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Abstract

In our paper we analyze the heterogeneity between various business models among systemically important banks in 65 countries over the period of 2000-2012. For the first time, we are able to identify true banking strategies consisting of different combinations of bank asset and funding sources and assess their impact on the mortgage crisis. We then estimate how distinct strategies have affected bank profitability and risk before the crisis, and what impact they have put on the mortgage crisis. Our results prove that the asset structure of banks was responsible for the systemic risk before the mortgage crisis, whereas the liability structure was responsible for the crisis itself. Finally, we show that countries with banks that rely on investment activities experienced a greater but more short-lived drop in GDP compared to countries that have a predominantly traditional banking sector.

JEL Codes: G21, G15, E58, G32

Keywords: Bank risk, business model, bank regulation, financial crisis, banking stability, systemic risk

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1. Introduction

The mortgage crisis has revealed that the general knowledge concerning bank activity undertaken by banks is limited. Regulators admitted that they lacked sufficient and reliable knowledge of banks' activities, which hampered their accurate assessment of banking sector risk and timely react to the banking sectors' problems during the mortgage crisis (Lo, 2009; McCarthy et al., 2010). Second and more importantly, banks themselves lost their grasp of their general level of risk. The Risk Management Officer of one of the largest banks admitted in one press conference that "*he was not aware of some bank practices*" (Frankfurt am Main, December, 2010).

This situation occurred because the complexity and size of banks have considerably increased recently. Banks have become more tied to the capital market performance and mutually interlinked with each other, and their products became more complex (Boot and Thakor, 2009; Borio and Drehmann, 2009; Song and Thakor, 2010). In some countries banks' size has exceeded the country's size in terms of GDP, for example in Belgium, the Netherlands, and Switzerland. Banking business models have also changed and became more heterogeneous than ever before. This has been particularly observable among global banks. Whereas the asset and liability structure of banks such as UBS, ING, Deutsche Bank, and Citibank exhibited an investment banking model, consisting mainly of trading assets and market funding, other banks have decided to follow alterative strategies. For example, the largest Chinese and Japanese banks such as Industrial and Commercial Bank of China or Sumitomo Mitsui, and Mitsubishi UFI decided to follow the trading asset structure while simultaneously maintaining the traditional structure of their liabilities. In contrast, Norwegian or Austrian banks retained a more diversified structure on both the asset and liability side, whereas

Brazilian banks mostly exhibited the traditional banking structure. Consequently, Gropp and Heider (2010) document that before the mortgage crisis there was substantial heterogeneity in the level of banks capital in various countries, which is not explained by the capital requirements, but rather by banks' specific features.

In our study, we consider how different combinations of asset and liability structure within a banking business model affected their risk-return profile as well as the correlation with the nature of crisis in individual countries. More specifically, we try to answer the following questions: How do various banking business models contribute to a financial crisis and its systemic risk effect, and how risky and profitable are they? Finally, do banking strategies affect the nature of the financial crisis in an individual country, and, if so, how?

Analyzing the literature, the answers to these questions are not very obvious. According to the theoretical literature the universal model is the one, which allows banks to boost their profitability, simultaneously limiting their risk. Therefore, it should render a positive effect on bank's business. However the mortgage crisis has documented that not all banks and countries following the universal model were resistant to consequences of the mortgage crisis. In fact, the heterogeneity in banks' and countries' affection by global distress was significant.

Neither the empirical literature presents the unambiguous results to our questions. Some studies point toward the separation of commercial and investment banking activities arguing that universal model tends to use capital inefficiently to cross-subsidize marginal or loss-making projects, draining resources from healthy business (Berger and Ofek, 1995; Laeven and Levine, 2009). This stream of literature also shows that investment business is more risky than any other banks activities, and thus banks should be restricted to render them (Demirgüç-

Kunt and Huizinga, 2010; Shleifer and Vishny, 2010; Diamond and Rajan, 2011; Beltratti and Stulz, 2012; Brunnermeier et al., 2012; Fahlenbrach et al., 2012). Also, the economy of scale and scope characterizing predominantly universal model caused banks to increase in size and complexity increasing the global systemic risk (Brunnermeier et al., 2012). In turn, other studies point toward stabilizing role of universal banking model pointing out its diversification effects, and thus its reduced exposure toward individual and domestic systemic risk (Saunders and Walter, 1994; 2012; Buch et al., 2013). However this stream of literature documents that investment banking activities may provide substantial diversification effects for bank's entire business, and thus should not be entirely eliminated from the scope of commercial banks' activities (Boost and Ratnovski, 2012).

Given a large heterogeneity between recent banking business models, in fact, we know very little about the effect of banking models on bank profitability and risk. The above cited studies, though they provide important insight into banking business, they do not assess banking business models entirely, controlling for various scale of bank individual activities, correlation within as well as between bank asset and liability structure. For example, although we know that bank non-interest activities, especially investment ones become the riskiest while they are funded by short-term sources, we still do not know how risky they will become once they are funded by deposits. Additionally, the combination of non-interest sources and liability sources that is the riskiest in a banking business becomes unclear. Furthermore, these existing shortcomings do not allow us to capture the non-linear effects of bank individual activities on profitability and riskiness of specific banking models. Finally, to the best of our knowledge there are no empirical studies examining the contribution of individual banking models to the systemic crises. More specifically, analyzing banking model riskiness it is important to know how individual banking strategies contribute to the nature of crisis in individual countries – its duration and deepness as well as systemic effects. Consequently, sole assessment of bank individual activities is not sufficient to formulate any policy-making conclusions. More important is to know how these activities behave in a portfolio context, that is with a specific bank's asset and/or liability structure. Without the answers to these questions, banking regulations inadequately address the potential problems in the banking industry and, at the same time, cannot ensure financial stability. This paper addresses above problems existing in the current literature.

To answer our research questions we investigate the characteristics and risk-return profile of 458 systemically important banks coming from 65 countries during the 2000-2012. In addition, we test the contribution of these models to global systemic risk, and the nature of financial crises in individual countries. Our analysis offers three important contributions to the existing literature. First, using the k-medoid clustering approach, we empirically select banks with different asset and liability structures. More specifically, the methodology allows us to cluster the banks with similar asset and liability exposure into one group. At the same time, we create different groups for these banks, which do not exhibit the same characteristics. Additionally, the sample banks categorized into groups may change in different sample periods (pre-crisis and crisis periods) if their business model has also changed. Importantly, this methodology, in contrast to other studies, assumes that banking business models are created empirically as a function of the bank's asset and liability structure, and therefore the business model is not assumed to be given. This approach distinguishes this study from other empirical papers and allows us to capture the heterogeneity between entire banking business models. Consequently, we address the non-linear nature of financial variables on bank risk-return profiles. Additionally, the model allows us to determine how the correlation of different asset exposures with specific liability sources directly affects the risk-return profile of banks. Second, in comparison to other studies, we extend the sample in both directions – the number of banks as well as considered time periods - to determine the risk-return profile of banking strategies. Demirgüç-Kunt and Huizinga (2010) examine the individual risk and return of different bank characteristics for a sample of 1,334 banks from 101 countries from the year 1999 until the end of 2008. Beltratti and Stulz's (2012) study on performance examined the stock returns of large banks from 32 countries. The period of analysis included the year prior to the mortgage crisis and the 2007 to 2008 crisis period. Fahlenbrach et al. (2012) analyzed bank characteristics and their effect on bank stock returns during the financial crisis of 1998 as well as during the recent financial crisis. The study sample included 347 publicly listed US financial institutions. Notably, our analysis period spans the years 2000 to 2012 – well beyond that of existing studies. Moreover, we also consider all systemically important institutions included in the V-LAB list since 2000. Our extended sample better captures the banking business models and their changes pre- and post-crisis. Finally, to the best knowledge of our knowledge, this is the first study to investigate how different banking business models affect the nature of financial crises in individual countries that is, the crisis depth and duration.

The results, using k-medoids, identify four banking strategies that simultaneously control the asset and funding structure: two banking models within a traditional group and two banking models among non-traditional entities. Consequently, within the former group we found a more *diversified* model as well as a *specialized* model, whereas within the latter we found a *trader* model as well as an *investment* model. Banks belonging to the respective groups differ in terms of their asset structure and liability structure mix. Our empirical results concerning the riskiness of the models confirm those of some studies that diversification matters for banks because it allows them to reduce their individual risk (Wagner, 2007; Brunnermeier et al., 2012; Buch et al., 2013). The result is consistent for the pre-crisis period and the crisis periods. The results also show that investment model risk is difficult to detect and thus understated most likely because of a high level of off-balance sheet activities and derivatives not reported in the regulatory capital. With respect to systemic risk, our results suggest that traditional banks are less risky than their nontraditional counterparts; however, we could not find any differences within the individual banking groups. This result would point toward significant policy implications because it suggests that asset structure and not liability structure was responsible for systemic risk before the mortgage crisis (the banks between the banking groups differ in terms of asset structure; however within a group the banks differ in terms of funding sources). By contrast, our empirical investigation documents however different results during the mortgage crisis. Consistent with studies such as Gorton and Metrick (2012), we prove that the liability structure was the main driver of systemic risk during the mortgage crisis. We find that the investment model was the riskiest and was even riskier than the trader model. The low share of deposits in banks that represents that model, and the consequent illiquidity problems after the collapse of Lehman Brothers, materialized bank losses causing bankruptcies. However, the high level of interconnectedness among institutions following the investment model resulted in the banks' simultaneous problems during the financial crisis. This evidence explains at least partially, why the systemic risk was not observable before the mortgage crisis. Banks with the same asset structure but different liability structure distorted the measures of the true systemic risk. Although the bank investment strategies were largely responsible for the bank losses and thus the systemic nature of the crisis, we find that the crisis in countries with investment business model dominance was deeper; however, the crisis was short-lived. In contrast, the countries whose banks rely predominantly on traditional banking experienced less of a reduction in GDP; however, the crisis was longer in duration. Our results seem to be robust and independent from the financial structure on which countries rely.

The paper proceeds as follows. Section 2 introduces the empirical strategy and the data set. Section 3 presents the results on banking business models' identification, and Section 4 shows the results of estimations of their riskiness. Section 5 documents the link between the banking business models and their profitability, and Section 6 documents the relationship between various banking business models and the nature of financial crises in crises. We present the conclusions in Section 7.

2. Data and empirical methodology

2.1. Data set and the banking business models

To test our research question concerning the riskiness and profitability of various banking business models, we use a sample of all systemically important banks listed on the V-LAB list between 2000 and 2012. To classify a bank as systemically important it was sufficient for us that a bank has been identified on the list at least once since 2000. In total, our sample consists of 458 banks from 65 countries and sample period covers the years of 2000-2012. Then using the k-medoid clustering we assign each bank to a specific banking business model given their asset and liability structure using k-medoid approach. The objective of the k-medoid is to group banks with a similar asset and liability structure into the same cluster, and banks with different characteristics to classify into different clusters (Kaufman and Rousseeuw, 1990). K-medoid approach identifies a cluster by minimizing the difference between individual financial variables of different banks using Euclidean distance. For the purpose of our analysis we perform the grouping based on earning asset and liability sources.

Among bank asset structure we distinguish such positions as: loans to entities other than banks, loans and advances to banks, volume of the securities held by banks, and other earning asset. All of them are scaled by bank total asset. Among bank funding sources we distinguish: deposit and short-term funding, other interest bearing liabilities, and non-interest bearing liability. All liability positions are scaled by total sum of bank's liabilities. The differences in the dominance of individual asset and liability variables in our sample banks would point toward differences in banking models. All bank-level financial data come from Bankscope. We prefer to use clusters from the balance sheet data as opposed to the income statements as they are not hampered by business cycles or monetary policy and thus, we argue that more accurately reflect the changes between the individual banking models. Importantly, we allow banks to change the strategy between our sample periods (pre-crisis and post-crisis period). **Table 1** shows the descriptive statistics for clustering variables.

[Table 1 about here]

To verify the impact of a banking model on a bank's individual and systemic risk and profitability measures, we use the equity-to-assets ratio (EQUITY) and Tier 1 capital ratio (TIER1) as individual risk measures, and ROA and ROE as profitability ratios. EQUITY and TIER1 are widely used measures of an individual bank's risk but, in some circumstances, these measures can deviate from the real risk borne by a given institution. For example, EQUITY does not incorporate off-balance sheet items, whereas TIER1 is influenced by the regulator's requirements, which proved not to be perfect during the recent crisis. With respect to the measure of systemic risk (SRISK), we use values quoted by V-LAB. The values represent equity risk at the end of each year and were calculated as expected capital shortfall of the bank in the event of another crisis. The measure incorporates the volatility of the bank's market value, its correlation with the market, and its performance in extreme contexts.[1]

[1] For details on systemic risk measures by the Volatility Institute of New York University Stern School of Business, please visit: http://vlab.stern.nyu.edu/doc?topic=mdls.

In the final step of our research, we analyze the effect of an existence of country's banking model on the depth and duration of the crisis from the year 2007 to 2012. At this end we calculate the average asset-weighted share of banks belonging to the most prevalent banking business model identified for each country during the crisis period. A crisis depth is defined as a ratio of two values: a) a difference between a country's GDP growth rate in 2006 and the lowest yearly GDP growth rate in the period of 2007-2012, and b) a country's GDP growth rate in 2006. However crisis duration is defined as maximum of two values: a) a number of years between 2006 and the last year with negative GDP growth rate, and b) a number of years between 2006 and the year with the minimum GDP growth rate in the period of 2007-2012. **Table 2** presents the descriptive statistics for bank and country variables used in our analysis.

[Table 2 about here]

2.2. Empirical strategy

To test the relationship between banking business models, profitability, individual risk, and systemic risk we apply the GLS estimator with random effects. We run regressions separately for each of the two sub-periods (2000 to 2006 and 2007 to 2012). The banking business models are included into the regression as dummies. We run regressions with three out of four business model dummies because four banking model dummies taken at the same time are collinear. Additionally, in line with the existing studies in each regression we also control for bank's and country's characteristics (Laeven and Levine, 2009; Demirgüç-Kunt and Huizinga, 2010). The bank-level controls include bank's size (in natural logarithm), liquidity ratio and cost to income. However to reflect the stage of the economic cycle within which profitability and risk are measured we use country's GDP growth rate as a country's control.

Finally, to check that country's institutional structure does not interfere our standard results, we include country-specific institutional variables – bank asset concentration, banking sector size, and stock market capitalization – as a share of a country's GDP (Čihák et al., 2012). Additionally, we cluster the standard errors of our estimations on a bank's level.

The general construction of our panel model is the following:

$$DEP_{it} = f\left(BANK_{it-1}; MODEL_{it-1}; COUNTRY_{kt}\right) \tag{1}$$

where:

DEP_{it} represents the dependent variable calculated for bank *i* in year *t* (EQUITY, TIER1, ROA, ROE, or SRISK); $BANK_{it-1}$ represents a set of bank characteristics including size (LN_A) and some financial ratios; $MODEL_{it-1}$ represents a set of banking business model dummies, and $COUNTRY_{kt}$ includes country-specific variables for country *k* at time *t* in which bank *i* is incorporated.

To answer the question how individual banking business models affect the nature of financial crisis in individual countries we run a cross-section OLS model in which crisis depth and crisis duration are regressed against a country's business model. Additionally, to ensure that the effect of a banking business model on the nature of a crisis does not depend on institutional infrastructure a country relies upon, we include country-specific institutional variables as banking sector concentration, the size of banking sector and capital market.

The description of all dataset is presented in the **Appendix 1**.

3. Banking business models' specifications

In this section we present the clustering results on banking business models. Panel A and Panel B of Table 3 present the clustering estimations based on earning asset structure and funding structure, respectively. However Panel C presents cluster results using both asset and liability variables simultaneously.

[Table 3 about here]

In Panel A, four different clusters reflecting distinct asset structure between the banks can be found. They can be divided into two groups. One is the traditional group of banks, which generates earnings from loans to households and companies (cluster A3) or loans in general (including loans to other banks, as in cluster A1), and the other is the nontraditional group of banks, with banks that possess a high proportion of securities shares (cluster A4) or both securities and other earning assets (cluster A2). Panel B presents differences between banking business model depending on banks' liability structure. Again, we can notice that there are banks which mostly funded their activities by deposits and short-term liabilities (clusters B1 and B2) and those who preferred less traditional sources of funding (clusters B3 and B4).

The most comprehensive results, incorporating earning asset structure and funding structure simultaneously, are presented in Panel C. Given above we can identify two nontraditional models in clusters C2 and C4, and two traditional models in clusters C1 and C3.

More specifically, cluster C4 seems to resemble the *trader* model because its dominant feature is the highest share of securities in earning assets. However, this cluster's funding structure is traditional because it is composed predominantly of deposits and short-term liabilities. Consequently, the *trader* model shows that a nontraditional asset structure is not necessarily related to capital market funding. This could however generate additional risk for that model. In our sample the *trader* model is represented by 136 institutions (32%) in the pre-crisis period, and 112 (25%) banks in the crisis period. Banks following this model include the Industrial and Commercial Bank of China, China Construction Bank, Agricultural Bank of China, Sumitomo Mitsui, Mitsubishi UFJ, Mizuho, Wachovia, State Bank of India, Banco Bilbao Vizcaya Argentaria, Sberbank, and the National Bank of Greece.

Cluster C2 seems to exhibit a nontraditional asset structure with nontraditional funding. This structure resembles the *investment* model. A high proportion of other earning assets (which includes derivatives), a substantial portion of securities, and an unremarkable ratio of loans to total earning assets characterizes this model. With respect to funding, this cluster is represented by a high proportion of other interest bearing liabilities such as derivatives, trading liabilities, and long-term funding. In the pre-crisis period, this cluster was the smallest including only 78 banks (18%), whereas in the crisis period this cluster grew to 101 institutions (22%). The cluster members include Dexia, KBC, BNP Paribas, Crédit Agricole, Société Générale, Commerzbank, Deutsche Bank, Intesa Sanpaolo, UniCredit, Santander, ING, UBS, Credit Suisse, HSBC, Royal Bank of Scotland, Barclays, JP Morgan Chase, Citibank, Merrill Lynch, Goldman Sachs, and Morgan Stanley among others.

The remaining two clusters represent traditional banking models. The main characteristics are a high proportion of loans to households, companies, and total earning assets with deposits as the primary source of funding. However, the first model, C1, shows more loans and advances to banks in total earning assets and more deposits and short-term funding than cluster C3. Thus, C1 represents a more *specialized* structure. Cluster C3 is treated as a *diversified* model but with traditional sources of funding. Cluster C3 is also more numerous than C1 – in the pre-crisis period, C3 was composed of 121 banks (28%) and, in the crisis years, 178 banks

(40%). Cluster C1 is represented by 91 (21%) and only 59 (13%) institutions in the pre-crisis and crisis periods, respectively. Finally, examples of cluster members for C3 include Wells Fargo, Washington Mutual, Capital One, and National City Corporation in the US, Korean KB and Woori Finance, Norwegian DNB, Italian Banca Nazionale del Lavoro, and Banco Comercial Português among others. Cluster C1 is composed of Canadian Scotiabank, Bank of New York Mellon, Banco do Brasil, Bank of China, and other Chinese banks including Bank of Communications, China Merchants Bank, China CITIC Bank, and Shanghai Pudong Development Bank.

The results of clustering using both earning asset structure and funding structure are applied further in our analyses. We label models C1, C2, C3, and C4 as *specialized*, *investment*, *diversified*, and *trader*, respectively.

3. The empirical effect of banking business models on risk

In this section we present the empirical results on the link between various banking business models and their individual and systemic risk.

3.1. Banking business models and their individual risk

Tables 4 and 5 present the results on the link between a business model and individual risk measures; that is, EQUITY and TIER1. In sub-specifications *b*, *c*, and *d* for each model, we present the results only for the business model dummies and the constant term, whereas other values are the same as sub-specification *a*.

[Table 4 about here]

[Table 5 about here]

In specifications explaining EQUITY, we find that the *diversified* model is less risky than the *trader* model in the pre-crisis period, and that the *diversified* model is less risky than the *specialized* and *trader* model in the crisis period. This supports the evidence that diversification pays off in the banking industry and allows banks to reduce their individual risk (Brunnermeier et al., 2012; Wheelock and Wilson, 2012). The results for the TIER1 specifications however present a distinct picture. In the pre-crisis period, the *diversified* model was statistically significantly the poorest, whereas other banking business models exhibit a positive effect on the TIER1 ratio. In contrast, in the crisis years, the *investment* model was statistically significantly the most capitalized in terms of TIER1, whereas other banking business models performed poorly with respect to the TIER1 ratio. This supports the evidence of Gorton (2009) and Diamond and Rajan (2011) who found that the TIER1 ratio understated the deterioration of bank assets because of book value treatment of capital in the TIER1 ratio. Thus, we can conclude that the TIER1 capital ratio does not match the equity-to-assets ratio as a measure of individual risk. The equity ratio as a measure of bank's individual risk shows that, in the crisis period, the *diversified* model was superior in terms of equity, but the model with a nontraditional funding structure (*investment*) led in terms of the TIER1 ratio.

Finally, in specifications (1) and (2) of both tables we find that, in the pre-crisis period, smaller, more profitable banks with higher liquidity had a healthier equity-to-assets ratio and Tier 1 capital ratio. The estimated coefficients for those variables were statistically significant at levels below 1%. However, specifications (3) and (4) show that all coefficients for these variables, except for L.LN_A, lack statistical significance for the crisis years. Thus, we can conclude that bank size matters during a crisis and negatively influences individual risk measures. This supports the "too big to fail" doctrine and a reduction in market discipline (Hett and Schmidt, 2013; Laeven et al., 2014).

3.2. Banking business models and their systemic risk

Table 6 presents the estimation results for the models explaining systemic risk generated by banks.

[Table 6 about here]

Specifications (2) and (4) document that the estimation results for the banking model dummies slightly differ between both sub-periods. First, in the pre-crisis period, we find that traditional banks generate statistically lower systemic risk than non-traditional banks, but we do not find statistically significant differences between the banking group models (traditional versus non-traditional). Given that the asset structure within the individual banking groups is the same and that liability structure is distinct, we argue that, in the pre-crisis period, systemic risk is mainly associated with earning asset structure. This implies a high interconnectedness between banks holding similar assets. Cifuentes et al. (2005) and Brunnermeier and Sannikov

(2014) suggest the contagion effect from asset price changes in an environment where banks hold similar assets.

Specifications (3) and (4) show a slight change in the situation during the crisis years. The nontraditional *trader* model (predominantly funded by deposits) appears no worse than both traditional models (*diversified* and *specialized*); that is, the results suggest that the trader model is the least systemically risky, but the respective estimated coefficients are statistically insignificant. During the crisis period, we find that the *investment* model (nontraditional asset structure with non-deposits) was the riskiest from the perspective of stability of the whole financial system. Systemic risk generated by the *investment* model was greater than that of both traditional models and greater than the risk generated by the *trader* model with a nontraditional earning asset structure. Therefore, the results suggest that, in the recent crisis, systemic risk was linked to funding structure. This supports the research, which documents that the run on repo and the illiquidity of the interbank market was the origination of the financial crisis because these factors materialized bank losses (Gorton and Metrick, 2012). The banks that funded their asset by deposits were less exposed to the interbank context and were less affected by the financial crisis (Demirgüç-Kunt and Huizinga, 2010; Ivashina and Scharfstein, 2010; Allen et al., 2014). Moreover, the low share of deposits in the *investment* model determined the high interconnectedness of banks from that business group, which resulted in their simultaneous problems during the crisis. The results for the *trader* model show that the nontraditional banking model could be ameliorated if backed by solid deposit funding. Finally, we can conclude that although the *investment* model is among the most systemically risky models even before the crisis, appropriate recognition of the source of its riskiness (which lies in its funding structure) was difficult at that time because, in the pre-crisis years, the *trader* model with a comparable earning asset structure similarly affected the expected systemic risk.

Finally, we can find that larger banks with higher cost to income ratios and greater liquidity contributed more to the total expected capital shortfall in the financial system in the recent crisis. Moreover, a country's high GDP growth rate expectedly hampers systemic risk (specifications (3) and (4)).

3.3. Systemic risk of banking business models and institutional structure – robustness check

The effect of banking models on systemic risk may also depend on a country's institutional infrastructure (Demirgüç-Kunt and Huizinga, 2010; Beltratti and Stultz, 2012). For example, banks operating in countries with developed capital markets will have greater exposure to capital market activity than banks from countries dependent on the banking sector. To check the robustness of our previous results, we re-estimated the models with additional institutional variables as regressors. The variables include the country's bank asset concentration (Table 7), the country's bank deposits to GDP ratio (Table 8), and stock market capitalization to GDP (Table 9).

[Table 7 about here]

[Table 8 about here]

[Table 9 about here]

The results are almost the same as the baseline estimations from the previous sub-section, with one exception. In the pre-crisis specifications using the country's bank deposits to GDP ratio as a regressor, we observe an additional statistically significant difference in the effect on systemic risk between both nontraditional models. Here, the *investment* model is the riskiest followed by the *trader* model. This result may suggest that large banking sectors create large institutions.

4. The effect of banking business models on profitability

Tables 10 and 11 present the results concerning the link between a banking business model and the profitability ratios ROA and ROE.

[Table 10 about here]

[Table 11 about here]

The estimation results document that with respect to the banking model dummy coefficients, no statistical evidence of the influence of banking models on profitability ratios in the pre-crisis period in terms of ROE can be found. However, some differences are observed if ROA is considered. The *investment* and *diversified* models outperformed the *specialized* and *trader* models. The results for the crisis period are statistically significant and dominant at levels below 1% in many cases. First, we find that an *investment* model (nontraditional funding with nontraditional earning asset structure) is the poorest. This result is consistent with Beltratti and Stulz (2012), who found that banks following the *investment* model were affected by the financial crisis to a greater extent because of significant losses from falling securities values. Additionally, Goh et al. (2015) found that banks with a significant portion of high-value securities experience greater losses because they were discounted. Second, specifications (4) of both tables show that the *specialized* and *trader* models generate the highest profits from their assets and equity (however, there is no statistical differences between the effects of these two business models on the profitability ratios). Interestingly, these two models are characterized by the highest proportion of deposits and short-term liabilities in the funding structure. Thus, accounting for completely different earning asset structures (traditional for the *specialized* model and nontraditional for the *trader* model) we might conclude that performance in the recent crisis years was linked to a greater extent with the funding structure than the structure of earning assets. This suggests that stable financing allows *trader* banks to counteract the “fire sale” and thus to limit losses, whereas traditional banks continue to lend. This supports the recent evidence of Allen et al. (2014), who find that banks that are not dependent on deposit funding, or that experienced difficulty in attracting new depositors, exhibited the sharpest decline in lending during the financial crisis.

Finally, the specification results document that smaller banks with superior cost-control and liquidity were more profitable in terms of ROA and ROE in both the pre-crisis and crisis period. The majority of the coefficients for the variables are statistically significant at levels below 1%.

5. The banking business models and the nature of financial crisis in individual countries

The mortgage crisis affected not only banks but also economic situation of different countries. For example, the cost of the crisis in Belgium, Germany, the Netherlands, Switzerland, the US, and the UK ranged from 3.5 of GDP to 18% of GDP, whereas in countries such as Austria, Italy, or Spain the cost amounted to approximately 1% to 2% of GDP. Reinhart and Rogoff (2009), using a sample of several financial crises including the mortgage crisis, argued that downturns in capital markets during financial downturns are more severe than downturns in the real estate market, but are shorter-lived. Thus, countries with bank activities predominantly concentrated in capital markets should experience greater consequences of financial crises than countries with traditional banking models. However, we also expect that the effects would be of a lesser duration than in countries with traditional banking. Moreover, on a country level, Allen et al. (2012) found that countries with developed capital and banking markets experience less contraction during financial crises than countries that rely solely on the banking sector. Consequently, the authors conclude that financial crises in countries dominated by banking sectors experience longer financial crises. Thus, based on this research, we try to assess how different banking strategies are linked with the countries they represent. To identify the most prevalent banking business model in a given country we rely on our bank clustering analysis. We assign a country a dominant banking model when a weighted share of banks in total banking sector asset falling into particular model is the highest. Our period covers the years of 2007 to 2012. **Table 12** shows the dominant banking business models for all countries in our analysis.

[Table 12 about here]

Given banking business model in individual countries, we run cross-section regressions to explain the depth (DEPTH) and duration (DURAT) of the crisis for each country. **Tables 13 and 14** show the estimation results.

[Table 13 about here]

[Table 14 about here]

For all specifications, the joint impact of all explanatory variables is statistically significant. However, the coefficients for all the institutional variables are statistically insignificant with the exception of stock market capitalization in the models explaining crisis duration. Here, we obtained negative coefficients, but their significance is natural; that is, a crisis is shorter when a stock exchange recovers earlier. In this case, a higher average relation of stock market capitalization to GDP between the years 2007 to 2012 is a result of earlier stock exchange recovery. In specifications for crisis depth (Table 13), we observe that many coefficients for the business model variables are statistically significant (mostly at levels below 1%). We find that the *investment* model generates the most crisis depth, the *specialized* model is the least risky, and the *diversified* model falls somewhere in-between these two models. These observations are consistent with the results of our previous panel regressions, which suggested that a nontraditional funding structure (a main characteristic of the *investment* model) stimulated systemic risk in the recent crisis. Although the nontraditional funding of banks in a country intensifies crisis depth, it does not stimulate crisis duration. From Table 14, we conclude that the longest crisis duration was observed in countries with the *specialized* model. Moreover, the coefficient for the *diversified* model suggests that it also generated longer crises than both nontraditional models (the *trader* model and the *investment* model), but the results are statistically insignificant. In summary, we presume that the business model that generates the deepest crisis is responsible for a comparatively short crisis duration, and the least risky business model in terms of crisis depth was simultaneously the riskiest in terms of crisis duration. **Figure 1** presents these observations and shows the expected changes in crisis depth and duration from a 30 percentage point increase in the country's share of a given banking business model.

[Figure 1 about here]

6. Conclusions and policy implications

The recent liberalization and globalization trend in the banking industry has contributed to greater heterogeneity among banking business strategies. The range stretches from *specialized* lending models to *diversified* models and ends with *investment* and *trader* models. The differences between the models are reflected in both bank's assets and their funding sources. This heterogeneity in banking strategies complicates the assessment of the individual effect of each strategy on financial crisis origination and propagation by regulators. We observe higher correlation between bank activities within certain models and lower levels of correlation in others.

Our results present important conclusions. First, we find that the asset structure was the main driver of systemic risk in the banking sector before the crisis. A high correlation of securities values between various banks determined the systemic risk for the banking sector. We find that, during the mortgage crisis, the funding structure was the main determinant of systemic risk. Consistent with other studies, we find that the *investment* model carried the most systemic risk. The model's systemic risk was greater than that of *traditional* banks and *trader* banks; that is, banks with an investment structure based on assets, but funded by deposits. The fire sale and subsequent illiquidity problems materialized bank losses from a decrease in asset values. However, the recognition of the source of investment model riskiness (which lies in the funding structure) was difficult at that time because, in the pre-crisis years, the *trader* model with a comparable earning asset structure similarly affected the expected systemic risk. Moreover, we find that the *investment* model generates the most depth to a crisis, whereas the *traditional* model is the least risky, and the *diversified* model lies somewhere between the two. Interestingly, although a nontraditional funding structure intensifies crisis depth, it does not stimulate crisis duration. The results suggest that the longest crisis occurred in countries with traditional banking models; that is, banks that are the most traditional in their asset and funding structure. Thus, the results support the hypothesis that the deepest crisis was responsible for a comparatively short crisis duration; however, the least risky model in terms of crisis depth simultaneously carried the most risk in terms of crisis duration.

The implications of the findings for policy-makers are that regulators should consider the simultaneous structure of banks assets and liabilities in assessment of banks' strategies. Only a specific combination creates risk in the banking sector. Thus, regulating asset structure individually from its funding sources is not likely to ensure banking sector stability. Consequently, greater emphasis should be placed on bank liability structure rather than solely on asset structure. Moreover, precise measures for banking sector stability are required. Concentrating solely on asset risk may not fully reflect the true risk of the banking sector, as our results on the *trader* and *investment* model show. Such measures should simultaneously include the asset and liability structure of banks and their correlations. Finally, diversification matters and should be encouraged in the banking sector because it ensures greater stability. In turn, the *specialization* models generate some risk. Thus, restricting banking sector activities, paradoxically, might imply greater risk in global banking sector.

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Table 1. Descriptive statistics for the clustering variables

Variable	Mean	Std. dev.	Median	5th perc.	25th perc.	75th perc.	95th perc.
A_LOANS	0.623	0.192	0.651	0.217	0.516	0.760	0.882
A_BANKS	0.111	0.116	0.079	0.003	0.032	0.151	0.319
A_SECUR	0.246	0.156	0.225	0.044	0.133	0.324	0.519
A_OTHER	0.024	0.060	0.000	0.000	0.000	0.018	0.126
F_DEPO	0.811	0.184	0.872	0.424	0.743	0.941	0.978
F_OIBL	0.133	0.160	0.073	0.000	0.023	0.189	0.445
F_NIBL	0.056	0.082	0.032	0.008	0.019	0.059	0.170

Table 2. Descriptive statistics for banks' characteristics and country's characteristics

Variable	Mean	Std. dev.	Median	5th perc.	25th perc.	75th perc.	95th perc.
Bank-level variables							
EQUITY	0.090	0.068	0.078	0.033	0.055	0.106	0.170
TIER1	0.112	0.045	0.102	0.062	0.081	0.130	0.196
ROA	0.011	0.018	0.009	-0.003	0.005	0.015	0.030
ROE	0.121	0.127	0.125	-0.025	0.070	0.183	0.284
CI	0.561	0.180	0.556	0.295	0.456	0.651	0.831
LIQUIDITY	0.262	0.237	0.197	0.036	0.104	0.343	0.712
LN_A	10.267	1.827	10.059	7.550	9.102	11.347	13.648
SRISK	2.323	17.388	-0.159	-8.611	-1.510	1.266	23.035
Country-specific variables							
CONCT	0.674	0.198	0.682	0.337	0.522	0.844	0.984
DEPO	0.758	0.606	0.581	0.173	0.378	0.957	2.068
GDP	0.036	0.039	0.036	-0.028	0.016	0.057	0.093
STMRKT	0.722	0.675	0.554	0.113	0.297	0.946	1.882

Table 3. Identification of banking business models using clustering analysis

The data present the clustering analysis using k-medoid approach. The methodology allows us to group banks with similar asset or/and liability structure into the same cluster. It considers the minimal distance between given financial variables among banks within one cluster using Euclidean distance. Our analysis limits to four financial variables representing bank asset structure (panel A) and four variables representing the liability structure (B). The panel C has been estimated based on asset and liability structures simultaneously. The clustering covers years of 2000-2006 for pre-crisis period and 2007-2012 for crisis period.

A. Clustering with the use of earning assets' structure					
	Financial variables	**cluster A1**	**cluster A2**	**cluster A3**	**cluster A4**
Medoids	A_LOANS	0.576	0.466	0.784	0.575
	A_BANKS	0.201	0.122	0.051	0.063
	A_SECUR	0.219	0.264	0.152	0.363
	A_OTHER	0.005	0.148	0.013	0.000
Clusters' sizes	pre-crisis period	123	25	141	144
	crisis period	86	51	217	104
	total	209	76	358	248
B. Clustering with the use of funding's structure					
	Financial variables	**cluster B1**	**cluster B2**	**cluster B3**	**cluster B4**
Medoids	F_DEPO	0.935	0.779	0.486	0.362
	F_OIBL	0.035	0.178	0.427	0.106
	F_NIBL	0.030	0.044	0.086	0.532
Clusters' sizes	pre-crisis period	253	134	42	7
	crisis period	235	145	67	9
	total	488	279	109	16
C. Clustering with the use of earning assets' and funding's structure					
	Financial variables	**cluster C1**	**cluster C2**	**cluster C3**	**cluster C4**
Medoids	A_LOANS	0.574	0.620	0.768	0.617
	A_BANKS	0.242	0.117	0.058	0.054
	A_SECUR	0.172	0.204	0.164	0.329
	A_OTHER	0.012	0.060	0.010	0.000
	F_DEPO	0.907	0.591	0.837	0.936
	F_OIBL	0.048	0.296	0.124	0.025
	F_NIBL	0.045	0.113	0.039	0.039
Clusters' sizes	pre-crisis period	91	78	121	136
	crisis period	59	101	178	112
	total	150	179	299	248

Table 4. Impact of banking business models on equity to total assets ratio

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are represented by dummy variables. Robust standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					**crisis period (2007-2012)**				
	(1) EQUITY	**(2a) EQUITY**	**(2b) EQUITY**	**(2c) EQUITY**	**(2d) EQUITY**	**(3) EQUITY**	**(4a) EQUITY**	**(4b) EQUITY**	**(4c) EQUITY**	**(4d) EQUITY**
L.ROA	0.479***	0.500***				0.104	0.0881			
	(0.114)	(0.121)				(0.0931)	(0.0909)			
L.CI	-0.0133*	-0.0151**				-0.00218	-0.00763			
	(0.00755)	(0.00762)				(0.00669)	(0.00677)			
L.LIQUIDITY	0.0201***	0.0207***				0.00602	0.00125			
	(0.00641)	(0.00645)				(0.00512)	(0.00437)			
L.LN_A	-0.0105***	-0.0104***				-0.00893***	-0.00787***			
	(0.00181)	(0.00189)				(0.00141)	(0.00125)			
GDP	0.0928***	0.0937***				0.00247	0.000824			
	(0.0318)	(0.0322)				(0.0108)	(0.0101)			
L.SPECIALIZED			-0.00712	-0.00667	0.00610			-0.00505	-0.00759***	-0.00276
			(0.00980)	(0.00494)	(0.00501)			(0.00383)	(0.00261)	(0.00247)
L.INVESTMENT		0.00712		0.000453	0.0132		0.00505		-0.00255	0.00229
		(0.00980)		(0.00798)	(0.00867)		(0.00383)		(0.00344)	(0.00385)
L.DIVERSIFIED		0.00667	-0.000453		0.0128***		0.00759***	0.00255		0.00483**
		(0.00494)	(0.00798)		(0.00443)		(0.00261)	(0.00344)		(0.00238)
L.TRADER		-0.00610	-0.0132	-0.0128***			0.00276	-0.00229	-0.00483**	
		(0.00501)	(0.00867)	(0.00443)			(0.00247)	(0.00385)	(0.00238)	
Constant	0.183***	0.179***	0.186***	0.186***	0.173***	0.182***	0.170***	0.175***	0.178***	0.173***
	(0.0195)	(0.0188)	(0.0253)	(0.0196)	(0.0195)	(0.0149)	(0.0140)	(0.0157)	(0.0140)	(0.0139)
Number of obs.	2,427	2,381				2,583	2,511			
Number of banks	432	421				458	450			
Chi-squared	80.18***	116.5***				46.06***	67.64***			
R-squared	0.255	0.297				0.222	0.239			

Table 5. Impact of banking business models on Tier 1 ratio

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are represented by dummy variables. Robust standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					crisis period (2007-2012)				
	(1) **TIER1**	**(2a)** **TIER1**	**(2b)** **TIER1**	**(2c)** **TIER1**	**(2d)** **TIER1**	**(3)** **TIER1**	**(4a)** **TIER1**	**(4b)** **TIER1**	**(4c)** **TIER1**	**(4d)** **TIER1**
L.ROA	0.724***	0.743***				-0.249	-0.209			
	(0.119)	(0.120)				(0.153)	(0.164)			
L.CI	-0.00265	-0.00130				0.00365	-0.00237			
	(0.00893)	(0.00890)				(0.0131)	(0.0128)			
L.LIQUIDITY	0.0338***	0.0308***				0.00715	0.00204			
	(0.00777)	(0.00790)				(0.00876)	(0.00867)			
L.LN_A	-0.00925***	-0.00861***				-0.00606***	-0.00681***			
	(0.00121)	(0.00148)				(0.00128)	(0.00136)			
GDP	-0.0570	-0.0775				0.0116	0.00713			
	(0.0481)	(0.0506)				(0.0178)	(0.0176)			
L.SPECIALIZED			0.0142	0.0256***	0.00625			-0.0210***	-0.00353	-0.00503
			(0.00880)	(0.00653)	(0.00672)			(0.00598)	(0.00402)	(0.00431)
L.INVESTMENT		-0.0142		0.0114*	-0.00797		0.0210***		0.0174***	0.0159***
		(0.00880)		(0.00675)	(0.00814)		(0.00598)		(0.00493)	(0.00559)
L.DIVERSIFIED		-0.0256***	-0.0114*		-0.0193***		0.00353	-0.0174***		-0.00150
		(0.00653)	(0.00675)		(0.00506)		(0.00402)	(0.00493)		(0.00331)
L.TRADER		-0.00625	0.00797	0.0193***			0.00503	-0.0159***	0.00150	
		(0.00672)	(0.00814)	(0.00506)			(0.00431)	(0.00559)	(0.00331)	
Constant	0.190***	0.195***	0.181***	0.170***	0.189***	0.182***	0.186***	0.207***	0.190***	0.191***
	(0.0148)	(0.0177)	(0.0213)	(0.0176)	(0.0163)	(0.0139)	(0.0147)	(0.0165)	(0.0145)	(0.0143)
Number of obs.	1,740	1,716				2,147	2,099			
Number of banks	361	357				410	403			
Chi-squared	122.6***	179.7***				29.06***	40.89***			
R-squared	0.304	0.324				0.0424	0.0347			

Table 6. Impact of banking business models on systemic risk generated by banks

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are represented by dummy variables. Robust standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					crisis period (2007-2012)				
	(1) SRISK	**(2a) SRISK**	**(2b) SRISK**	**(2c) SRISK**	**(2d) SRISK**	**(3) SRISK**	**(4a) SRISK**	**(4b) SRISK**	**(4c) SRISK**	**(4d) SRISK**
L.ROA	-18.44	-18.32*				26.90	29.33			
	(11.61)	(11.02)				(21.84)	(22.72)			
L.CI	1.774*	1.472				4.214**	3.806**			
	(0.974)	(0.920)				(1.827)	(1.785)			
L.LIQUIDITY	3.111**	2.697*				5.389***	3.565*			
	(1.403)	(1.449)				(2.033)	(1.989)			
L.EQUITY	-23.63***	-21.99***				-3.883	-9.856			
	(6.032)	(5.576)				(9.769)	(11.53)			
L.LN_A	-0.127	-0.305				6.407***	6.017***			
	(0.537)	(0.559)				(0.837)	(0.843)			
GDP	-15.70***	-15.50***				-23.67***	-22.33***			
	(4.150)	(4.143)				(5.799)	(6.256)			
L.SPECIALIZED			-4.965***	-0.497	-2.942***			-5.432**	0.986	0.877
			(1.734)	(1.085)	(1.100)			(2.674)	(1.554)	(2.598)
L.INVESTMENT		4.965***		4.468**	2.023		5.432**		6.418**	6.309**
		(1.734)		(1.826)	(1.973)		(2.674)		(2.600)	(2.661)
L.DIVERSIFIED		0.497	-4.468**		-2.445**		-0.986	-6.418**		-0.109
		(1.085)	(1.826)		(1.095)		(1.554)	(2.600)		(1.495)
L.TRADER		2.942***	-2.023	2.445**			-0.877	-6.309**	0.109	
		(1.100)	(1.973)	(1.095)			(2.598)	(2.661)	(1.495)	
Constant	1.491	1.432	6.397	1.929	4.374	-65.93***	-61.16***	-55.73***	-62.14***	-62.03***
	(5.282)	(5.718)	(5.975)	(5.589)	(5.270)	(8.966)	(9.073)	(9.414)	(9.192)	(8.757)
Number of obs.	1,680	1,650				2,374	2,314			
Number of banks	352	346				445	437			
Chi-squared	40.12***	48.07***				86.20***	115.4***			
R-squared	0.0911	0.0929				0.327	0.341			

Table 7. Robustness check: Impact of banking business models on systemic risk after controlling for a country's bank asset concentration

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are represented by dummy variables. Robust standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					crisis period (2007-2012)				
	(1) SRISK	(2a) SRISK	(2b) SRISK	(2c) SRISK	(2d) SRISK	(3) SRISK	(4a) SRISK	(4b) SRISK	(4c) SRISK	(4d) SRISK
L.ROA	-18.23	-18.17				38.82	39.86			
	(11.86)	(11.25)				(24.24)	(25.73)			
L.CI	1.812*	1.503				5.693***	5.248***			
	(1.010)	(0.954)				(2.059)	(2.031)			
L.LIQUIDITY	3.321**	2.877**				6.133**	4.019*			
	(1.420)	(1.467)				(2.419)	(2.407)			
L.EQUITY	-24.35***	-22.56***				-1.217	-5.784			
	(6.230)	(5.745)				(10.17)	(12.66)			
L.LN_A	-0.0997	-0.268				6.637***	6.164***			
	(0.542)	(0.566)				(0.890)	(0.892)			
GDP	-16.08***	-15.97***				-23.76***	-22.64***			
	(4.195)	(4.197)				(5.631)	(6.040)			
CONCT	-0.0692	-0.0381				0.663	-1.948			
	(1.244)	(1.281)				(3.004)	(3.540)			
L.SPECIALIZED			-4.843***	-0.480	-2.921**			-6.304**	0.525	0.375
			(1.738)	(1.098)	(1.135)			(2.601)	(1.408)	(2.419)
L.INVESTMENT		4.843***		4.363**	1.922		6.304**		6.829**	6.679**
		(1.738)		(1.838)	(2.012)		(2.601)		(2.792)	(2.928)
L.DIVERSIFIED		0.480	-4.363**		-2.442**		-0.525	-6.829**		-0.150
		(1.098)	(1.838)		(1.112)		(1.408)	(2.792)		(1.514)
L.TRADER		2.921**	-1.922	2.442**			-0.375	-6.679**	0.150	
		(1.135)	(2.012)	(1.112)			(2.419)	(2.928)	(1.514)	
Constant	1.217	-18.17	-18.17	-18.17	-18.17	-70.11***	-63.45***	-57.15***	-63.98***	-63.83***
	(5.453)	(11.25)	(11.25)	(11.25)	(11.25)	(9.682)	(10.30)	(10.50)	(10.12)	(9.386)
Number of obs.	1,640	1,610				1,927	1,880			
Number of banks	351	345				436	429			
Chi-squared	40.35***	47.85***				99.06***	123.7***			
R2	0.0915	0.0957				0.327	0.345			

Table 8. Robustness check: Impact of banking business models on systemic risk after controlling for a country's bank deposits to GDP

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are represented by dummy variables. Standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					**crisis period (2007-2012)**				
	(1) SRISK	**(2a) SRISK**	**(2b) SRISK**	**(2c) SRISK**	**(2d) SRISK**	**(3) SRISK**	**(4a) SRISK**	**(4b) SRISK**	**(4c) SRISK**	**(4d) SRISK**
L.ROA	-15.61	-14.99				45.83*	48.05*			
	(10.85)	(10.01)				(23.44)	(25.02)			
L.CI	1.680*	1.396				6.345***	5.914***			
	(0.908)	(0.849)				(1.825)	(1.758)			
L.LIQUIDITY	2.562**	1.835				6.263***	4.244*			
	(1.286)	(1.316)				(2.223)	(2.213)			
L.EQUITY	-21.88***	-20.24***				0.571	-3.492			
	(5.962)	(5.316)				(9.704)	(12.29)			
L.LN_A	-0.188	-0.486				5.601***	5.199***			
	(0.515)	(0.531)				(0.847)	(0.836)			
GDP	-16.76***	-16.13***				-18.23***	-16.69***			
	(4.230)	(4.125)				(4.911)	(5.147)			
DEPO	2.181*	2.827***				4.389**	4.518**			
	(1.131)	(1.094)				(1.797)	(1.827)			
L.SPECIALIZED			-6.716***	-0.329	-2.800**			-5.533**	0.631	0.911
			(1.690)	(1.196)	(1.184)			(2.686)	(1.513)	(2.442)
L.INVESTMENT		6.716***		6.387***	3.916**		5.533**		6.163**	6.444**
		(1.690)		(1.730)	(1.756)		(2.686)		(2.752)	(2.727)
L.DIVERSIFIED		0.329	-6.387***		-2.471**		-0.631	-6.163**		0.281
		(1.196)	(1.730)		(1.054)		(1.513)	(2.752)		(1.413)
L.TRADER		2.800**	-3.916**	2.471**			-0.911	-6.444**	-0.281	
		(1.184)	(1.756)	(1.054)			(2.442)	(2.727)	(1.413)	
Constant	0.694	1.135	7.851	1.464	3.935	-63.78***	-59.18***	-53.65***	-59.82***	-60.10***
	(4.948)	(5.451)	(5.694)	(5.265)	(4.959)	(9.541)	(9.725)	(9.826)	(9.706)	(9.176)
Number of obs.	1,589	1,559				1,876	1,829			
Number of banks	332	326				426	419			
Chi-squared	42.22***	51.04***				81.95***	104.6***			
R-squared	0.0954	0.130				0.297	0.312			

Table 9. Robustness check: Impact of banking business models on systemic risk after controlling for a country's stock market capitalization to GDP

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are represented by dummy variables. Standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					crisis period (2007-2012)				
	(1) SRISK	(2a) SRISK	(2b) SRISK	(2c) SRISK	(2d) SRISK	(3) SRISK	(4a) SRISK	(4b) SRISK	(4c) SRISK	(4d) SRISK
L.ROA	-15.81	-15.91				48.78**	48.62*			
	(10.93)	(10.51)				(23.66)	(25.23)			
L.CI	1.207	0.990				5.151**	4.678**			
	(0.958)	(0.917)				(2.022)	(2.000)			
L.LIQUIDITY	2.928**	2.570*				6.749***	4.570*			
	(1.425)	(1.475)				(2.493)	(2.463)			
L.EQUITY	-22.64***	-21.33***				-5.716	-9.814			
	(6.228)	(5.868)				(10.24)	(12.68)			
L.LN_A	0.149	-0.0190				6.354***	5.920***			
	(0.572)	(0.597)				(0.885)	(0.885)			
GDP	-13.26***	-13.39***				-17.79***	-16.72***			
	(3.985)	(3.984)				(4.679)	(5.084)			
STMRKT	-2.852***	-2.652***				-3.595***	-3.442***			
	(0.556)	(0.554)				(0.912)	(0.930)			
L.SPECIALIZED			-4.584***	-0.710	-2.640**			-5.817**	0.869	0.429
			(1.772)	(1.221)	(1.178)			(2.605)	(1.525)	(2.384)
L.INVESTMENT		4.584***		3.874**	1.944		5.817**		6.686**	6.245**
		(1.772)		(1.868)	(1.965)		(2.605)		(2.671)	(2.723)
L.DIVERSIFIED		0.710	-3.874**		-1.930*		-0.869	-6.686**		-0.441
		(1.221)	(1.868)		(1.104)		(1.525)	(2.671)		(1.399)
L.TRADER		2.640**	-1.944	1.930*			-0.429	-6.245**	0.441	
		(1.178)	(1.965)	(1.104)			(2.384)	(2.723)	(1.399)	
Constant	1.335	1.032	5.616	1.742	3.672	-63.41***	-58.52***	-52.70***	-59.39***	-58.95***
	(5.456)	(5.982)	(6.208)	(5.769)	(5.501)	(9.359)	(9.625)	(9.747)	(9.541)	(8.915)
Number of obs.	1,627	1,597				1,937	1,890			
Number of banks	338	332				436	429			
Chi-squared	64.66***	65.56***				89.24***	114.7***			
R-squared	0.0658	0.0804				0.308	0.323			

Table 10. Impact of banking business models on ROA

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are presented by dummy variables. Robust standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					**crisis period (2007-2012)**				
	(1) ROA	**(2a) ROA**	**(2b) ROA**	**(2c) ROA**	**(2d) ROA**	**(3) ROA**	**(4a) ROA**	**(4b) ROA**	**(4c) ROA**	**(4d) ROA**
L.EQUITY	0.0610**	0.0634**				0.0943***	0.106***			
	(0.0300)	(0.0321)				(0.0270)	(0.0338)			
L.CI	-0.0128***	-0.0134***				-0.0150***	-0.0154***			
	(0.00403)	(0.00411)				(0.00284)	(0.00285)			
L.LIQUIDITY	0.00521**	0.00485**				0.00873***	0.00960***			
	(0.00226)	(0.00228)				(0.00174)	(0.00218)			
L.LN_A	-0.00107**	-0.00119**				-0.00149***	-0.00129***			
	(0.000424)	(0.000493)				(0.000294)	(0.000307)			
GDP	0.122***	0.124***				0.0669***	0.0592***			
	(0.0213)	(0.0219)				(0.0105)	(0.00987)			
L.SPECIALIZED			-0.00484*	-0.00435**	-0.00101			0.00248	0.00266***	-0.000747
			(0.00263)	(0.00198)	(0.00134)			(0.00193)	(0.001000)	(0.000909)
L.INVESTMENT		0.00484*		0.000497	0.00383*		-0.00248		0.000183	-0.00323*
		(0.00263)		(0.00187)	(0.00219)		(0.00193)		(0.00224)	(0.00190)
L.DIVERSIFIED		0.00435**	-0.000497		0.00333**		-0.00266***	-0.000183		-0.00341***
		(0.00198)	(0.00187)		(0.00155)		(0.001000)	(0.00224)		(0.000831)
L.TRADER		0.00101	-0.00383*	-0.00333**			0.000747	0.00323*	0.00341***	
		(0.00134)	(0.00219)	(0.00155)			(0.000909)	(0.00190)	(0.000831)	
Constant	0.0181***	0.0169**	0.0217***	0.0212***	0.0179***	0.0206***	0.0191***	0.0167***	0.0165***	0.0199***
	(0.00655)	(0.00659)	(0.00762)	(0.00739)	(0.00670)	(0.00409)	(0.00438)	(0.00490)	(0.00424)	(0.00416)
Number of obs.	2,415	2,369				2,574	2,502			
Number of banks	432	421				458	450			
Chi-squared	86.27***	102.7***				192.6***	219.6***			
R-squared	0.269	0.287				0.334	0.341			

Table 11. Impact of banking business models on ROE

The data present bank-level estimations based on GLS regressions with a random effect. Bank-specific characteristics appear as lagged variables. Banking business models are represented by dummy variables. Robust standard errors that control for clustering at the bank-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	pre-crisis period (2000-2006)					crisis period (2007-2012)				
	(1) ROE	**(2a) ROE**	**(2b) ROE**	**(2c) ROE**	**(2d) ROE**	**(3) ROE**	**(4a) ROE**	**(4b) ROE**	**(4c) ROE**	**(4d) ROE**
L.EQUITY	-0.368***	-0.396***				-0.145	-0.0855	-0.0855	-0.0855	-0.0855
	(0.110)	(0.122)				(0.0885)	(0.115)	(0.115)	(0.115)	(0.115)
L.CI	-0.112***	-0.115***				-0.168***	-0.168***	-0.168***	-0.168***	-0.168***
	(0.0270)	(0.0272)				(0.0308)	(0.0322)	(0.0322)	(0.0322)	(0.0322)
L.LIQUIDITY	0.0551***	0.0601***				0.0767***	0.102***	0.102***	0.102***	0.102***
	(0.0116)	(0.0142)				(0.0199)	(0.0204)	(0.0204)	(0.0204)	(0.0204)
L.LN_A	-0.00347	-0.00379				-0.0130***	-0.00966***	-0.00966***	-0.00966***	-0.00966***
	(0.00225)	(0.00300)				(0.00222)	(0.00230)	(0.00230)	(0.00230)	(0.00230)
GDP	0.859***	0.873***				0.765***	0.679***	0.679***	0.679***	0.679***
	(0.134)	(0.140)				(0.0881)	(0.0860)	(0.0860)	(0.0860)	(0.0860)
L.SPECIALIZED			-0.00817	-0.0117	-0.0113			0.0522***	0.0265***	-0.000422
			(0.0166)	(0.0106)	(0.00991)			(0.0125)	(0.00904)	(0.00989)
L.INVESTMENT		0.00817		-0.00352	-0.00311		-0.0522***		-0.0258**	-0.0527***
		(0.0166)		(0.0162)	(0.0173)		(0.0125)		(0.0127)	(0.0118)
L.DIVERSIFIED		0.0117	0.00352		0.000416		-0.0265***	0.0258**		-0.0269***
		(0.0106)	(0.0162)		(0.00990)		(0.00904)	(0.0127)		(0.00842)
L.TRADER		0.0113	0.00311	-0.000416			0.000422	0.0527***	0.0269***	
		(0.00991)	(0.0173)	(0.00990)			(0.00989)	(0.0118)	(0.00842)	
Constant	0.217***	0.212***	0.220***	0.224***	0.224***	0.303***	0.280***	0.228***	0.253***	0.280***
	(0.0335)	(0.0382)	(0.0462)	(0.0392)	(0.0368)	(0.0341)	(0.0377)	(0.0421)	(0.0384)	(0.0372)
Number of obs.	2,407	2,361				2,551	2,479			
Number of banks	431	420				458	450			
Chi-squared	91.03***	95.54***				198.0***	233.8***			
R-squared	0.148	0.154				0.244	0.255			

Table 12. Dominant banking business models in countries

SPECIALIZED	INVESTMENT	DIVERSIFIED	TRADER
Brazil	Australia	Argentina	Hong Kong
China	Belgium	Austria	India
Jordan	Canada	Chile	Indonesia
Kuwait	Denmark	Colombia	Japan
Philippines	Finland	Croatia	Lebanon
Qatar	France	Cyprus	Malta
	Germany	Greece	Mexico
	Ireland	Hungary	Pakistan
	Italy	Israel	Saudi Arabia
	Netherlands	Kazakhstan	Turkey
	Portugal	Malaysia	
	Spain	Norway	
	Sweden	Peru	
	Switzerland	Poland	
	United Kingdom	Romania	
	United States	Russia	
		Singapore	
		South Korea	
		Thailand	
		Ukraine	
		United Arab Emirates	

Table 13. Impact of banking business models on a country's crisis depth

The data present cross-country estimations using OLS. Crisis depth has been calculated as a ratio of two values: 1) a difference between a country's GDP growth rate in 2006 and the lowest yearly GDP growth rate in the period of 2007-2012; and 2) a country's GDP growth rate in 2006. Banking business models representative for individual countries are included as dummy variables. Standard errors that control for clustering at the country-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	(1) DEPTH	(2) DEPTH	(3) DEPTH	(4) DEPTH	(5) DEPTH	(6) DEPTH	(7) DEPTH	(8) DEPTH	(9) DEPTH	(10) DEPTH	(11) DEPTH	(12) DEPTH
SPECIALIZED		-2.000***	-1.255***	-1.286*		-1.960***	-1.217***	-1.027		-2.021***	-1.141***	-1.059
		(0.370)	(0.353)	(0.708)		(0.393)	(0.352)	(0.651)		(0.368)	(0.372)	(0.721)
INVESTMENT	1.767***		0.702**	0.686	1.707***		0.692**	0.898	1.772***		0.829***	0.927
	(0.372)		(0.278)	(0.599)	(0.407)		(0.273)	(0.585)	(0.385)		(0.244)	(0.624)
DIVERSIFIED	1.057***	-0.736**		-0.0328	0.990***	-0.737***		0.172	0.924**	-0.870***		0.0692
	(0.355)	(0.282)		(0.611)	(0.368)	(0.272)		(0.543)	(0.384)	(0.243)		(0.664)
TRADER	0.997	-0.767	-0.0474		0.691	-0.996	-0.293		0.735	-1.012	-0.178	
	(0.730)	(0.646)	(0.647)		(0.670)	(0.599)	(0.556)		(0.752)	(0.655)	(0.693)	
CONCT	0.905	0.822	0.871	0.906								
	(0.591)	(0.595)	(0.587)	(0.589)								
DEPO					0.157	0.174	0.173	0.158				
					(0.289)	(0.281)	(0.283)	(0.288)				
STMRKT									-0.101	-0.103	-0.0951	-0.101
									(0.153)	(0.159)	(0.155)	(0.152)
Constant	-0.0804	1.757***	1.010**	1.002	0.466	2.173***	1.465***	1.276***	0.686*	2.472***	1.625***	1.534**
	(0.506)	(0.512)	(0.379)	(0.696)	(0.368)	(0.332)	(0.278)	(0.409)	(0.383)	(0.210)	(0.191)	(0.644)
Number of obs.	53	53	53	53	51	51	51	51	53	53	53	53
R-squared	0.293	0.319	0.314	0.314	0.259	0.291	0.283	0.279	0.274	0.304	0.296	0.294
F-test	8.162***	9.390***	9.302***	9.219***	7.049***	9.298***	9.135***	8.667***	7.766***	10.07***	9.828***	10.10***

Table 14. Impact of banking business models on a crisis duration in a country

The data present cross-section estimations using OLS. Crisis duration has been defined as maximum of two values: 1) a number of years between 2006 and the last year with negative GDP growth rate; and 2) a number of years between 2006 and the year with the minimum GDP growth rate in the period of 2007-2012. Banking business models representative for individual countries are included as dummy variables. Standard errors that control for clustering at the country-level are reported in brackets. The symbols *, represent statistical significance at the 10%, 5%, and 1% levels, respectively.**, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	DURAT	**DURAT**	**DURAT**	**DURAT**	**DURAT**	**DURAT**	**DURAT**	**DURAT**	**DURAT**	**DURAT**	**DURAT**	**DURAT**
SPECIALIZED		1.799***	1.494**	1.766**		1.842***	1.428**	2.056**		1.788**	1.645**	1.951**
		(0.655)	(0.680)	(0.826)		(0.684)	(0.686)	(0.857)		(0.676)	(0.691)	(0.804)
INVESTMENT	-1.525**		-0.265	-0.0192	-1.608**		-0.381	0.214	-1.532**		-0.117	0.166
	(0.634)		(0.233)	(0.417)	(0.651)		(0.254)	(0.446)	(0.638)		(0.201)	(0.382)
DIVERSIFIED	-1.248*	0.320		0.271	-1.211*	0.415		0.617	-1.405**	0.157		0.306
	(0.657)	(0.240)		(0.425)	(0.651)	(0.251)		(0.499)	(0.649)	(0.203)		(0.436)
TRADER	-1.416*	0.117	-0.181		-1.776**	-0.187	-0.578		-1.627**	-0.112	-0.247	
	(0.804)	(0.439)	(0.433)		(0.831)	(0.463)	(0.518)		(0.769)	(0.392)	(0.443)	
CONCT	0.710	0.788	0.747	0.725								
	(0.712)	(0.716)	(0.706)	(0.700)								
DEPO					0.503	0.487	0.486	0.485				
					(0.339)	(0.336)	(0.339)	(0.336)				
STMRKT									-0.193*	-0.192*	-0.196*	-0.191*
									(0.109)	(0.107)	(0.109)	(0.108)
Constant	4.053***	2.444***	2.764***	2.533***	4.179***	2.572***	2.968***	2.372***	4.768***	3.213***	3.354***	3.064***
	(0.846)	(0.517)	(0.375)	(0.515)	(0.668)	(0.345)	(0.195)	(0.490)	(0.654)	(0.175)	(0.204)	(0.393)
Number of obs.	53	53	53	53	51	51	51	51	53	53	53	53
R-squared	0.201	0.239	0.235	0.238	0.266	0.295	0.291	0.296	0.205	0.238	0.237	0.240
F-test	1.922	2.529	2.491	2.531	1.947	2.236	2.199	2.231	1.881	2.082	2.075	2.074

Figure 1. Expected changes in crisis depth and crisis duration due to 30 pp. increase in the country's share of a given banking business model

Each point in the figure represents expected increases in crisis depth and crisis duration in a country due to a 30 pp. increase in a bank's asset-weighted share of a given banking business model in total banking sector asset, and a simultaneous 10 pp. decrease in the share of each of the remaining three banking business models. The results were obtained with the use of regression results for the equations (2) from tables 13-14.