent variable is the measure for systemic risk *SR*. The independent variables are the regulation and supervision variables as in Table 3, with further including three bank level characteristics: return on equity (RoE), logarithm of the total assets (Size) and the loans-to-assets ratio (Loan), and three macroeconomic variables: inflation, economic growth and the current account balance. D indicates a time dummy that equals one for the period 2012-2015. The standard errors are clustered at the country level. Significance levels: *-0.05, **-0.01, ***-0.001.

Table 7: Extension with control variables: individual risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IR	IR	IR	IR	IR	IR	IR
D	-0.415*	-0.367*	-0.271	-0.316	-0.515*	-0.343	-0.269
	(0.217)	(0.216)	(0.221)	(0.223)	(0.302)	(0.219)	(0.230)
AR	0.152						
	(0.095)						
D*AR	-0.097						
	(0.113)						
CR		0.039					
		(0.064)					
D*CR		0.020					
		(0.259)					
SC			-0.047				
			(0.076)				
D*SC			-0.172				
			(0.189)				
DI				0.014			
				(0.115)			
D*DI				0.074			
				(0.162)			
PSM					0.149		
					(0.093)		
D*PSM					0.041		
					(0.250)		
LR						0.028	
						(0.066)	
D*LR						-0.297*	
						(0.153)	
ER							0.084
							(0.094)
D*ER							-0.267*
							(0.155)
Const	0.202	0.211	0.310	0.328	0.324	0.346	0.311
	(0.281)	(0.310)	(0.284)	(0.306)	(0.280)	(0.277)	(0.278)
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	146	146	146	146	146	146	146
R-squared	0.095	0.078	0.088	0.079	0.098	0.101	0.095

Note: The dependent variable is the measure for individual risk IR. The independent variables are the regulation and supervision variables as in Table 3, with further including three bank level characteristics: return on equity (RoE), logarithm of the total assets (Size) and the loans-to-assets ratio (Loan), and three macroeconomic variables: inflation, economic growth and the current account balance. D indicates a time dummy that equals one for the period 2012-2015. The standard errors are clustered at country level. Significance levels: *-0.05, **-0.01, ***-0.001.

Table 8: Extension with control variables: systemic linkage

	(1) SL	(2) SL	(3) SL	(4) SL	(5) SL	(6) SL	(7) SL
D	-0.421***	-0.405***	-0.382***	-0.390***	-0.399***	-0.377***	-0.450***
	(0.075)	(0.077)	(0.079)	(0.080)	(0.110)	(0.079)	(0.079)
AR	0.092***						
	(0.033)						
D*AR	-0.039						
	(0.039)						
CR		0.015					
		(0.023)					
D*CR		-0.077					
		(0.093)					
SC			-0.044				
			(0.027)				
D*SC			0.065				
			(0.067)				
DI				0.029			
				(0.041)			
D*DI				-0.007			
				(0.058)			
PSM					0.006		
					(0.034)		
D*PSM					-0.000		
					(0.090)		
LR						0.016	
						(0.024)	
D*LR						0.070	
						(0.055)	
ER							0.123***
							(0.032)
D*ER							-0.105*
							(0.053)
Const	-1.046***	-1.023***	-1.026***	-1.007***	-0.989***	-1.017***	-1.030***
	(0.098)	(0.111)	(0.102)	(0.110)	(0.102)	(0.100)	(0.096)
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	147	147	147	147	147	147	147
R-squared	0.340	0.286	0.296	0.286	0.282	0.299	0.351

Note: The dependent variable is the measure for systemic linkage SL. The independent variables are the regulation and supervision variables as in Table 3, with further including three bank level characteristics: return on equity (RoE), logarithm of the total assets (Size) and the loans-to-assets ratio (Loan), and three macroeconomic variables: inflation, economic growth and the current account balance. D indicates a time dummy that equals one for the period 2012-2015. The standard errors are clustered at country level. Significance levels: *-0.05, **-0.01, ***-0.001.

find that for entry regulation, the positive impact before the crisis is due to the systemic linkage channel, while the change after the crisis is due to both a stronger negative impact via the individual risk channel and also a weakening of the positive impact via the systemic linkage channel (the coefficient on entry regulation of systemic linkage changed from 0.123 to $0.123 - 0.105 = 0.018$). In other words, in the post crisis era, the positive impact of entry regulation is virtually gone. After the crisis, regulating entry is therefore a useful tool that limits bank risk-taking, while it does not necessarily increase interconnectedness. This might be due to regulations for systemically important financial institutions as introduced in the aftermath of the crisis. Monopolistic banks are now more carefully monitored which limits the potential downside of entry screening.

Compared to the baseline results, we do not observe a significant positive relation between liquidity regulation and systemic risk before the crisis. This shows that the relation between liquidity regulation and (the subcomponents of) systemic risk is mediated by the control variables before the crisis. In other words, there is no direct impact of liquidity regulation on systemic risk, while the observed total impact of liquidity regulation in Table 3 is via the control variables. Recall that our theoretical argument on the relation between liquidity regulation and the two subcomponents of systemic risk relies on the asset quality of banks. For example, the argument that liquidity regulation may be positively related to systemic linkage is based on the fact that banks holding common liquid asset might suffer from simultaneous shocks. Since our control variables contain the return on equity which proxies banks' asset quality, the impact of liquidity regulations on (the subcomponents of) systemic risk might be captured via the bank level characteristics.

Our finding that liquidity regulation has a significantly negative relation with individual risk after the crisis when we include the control variables implies that liquidity regulation helps to maintain systemic risk by lowering banks' individual risk taking. This differs from the baseline results in Table 3. In other words, there is a negative direct impact of liquidity regulation on individual risk in the post-crisis period, while the indirect impact impact of liquidity regulation on individual risk points towards the opposite side.

On the one hand, liquidity regulation reduces the chance of fire sales and thus reduces bank level individual risk. On the other hand, liquidity regulation limits banks' diversification possibilities which may lead to market illiquidity. This lower level of diversification might be reflected in bank level characteristics such as the loan-to-asset ratio. This might explain why we found a positive total impact of liquidity regulation in Table 3, but a negative impact after including the control variables.

5 Conclusions

In this paper, we examine how micro-prudential regulatory regimes of different countries are related to their banks' systemic risk. Our analysis uses a systemic risk measure that can be decomposed into two subcomponents representing individual risk and systemic linkage. This allows us to examine via which channel of systemic risk regulation affects systemic risk. We summarize our findings in Table 9.

We find that tightening some regulations may lead to a higher level of systemic risk. This holds for activity restrictions that affect systemic risk via both subcomponents of systemic risk. Having fewer activity restrictions would encourage both better risk management at the individual bank level (i.e. lower individual risk) and more diversity across the banking system (i.e. less systemic linkage).

We also find that the relationship between the regulatory regime in place and systemic risk has changed after the global financial crisis. For example, before the crisis stricter entry regulations correspond to higher systemic risk via systemic linkage. After the crisis, this impact is weakened while the relationship with individual risk is significantly negative. That makes entry regulation an effective tool to reduce systemic risk in the post-crisis era.

Our results for the model with control variables suggests that liquidity regulation reduces bank individual risk after the crisis. Combining liquidity regulation with other policies that enhance banks' asset quality and market liquidity would therefore be helpful for reducing individual risk-taking. In addition, liquidity regulation would have little impact on the systemic linkage aspect of systemic risk.

Finally, other regulation categories, including capital regulation, do not have a statistically significant relationship with systemic risk or its subcomponents.

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Table 9: Regulatory impact summary

Variable	*Individual risk*	*Systemic linkage*	*Systemic risk*
Activity restrictions	+	+	+
Capital regulation			
Supervisory control			
Deposit insurance			
Private sector monitoring			
Liquidity regulation (total)	+ (pre)	+ (pre)	+ (pre)
Liquidity regulation (direct)	− (post)		− (post)
Entry regulation	− (post)	+ (pre)/ − (post)	+ (pre)/ − (post)

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