DEUTSCHE
BUNDESBANK
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Discussion Paper

Deutsche Bundesbank
No 14/2021

Banks' complexity-risk nexus and the role of regulation

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Internet http://www.bundesbank.de

ISBN 978–3–95729–822–5 (Internetversion)

Non-technical summary

Research Question

Since the global financial crisis of 2008/2009 the issue of bank complexity is perceived by regulators as a feature that impedes bank resolution and favours bank risk taking. Therefore, new regulations have been put in place to ensure that large and complex financial institutions worldwide become more resilient. Yet, despite its application in regulatory policy, the notion of bank complexity remains ambiguous, and its implications for bank risk are not yet well understood in the academic literature. In this paper, we answer the following questions. First, what is the relationship between bank complexity and bank risk? Second, how does the tightening of bank regulations affect bank complexity? Finally, how do the changes in bank complexity induced by regulatory reforms affect bank risk-taking? To determine banks' complexity we rely on measures capturing the organizational structures that stretch across geographical locations and business areas in bank holding companies.

Contribution

This paper contributes to the existing literature by providing insights into the complexity of banks in Germany, as well as the relationship between bank complexity and bank risk-taking, which is the complexity-risk nexus. We investigate the relationship between bank complexity and risk taking for a sample of 84 large banks in Germany over the period 2005-2017. Further it investigates how tightenings in post-crisis bank regulations affect this nexus.

Results

We find that more complex banking organizations tend to take on more risk, but the strength of this complexity-risk nexus decreased over time and against the background of regulatory tightenings. Banks reduce their complexity in response to regulatory tightenings. This is in particular observable for systemically important banks (SIBs), which also manage to reduce their related regulatory costs more than other banks. As to complexity related benefits we find that SIBs, despite their reduced complexity, increase organizational and income diversification, and thereby decrease their overall risk. Overall do banks show a lower complexity-risk nexus after regulatory tightenings. Thus, our results point towards bank regulations introduced after the global financial crisis being effective in reducing banks' complexity-risk nexus.

Nichttechnische Zusammenfassung

Fragestellung

Seit der globalen Finanzkrise 2008/2009 sehen die Regulierungsbehörden die Komplexität von Banken als ein Problem an, welches die Abwicklung von Banken erschwert und gleichzeitig den Banken Anreize setzt, schwer zu überwachende Risiken einzugehen. Daher wurden neue Regulierungen eingeführt, um die Widerstandsfähigkeit großer und komplexer Finanzinstitutionen zu erhöhen. Die Implikationen von Komplexität für das Risiko von Banken wurden in der akademischen Literatur bislang nicht umfassend untersucht. In diesem Papier gehen wir den folgenden Fragen nach. Erstens, wie ist der Zusammenhang zwischen dem Risiko und der Komplexität von Banken? Zweitens, wie beeinflussen Verschärfungen regulatorischer Anforderungen die Komplexität von Banken? Drittens, wie passen Banken ihr Risikoverhalten an, wenn regulatorische Maßnahmen sich auf ihre Komplexität auswirken? Zur Bestimmung der Komplexität von Banken greifen wir auf Maße zurück, die die organisatorischen Strukturen erfassen, sowohl in geografischer Hinsicht als auch über Geschäftsfelder hinweg.

Beitrag

Dieses Papier leistet einen Beitrag zur bestehenden Literatur, indem es einen Einblick in die organisatorische Komplexität von Banken in Deutschland gibt, wobei wir den Zusammenhang zwischen der Komplexität und dem Risiko, d.h. den Komplexitäts-Risiko-Nexus für 84 große Banken über den Zeitraum 2005-2017 betrachten. Darüber hinaus untersuchen wir, wie sich Verschärfungen in der Bankenregulierung nach der globalen Finanzkrise auf diesen Nexus auswirken.

Ergebnisse

Unsere Ergebnisse zeigen, dass komplexere Banken ein höheres Risiko aufweisen, wobei dieser Zusammenhang über die Zeit jedoch schwächer wird. Auch finden wir, dass Banken ihre Komplexität als Reaktion auf verschärfte Regulierungen verringern. Dies gilt insbesondere für systemrelevante Banken (SIBs), die gleichzeitig ihre damit verbundenen regulatorischen Kosten stärker reduzieren als andere Banken. Darüber hinaus finden wir, dass SIBs ihre organisatorische und Einkommensdiversifikation erhöhen konnten, obwohl sie ihre Komplexität verringerten. Dies hat insgesamt zu einem geringeren Risiko bei SIBs geführt. Insgesamt zeigen alle Banken einen geringeren Komplexitäts-Risiko-Nexus infolge regulatorischer Verschärfungen. Daher deuten unsere Ergebnisse darauf hin, dass die Regulierungen nach der Finanzkrise den Komplexitäts-Risiko-Nexus reduziert haben.

Banks' complexity-risk nexus and the role of regulation

Natalya Martynova[a] Ursula Vogel[b]

Abstract

We investigate the relationship between bank complexity and bank risk-taking using German banking data over the period 2005-2017. We find that more complex banking organizations tend to take on more risk, but that this complexity-risk nexus decreases over time. We study how regulatory tightenings inherent in this period, and addressing systemically important banks (SIBs) in general and complexity more specifically, alter banks' choices of complexity and risk. Banks reduce their complexity in response to regulatory tightenings, as these increase the related regulatory costs. Surprisingly, for SIBs in particular, the reduction of regulatory costs is associated with an increase in diversification benefits. As a result, they are able to lower their idiosyncratic risk more than other banks. The overall complexity-risk nexus is lower after regulatory tightenings. Thus, our results indicate that post-crisis regulation is effective in reducing banks' complexity-risk nexus.

Keywords: bank complexity, bank risk-taking, bank regulation, too-big-to-fail.

JEL-Codes: G21, G28, G30.

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This paper is part of a broader initiative by the International Banking Research Network (IBRN) to coordinate research on the implications of banking organization complexity for risk outcomes. We thank two anonymous referees and the editors Thorsten Beck and Linda Goldberg for their helpful comments. Further, the paper benefitted from comments from and discussions with Claudia Buch, Benedikt Fritz, Justine Pedrono, Iman van Lelyveld, Yuji Sakurai, and participants at the IBRN meetings in Paris and New York, the 33rd AFBC in Sydney (virtual), as well as an internal Bundesbank Seminar. The views expressed in this paper are those of the authors alone and do not necessarily reflect the policy or positions of the Deutsche Bundesbank or the Eurosystem.

1. Introduction

Since the global financial crisis of 2008/2009, the issue of bank complexity has been perceived by regulators as a feature that impedes bank resolution (Carmassi and Herring 2016) and favors bank risk-taking. Therefore, some provisions of the Basel III package[1] address the issue of too-big-to-fail (TBTF) financial institutions, and some of the capital surcharges increase with bank peculiarities associated with bank complexity. Yet, despite its application in regulatory policy, the notion of bank complexity remains ambiguous. The issue of bank complexity as well as its implications for bank risk are not yet well understood in the academic literature. Nevertheless, some studies argue that banks' complexity is adequately captured by measures describing banks' organizational structures as to geographical footprint and the scope of business activities (Cetorelli and Goldberg 2014). Some studies suggest that more complex banks can become safer by being able to diversify their activities (Goetz et al. 2016, Cetorelli et al. 2017) or use internal capital markets for efficient liquidity management (Cetorelli and Goldberg 2016). Others show that more complex banks take more risk because of the moral hazard problem that arises due to agency problems (Scharfstein and Stein 2000), regulatory arbitrage (Houston et al. 2012) and reduced market discipline (Boot and Schmeits 2000) exacerbated by implicit subsidies from the government (Dam and Koetter 2012). It is therefore important to understand whether regulatory tightenings, addressing systemic importance and bank complexity internalize related externalities without impairing the benefits complex banks obtain from diversification. This paper contributes to the understanding of bank complexity, of its relationship to banks' risk-taking, and of the role that regulation plays in these dynamics.

In this paper, we use German banking data to answer the following questions. First, what is the relationship between bank complexity and bank risk? Second, how does the tightening of bank regulations affect bank complexity? Finally, how do the changes in bank complexity induced by regulatory reforms affect bank diversification benefits as well as bank risk taking?

[1] See BCBS (2010) for the first rules text on the Basel III regulatory framework.

To determine banks' complexity, we follow the concepts of Cetorelli and Goldberg (2014) and Goldberg and Meehl (2020) and rely on measures capturing the organizational structures that stretch across geographical locations and business areas in bank holding companies. We measure bank risk with the natural log of the inverse of the z-score (Lepetit and Strobel 2015).

Starting from the conjecture that more complex banks take more risk, we begin by investigating the empirical relationship between different measures of geographical and business complexity and our measure of bank risk-taking using a sample of 84 German banks in the period of 2005 to 2017.[2] We indeed find a positive complexity-risk nexus, indicating that higher bank complexity is associated with higher bank risk-taking. This suggests that the diversification motive of complexity is less important than moral hazard that may arise due to agency problems or the lack of market discipline. This complexity-risk nexus varies over time and is most pronounced around the global financial crisis. We note that the decrease of the nexus coincides with regulatory tightenings, also addressing the TBTF issue and including capital surcharges increasing with bank complexity.

Further we examine how the post-crisis regulatory changes affect banks' incentives to adjust their complexity and risk-taking, and hence the nexus. For our identification, we distinguish between two different regulatory treatments: bank capital requirements and being assessed as a systemically important bank (SIB), which involves being subject to a broader set of regulatory requirements (FSB 2020). A further distinct feature of our analysis is that we look at the announcements of regulatory changes.

We argue that banks choose their level of organizational complexity by trading off the associated costs and benefits. While different costs and benefits of complexity exist, we focus on the trade-off between the regulatory costs of complexity and the benefits of bank complexity stemming from organizational and income diversification (Laeven and Levine 2007, Wagner 2010). The regulatory

[2] The issue of bank complexity and bank risk-taking is of high relevance for the German banking system, as it has more SIBs than any other country in the EU. SIBs account for about 50% of assets and 67% of systemic risk (measured by systemic risk scores) in the German banking system. Our sample includes 14 SIBs.

tightenings alter this trade-off by raising the regulatory costs of bank complexity. SIBs face higher requirements as well as closer regulatory scrutiny, and capital buffers also increase with bank complexity. More specifically, capital needs are substantial for banks' equity investments as these carry comparatively high risk weights. We argue that announcements of future regulatory tightenings immediately affect banks' strategic choices which may have implications for banks' organizational structures as well as banks' risk-taking. Increases in capital requirements bring banks below their individual target capital ratio, thus making them immediately more capital-constrained.

We study how banks react to the elevated regulatory costs of complexity induced by regulatory changes. In particular, we examine whether banks change their organizational complexity, and how they manage their regulatory costs by looking at the changes in risk-weighted asset densities for equity investments.[3]

Next, to explore how banks manage their complexity-related diversification benefits, we estimate how regulatory tightenings affect the organizational and income diversifications of banks' operations. In particular, we assess what drives the changes in the organizational geographical and business diversification and whether or not this translates into the changes in income diversification.

Finally, we are interested in how regulatory tightenings ultimately affect bank risk and alter the overall complexity-risk nexus.

We show that, in response to regulatory tightenings, banks decrease their complexity by reducing the number of their affiliates,[4] and thus reduce their risk-weighted assets and associated regulatory costs. Surprisingly the reduction in bank complexity does not translate into the decrease of diversification of banks' business operations and banks' income. What's more, we show that

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[3] If banks become more constrained due to stricter capital regulation, more capital-constrained banks react by reducing the risk density of their assets (Berger and Udell 1994, Peek and Rosengren 1995, Albertazzi and Marchetti 2010, Imbierowicz et al. 2018).

[4] Throughout the paper we use the term "banks" to refer to the universal bank, and the term "bank affiliates" or "affiliated entities" for entities majorly owned by universal banks (such as subsidiaries). Equity investments relate to bank affiliates.

systemically important banks even manage to increase their organizational diversification. This is achieved by increasing the share of their non-bank financial subsidiaries and their span and reducing the share of non-financial entities. Furthermore, by doing so systemically important banks could achieve higher income diversification.

Next, we demonstrate that regulatory tightenings are related to lower risk-taking for SIBs, yet not for other banks. This suggests that SIBs reduced complexity and increased their income diversification, while other banks did not reduce their overall risk-taking in order not to harm their profitability. This may be especially true in the post-crisis period where some bank affiliates became loss making. However, SIBs reduced their risk-taking compared to other banks after regulatory tightenings. This suggests that, on the one hand, SIBs' ability to diversify in combination with increasing capitalization may have played a role in lowering their risk. On the other, this could indicate that extra capital surcharges and other reforms aimed at curbing bank complexity were successful at reducing bank risk. Finally, we show that regulatory tightenings are associated with a reduced overall complexity-risk nexus.

Contribution of the paper

Our paper contributes to three strands of the literature. First, we relate to the quite scarce empirical literature linking different forms of complexity and bank risk. Existing papers study the effect of bank complexity on idiosyncratic (Chernobai et al. 2020) as well as systemic risk (Liu et al. 2015) or both (Krause et al. 2017). In contrast to Chernobai et al. (2020), who focus on off-balance sheet activities as a measure of complexity and operational risk as a source of idiosyncratic bank risk, we study the link between geographical as well as business complexity and banks' idiosyncratic risk.

Second, we connect to the theoretical literature exploring banks' risk-taking. These studies mainly focus on the effect of conglomeration on market discipline. Most studies highlight the presence of the diversification benefits in integrated conglomerates (Allen and Jagtiani 2000, Dewatripont and Mitchell 2005). However, Boot and Schmeits (2000) argue that higher diversification benefits decrease the sensitivity of a conglomerate's cash flows to the investment decisions of its divisions, thus reducing market discipline.

While acknowledging diversification benefits of conglomerates, some studies highlight that the reach of the banks' safety net can be more important in shaping conglomerates' risk incentives. Dewatripont and Mitchell (2005) show that extending the reach of the deposit insurance safety net to a non-bank division within an integrated entity may reduce market discipline and encourage risk-taking. Freixas et al. (2007) argue that an integrated conglomerate can increase risk-taking because of the reach of the safety net and become riskier despite its higher diversification. As a result, it calls for higher capital requirements to reduce its risk-taking. Our paper provides empirical evidence on how regulatory tightening affects banks' incentives to be complex as well as their incentives to take risk in the presence of the regulatory cost and diversification benefits of complexity.

Finally, we add insights to the literature on the evaluation of bank regulatory reforms. The largest set of studies evaluates the consequences of the capital regulation tightening for bank lending (e.g. Buch and Prieto 2014, Bridges et al. 2014, Aiyar et al. 2014, Mesonnier and Monks 2014, Fraisse et al. 2020, Imbierowicz et al 2018). Yet regulatory reforms have also been shown to have unintended consequences. For instance, regulatory tightening in banks' home countries increases their risk-taking abroad (Ongena et al. 2013). The introduction of the Single Supervisory Mechanism reduced lending of significant banks relative to that of less significant institutions (Fiordelisi et al 2017). We provide evidence that banks respond to regulatory tightenings by adjusting their organizational structures, the underlying determinants, and risk-taking. We highlight the novel complexity-related channel of regulatory tightening, namely that banks reduce their complexity to reduce their regulatory costs, but at the same time try to keep their diversification benefits in order to reduce bank risk.

The structure of the paper is as follows. Section 2 presents our data and stylized facts on banks' complexity-risk nexus in the German banking system. Section 3 develops testable hypotheses relating the complexity-risk nexus to regulatory changes. Section 4 explores the impact of changes in regulations on bank complexity and risk-taking, as well as on the underlying trade-offs. Section 5 concludes.

2. Data and stylized facts

In this section, we present our data and some stylized facts relating to banks' complexity-risk nexus as well as changes in regulatory capital requirements and banks' capitalization in the German banking system. Our analysis covers the years 2005 to 2017 and includes 84 banks[5] representing more than 60% of the total banking system assets in Germany as of end-2017.[6]

2.1 Bank complexity

We make a distinction between two different dimensions of the overall *organizational complexity* of a bank: *geographic complexity* captures the number and the cross-country spread of banks' affiliated entities, and *business complexity* captures the range of activities and business lines within a banking organization.[7] We distinguish different measures for each dimension. Bank-level data for measures of geographic and business complexity come from a proprietary supervisory Bundesbank database. For this database banks report information on all their equity investments at an annual frequency.[8]

Geographic complexity

Measures of geographic complexity gauge how a bank holding company stretches out over different countries and regions. Affiliates spread among a large number of geographical locations could make it difficult for insiders to manage such a banking organization as well as for outsiders (including investors and supervisors) to evaluate the risks it is undertaking. Positive diversification

[5] In order to select the sample banks we start with the 100 largest banks in Germany as of end-2017. We then exclude foreign branches and banks that are subsidiaries of other banks in the sample, and we lose some banks because of data availability limitations.

[6] A structural change in the data series prevents us from using data for earlier years.

[7] For descriptions and discussions of bank complexity measures see Cetorelli and Goldberg (2014) and Goldberg and Meehl (2020).

[8] See https://www.bundesbank.de/resource/blob/613324/401aefae5679e50377816a14f9564f35/mL/ab-data.pdf for the reporting form (available only in German).

effects can be reduced further if geographical complexity is used to circumvent some regulations by setting up subsidiaries in the countries with looser regulation.

More than 75% of the banking organizations have foreign affiliates at some point during the observation period. We consider four different measures of geographical complexity. The span of countries where banks' affiliates – banks as well as non-banks – operate (*span_location*) and the overall number of affiliates abroad (*count_foreign*) keep increasing slightly until the global financial crisis and decrease afterwards, in particular for the highest quartile of banks in our sample[9] (Panel A of Figure 1, graphs on the left-hand side). For two similar measures that consider bank affiliates only (*span_location_b* and *count_foreign_b* respectively) the developments are broadly similar, yet bank-affiliates-related complexity appears to be much smaller (Panel A of Figure 1, graphs on the right hand side). These observations may be linked to the overall trend of declining internationalization in banking (see CGFS (2018) for a comprehensive examination of trends in bank business models and market structures). Table 1 provides detailed summary statistics for complexity measures of the 84 banks included in the analysis.

Business complexity

Measures of business complexity capture how diversified business activities of affiliates of banking organizations are. Large numbers of business types within a banking organization can raise the difficulty of valuing and managing it and are to be seen alongside possible positive diversification effects. We consider four different measures of business complexity. We observe decreasing complexity over time for all our measures, and the most variation in complexity over time is again observable for the banks in the highest quartile, i.e. the most complex banks (Figure 1, Panel B). Our measures for business complexity are the total number of affiliates (*total_count*), and subsets for bank affiliates (*count_bank*) and non-bank affiliates (*count_non_bank*) respectively. We also

[9] As we rely on confidential regulatory data, we are not permitted to disclose the maximum values per complexity measures. Yet it should be noted at this point that the most complex banks in Germany show much higher values than displayed in the figures.

measure the number of affiliates in the financial sector (*count_fs*). The decreasing business complexity may reflect mounting regulatory pressure and the low interest rate environment following the global financial crisis that made banks more sensitive to the costs of managing such vast and complex structures as well as of meeting new regulatory standards.

2.2 Bank risk measure and other bank statistics

To construct our main measure of bank risk and control variables, we rely on confidential regulatory data and other internal Bundesbank data. For a more detailed overview of the different variables and their data sources, see Table 2.

Measure of bank risk

Given that banking organizations in our sample are mostly not listed institutions, we abstract from any market-based measures of risk and use an accounting measure. We use the natural log of the inverse of the z-score as a measure of idiosyncratic bank risk (Laeven and Levine 2009, Berger et al. 2017), as the z-score is shown to be negatively proportional to the log odds of insolvency (Lepetit and Strobel 2015). The z-score of bank *i* in year *t* is the ratio of the average return on assets in a given period ROA_{it} plus the equity to assets ratio cap_{it}, and divided by the standard deviation of the return on assets $\sigma(ROA)$ over the last four years:

$$risk_{it} = (-1)\cdot \ln\left(z - score\right)_{it} = (-1)\cdot \ln\left(\frac{\left(ROA_{it} + cap_{it}\right)}{\sigma\left(ROA\right)_{it}}\right) . \tag{1}$$

Hence, *risk* measures profitability and capitalization of a bank relative to the volatility of its returns (profitability), a higher value indicating higher bank risk-taking. We winsorize the risk variable 1% in each tail. *risk* shows, on average as well as for the median bank, a slight increase in bank risk after the financial crisis with a peak in 2011 (Figure 2). The distribution of the measure is mostly even over time for our sample of banks. Only banks in the 95th percentile of the risk distribution seem to show a slightly different evolution of bank risk. For these banks our risk measure already peaks in 2008 and decreases afterwards.

Control variables

In all estimations we include a vector of variables $X_{b,t}$ to control for time-varying bank-specific characteristics that are other determinants of risk commonly employed in the literature (see e.g. Goetz et al. 2013, Jiang et al. 2017, Ly et al. 2018). For bank size we control with the natural log of total assets, for the business model with the loan-to-assets ratio, for earnings with the return on assets, for management quality with the cost-to-income ratio and as a measure for capital adequacy we use the equity-to-assets ratio (see Table 2 for descriptive statistics and further information related to the control variables).

2.3 Banks' complexity-risk nexus

In this section, we explore the relationship between banks' complexity and their risk. We hypothesize that banks strategically choose to be more complex in order to take more risks. Hence, we expect a positive relationship between the two measures.

In order to set up our empirical approach, we investigate whether to account for time fixed effects only, or whether a specification that additionally uses bank fixed effects would be more suitable. Our main independent variables, i.e. measures of complexity, show a limited variation over time. Accordingly including bank fixed effects may eliminate too much of the variation in complexity, leading to an underestimation of coefficients (Zhou 2001). To select the preferable empirical set up we follow the approach of Berger et al. (2017) and conduct two tests. For the first one, we compute the within variation (i.e. the standard deviation of complexity by bank across years and then take the average across all banks) and the between variation of complexity variables (i.e. the standard deviation of complexity by year across banks, and then take the average across years). A comparison of the two variation measures shows that between variation is larger by factors of between 3.2 and 8.8. The second test looks at the serial correlation of complexity. As the within-bank variation in all complexity measures is not very large, including bank fixed effects may reduce the power to detect an effect if one exists. For relevant complexity measures the serial correlation coefficient is between 0.82 and 0.99, suggesting that including bank fixed effects is not appropriate.

Based on the results of those two tests, we choose to work further with the specification including time fixed effects, but excluding bank fixed effects. To investigate the relationship between bank complexity and bank risk, we estimate the following equation:

$$risk_{i,t} = \alpha + \beta \cdot \ln CX_{i,t-1} + \gamma \cdot X_{i,t-1} + f_t + \varepsilon_{i,t} \tag{2}$$

This specification relates the measure of bank risk $risk_{it}$ to the natural logarithm of measures of bank complexity, lagged by one period, CX_{it-1}. For the empirical analysis we take the log of the complexity variables in order to account for the skewed distribution of these variables. The vector X_{it-1} contains different sets of lagged control variables that are possibly related to bank risk. As these risk determinants may be correlated with measures of bank complexity, they may capture the effect of complexity and vice versa. f_t denotes time fixed effects accounting for general macroeconomic developments affecting all banks to the same degree. Robust standard errors are clustered by bank. We run the regression separately with and without controls.

Estimation results for equation (2) are summarized in Table 3 for estimations excluding bank controls (Panel A) and including controls (Panel B). We find a positive and statistically significant relationship for all of our complexity variables in terms of our measure of bank risk. Thus, as complexity is stickier than risk-taking, we argue that more complex banks tend to take higher risk. The economic significance of the positive relationship that we find is only meaningful in the cross-section, as annual within changes (positive as well as negative) of bank complexity rarely exceed two percent. In the cross-section a 10 percent higher complexity is on average associated with higher risk of between about 1.6 and 3.9 times the standard deviation of our *risk* measure. Beyond that it is notable that, when including bank fixed effects in the above regressions, the coefficient estimates of CX_{it-1} remain highly statistically significant, but are considerably smaller in size. While this further speaks in favor of the existence of an actual complexity-risk nexus, there is no economic significance in this result.

Banks' complexity-risk nexus over time

Our sample period is marked by the deployment of the post-crisis regulatory reforms. In the wake of the global financial crisis of 2007/08 regulatory authorities announced a comprehensive program of financial regulatory reforms to increase the resilience of banking systems. The reforms' various objectives included making financial institutions more resilient and ending too-big-to-fail (TBTF). Therefore, we explore whether banks' complexity-nexus varied over the roughly ten years covered by our sample period. To do so we estimate regression equation (2) with a rolling time window of three years.[10] Plots of the time-variant coefficient estimates for each complexity measure are provided in Figure 3.

For all complexity measures alike, we observe an increase in the complexity-risk nexus in the years preceding the global financial crisis, followed by a decrease and subsequent increase in the years thereafter. These dynamics may be related to the stages of the financial cycle as during a boom complexity allows banks to take on more risks while during a downturn the materialization of risk affects all banks irrespective of their complexity. However, regulatory tightening may also have constrained banks' ability to engage in more risk-taking. The uptick in banks' complexity risk nexus observable for the latest years in the sample stems from more banks showing lower values for risk-taking and thereby aligning lower complexity and lower risk-taking.

2.4 Post-crisis changes in bank regulation

The global financial crisis of 2008/2009 was followed by a substantial overhaul of the bank regulatory framework. In particular regulatory capital requirements for banks were increased with respect to quality and quantity. We specifically look at changes in capital regulations as some of

[10] Time window of two years shows very similar dynamics.

these explicitly increase with bank complexity. Yet the framework for tackling the too-big-to-fail problem comprises additional standards for higher loss absorbency, for higher supervisory scrutiny, as well as policies to improve the resolvability of banks. Accordingly, all banks designated as systemically important banks (SIBs) operate in a regulatory environment different to the one prior to the regulatory reforms, as well as compared to other, non-systemically important banks. In the empirical analysis we account for this difference with a simple dummy variable SIB which equals one for all banks assessed as systemically important by regulators in 2016 and is zero otherwise. We further explore the implications of bank capital requirements below.

Bank capital-related regulatory reforms

As to bank capital requirements public announcements of changes were made beginning in 2010. The first announcement about the new Basel III regulatory framework was published at the end of 2010 (BCBS 2010) and contained detailed information on some capital buffers that were to be applied equally to all banks. Then, in October 2011 the European Banking Authority (EBA) published its stress test results and imposed additional capital surcharges on 61 European banks, including 13 in Germany. These surcharges were to be fulfilled by the middle of the following year already, and these particular requirements are shown to have affected banks' operations significantly (Gropp et al. 2019). In 2012 a G-SIB buffer of 2.5% for Deutsche Bank was announced, and its reduction to 2% a year later. In 2014, based on the comprehensive assessment, the ECB imposed bank-specific so-called Pillar 2 capital requirements. These requirements are revised on an annual basis and we consider the Pillar 2 Requirements (P2R; but not the Pillar 2 Guidance (P2G)) part of it as the binding force of the former is comparable to the other requirements considered. In June 2016 the German national supervisor Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) designated 16 banks[11] in Germany as SIBs on the national level and announced that capital buffers of between 0.5% and 2% would be imposed on these institutions. Finally, we also consider small surcharges stemming from requirements for foreign

[11] 14 of these SIBs are part of our sample in this analysis.

exposures in jurisdictions where the Countercyclical Capital Buffer (CCyB) is applicable and that are to be reciprocated.

The upper panel of Figure 4 shows for each year the maximum and the minimum level of capital requirements across our sample of banks. An important feature of our data and analysis is that we care about the moment when the regulatory change was *announced*, rather than the moment when banks actually had to comply with it. We do so in order to consider the implications of regulatory announcements for banks' excess capitalization as follows.

Banks' (excess) capitalization

In general, as one of their business objectives, banks target a specific level of capitalization which gives them some buffer before reaching the minimum capital requirements and thus to account for some downside risk in their business model (Lindquist 2004, Memmel and Raupach 2010). Bank capital regulation has been shown to be a determinant of little importance for these time-invariant capital levels that are specific to each bank (Gropp and Heider 2010). Other evidence points toward the relevance of excess capitalization for banks' operations (Gambacorta and Mistrulli 2004) and that banks, in fact, target their level of excess capitalization (De Jonghe et al. 2020). This leads us to argue that banks choose a certain level of capitalization beyond what is required by regulations.

While regulatory interventions may be not binding in the sense that increases in requirements are higher than a bank's excess buffer, any increase in regulatory requirements will move a bank away from its strategic capitalization target. We proceed to argue that announcements of future regulatory capital requirements represent deviations from banks' target capital levels and therefore cause banks to adjust their operations in order to return to those levels prior to the announced regulatory changes.

Our variable capturing banks' excess capitalization ($Xcap$) is computed as the difference between banks' actual level of Tier 1 capital and the bank and time specific announced capital requirements a bank faces.[12] To reduce the effect of possibly spurious outliers, we winsorize the variable 1% in each tail. The lower graph of Panel A in Figure 4 shows how excess capital ($Xcap$) varies across our sample banks and over time. We observe indeed substantial cross-sectional variation in banks' excess capitalization and that banks tend to increase their level of excess capital from 2010 onwards. As there are numerous potential reasons for changes in banks' excess capitalization, we need to ensure for our analysis that a substantial part of the variation in $Xcap$ stems from changes in capital requirements. Panel B of Figure 4 shows how changes in capital requirements relate to changes in banks' excess capitalization. The downward sloping line is the linear fit and almost matches a 45° line. The correlation coefficient is 0.75 and highly significant. This shows us that from 2010 onwards changes in banks' excess capitalization are for the most part determined by the announcements of changes in regulatory capital requirements.

In the sections below we further investigate the relationships between regulation, bank complexity and bank risk.

3. Theoretical arguments and hypotheses development

In order to understand the drivers behind the reduced relationship between bank complexity and risk, we start with the theoretical framework. Both theoretical and empirical studies suggest that banks face different trade-offs when choosing their level of complexity. They take into account benefits like economies of scope, efficient liquidity management and diversification benefits. At the same time they face costs such as costs of managing their complex structures, agency costs, and regulatory costs.

In this paper, we focus on the trade-off between the regulatory costs of complexity and the benefits of bank complexity stemming from organizational and income diversification (Wagner 2010,

[12] We use the Tier 1 capital ratio to calculate banks' excess capital instead of the CET 1 ratio as the latter, while more closely related to the regulatory changes, was introduced only in the later years of our sample period.

Laeven and Levine 2007). The post-crisis regulatory tightenings change this trade-off by raising the regulatory costs of bank complexity. For instance, more capital needs to be posted for banks' equity investments that carry comparatively high risk weights. To reduce the costs of complexity, we expect banks reduce their complexity by selling their affiliates. However, such a reduction in complexity must decrease diversification benefits banks enjoy, and can ultimately lead to the increase in idiosyncratic bank risk. This would imply that regulatory tightening aimed at lowering systemic risk can lead to the increase in banks' idiosyncratic risk (reminiscent of the finding of Wagner 2010).

We examine whether announced regulatory changes, including those addressing TBTF in general as well as capital surcharges that increase with bank complexity more specifically, affect banks' complexity as well as their risk. Our starting point is that banks, when subject to tighter regulatory requirements in the future, change their strategies immediately. We argue that the need to satisfy higher regulatory standards in the future can affect banks' strategic choices of risk and complexity from today. For instance, after the announcement of stricter capital regulation, banks may need or want to increase their capital ratio in the future. This is especially true for banks with a relatively high excess capital buffer, or in other words, banks becoming relatively more capital-constrained. By imposing an immediate constraint on banks, an announcement of higher capital requirements impacts their action as the need to satisfy higher capital requirements in the future calls for an increase in equity, a decrease in assets or a reduction in asset risk. One of the most common immediate reactions among banks is the adjustment of asset risk (Imbierowicz et al. 2018) through rebalancing their portfolio towards assets with lower risk weights (Kim and Santomero 1988).

Based on the literature, we would then expect capital-constrained banks to reduce their regulatory burden by lowering their assets that carry relatively high risk weights, such as risk-weighted assets for equity investments. This is achieved by selling shares in banks' affiliated entities. In other words, regulatory tightening increases the regulatory costs of complexity and incentivizes banks to reduce the optimal level of complexity. Therefore, we formulate the following two hypotheses:

H1a: Regulatory tightenings lead to a reduction of bank complexity.

H1b: Regulatory tightenings lead to a reduction of risk-weighted assets for equity investments.

Furthermore, we aim to establish the ultimate effect regulatory tightening on bank risk. Let us consider two effects of more stringent capital regulation on bank risk. Higher capital requirement reduces banks' incentives to take risk (Furlong and Keeley 1989, Rochet 1992). Bank shareholders are protected by limited liability and have access to the safety net; therefore they enjoy the upside returns and do not internalize asset losses fully. This encourages risk-taking (Kane 1989, Cole et al. 1995). A higher level of capital, however, exposes shareholders to more downside risk and thus reduces risk-taking.

However, some studies show that stricter capital regulation leads to higher bank risk-taking. First, higher capital requirements can lead to lower profits, which in turn reduce banks' franchise value defined as the stream of future profits. Lower franchise value decreases the shareholder value that can be lost in case of low asset returns and thus induces risk-taking incentives. This can undermine the main effect of capital regulation (Hellman et al. 2000, Repullo 2004). Second, Blum and Hellwig (1995) argue that the anticipation of tomorrow's capital requirements may enhance excessive risk-taking today. Based on the previous empirical literature (Imbierowicz et al. 2018), we expect the risk reduction effect of regulatory tightening to be reflected in the following hypothesis:

H2: Regulatory tightening disincentivizes bank risk-taking.

Next, we are interested to see how regulatory tightening affects not just bank complexity, but banks' ability to diversify and thus reduce risk. Banks with affiliates in different locations as well as business areas tend to take less risk (Krause et al. 2016, Goetz et al. 2016). Therefore, one could be concerned that those banks reducing complexity due to regulatory tightening may reduce their diversity and income diversification. On the other hand, banks may be incentivized to reduce their risk (Furlong and Keeley 1989, Rochet 1992) by carefully getting rid of some affiliates while keeping those that provide diversity of bank operations. We summarize these arguments in the following hypothesis:

H3: Regulatory tightening reduces the diversification benefits stemming from complexity.

We argue though that more complex banks (such as on average SIBs) are better equipped to retain diversity as well as diversification benefits and thus reduce their idiosyncratic risk. First, it is easier for a complex bank to retain diversification after shedding off some of its affiliates when it has a large number of affiliates across multiple business areas than for less complex banks with just a few affiliates. Second, the marginal diversification benefit of a more complex bank is smaller; hence giving up one affiliate does not have a big effect on the diversification gains.

Given that we expect the reduction in diversification benefit stemming from complexity, we expect that:

H4: Changes in bank complexity, when attributed to regulatory tightenings, lead to more risk-taking.

4. Empirical analysis of bank complexity, bank risk, and regulation

In this section we proceed to explore empirically the role of changes in bank regulations, in particular capital requirements and regulations addressing TBTF, for bank complexity and bank risk-taking, and thus for the complexity-risk nexus. Two different regulatory treatments are explored: first banks' excess capitalization $Xcap$, and second the distinction between SIBs, which are subject to TBTF regulations, and other banks (see section 2.4 for details on regulatory changes and how we capture them). We start with investigating the relationship between regulation and bank complexity (4.1), then between regulation and bank risk-taking (4.2), and finally we explore how bank complexity affects the implications of tighter regulations for bank risk (4.3).

4.1 Regulation and bank complexity

Beginning in 2010 regulators announced regulatory tightenings that banks had to comply with in the future. We argue that, upon becoming aware of future regulations, banks immediately start making strategic decisions in order to deal with the new regulatory costs. As to capital surcharges, banks start taking strategic adjustment decisions with the aim of rebuilding their target capital buffers as they already feel capital-constrained at the moment of the announcement. Banks' strategic decisions in response to regulatory tightenings and unexpected deviations from their target capitalization may also affect their organizational structures, and therefore have implications for bank complexity. To explore the relationship between changes in regulation and bank complexity, we estimate versions of the following set of difference-in-differences (diff-in-diff) type regressions, where the dependent variable $\ln CX_{i,t}$ is the natural log of bank *i*'s complexity in year *t*, and we estimate the equations for each of our complexity measures. We start with:

$$\ln CX_{i,t} = \beta \cdot \left(post_t \cdot Xcap_{i,t-1} \right) + \alpha \cdot Xcap_{i,t-1} + f_i + f_t + \varepsilon_{i,t} , \tag{3a}$$

where $Xcap_{i,t}$, as the difference between a bank's current capitalization and the known future capital requirements, is our treatment variable with continuous treatment intensities. $post_t$ is a dummy that equals one for the years 2011-2017, i.e. the part of our sample period where regulatory tightenings were announced, and zero for the years 2005-2010. Distinguishing these two sub-periods is of crucial importance as only during the former period are changes in banks' excess capitalization associated with changes in capital requirements (see Section 2.4 and Figure 4).

As our second treatment variable we introduce SIB_i which is a dummy variable that equals one for all banks designated as SIBs. We estimate the following regression:

$$\ln CX_{i,t} = \delta \cdot \left(post_t \cdot SIB_i \right) + f_i + f_t + \varepsilon_{i,t} , \tag{3b}$$

where the coefficient estimate for δ provides us with the differential effect for those banks deemed systemically important, and therefore being subject to regulatory measures addressing TBTF.

Finally, in eq. (3c), we account for the distinct implications of capital surcharges for SIBs by augmenting eq. (3b) with an additional interaction term for capturing banks' capital constraints:

$$\begin{aligned}\ln CX_{i,t} = {} & \delta\cdot\left(post_t\cdot SIB_i\right)+\gamma\cdot\left(Xcap_{i,t-1}\cdot post_t\cdot SIB_i\right)\\ & +\beta\cdot\left(post_t\cdot Xcap_{i,t-1}\right)+\chi\cdot\left(Xcap_{i,t-1}\cdot SIB_i\right)\\ & +\alpha\cdot Xcap_{i,t-1}+f_i+f_t+\varepsilon_{i,t}\end{aligned} \quad . \tag{3c}$$

Of primary interest for us is δ as the difference-in-discontinuities (diff-in-disc) estimator.[13] The diff-in-disc estimator provides us the differential effect of being a SIB during the years when regulatory requirements were increased and compared to non-SIBs and when controlling for banks' excess capitalization. γ provides the differential effect of SIBs' capital surcharges.

In all regressions we include bank-fixed effects f_i in order to capture banks' average reaction by focussing on the within variation. The within estimation further allows us to "bake in" banks' reactions, for instance their choice to deleverage and/or ability to rebuild capital in order to move back to the individual target capitalization. f_t are time fixed effects capturing unobserved year-specific shocks. The main terms, $post_t$ in eq.(3a) and $post_t$ and SIB_i in eqs.(3b) and (3c), are subsumed in the bank and time fixed effects, which is why we can solely interpret the differential effect of the interaction term.

In line with our hypothesis H1a we expect $\beta > 0$ in eq. (3a), $\delta < 0$ in eq. (3b), and $\delta < 0$ as well as $\gamma > 0$ in eq. (3c), as these outcomes would indicate lower bank complexity following a tightening of regulations.

[13] See Grembi et al. (2016) for some econometric foundations of the difference-in-discontinuities approach, and an empirical application in the context of policy evaluation.

Estimation results are shown in Table 4. Panel A presents results as to eq. (3a). In most cases the coefficient estimate for β is positive and significant while the estimate for α is negative and significant. Regarding β, note that other coefficient estimates are only borderline insignificant. Estimation results therefore indicate that during the earlier years of our sample period banks on average have lower complexity in years following higher excess capitalization. A one pp. higher excess capitalization is on average associated with 1-2% lower complexity in the following year, depending on the specific measure. This is economically significant given the low within variation in complexity in our sample. But this relationship changes beginning in 2011, when banks learn they will be slapped with higher capital requirements over the following years. The positive coefficient estimate of the interaction term indicates a reversal of the relationship during the latter period. Now banks have lower complexity following the years they were more capital-constrained. From 2010 on the average annual change in capital requirements has been 0.73 pp with a standard deviation of 1.82 which underlines the economic significance of the results.

Results related to eq. (3b) are presented in Panel B of Table 4 and show that SIBs have a significantly lower complexity in the later years and compared to other banks. Estimation results are about the same when additionally controlling for banks' excess capitalization $Xcap_{i,t}$ (Panel C of Table 4). SIBs' excess capitalization only seems to matter with regard to the number of affiliated entities abroad (columns (2) and (4)). All estimation results are robust to the exclusion of bank fixed effects, the inclusion of bank group fixed effects, and different time lags of $Xcap_{i,t}$.

Our results are strongest for those complexity measures that capture organizational structures including bank affiliates (i.e. columns (3), (4), (5), (6) and also (8)). According to prevailing expert views, affiliated banks account for a substantial higher share in risk-weighted assets in banking organizations than other non-bank or non-financial affiliates, as their balance sheets are substantially larger than those of other affiliated entities. This makes bank affiliates relatively more expensive when capital requirements are tightened. Accordingly, banks seem to be more eager to reduce bank affiliate-related organizational complexity when being capital-constrained,[14] possibly shifting activities to less regulated entities (Demyanyk and Loutskina 2016). In contrast, the results are weakest – in terms of significance and size of coefficients – for complexity measures capturing geographic complexity beyond banking (i.e. *span_location* and *count_foreign* in columns (1) and (2)). This may be due to other incentives for geographic complexity, for instance related to taxes and regulations abroad (Houston et al. 2012) or requested by clients. Home country regulation has also been shown to incentivize increased activity abroad (Ongena et al. 2013).

Note that the set of estimations in this section of the paper may well suffer from an omitted variable bias. While other studies have also shown regulations to be an important determinant of bank complexity (see e.g. Chernobai et al. 2020, Correa and Goldberg 2020) the role of other factors, for instance business models and path dependencies, is unknown. We do not know why some banks become complex and others do not. Therefore, we are unable to control appropriately for relevant determinants, and because determinants of complexity are not well understood we cannot even infer the direction of the bias to which we may be subject. Further, this leads to the R-squared of the regressions being excessively low.

Overall, we find our hypothesis H1a confirmed and conclude that post-crisis regulatory reforms are followed by a significant decrease in banks' complexity. This is in line with findings of FSB (2020) as well as Correa and Goldberg (2020) showing that – for an international and a US sample of banks – post-crisis regulations were successful in providing incentives to downsize. Banks in Germany reduced their complexity in response to regulation, and these reductions are more pronounced for those complexity measures related to business complexity as well as to bank affiliates, and less pronounced for measures related to geographic complexity. We argue that banks chose their complexity by making a trade-off between (regulatory) costs and (diversification) benefits. As regulatory tightenings increase costs and therefore incentivize a reduction in bank

[14] Ideally, we would proceed to explore further the balance sheets of banks' affiliated entities and their share in the banks' assets, but unfortunately data limitations prevent us from doing so.

complexity, we proceed to explore how regulatory changes affected the costs associated with bank complexity.

Complexity-related costs

We have just shown that banks decrease their complexity in response to regulatory tightenings. Reducing complexity directly changes banks' risk exposure, and thus the associated regulatory costs. Banks' equity investments carry relatively high risk weights compared to other assets. Therefore, selling off equity investments reduces the risk-weighted asset density of banks' assets, thereby increasing the capitalization required against risk-weighted assets. In order to explore the changes in risk-weighted asset densities induced by the regulatory tightenings, we estimate versions of eqs.(3a)-(3c), yet with the following two variables on the left-hand side:

- Risk-weighted assets for equity investments to total risk-weighted assets ($RWAequ/RWAtot$), and
- Risk-weighted assets for equity investments to total assets ($RWAequ/TA$).

In line with our hypothesis H1b we again expect $\beta > 0$ in eq. (3a), $\delta < 0$ in eq. (3b), and $\delta < 0$ as well as $\gamma > 0$ in eq. (3c), as this would indicate a lower risk-weighted asset density for bank equity investments following a tightening of regulations. Estimation results are presented in Table 5. We observe that in the more recent years risk-weighted asset densities for banks' equity investments are significantly lower for SIBs compared to other banks and compared to the earlier years (negative and mostly significant coefficient estimate for $post \cdot SIB$). This holds for the risk-weighted assets' density as to equity investments relative to total risk-weighted assets (columns (1)-(4)), as well as relative to total assets (columns (5)-(8)), and this relationship is slightly mitigated by higher excess capitalization.

Recall that banks in particular have reduced their bank-related complexity. Furthermore, we examine how the overall change in bank-related complexity between 2009 and 2017 is associated with the changes in our regulatory cost measures over the same period. Simple correlation analyses show that the higher the reduction in *count_bank*, the higher the reduction in regulatory costs as confidence intervals indicate the relationship being different from zero in this range (see Figure 5).

4.2 Regulation and bank risk-taking

Regulatory tightenings may have changed incentives for banks' risk-taking. On the one hand, banks may have increased their risk-taking in order to compensate higher regulatory costs with higher returns. On the other hand, banks may have reduced their risk – for instance, SIBs may have reduced their risk-weighted assets' densities – probably in order to reduce the capitalization required by regulators relative to their assets. To investigate the relationship between regulatory tightenings and banks' risk-taking, we estimate versions of the following set of regressions, mimicking the estimation sequence of the previous section:

$$risk_{i,t} = \beta \cdot \left(post_t \cdot Xcap_{i,t-k} \right) + \alpha \cdot Xcap_{i,t-k} + X_{i,t-1} + f_i + f_t + \varepsilon_{i,t}\,, \tag{4a}$$

and

$$risk_{i,t} = \delta \cdot \left(post_t \cdot SIB_i \right) + \alpha \cdot Xcap_{i,t-1} + X_{i,t-1} + f_i + f_t + \varepsilon_{i,t}\,, \tag{4b}$$

and

$$\begin{aligned} risk_{i,t} &= \delta \cdot \left(post_t \cdot SIB_i \right) + \beta \cdot \left(Xcap_{i,t-1} \cdot post_t \cdot SIB_i \right) + \chi \cdot \left(Xcap_{i,t-1} \cdot SIB_i \right) \\ &+ \lambda \cdot \left(post_t \cdot Xcap_{i,t-1} \right) + \alpha \cdot Xcap_{i,t-1} + X_{i,t-1} + f_i + f_t + \varepsilon_{i,t} \end{aligned}. \tag{4c}$$

The dependent variable $risk_{i,t}$ is again the natural log of bank *i*'s inverse z-score in year *t* (see eq. 1). $X_{i,t}$ is the set of bank-specific controls including variables for banks' size, business models, earnings and management quality. All other variables are defined as in the regressions in the previous section. $Xcap_{i,t}$ enters the regressions with $k \in \{1,2\}$ lags. We again include bank-fixed effects f_i in order to capture banks' average reaction by focusing on the within-variation. Main terms $post_t$ and SIB_i are subsumed in the time and bank fixed effects, respectively.

In line with our hypothesis H2 we expect $\beta > 0$ in eq. (4a), and $\delta < 0$ in eqs. (4b) and (4c) as this would indicate that banks take less risk when facing a regulatory tightening. Table 6 presents the estimation results.

We do not observe a significant relationship between being capital-constrained and risk-taking during the $post_t$ -period (see columns (1)-(2)). Yet the negative and significant coefficient estimates for the interaction $post_t \cdot SIB_i$ (columns (3)-(4)) indicate that SIBs show significantly lower risk-taking during the latter years of our sample and compared to other banks. This also holds when testing for the additional interaction with *Xcap* (columns (5) and (6)). We do not find a significant effect of capital requirements, though. This may be due to the relatively small related capital surcharges (between 0.5 and 2%) that are mostly below the average change in capital requirements between 2010 and 2017 (which is 1.8 pp). Further, while the actual capital surcharges related to systemic importance were only announced in 2012 and 2016, in 2010 the writing was already on the wall that TBTF would come into the crosshairs of future regulation, going even further than capital surcharges. Our estimation results indicate that the overall package of regulations aiming to reduce the TBTF indeed contributed to reducing the TBTF problem for our sample of banks and our measure of bank risk-taking. However, note that TBTF-related regulatory changes as well as capital surcharges were accompanied by other regulatory changes that may not be independent of banks' risk-taking under certain circumstances. This includes, for instance, the leverage ratio (Acosta Smith et al. 2017) and the entry into force of the banking union (Haselmann et al. 2020).

At this point we have observed that bank complexity is reduced in response to regulatory tightenings across all banks. Yet SIBs reduce their regulatory costs as well as their risk-taking significantly more than other banks which are not subject to the same regulatory treatment. From this observation the question emerges as to how the complexity-related benefits emerge in response to the regulatory tightenings, and whether SIBs show a significantly different response.

Banks' diversification

The choice of a bank to reduce its organizational complexity in response to regulatory tightenings may be associated with a reduction in banks' associated diversification benefits. Benefits of bank complexity relate to diversification, across countries as well as across financial sectors. To explore how regulatory tightenings affected banks' diversification we distinguish between organizational and income diversification.

To capture the banks' organizational diversification, we construct the normalized Herfindahl-type indices (following Goldberg and Meehl 2019). The dispersion of affiliate business types within a bank and across countries is computed as $CHHI = \frac{CountC}{CountC - 1}\left(1 - \sum_{c=1}^{C}\left(\frac{count_c}{\sum_{c=1}^{C} count_c}\right)^2\right)$, and across (financial) business types $BHHI = \frac{CountB}{CountB - 1}\left(1 - \sum_{b=1}^{B}\left(\frac{count_b}{\sum_{b=1}^{B} count_b}\right)^2\right)$, where $CountC$ ($CountB$) is the number of countries (business types), and $count_c$ ($count_b$) the number of a bank's affiliates per country (business type). $CHHI$ and $BHHI$ are zero if all of a banks' entities are in Germany (for $CHHI$) or all entities are in banking (for $BHHI$). Both indices increase as the dispersion of entities across countries and types of business/sectors rises, and both are one if the dispersion is totally equal.

In order to explore how changes in regulations affect banks' organizational diversification, we estimate the usual set of regressions, with $CHHI$ and $BHHI$ as the dependent variables. We estimate this equation including bank fixed effects f_i in order to account for heterogeneity in excess capitalization related to banks' business models. In line with hypothesis H3, we expect $\beta > 0$ in eq. (4a), $\delta < 0$ in eq. (4b), and $\delta < 0$ as well as $\gamma > 0$ in eq. (4c), as this would indicate lower diversification following a tightening of regulations. Results are presented in Table 7.

Estimation results show no relationship between regulatory tightenings and the $CHHI$ (columns (1)-(4)). Nevertheless, note that the overall number of countries where banks are present as well as the overall number of affiliated entities abroad decrease substantially over the sample period. We continue to explore possible determining factors of the change in geographic complexity. We examine characteristics of the countries that banks retrench from, since banks may reduce their complexity in particular in countries with stricter regulation. More specifically, we look at whether the regulatory quality of host countries can be related to banks' decisions to stay there. Using WGI governance indicators (see Kaufmann et al. 2010) we do not observe any indication that banks systematically increase or maintain their international presence in countries with lower regulatory quality.[15]

As to diversification across business areas $BHHI$ we observe a higher dispersion following years with higher excess capitalization in the early years of our sample, but lower dispersion during the later years when excess capitalization is primarily determined by changes in capital requirements (column (5)). SIBs do not differ significantly from other banks as to dispersion across business areas (columns (6) and (7)). Yet when accounting for differences between SIBs and other banks (column (8)) we find a significantly more negative relationship for SIBs during the post-period (negative and significant δ). As the base effect of SIB is subsumed in the bank fixed effects, the initial difference between SIBs and other banks is unclear and we cannot infer the direction of the impact. The graphical representation in Figure 6 sheds light on this.

The graphs compare the average $BHHI$ across groups of banks before regulatory changes (in 2009) and afterwards (in 2017). While organizational diversification is higher and increases with lower bank complexity, SIBs (indicated by 1) increase their diversification across business types more than other banks (indicated by 0). Yet SIBs' overall level of diversification remained significantly lower. This means that SIBs, while reducing their complexity more than other banks,

[15] Estimation results not provided but available upon request.

at the same time increase their diversification across business types more than other banks. This relationship is moderated by higher excess capitalization (positive beta coefficient estimate of the triple interaction term), possibly because higher capitalization represents an alternative to reduce bank risk. The average $Xcap$ in the post-period among SIBs is 5.4%.

In order to understand better the role of different kinds of affiliated entities for organizational diversification we run simple regressions relating the share of banks, of non-bank financial entities and non-financial entities in total affiliated entities to the $BHHI$.[16] Regression results show that a higher share of non-bank financial entities is positively related to organizational diversification for all banks, but significantly more so for SIBs. This happens against the background of an increasing average number of sectors that a strongly declining number of non-bank financial entities of SIBs stretch across. It may be easier to manage these changes and to expand in new business areas for SIBs due to their size and experience of working in many business areas. We see these changes in the share of non-bank financial entities as the main driver of the increase in $BHHI$ for SIBs. As for the share of non-financial entities, it decreases for both SIBs and other banks during the regulatory tightening. However, our regression results show that its reduction is related to the increase in organizational diversification for SIBs but not for other banks. A higher share of bank entities is associated with higher organizational diversification for SIBs, but with lower for other banks. During the regulatory period the share of bank entities slightly declines on average both for SIBs and other banks thus driving the $BHHI$ of SIBs down and $BHHI$ of other banks up. It appears that this effect cannot explain the increase in organizational diversification for SIBs we observe. Thus, while reducing the number of their entities, banks on average shift from non-financial business areas and banking towards financial non-bank businesses. In spite of the differences in business models, banks on average seem to follow the same strategy during the

[16] Regression results not shown but available from the authors upon request.

regulatory tightening, however the contribution of these changes towards organizational diversification is different.[17]

Note that our measures for organizational diversification suffer from the drawback of not considering the span of countries and sectors covered, but focus on how balanced the distribution of affiliated entities is across sectors. This may lead to distorted figures against the background of decreasing complexity over time (see Figure 1). Thus, to further explore implications for diversification and to fortify our findings, we proceed by conducting the same empirical exercise for income diversification. As measures for income diversification, we use the

- Ratio of net non-interest income to total operating income (*NNII*), and the
- Ratio of trading income to total operating income (*TRAD*).

With these ratios as dependent variables we estimate the usual set of regressions. Estimation results are in Table 8.

We observe a significantly higher income diversification for SIBs during the later period of our sample and compared to other banks. This is surprising as in particular SIBs reduced their complexity and their risk weighted assets density from equity investments. Yet this confirms our previous results as to organizational diversification. In order to understand the overall effect (in addition from the differential in the regression output) we compile a graph to inspect visually the average income diversification in 2009 and in 2017 across SIBs and other banks (see Figure 7).

For both of our measures we observe a large increase in income diversification for SIBs over the years. For other banks, in contrast, average income diversification hardly increases (*NNII*) or even decreases slightly (*TRAD*).

[17] As Cetorelli et al. (2017) argue, such a strategy in response to the regulatory changes as opposed to the generic diversification can increase bank performance.

Pointing in the same direction, organizational and income diversification seem to go hand in hand. Yet simple correlations and regressions do not reveal a direct and simple relationship between our chosen measures. The transmission from organizational changes into profitability is difficult to capture in the current setup, especially without examining affiliates' balance sheet data. To conclude, more complex banks, such as SIBs, manage to reduce their complexity while at the same time increasing complexity-related benefits, i.e. organizational and income diversification. A simple correlation showing that a higher reduction in overall complexity between 2009 and 2017 is significantly related to higher overall profitability for our sample of banks provides some support for this (see Figure 8). Overall this leads to lower risk in these banks.

4.3 Bank regulation and banks' complexity-risk nexus

In order to close the loop, we address in this section the question of whether changes in complexity, when attributable to regulatory changes, affect risk-taking. As we have shown in the previous sections, being capital-constrained does not affect banks' risk-taking, while the overall package of regulations addressing TBTF does. Further, being capital-constrained – be it because of a regulatory change or not – is related to banks' complexity in one way or another. Given these findings, we proceed to explore whether the change in banks' complexity attributed to being more capital-constrained after regulatory changes affects banks' risk-taking. In order to investigate this relationship with respect to capital constraints we estimate the following equation:

$$\begin{aligned} risk_{i,t} &= \beta \cdot \left(\ln CX_{i,t-1} \cdot post_t \cdot low_{i,t-2} \right) + \alpha \cdot \left(\ln CX_{i,t-1} \cdot post_t \right) + \gamma \cdot \left(\ln CX_{i,t-1} \cdot low_{i,t-2} \right) \\ &+ \chi \cdot \left(post_t \cdot low_{i,t-2} \right) + \mu \cdot \ln CX_{i,t-1} + \rho \cdot low_{i,t-2} + \lambda \cdot X_{i,t-1} + f_t + \varepsilon_{i,t} \end{aligned} \tag{5a}$$

The new variable $low_{i,t}$ is a dummy that equals one when a bank *i*'s excess capitalization $Xcap$ in year *t* is below the sample period mean of the same bank. Accordingly, the dummy marks for each bank those observations in the sample where the bank is more capital-constrained. We cannot use the variable $Xcap_{i,t}$ itself for this estimation approach as the preferable specification for the complexity-risk nexus is a random-effects model (see section 2.3), and therefore does not include bank fixed effects. Considering that banks choose their target (excess) capitalization in conjunction with their specific business models (e.g. Memmel and Raupach 2010), an econometric approach relying on cross-sectional variation would not work.

In line with hypothesis H4 we expect $\beta > 0$ in eq. (3a), $\delta < 0$ in eq. (3b), and $\delta < 0$ as well as $\gamma > 0$ in eq. (3c), as this would indicate a lower complexity-risk nexus following a tightening of regulations.

Estimation results (Panel A in Table 9) confirm our previous findings regarding the complexity-risk nexus and the role of banks' excess capitalization. Until 2010 higher complexity is associated with higher risk-taking (positive μ), a relationship that decreases during the later years (negative α). This mirrors the positive but time-varying complexity-risk nexus we observed earlier. The coefficient of our main interest β provides us the differential effect of being more capital-constrained during the later years (where predominantly regulatory changes determine whether a bank is capital-constrained) for the complexity-risk nexus. We observe that β is negative and significant (or borderline insignificant) in most cases (columns (3) to (8)). Hence banks did show a significantly lower complexity-risk nexus after being capital-constrained and during the years when changes in excess capitalization were primarily determined by changes in regulatory requirements.

This indicates that regulatory tightenings – besides being associated with a decline in complexity – further can be associated with a weakening of the complexity-risk nexus.

A difference in the nexus cannot be observed for measures of geographic complexity and considering organizational entities beyond banks (i.e. *span_location* and *count_foreign* in columns (1) and (2)). As in the previous section this may again be related to possible determinants that are inherent in these kinds of geographic complexity, such as differences in regulation and taxation across countries, as well as demand from clients, which make structural changes independent from regulatory changes in the home country. While the statistical significance of these results is borderline, we see them nevertheless pointing in a certain direction: that the regulatory changes are at least to some degree effective.

In the last step and following the usual logic of our empirical analysis, we estimate the following regression in order to explore the differential impact of SIBs for the complexity risk-nexus:

$$\begin{aligned} risk_{i,t} = {} & \beta \cdot \left(\ln CX_{i,t-1} \cdot post_t \cdot SIB_i \right) + \alpha \cdot \left(\ln CX_{i,t-1} \cdot post_t \right) + \gamma \cdot \left(\ln CX_{i,t-1} \cdot SIB_i \right) \\ & + \chi \cdot \left(post_t \cdot SIB_i \right) + \mu \cdot \ln CX_{i,t-1} + \rho \cdot SIB_i + \lambda \cdot X_{i,t-1} + f_t + \varepsilon_{i,t} \end{aligned} \tag{5b}$$

We present our results in Panel B of Table 9. We find the positive complexity-risk nexus confirmed. Also, we observe that this nexus is significantly lower during the later years of our sample. Surprisingly, though, we do not observe a significant difference in this nexus for SIBs. Accordingly, while being capital-constrained makes a significant difference for the nexus, being systemically important does not.

5. Conclusion

We aim to enhance understanding of the notion of bank complexity, a concept already applied in regulation, yet ambiguous as to its drivers and implications, and still under-explored in the literature. We start by exploring the relationship between bank complexity and bank risk-taking for a sample of 84 banks in Germany between 2005 and 2017. We use different measures capturing the geographic and business complexity of banking organizations. We find that, for all those measures, higher bank complexity is associated with higher bank risk. Yet the strength of this complexity-risk nexus changes over time. The nexus is substantially lower for the more recent years that are marked by a comprehensive overhaul of bank regulations, in particular regarding capital requirements. Thus, we explore how these regulatory reforms affect bank complexity and bank risk-taking, as well as banks' complexity-risk nexus. For identification we rely on two different regulatory treatments, one related to capital requirements and another related to TBTF regulation.

We argue that the announcement of regulatory tightenings immediately affects banks' strategic choices and therefore banks' organizational structures and risk-taking.

To understand the underlying dynamics, we develop testable hypotheses and explore the implications empirically. In line with our hypotheses, we find that banks reduce their complexity after regulatory tightenings. This translates to significantly lower risk-weighted asset densities for equity investments, i.e. the regulatory costs of complexity. At the same time banks' organizational and income diversification, surprisingly, did not go down. Moreover, SIBs managed to increase their diversification with regard to their organizational structures as well as to their income despite reducing their organizational complexity. In particular, they reduced the share of their bank entities and non-financial subsidiaries, whereas increased the share of non-bank financial entities and even managed to expand into new financial business areas. Other banks pursued a similar strategy by shifting from non-financial business areas and banking towards non-bank financial areas. However, there may be a concern that although organizational diversification becomes higher for SIBs, the similar shift in banks' portfolios can have negative systemic risk implications (Wagner 2010).

As regards bank risk-taking, we find that it is unrelated to banks' capital constraints, yet SIBs reduce risk significantly in response to regulatory tightening. Such a reduction in risk-taking by most complex financial institutions may indicate those conglomerates' reduced ability to exploit the deposit insurance safety net (as in Freixas et al. 2007). And as the reach of the deposit insurance safety net fades, risk-taking incentives go down whereas the incentives for diversification increase (Dewatripont and Mitchell 2005) as we see is the case of SIBs.

Finally, the overall complexity-risk nexus is significantly lower when banks face increases in capital requirements. Yet this is not different for SIBs.

Our findings bode well for the efficacy of the post-crisis regulatory tightenings imposed on banks. Those banks that regulators deem systemically important have reduced complexity and risk-taking more than others in response to the regulatory tightenings. Stability-impeding features of bank complexity are associated with the possibility of increased benefits in conjunction with organizational changes. While we are confident as to the direction of the impact of changes in regulatory capital requirements, we refrain from assessing the extent of the impact, and do not judge whether systemic risk externalities have been fully internalized. Finally, our work may provide insights for policymakers as to the assessment of banks' systemic importance, where bank complexity is considered, yet based on different measures.

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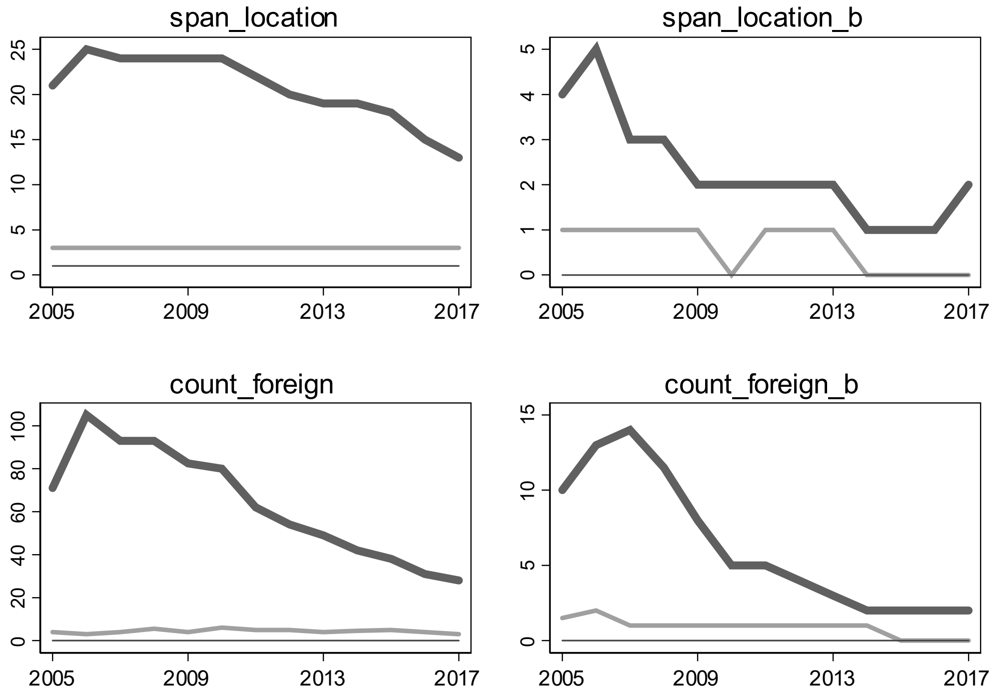
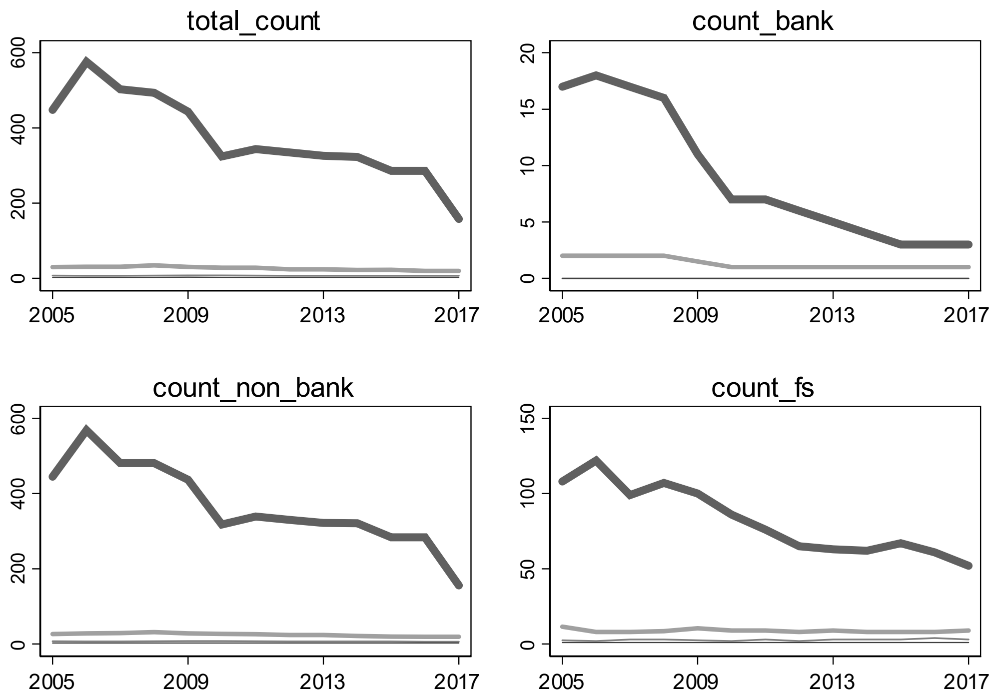
Figure 1: Banks' organizational complexity

Panel A: Banks' geographic complexity



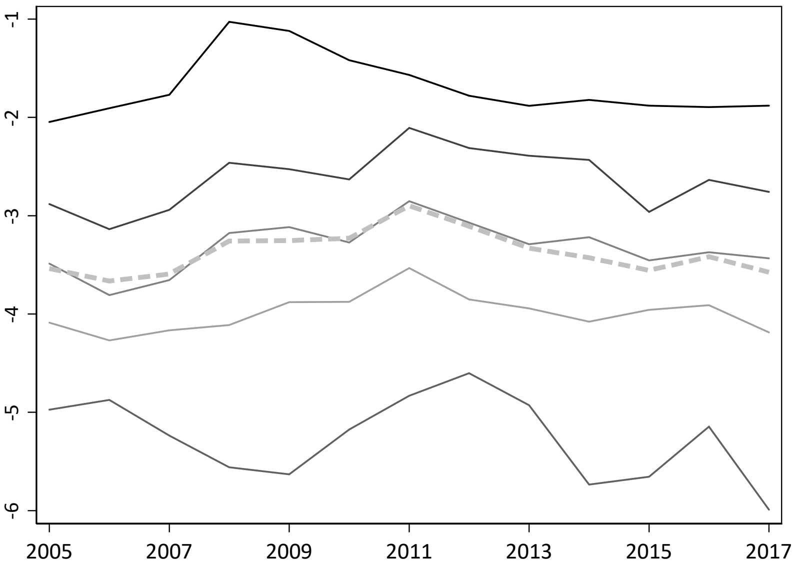
Panel B: Banks' business complexity



The figures shows the 95th, 75th, 50th and, if different from zero, 25th percentile of banks' geographic and business complexity measures for a sample of 84 banks between 2005 and 2017. Thicker lines indicate higher percentiles. The y-axis provides the values of each complexity measure as described in section 2.1 of the paper.

Sources: Bundesbank, authors' calculations.

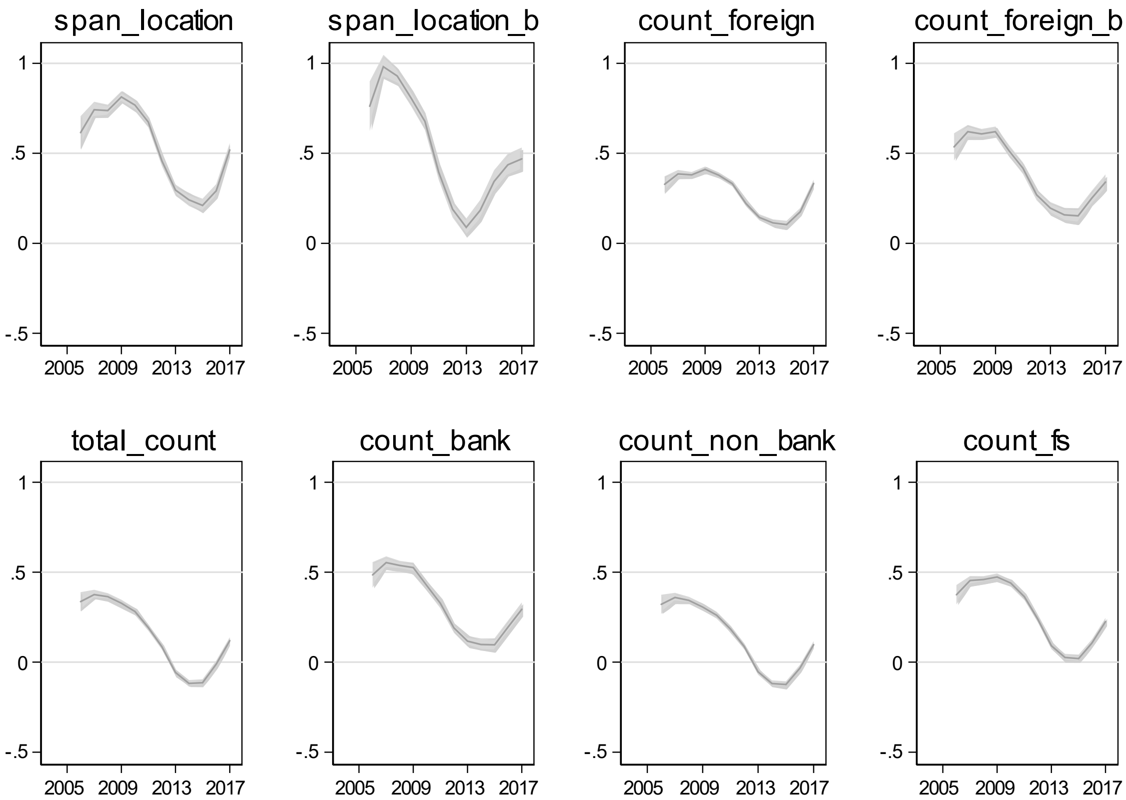
Figure 2: Measure of bank risk



The solid lines show the 95th, 75th, 50th, 25th and 5th percentile of banks' risk per year, measured by our *risk* measure as defined in Section 2.2 from 2005 until 2017 for a sample of 84 banks. Higher values of *risk* indicate higher risk-taking. The bold dashed line shows the average bank risk per year for our sample.

Sources: Bundesbank, authors' calculations.

Figure 3: Time variation of banks' complexity-risk nexus

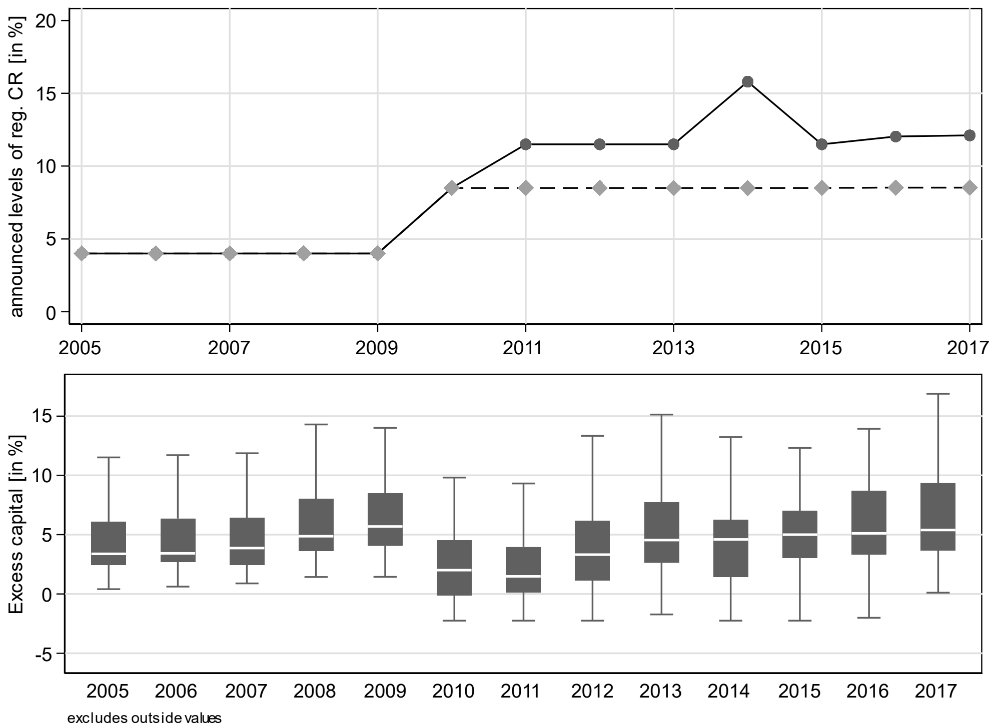


The figures show the time variation of banks' complexity-risk nexus based on estimations of equation (3) for a sample of 84 banks between 2005 and 2017 by complexity measure. The line represents the time-varying coefficient estimate (y-axis) and the grey-shaded area the 95% confidence intervals. The respective complexity variable is given above each graph (see section 2.1 for definitions of all complexity variables), and the risk variable is *risk* as defined in section 2.2 of the paper. The length of the rolling window is three years.

Sources: Bundesbank, authors' calculations

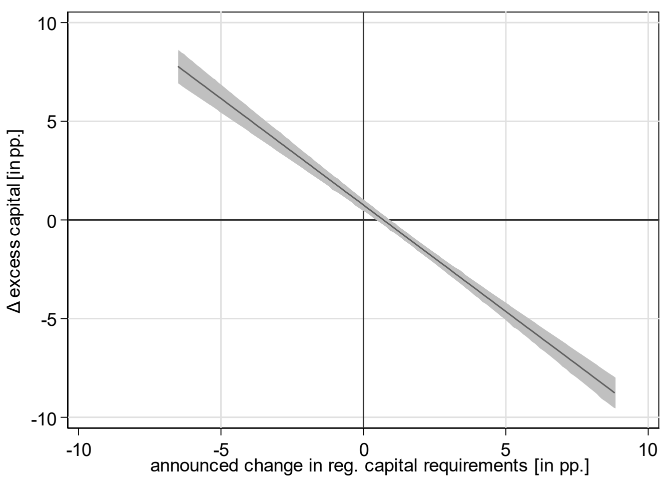
Figure 4: Capital regulation and banks' excess capitalization

Panel A: Levels of capital requirements and excess capitalization



The upper graph shows the 5th and the 95th percentiles of announced levels in regulatory capital requirements across the 84 sample banks per year. The lower graph shows the distribution of these banks' excess capitalization per year.

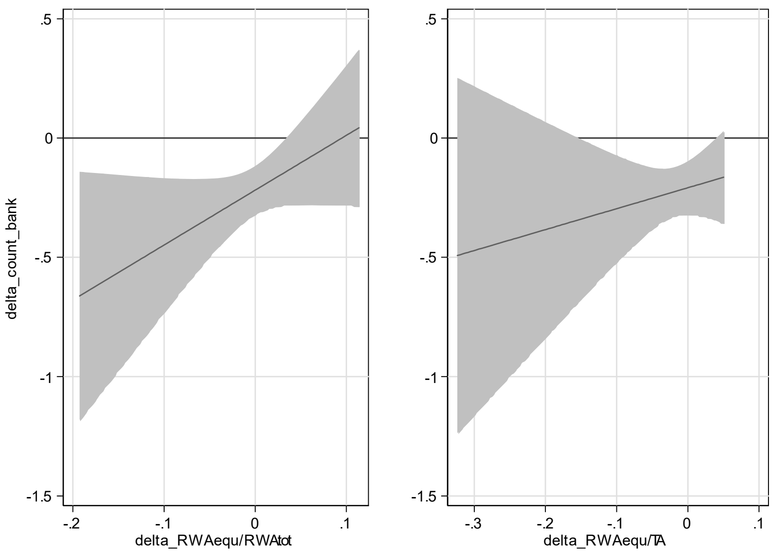
Panel B: Changes in capital requirements and excess capitalization



The graph shows the relationship between announced changes in banks' regulatory capital requirements and annual changes in banks' excess capitalization for the years 2010 to 2017 for our sample of 84 banks. The downward sloping line is the linear fit, the shaded area is the 95% confidence interval. The correlation coefficient is -0.75 and highly significant.

Sources: Bundesbank, authors' calculations.

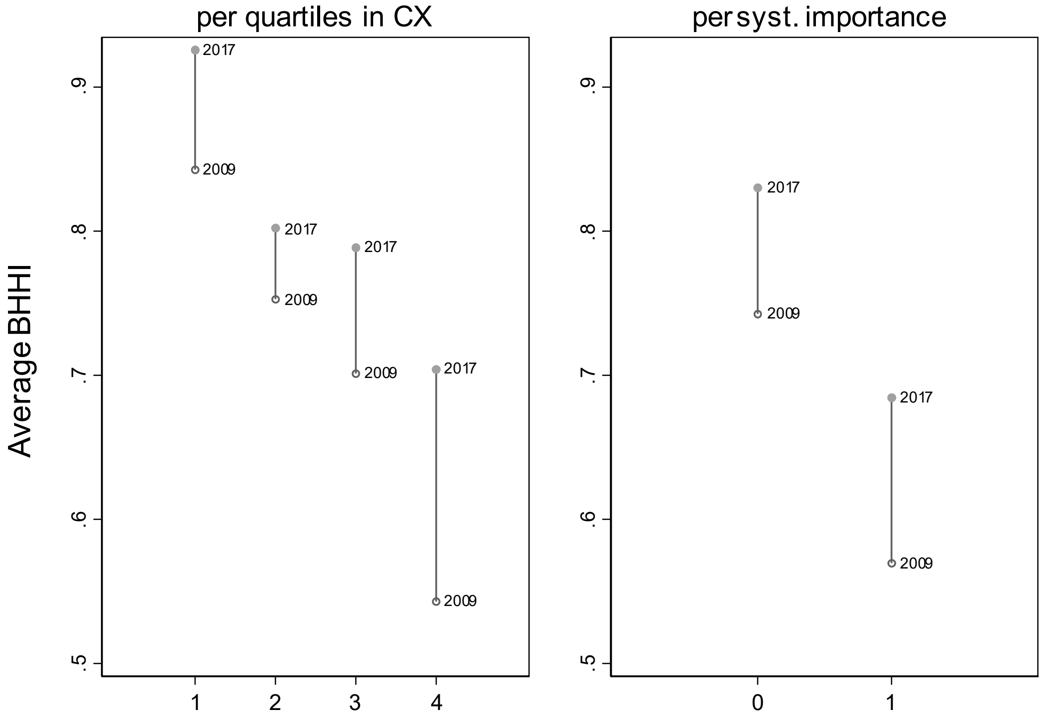
Figure 5: Change in bank organizational structures and regulatory costs



The graphs relate for our sample of 84 banks the difference in the natural log of *count_bank* between 2009 and 2017 (*delta_count_bank*) in percent on the y-axis to the change in *RWAequ/RWAtot* (*delta RWAequ/TWAtot*) (left graph), and to the change in *RWAequ/TA* (*delta_RWAequ/TA*) (right graph) both over the same years and in percentage points. The downward sloping line is the linear fit, and the grey-shaded area is the 95% confidence interval.

Sources: Bundesbank, authors' calculations.

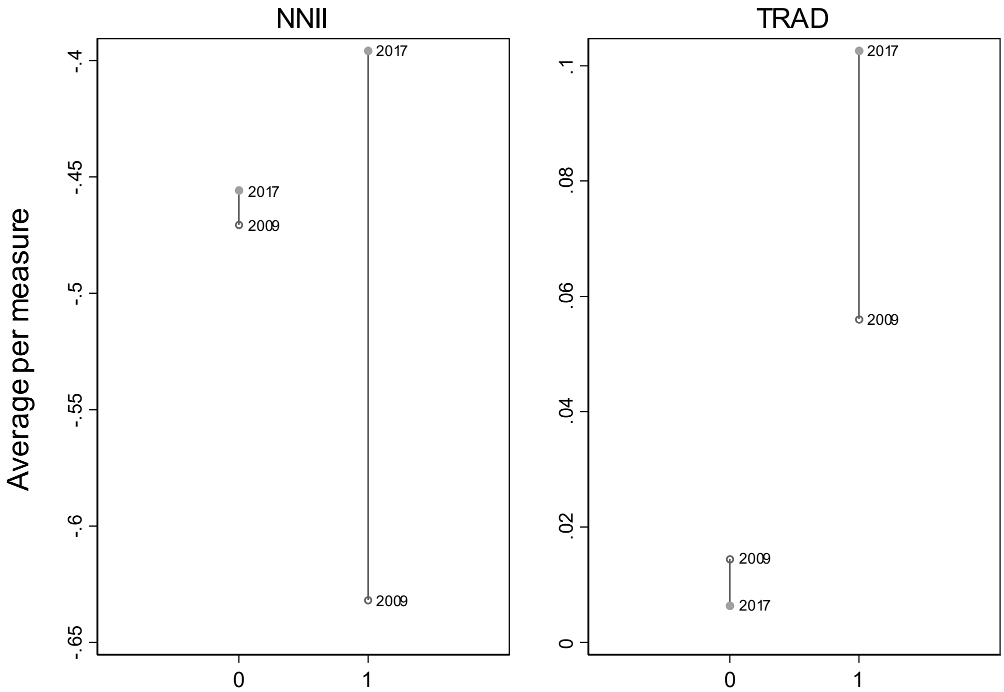
Figure 6: Banks' organizational diversification



The graphs show the change between the average *BHHI* between 2009 and 2017 for different groups of banks. On the left-hand side banks are grouped based on their complexity with 1 marking the least and 4 the most complex banks. On the right-hand side banks are grouped based on their systemic importance with 1 marking SIBs and 0 marking the group of other banks.

Sources: Bundesbank, authors' calculations.

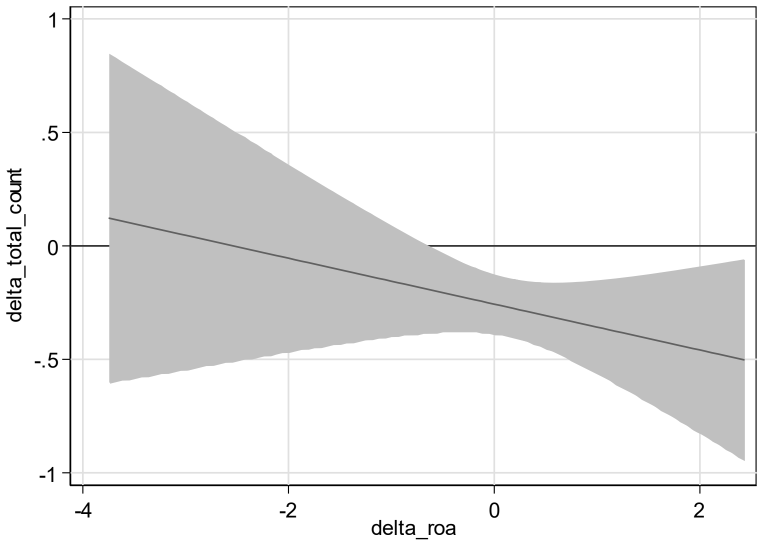
Figure 7: Banks' income diversification



The graphs show the difference in average measures for income diversification between 2009 and 2017 for two groups of banks. Banks are grouped based on their systemic importance with 1 marking SIBs and 0 marking the group of other banks. *NNII* is the ratio of net non-interest income to total operating income and *TRAD* the ratio of net trading income to net operating income.

Sources: Bundesbank, authors' calculations.

Figure 8: Change in organizational complexity and profitability



The graph relates for our sample of 84 banks the change in RoA between 2009 and 2017 (*delta_roa*) in pp. on the x-axis to the difference in the natural log of total_count between 2009 and 2017 (*delta_total_count*) in percent on the y-axis. The downward sloping line is the linear fit, and the grey shaded area is the 95% confidence interval.

Sources: Bundesbank, authors' calculations.

Table 1: Descriptive statistics of complexity variables

This table shows some detailed summary statistics for our main complexity variables *CX* as described in section 3.1. The sample is unbalanced and covers the years 2005 to 2017.

	CX	**# banks**	**# obs**	**Mean**	**S.D.**	**Percentiles**			
						p25	**p50**	**p75**	**p95**
Geographic complexity	span_location	84	945	4.29	8.47	1	1	3	21
	span_location_b	84	945	0.44	1.4	0	0	0	2
	count_foreign	84	945	21.74	115.6	0	0	3	57
	count_foreign_b	84	945	2.33	14.55	0	0	1	5
Business complexity	total_count	84	945	63.18	190.67	3	7	24	343
	count_bank	84	945	2.83	15.4	0	0	1	7
	count_non_bank	84	945	60.4	178.35	3	7	23	336
	count_fs	84	945	24.55	101.48	1	3	8	74

Table 2: Summary statistics and variable information

Measure	Variable		Mean	S.D.	Variable description	Data source
Bank risk-taking	*risk=(-1)*ln(z-score)*		-3.363	1.211	See section 2.2 of the paper.	Regulatory and balance sheet reporting
Bank size	ln(total assets)		23.692	1.349	Natural log of total assets (in €)	Balance sheet reporting
Business model	loan-to-asset ratio		0.674	0.164	Total loans to the non-financial private sector over total assets	Balance sheet reporting
Earnings	return on assets		0.006	0.008	Total net earnings over total assets	P&L and balance sheet reporting
Management quality	cost-to-income ratio		0.623	0.31	Total costs over total earnings	P&L reporting
Capital adequacy	equity/assets		0.057	0.062	Total capital over total assets	Balance sheet reporting
Excess capitalization	*Xcap*: excess T1/RWA	(in %)	5.422	5.412	Tier 1 capital over total risk weighted assets	Regulatory reporting
Capital requirements	*CR*: CR/RWA	(in %)	7.630	2.776	See Section 2.4 of the paper.	Public information and regulatory reporting

Table 3: Banks' complexity-risk nexus

These tables show estimation results from equation (2). Our measure *risk* (as defined in section 2.2) is the dependent variable. Coefficient estimates relate to the respective measure of complexity *CX* that enter the regression as a lagged independent variable in natural logs. For definitions of the complexity variables see section 2.1 of this paper. Standard errors are clustered by bank and robust p-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Regression equation (2) without bank control variables								
	Geographic complexity				**Business complexity**			
CX:	*span_location*	*count_foreign*	*span_location_b*	*count_foreign_b*	*total_count*	*count_bank*	*count_non_bank*	*count_fs*
CX_{t-1}	0.333***	0.212***	0.347***	0.470***	0.207***	0.401***	0.196***	0.264***
	(0.001)	(0.000)	(0.005)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)
R2	0.065	0.070	0.068	0.089	0.075	0.085	0.074	0.080
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	no	no	no	no	no	no	no	no
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank Controls	no	no	no	no	no	no	no	no
Panel B: Regression equation (2) with bank control variables included								
	Geographic complexity				**Business complexity**			
CX:	*span_location*	*count_foreign*	*span_location_b*	*count_foreign_b*	*total_count*	*count_bank*	*count_non_bank*	*count_fs*
CX_{t-1}	0.469***	0.300***	0.315**	0.546***	0.252***	0.459***	0.229***	0.320***
	(0.000)	(0.000)	(0.014)	(0.000)	(0.002)	(0.000)	(0.004)	(0.000)
R2	0.085	0.092	0.087	0.106	0.095	0.102	0.094	0.098
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	no	no	no	no	no	no	no	no
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank Controls	yes	yes	yes	yes	yes	yes	yes	yes

Table 4: Bank regulation and bank complexity

This table shows estimation output related to equations (3a)-(3c). The natural logarithm of the respective complexity measure *CX* is the dependent variable. For definitions of the complexity variables see section 2.1 of this paper. *Xcap* is banks' capitalization in excess of what is required by regulations. *post* is a dummy that equals one for the years 2011 to 2017 and 0 for the years 2005 to 2010. *SIB* is a dummy that equals one for all banks that are designated as systemically important. Standard errors are clustered by bank and robust p-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Estimation results for equation (3a)								
	Geographic complexity				**Business complexity**			
CX:	*span_location*	*count_foreign*	*span_location_b*	*count_foreign_b*	*total_count*	*count_bank*	*count_non_bank*	*count_fs*
$Xcap_{t-1}$	-0.004	-0.004	-0.017**	-0.009**	-0.019***	-0.009**	-0.017***	-0.014**
	(0.113)	(0.162)	(0.013)	(0.014)	(0.000)	(0.011)	(0.001)	(0.031)
post * $Xcap_{t-1}$	0.006	0.010**	0.018**	0.013***	0.014***	0.016***	0.011	0.012*
	(0.108)	(0.045)	(0.012)	(0.007)	(0.009)	(0.002)	(0.116)	(0.064)
R^2	0.030	0.080	0.052	0.156	0.151	0.172	0.127	0.030
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Panel B: Estimation results for equation (3b)								
	Geographic complexity				**Business complexity**			
CX:	*span_location*	*count_foreign*	*span_location_b*	*count_foreign_b*	*total_count*	*count_bank*	*count_non_bank*	*count_fs*
post * SIB	-0.193***	-0.248***	-0.371***	-0.430***	-0.241**	-0.345***	-0.237**	-0.308***
	(0.001)	(0.000)	(0.002)	(0.000)	(0.024)	(0.002)	(0.029)	(0.005)
R^2	0.082	0.113	0.089	0.257	0.153	0.223	0.133	0.057
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes

Panel C: Estimation results for equation (3c)

	Geographic complexity				Business complexity			
CX:	*span_location*	*count_foreign*	*span_location_b*	*count_foreign_b*	*total_count*	*count_bank*	*count_non_bank*	*count_fs*
post * SIB	-0.229***	-0.445***	-0.432**	-0.589***	-0.330**	-0.432***	-0.343**	-0.401**
	(0.006)	(0.000)	(0.024)	(0.000)	(0.039)	(0.002)	(0.036)	(0.014)
post * SIB * $Xcap_{t-1}$	0.007	0.038***	0.014	0.031**	0.021	0.017	0.024	0.020
	(0.338)	(0.001)	(0.452)	(0.040)	(0.141)	(0.226)	(0.119)	(0.187)
SIB * $Xcap_{t-1}$	-0.006	-0.031***	-0.012	-0.030***	-0.004	-0.019	-0.006	-0.013
	(0.481)	(0.005)	(0.542)	(0.009)	(0.780)	(0.102)	(0.685)	(0.393)
post * $Xcap_{t-1}$	0.004	0.004	0.015*	0.008***	0.009	0.013***	0.005	0.008
	(0.301)	(0.396)	(0.052)	(0.009)	(0.127)	(0.003)	(0.540)	(0.235)
$Xcap_{t-1}$	-0.003	-0.000	-0.014*	-0.003	-0.019***	-0.005*	-0.016***	-0.011*
	(0.361)	(0.970)	(0.065)	(0.235)	(0.000)	(0.079)	(0.003)	(0.095)
R^2	0.089	0.140	0.108	0.280	0.188	0.244	0.163	0.069
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes

Table 5: Bank regulation and banks' risk weighted assets

This table shows estimation output related to variations of equations (3a)-(3c). The share of risk-weighted assets for equity investments in total risk weighted assets (*RWAequ/RWAtot*) and the share of risk-weighted assets for equity investments in total assets (*RWAequ/TA*) are the dependent variables. *Xcap* is banks' capitalization in excess of what is required by regulation. *post* is a dummy that equals one for the years 2011 to 2017 and 0 for the years 2005 to 2010. *SIB* is a dummy that equals one for all banks that are designated as systemically important. Standard errors are clustered by bank and robust p-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**RWAequ/RWAtot**				**RWAequ/TA**			
$Xcap_{t-1}$	0.003*		0.002**	0.003*	0.002		0.001	0.002
	(0.050)		(0.023)	(0.051)	(0.178)		(0.166)	(0.141)
post * $Xcap_{t-1}$	-0.001			-0.002*	-0.001			-0.002
	(0.260)			(0.097)	(0.307)			(0.184)
post * SIB		-0.014*	-0.015**	-0.038***		-0.005	-0.006	-0.024***
		(0.100)	(0.044)	(0.003)		(0.280)	(0.161)	(0.001)
SIB * $Xcap_{t-1}$				-0.003				-0.003**
				(0.101)				(0.049)
post * SIB * $Xcap_{t-1}$				0.004**				0.003***
				(0.012)				(0.007)
R^2	0.112	0.041	0.113	0.144	0.175	0.117	0.161	0.194
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank Controls	yes	yes	yes	yes	yes	yes	yes	yes

Table 6: Bank regulation and bank risk-taking

This table shows estimation output related to equations (4a)-(4c). Our measure *risk* (as defined in section 2.2) is the dependent variable. *Xcap* is banks' capitalization in excess of what is required by regulation, and *k* is the number of lags. *post* is a dummy that equals one for the years 2011 to 2017 and 0 for the years 2005 to 2010. *SIB* is a dummy that equals one for all banks that are designated as systemically important. Standard errors are clustered by bank and robust p-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	[eq. 4a] k=1	[eq. 4a] k=2	[eq. 4b]	[eq. 4b] k=1	[eq. 4c] k=1	[eq. 4c] k=2
$Xcap_{t-k}$	-0.014	-0.017		-0.003	-0.006	-0.010
	(0.418)	(0.355)		(0.826)	(0.753)	(0.613)
post * $Xcap_{t-k}$	0.015	0.015			0.011	0.005
	(0.559)	(0.531)			(0.700)	(0.874)
post * SIB			-0.610**	-0.608**	-0.833**	-0.903***
			(0.023)	(0.024)	(0.011)	(0.005)
SIB * $Xcap_{t-k}$					-0.051	-0.061
					(0.184)	(0.107)
post * SIB* $Xcap_{t-k}$					0.041	0.073
					(0.425)	(0.150)
R2 within	0.093	0.095	0.110	0.110	0.114	0.114
Observations	945	873	945	945	945	873
Banks	84	84	84	84	84	84
Bank FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Bank Controls	yes	yes	yes	yes	yes	yes

Table 7: Bank regulation and banks' organizational diversification

This table shows estimation output related to variations of equations (4a)-(4c). The normalized Herfindahl-Hirschman index is the dependent variable for banks' affiliates across countries *CHHI,* or across business types *BHHI*. *Xcap* is banks' capitalization in excess of what is required by regulation. *post* is a dummy that equals one for the years 2011 to 2017 and 0 for the years 2005 to 2010. *SIB* is a dummy that equals one for all banks that are designated as systemically important. Standard errors are clustered by bank and robust p-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**CHHI**	**CHHI**	**CHHI**	**CHHI**	**BHHI**	**BHHI**	**BHHI**	**BHHI**
$Xcap_{t-1}$	-0.004		-0.001	-0.004	0.007**		-0.000	0.007**
	(0.341)		(0.783)	(0.415)	(0.032)		(0.907)	(0.036)
post * $Xcap_{t-1}$	0.004			0.006	-0.011**			-0.013**
	(0.195)			(0.119)	(0.017)			(0.025)
post * SIB		-0.040	-0.039	0.006		-0.003	-0.003	-0.061*
		(0.196)	(0.214)	(0.887)		(0.925)	(0.933)	(0.089)
SIB * $Xcap_{t-1}$				0.005				-0.008*
				(0.480)				(0.081)
post * SIB * $Xcap_{t-1}$				-0.009				0.011*
				(0.125)				(0.077)
R^2	0.012	0.009	0.01	0.02	0.124	0.085	0.085	0.129
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes

Table 8: Bank regulation and banks' income diversification

This table shows estimation output related to variations of equations (4a)-(4c). *NNII* (ratio of net non-interest income to total operating income) and *TRAD* (ratio of trading income to total operating income) are the dependent variables. *Xcap* is banks' capitalization in excess of what is required by regulation. *post* is a dummy that equals one for the years 2011 to 2017 and 0 for the years 2005 to 2010. *SIB* is a dummy that equals one for all banks that are designated as systemically important. Standard errors are clustered by bank and robust p-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**NNII**	**NNII**	**NNII**	**NNII**	**TRAD**	**TRAD**	**TRAD**	**TRAD**
$Xcap_{t-1}$	-0.004*		-0.001	-0.006**	0.000		0.000	-0.000
	(0.082)		(0.707)	(0.045)	(0.447)		(0.995)	(0.637)
post * $Xcap_{t-1}$	0.006*			0.006*	-0.001			0.000
	(0.054)			(0.098)	(0.467)			(0.467)
post * SIB		0.101*	0.101*	0.121		0.048**	0.048**	0.086***
		(0.071)	(0.071)	(0.158)		(0.011)	(0.011)	(0.005)
SIB * $Xcap_{t-1}$				0.006				0.006**
				(0.521)				(0.043)
post * SIB * $Xcap_{t-1}$				-0.003				-0.007**
				(0.717)				(0.029)
R2	0.066	0.070	0.070	0.074	0.068	0.100	0.100	0.113
Observations	935	935	935	935	935	935	935	935
Banks	82	82	82	82	82	82	82	82
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank Controls	yes	yes	yes	yes	yes	yes	yes	yes

Table 9: Bank regulation and banks' complexity-risk nexus

This table shows estimation output related to section 4.4. Our measure *risk* (as defined in section 2.2) is the dependent variable. Coefficient estimates relate to the respective measure of complexity *CX* that enters the regression as a lagged independent variable in natural logs. For definitions of the complexity variables see section 2.1 of this paper. *post* is a dummy that equals one for the years 2011 to 2017 and 0 for the years 2005 to 2010. *low* in Panel A is a dummy variable that equals one for observations where a bank's excess capitalization *Xcap* was below its individual sample mean. *SIB* in Panel B is a dummy that equals one for systemically important banks and zero otherwise. Standard errors are clustered by bank and robust p-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Estimation results for equation (5a)								
	Geographic complexity				**Business complexity**			
CX:	*span_location*	*count_foreign*	*span_location_b*	*count_foreign_b*	*total_count*	*count_bank*	*count_non_bank*	*count_fs*
CX_{t-1} * post * low_{t-2}	-0.150	-0.156	-0.104	-0.204*	-0.123**	-0.177	-0.124**	-0.135**
	(0.212)	(0.502)	(0.109)	(0.082)	(0.049)	(0.116)	(0.048)	(0.031)
CX_{t-1} * post	-0.456***	-0.675***	-0.213***	-0.305***	-0.226***	-0.303***	-0.221***	-0.246***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CX_{t-1} * low_{t-2}	0.036	0.058	0.031	0.072	0.047	0.068	0.047	0.064
	(0.774)	(0.796)	(0.644)	(0.563)	(0.484)	(0.569)	(0.482)	(0.340)
post * low_{t-2}	0.178	-0.005	0.083	0.049	0.241	0.019	0.242	0.199
	(0.494)	(0.981)	(0.671)	(0.792)	(0.354)	(0.921)	(0.351)	(0.370)
CX_{t-1}	0.673***	0.666***	0.364***	0.558***	0.353***	0.508***	0.344***	0.424***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
low_{t-2}	0.026	0.095	0.057	0.075	0.016	0.111	0.013	-0.008
	(0.914)	(0.608)	(0.757)	(0.673)	(0.949)	(0.548)	(0.957)	(0.968)
R^2	0.152	0.131	0.152	0.145	0.164	0.145	0.163	0.170
Observations	873	873	873	873	873	873	873	873
Banks	84	84	84	84	84	84	84	84
Bank FE	no	no	no	no	no	no	no	no
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank Controls	yes	yes	yes	yes	yes	yes	yes	yes

Panel B: Estimation results for equation (5b)

	Geographic complexity				Business complexity			
CX:	*span_location*	*count_foreign*	*span_location_b*	*count_foreign_b*	*total_count*	*count_bank*	*count_non_bank*	*count_fs*
CX_{t-1}	0.737***	0.644***	0.392***	0.635***	0.389***	0.521***	0.373***	0.464***
	(0.000)	(0.006)	(0.000)	(0.002)	(0.003)	(0.004)	(0.004)	(0.000)
CX_{t-1} * post	-0.653***	-0.646**	-0.301***	-0.395	-0.293***	-0.328*	-0.281***	-0.310***
	(0.001)	(0.042)	(0.007)	(0.180)	(0.007)	(0.099)	(0.009)	(0.007)
CX_{t-1} * SIB	0.008	-0.124	0.002	-0.102	0.006	-0.002	0.015	-0.054
	(0.971)	(0.696)	(0.985)	(0.663)	(0.972)	(0.994)	(0.924)	(0.686)
post * SIB	0.055	-0.233	0.089	-0.093	0.508	-0.009	0.532	0.452
	(0.919)	(0.473)	(0.822)	(0.768)	(0.234)	(0.980)	(0.214)	(0.213)
CX_{t-1} * SIB * post	0.102	-0.043	0.024	0.012	-0.082	-0.070	-0.093	-0.089
	(0.713)	(0.918)	(0.875)	(0.969)	(0.544)	(0.766)	(0.490)	(0.538)
R^2	0.148	0.132	0.149	0.142	0.162	0.143	0.160	0.162
Observations	945	945	945	945	945	945	945	945
Banks	84	84	84	84	84	84	84	84
Bank FE	no	no	no	no	no	no	no	no
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank Controls	yes	yes	yes	yes	yes	yes	yes	yes