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2014

CZECH NATIONAL BANK

RESEARCH AND POLICY NOTES

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4/2014

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Reviewed by: Tuomas Peltonen (European Central Bank)
Pavol Jurča (National Bank of Slovakia)
Michal Nyklíček (Czech National Bank)

Project Coordinator: Bořek Vašíček

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Josef Brechler, Václav Hausenblas, Zlatuše Komárková, Miroslav Plašil

Similarity and Clustering of Banks: Application to the Credit Exposures of the Czech Banking Sector

Josef Brechler, Václav Hausenblas, Zlatuše Komárková, and Miroslav Plašil *

Abstract

After the recent events in the global financial system there has been significant progress in the literature focusing on the sources of systemic importance of financial institutions. However, the concept of systemic importance is in practice often simplified to the problem of size and contagion due to interbank market interconnectedness. Against this backdrop, we explore additional features of systemic importance stemming from similarities between bank asset portfolios and investigate whether they can contribute to the build-up of systemic risks. We propose a set of descriptive methods to address this aspect empirically in the context of the Czech banking system. Our main findings suggest that the overall measure of the portfolio similarity of individual banks is relatively stable over time and is driven mainly by large and well-established banks. However, we identified several clusters of very similar banks whose market share is small individually but which could become systemically important when considered as a group. After taking into account the credit risk characteristics of portfolios we conclude that the importance of these clusters is even higher.

Abstrakt

Po událostech nedávné finanční krize došlo k výraznému pokroku v literatuře zkoumající zdroje systémové významnosti bankovních institucí. Vymezení systémové významnosti se však v praxi často zjednodušuje pouze na problém velikosti a nákazy vyplývající z propojenosti na mezibankovním trhu. Tato práce se proto v rámci analýzy dalších aspektů systémové významnosti zabývá problematikou podobnosti struktury bankovních portfolií a zkoumá, zda může přispívat ke vzniku systémových rizik. V článku je navržena sada metod pro empirickou analýzu tohoto problému v českém bankovním sektoru. Mezi hlavní zjištění patří to, že celková míra podobnosti portfolií českých bank byla v uplynulých letech relativně stálá a výrazně k ní přispívají především velké a zavedené banky. Identifikovali jsme ale také shluky velmi podobných bank, jejichž individuální tržní podíl je malý, ale které jako celek mohou tvořit systémově významný segment. Pokud navíc při měření podobnosti vezmeme v úvahu i pozorované úvěrové riziko, je význam těchto shluků ještě větší.

JEL Codes: B6, B12, B52, Z80.
Keywords: Contagion, correlation, financial stability, systemic risk, too-many-to-fail.

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* Josef Brechler, Czech National Bank, IES FSV UK, josef.brechler@cnb.cz
Václav Hausenblas, corresponding author, Czech National Bank, IES FSV UK, vaclav.hausenblas@cnb.cz
Zlatuše Komárková, Czech National Bank, zlatuse.komarkova.cnb.cz
Miroslav Plašil, Czech National Bank, miroslav.plasil@cnb.cz
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Nontechnical Summary

After the recent events in the global financial system there has been significant progress in the literature analysing systemic importance within banking systems. We argue, however, that the concept of systemic importance of financial institutions is too often simplified to the problem of size and interbank market interconnectedness. The purpose of this paper is to emphasise the importance of the so-called *too-many-to-fail* syndrome in the propagation of financial distress stemming from similarity of banks' balance sheets and their exposure to common macroeconomic shocks.

We propose a toolkit of methods to address this aspect empirically in the context of the Czech banking system. We assess the existence of clusters of similar banks based on both their balance-sheet structure and their credit-portfolio performance. We study the overall diversification (similarity) of the banking system and discuss the potential implications for financial stability.

The proposed methods take into account the fact that seemingly uncorrelated risk exposures can become highly correlated under certain circumstances. Under weak economic conditions and elevated financial stress there tends to be a higher probability that financial losses will be correlated and failures of even relatively unimportant elements of the financial sector will become triggers of losses of confidence. In contrast to other existing literature our findings are based on fundamental factors and do not rely on efficiency of capital markets in pricing risks.

Our main findings suggest that over the period of 2002–2013 the overall similarity of individual banks was relatively stable and not excessively high compared to selected benchmarks and that it was driven mainly by large and well-established banks. We also identify several separate clusters of banks whose market share is small when assessed individually but which could become systemically important under adverse circumstances when considered as a group. After taking into account measures of the realised credit risk (measured by the non-performing loan ratio) of the individual sectors and industries that banks are exposed to, we find that the importance of these clusters is even higher.

1. Introduction

The recent global financial crisis has significantly increased interest in the linkages within the financial system and the collective behaviour of financial institutions. The key observation is that certain banks were so important that their failures spilled over to the whole financial system, leading to serious negative impacts on the real economy and, via a feedback loop, back on the financial system. The transmission of the idiosyncratic risks of these banks (now labelled as systemically important financial institutions or SIFIs) to other institutions was channelled most noticeably through direct financial exposures such as loans and derivative contracts and was boosted by excessive complexity of financial markets and information asymmetries.

Initially, systemic importance was associated mainly with the moral hazard problem stemming from high concentration in financial markets. This so-called *too-big-to-fail* syndrome refers to the situation where a large bank's risk-taking is motivated by relying on government support in the form of a bail-out. The literature later identified other factors that contribute to this dimension of systemic risk. Following Thomson (2009), these can be summarised as *concentration*, *contagion*, *complexity* and *correlation*.

The original method for identifying SIFIs was based on the assessment of the institution's size. However, with recognition of the increased interdependence and globalisation of the financial system the definition of systemic importance has been extended to include also the *too-interconnected-to-fail* syndrome. This broader definition admits that even small or mid-sized banks can significantly contribute to systemic risk if they are sufficiently interconnected within the system.

In both cases, stress in one financial institution spreads to the rest of the system through a process called contagion. Direct financial contagion occurs when a bank is connected to others by contractual obligations and involves domino effects. If one bank goes bankrupt, all other banks with claims on the defaulting bank could be damaged. By contrast, indirect channels of contagion do not require any breach of contract. This kind of contagion occurs when a bank's actions generate externalities which affect other banks mainly through the information or asset-price channels. At the centre of indirect contagion is what we call "similarity" or "correlation". This refers to a situation where banks follow similar risk management or trading strategies and have exposures to the same market segments or even to the very same debtors (such as governments or large corporations). In such an environment, banks become more vulnerable to common shocks and their probabilities of default can therefore get highly correlated. Moreover, stress in a single bank can spread to the rest of the system due to the asset-price and information channels. The bank in difficulties may choose to sell part of its assets in order to raise cash or to reduce its leverage. This activity may in turn put pressure on the market prices of these assets. If market prices fall, all other banks that hold these assets have to write down their positions. Due to the information channel, investors may find negative news about a single bank to be relevant to other banks which are believed to have similar risk exposures as the bank in trouble. The loss of confidence may increase their funding costs or trigger bank runs (liquidity hoarding). These sources of systemic risk are associated to the so-called *too-many-to-fail* syndrome.

While direct channels of contagion are frequently analysed in the current literature (see the next section for references), indirect channels of contagion have so far been explored considerably less. Against this background, the purpose of this paper is to emphasise the importance of the *too-many-to-fail* problem in the propagation of financial distress and to present a set of methods for measuring this aspect of systemic risk. Our aim is to explore the existence of clusters of banks similar both in the structure of their balance sheets and in their credit portfolio risk performance. We study the overall diversification (similarity) of the banking system and discuss its potential implications for financial stability. When assessing correlation risk, it should be taken into account that seemingly uncorrelated risk exposures can become highly correlated under certain circumstances. Under weak economic conditions and elevated financial stress there tends to be a higher probability that financial losses will be correlated and failures of even relatively unimportant elements of the financial sector will become triggers of loss of confidence.

Our study contributes to the existing literature in several ways. From the methodological point of view, we contribute to empirical measurement of the cross-sectional dimension of systemic risk by proposing a simple measure of indirect interconnectedness between banks via common exposures. For a financial supervisory authority, this constitutes a practical and applicable monitoring tool which circumvents many of the problems associated with empirical methods relying on capital market data. It could be incorporated into the assessment toolkit of policymakers, who need to be able to set up appropriate macroprudential instruments for mitigating sources of systemic risk. In the context of the literature focusing on the Czech banking system, this work is a follow-up to Komarkova et al. (2012) and Hausenblas et al. (2012) and fills a gap in the empirical evidence on correlation and the too-many-to-fail problem. Last but not least, we are the first to present an analysis of credit performance using highly granular data on credit provided to the Czech real-economy sector.

The paper is structured as follows. Section 2 provides a review of literature related to the subject matter and to the methodology applied. Section 3 presents our methodological background, including our newly proposed measure, while Section 4 contains the main empirical results. Section 5 concludes.

2. Related Literature

There are several streams of literature that focus on the measurement of systemic importance. One of the frequently used approaches assigns the level of market risk to individual institutions based on traditional financial modelling methods for asset market (co-)movements. Any arbitrary risk measure, be it co-value-at-risk, marginal expected shortfall (Acharya et al., 2010) or the Shapley value of expected shortfall (Drehmann and Tarashev, 2013), is then modelled for a single institution as a stochastic variable interdependent with the value of the given measure for the system as a whole. In general, this approach may suffer from the absence of market prices needed to empirically identify the models, in particular if one wants to describe a financial system with an under-developed capital market. Another downside of these models is that they rely heavily on market efficiency. Therefore, they do not account for the bias in market prices caused by the fact that systemic importance is already implicitly included in market prices, as market participants assume that some institutions will be rescued by governments if they are at risk of failing (Atle Berg, 2011).

Another stream of research is the stress-testing approach, which is usually based on deterministic simulations of shocks and their propagation through the financial system. Stress tests make use of individual bank balance-sheet items (such as loans, interbank lending and cross-holdings of securities) and assess the robustness of the financial system to a wide range of shocks. These may be either random bank failures (Hausenblas et al., 2012) or common macroeconomic shocks (Elsinger et al., 2006a; Gersl et al., 2012; Alves et al., 2013). In addition to the different nature of shocks, the difference may lie in the assumptions made about possible channels of contagion. Besides the basic domino channel via direct credit exposures (Allen and Gale, 2000), some theoretical (Cifuentes et al., 2005; Bluhm and Krahnen, 2011; Adrian and Shin, 2008) as well as empirical studies

(Hausenblas et al., 2012) assume that contagion might additionally spread through the financial system via the liquidity and asset-price channels. When banks' capitalisation is impaired by the initial shock, they try to get rid of assets that have a non-zero risk weight in order to increase their capital adequacy ratio. In illiquid markets, such fire sales depress the prices of such assets, spreading the stress even further. In a more complex approach, the systemic importance of banks can also be modelled jointly as PD and LGD in a copula model (Elsinger et al., 2006b).

A relatively new branch of literature has adopted networks and their topology as the main vehicle for the analysis of systemic risk. The network approach represents a suite of methods for analysing the structure and interconnectedness of the system. This helps to determine the key players and critical exposures according to their position within the financial network (Boss et al., 2004). The network consists of nodes (usually financial institutions, but in general also firms, households, governments, etc.) connected by links (financial exposures). Measures of centrality or relative importance are defined such that they increase with the number of links going in and out of a node (degree centrality), the number of other nodes it connects (betweenness), its proximity to other nodes (closeness) and the number of links it has with other significant nodes (prestige). Based on these metrics, Alves et al. (2013) identified several important European banks on the interbank market, and similarly Brunnermeier et al. (2013) found high concentration with a potential systemic impact in the context of the European CDS market. The Bank of England (Langfield et al., 2014) applies network analysis on a very granular balance- and off-balance-sheet structure dataset as a risk monitoring tool which classifies banks' business models based on their trading activity.

As we have already mentioned, the too-many-to-fail syndrome is strongly connected to market failures due to moral hazard. Using a theoretical model, Acharya and Yorulmazer (2007) conclude that banks have incentives to herd, since when the number of failing banks is too large the surviving institutions do not have enough acquisition capacity and the government finds it optimal to bail-out the failed banks. The too-many-to-fail moral hazard is stronger for small agents and at times when markets are weak. Additional incentives to herd might theoretically stem from a strategy to minimise the informal spillover effect of the disclosure of financial results on borrowing costs or bank runs (Acharya and Yorulmazer, 2008). Empirical evidence that governments are less likely to let a bank fail if there are other weak banks in the system is provided by Brown and Dinç (2009).

The subject matter of this study is also closely connected to the problem of optimal portfolio diversification. Theoretical studies (Wagner, 2010) show that diversification on a micro level does not automatically ensure enough diversification on the macro level. When banks' portfolios are very similar, premature liquidation of assets in the economy is more likely and thus a lower probability of a single bank failing is traded off with higher systemic risk.

The concept of insufficient portfolio diversification can be empirically captured by the notion of an aggregate portfolio similarity measure. Although in the domain of systemic risk quantification such measures are rare, it is possible to draw inspiration from closely related fields. Studying capital flow contagion in financial markets, Blocher (2011) constructs a similarity index and shows empirically that it has very high explanatory power for forecasting asset managers' portfolio returns. He finds that spillover effects between agents with similar portfolios affect funds' returns via crowded trades. Using a similar concept, Bank of Israel (2012) analyses funds managing the public's long-term savings (e.g. pension funds). It finds that due to the limited supply of investment opportunities in Israel there is a high level of similarity in the asset portfolios managed in terms of both selection of very similar assets and even the weighting of these assets in the portfolio. The considerable similarity between the portfolios managed makes the sector vulnerable to common shocks. This calls for increasing the exposure of institutional investors to markets abroad. Methodologically, these are the papers most closely related to our study.

The concept of interconnectedness introduced by Cai et al. (2014) to some extent resembles the similarity measure developed in our work. The authors use data on syndicated loans to calculate the distance between pairs of banks using the Euclidean distance applied to banks' portfolios. Bank-level and market-aggregate interconnectedness indicators are calculated by aggregating the distance measure. The empirical part of the study focuses on assessing factors that influence the formation of a loan syndicate and on finding drivers of banks' interconnectedness. The paper also offers a battery of models that capture the relationship between the interconnectedness of banks and various measures of systemic risk, such as CoVar, SRISK and DIP.

Our work is also somewhat related to the literature on contagion and frailty risk in real-economy sectors. These contagion models focus on the interlinkages within production chains or business networks (Azizpour et al., 2008). Contagion seems to be concentrated mainly within individual industries (Lando and Nielsen, 2010) and is particularly relevant through supply chain relationships. As a result, contagion may explain default dependence at the industry level beyond that induced by macro and frailty factors. The frailty effect captures default dependence above and beyond what is already implied by the observed macroeconomic variable and corporate-level information. Empirical studies on the variation in default intensities generally model frailty as an unobserved dynamic component (Koopman et al., 2011, 2012).

3. Methodology

In the following section, we present several concepts of similarity between bank portfolios and show how they can be combined into a unified framework. First, we design a measure of portfolio similarity which takes into account the correspondence of the shares of selected asset categories in total assets between individual banks, but ignores the actual (credit) risk profiles of these assets. Such a measure may indicate seeds of potential vulnerabilities, but the system can still remain stable in the absence of negative shocks and elevated risks. An analysis of common risks may thus be necessary to get a more realistic picture of the banking system. In particular, it may provide a relevant indication of whether a state of vulnerability is turning into a state of financial instability. For this reason, we investigate how the similarity in the risk profile changes over time across selected asset categories and across the banking sector. While this information may be interesting in its own right, it is first of all used to derive risk weights for individual asset categories. These are in turn used to calculate a risk-adjusted version of the portfolio similarity measure. The main intuition behind the risk-adjusted indicator is that portfolio similarity is more dangerous if all banks tend to hold similar and, at the same time, riskier assets. The measures under study can be used for monitoring overall changes in asset diversification within the banking sector or for identifying clusters of very similar banks at a given point in time. The latter may be relevant for spotting situations where a cluster of individually small banks turns out to gain systemic importance if considered as a group.

3.1 Balance-Sheet Similarity

In practice, a bank a can described by a real-valued vector containing various characteristics, such as the portfolio structure of its loans and securities, its funding structure, its liquidity mismatch profile and its off-balance-sheet business. Since our study is primarily concerned with credit risk, we limit our attention to the asset side of the balance sheet. Specifically, a vector $a = \{a_1 ... a_k\}$, where k stands for data granularity, represents the asset portfolio, characterised by the aggregate gross nominal value of each asset category $i \in 1,...k$. Asset categories are defined as exposures to different institutional sectors (debtors), which can be further broken down by financial instruments or branches of activity (see Section 4 for precise definitions of the individual asset categories). Following Blocher (2011) we measure the similarity between the portfolios of any two banks (e.g. a and b) using a cosine similarity function. The cosine similarity between two vectors is defined as the cosine of the angle between the vectors:

$$similarity(a,b) = cos(\theta) = \frac{a \cdot b}{\|a\|\|b\|} = \frac{\sum a_i b_i}{\sqrt{\sum a_i^2 \times \sum b_i^2}} \tag{3.1}$$

The choice of cosine similarity has several practical advantages over its potential competitors.[1] First, alternative measures are usually based on the concept of the distance between two vectors and as such they represent a measure of *dissimilarity* rather than similarity. Thus, some initial transformation has to be done to obtain a genuine similarity measure. Second, cosine similarity is a scale-independent measure and therefore orientation rather than magnitude (bank size) drives the similarity. While scale-independence can also be obtained for other measures (for instance Euclidean distance) by prior normalisation of the data to unit vectors, the cosine similarity is, in addition, bounded to $\{a,b \in R\} \mapsto [-1,1]$ by definition. Moreover, given that on-balance-sheet assets can only take positive values, we further obtain $\{a,b \in R_+\} \mapsto [0,1]$, 0 for orthogonal vectors (complete dissimilarity) and 1 for identically oriented vectors (completely identical portfolio composition). This greatly facilitates the interpretation of the results.

If it is necessary to put a higher weight on the similarity between any of the asset categories, we can use the weighted form of cosine similarity (in our case, varying weights will reflect different risk profiles of individual asset categories):

$$similarity_{wt}(a,b,w) = \frac{\sum w_i a_i b_i}{\sqrt{\sum w_i a_i^2 \times \sum w_i b_i^2}} \tag{3.2}$$

If we compute a *similarity* measure (3.1) for each pair of n banks, we get an $n \times n$ symmetric similarity matrix $S = \{s_{i,j}\}$, which represents a key input for deriving several characteristics of the banking system. In particular, based on matrix S we *(i)* propose a measure of the overall similarity of banks in the system and *(ii)* detect clusters of banks exposed to common (systemic) risks.

To explore the existence of clusters we make use of multivariate visualisation methods which are similar in spirit to Friendly (2002). These methods allow us to visualise the existing structure in the data by "optimally" reordering the rows (and columns equally) of matrix S. The reordering algorithm puts similar banks close to each other and dissimilar banks far from each other with respect to a predefined criterion. In particular, we apply the fast optimal leaf ordering algorithm (Bar-Joseph et al., 2001) as implemented in the R package *seriation*.

[1] Later, we will demonstrate that cosine similarity also has some less desirable properties when measuring portfolio similarity at the level of the whole banking sector. However, these drawbacks cannot easily be rectified by choosing other candidates, as these alternative measures suffer from the very same problems.

To obtain the measure of overall similarity among banks we stick to a simple solution and define it as a weighted average of the pairwise similarities.[2] We consider three different weighting schemes for computing the average similarity. (1) The trivial way is to consider equal weights (a unit matrix). This, however, may not be the desirable choice for heterogeneous banking systems, where data on smaller banks (yet to start diversifying their portfolios) can potentially add noise to the measurement. In order to get an estimate that is representative of the system in terms of total assets, we alternatively use weights computed as (2) the sum of the total assets of banks i and j or even as (3) the total assets of the smaller of the two banks measured.

Even though the cosine similarity measure is bounded to $[0,1]$, it does not provide much guidance about what levels of overall (average) similarity should be considered too high for a given banking system. Therefore, we assess the actual values of the average similarity against two benchmark levels of cosine similarity computed on simulated random banking portfolios. In Monte Carlo simulations, random banking portfolios are drawn from several alternative distributions reflecting different assumptions we arbitrarily impose on the portfolio structure of banks. These assumptions concern the random distribution family and its parameters as well as the aggregate structure of random banking systems. The two selected benchmarks do not in any way define limits on the potentially observable values of cosine similarity.

The first, rather theoretical, benchmark is based on an assumption of high diversification at the individual bank level, which corresponds to a roughly *uniform distribution* of individual balance-sheet exposures (we abstract from the role of risk weights and other factors which may have an impact on the diversification strategy of a bank). In the case of very low data granularity ($k < 10$), the cosine similarity is driven by k. With higher k (i.e. for a high number of balance-sheet categories) the average cosine similarity of such a hypothetical system converges to 75%.[3]

On the other hand, in the case of a real banking system with more specialized banks we would assume a distribution with exponential or power-law properties. This is also somewhat more in line with the fact that the Czech banking sector and the composition of the real economy are rather heterogeneous (see Section 4). This prior assumption was supported by our empirical analysis of the observed sample distribution of banks' portfolios across the whole period. Based on the Akaike and Bayesian information criteria, we found that the gamma distribution best fits the observed data (Figure 6 in Appendix A). The second, more realistic benchmark is therefore based on a random generating process following the gamma distribution. The *shape* and *rate* parameters were estimated using the moment matching estimator of Delignette-Muller et al. (2014).[4]

In the next step, we impose additional restrictions on the hypothetical banking portfolios. By limiting the sizes of sectors and banks in the random systems to fit the real data we control for the aggregate structure of the total credit provided by the banking sector as a whole and for the real banking sector concentration, both of which might affect the aggregate similarity. Once a matrix of (unrestricted) random portfolios has been drawn from a particular distribution, the restrictions imposed on the bank and sector sizes are met via an iterative matrix balancing procedure (RAS). Subsequently, we compute cosine similarities for all combinations of hypothetical banks. The whole

[2] Alternatively, one may define the overall measure as the sum of all pairwise similarities. However, dependence on the number of banks may complicate international and temporal comparisons. The latter is given by the fact that the number of banks in the Czech banking system has been changing over time.

[3] See Figure 5 in Appendix A.

[4] Although the convergence of the cosine similarity to its limit with increasing k is somewhat slower than in the case of the uniform distribution, it does not discredit the selected benchmark as long as the granularity of the data remains constant.

procedure is repeated to generate 1,000 hypothetical banking systems for each point in time to obtain a sufficient number of measurements.

3.2 Similarity in Credit Risk Performance

As indicated above, we aim to incorporate some measure of credit risk materialisation into the similarity analysis. To do so, we choose the non-performing loan (NPL) ratio as our preferred measure. This choice was motivated by several practical reasons. First, the NPL ratio is a simple and widely understood measure which exhibits relatively smooth changes over time. Second, and more importantly, it is arguably the only measure that is generally available for all banks, can be readily broken down with respect to asset subcategories and comes with sufficient granularity. On the other hand, one should also be mindful of its potential drawbacks. In particular, the NPL ratio not only reflects the risk profile of a given asset category, but also may mirror the bank's internal processes (e.g. the work-out phase) and risk appetite. In addition, contrary to other measures (such as provisions), it does not take into account recovery rates and thus ignores the real size of losses related to a given asset category.

In what follows, the level of credit risk related to a given asset category at time t, μ_t, is measured by the aggregate value for the banking sector in a given period (i.e. levels for individual banks are neglected). The overall similarity of NPL ratios across banks is then proxied by the coefficient of variation $V_t = s_t/\mu_t$, where s_t denotes the standard deviation of the NPL ratios across banks at time t. The lower is its value, the more similar are the credit risk levels observed across banks for a given asset category in a given period. As an additional time-invariant measure of credit risk similarity capturing the strength of co-movements over time, we also compute the average correlation coefficient based on the pairwise correlations between the time series measuring the credit risk levels observed by individual banks for a given asset category.[5] High values might indicate that a potential increase in credit risk will be common to a significant part of the system, which again constitutes a source of indirect contagion and systemic risk.

The measures defined in this subsection may provide some interesting insights into the risk characteristics of the banking system, and may also serve as an input for other analyses. As we mentioned earlier, it might be worth adjusting the portfolio similarity measure for risk characteristics so that riskier assets receive higher weight. To follow this track, we apply information on both the level and the dispersion of credit risk. In general, we assume that a high level of the NPL ratio associated with a certain asset category combined with a low dispersion of its values across banks implies a higher risk of indirect contagion stemming from exposures to that category. Applying this reasoning, we define the risk weights as an interaction term of the level and the dispersion. Since higher levels of dispersion indicate lower similarity, we use the inverse of this term to derive weights of the form:

$$W_t = \mu_t * V_t^{-1} = \mu_t * \frac{\mu_t}{s_t} = \frac{\mu_t^2}{s_t} \tag{3.3}$$

These weights are used to compute the similarity measure (3.2) which we refer to as the risk-adjusted portfolio similarity.

[5] Only banks which were active throughout the whole time span are included. The average correlation was calculated using Fisher's z-transformation.

4. Data

Since the transformation of the Czech economy in the 1990s, the credit market in the Czech Republic has been constantly dominated by the banking sector. However, following an overall restructuring process, the banking sector and credit market have seen some major changes. These relate to the structural metamorphosis of the banking sector and to the generally growing popularity of some financial instruments. Among other things, this is clearly reflected in the aggregate developments in the portfolio composition of the banking sector. In this light, it is worth recalling some basic facts.

A relatively large volume of loans to non-financial corporations accumulated in bank balance sheets during the first half of the 1990s, while the share of loans to the household sector was largely negligible at that time. Worsening loan portfolio quality led to a banking crisis between 1997 and 1998, which resulted in the closure of several small and mid-sized banks. The subsequent deleveraging of the banking sector was reflected in a decrease in the total amount of credit provided between 1998 and 2002. During that time, the state sold its stakes in major banks to foreign banking groups. Since then the volume of credit has been steadily rising. This holds true for non-financial corporations and above all for households, thanks to growing interest in mortgage loans. A slowdown was observed around 2009, when the Czech economy fell into recession, and the credit market has been characterised by muted activity ever since.

The dataset used to quantify the similarity of banks' portfolios contains yearly observations from 2002 to 2013 (i.e. 12 years in total) and covers 42 unique banks (including subsidiaries and branches of international banking groups).[6] It comes from regular reporting for supervisory purposes and from the Czech central credit register. The data on non-performing loans broken down by individual banks and individual asset categories have monthly frequency. Given the high level of disaggregation and the length of the period covered, the issue of unbalanced data is significant. Since we put the main priority on assessing currently active institutions, the data on any bank whose activity ended during the period under study were consolidated with the data of the bank which bought out the closing bank.

In order to study the similarity between banks' exposures to their clients, we split the total volume of credit into categories with respect to the debtor's sector. Our motivation for such categorisation is that economic agents within a single sector or branch of activity (industry) are usually exposed to common shocks. A certain amount of the credit risk of banks' exposures is thus attributable to the financial situation in the debtor's sector, in addition to the idiosyncratic component of credit risk, which is specific to a particular agent. Based on this reasoning we understand each bank's portfolio as a set of exposures to 16 different categories.

As we already noted, the level of data granularity can affect the resulting value of the observed similarity. Most measures of similarity tend to show a decreasing value of similarity with increasing data granularity. The choice of the optimal level of data granularity for the purposes of systemic risk measurement is a compromise between data availability, economic reasoning and statistical properties. Banks' exposures within each category should exhibit as high a level of homogeneity as possible in terms of credit risk. At the same time, however, the data should not be too granular in order to keep some between-group difference and to prevent excessive sparsity.

[6] The data for individual banks that belong to the same banking group within the Czech Republic were (sub)consolidated.

Table 1: Descriptive Statistics for Bank Credit (As of the End of 2013)

	Credit provided (CZK billion)	Share in total (in %)	Change since 2002 (in %)	Concentration within sector, HHI average over 2002 to 2013
Non-financial corporations				
– Real estate, renting and business	237	5.7	544	0.18
– Manufacturing	195	4.7	54	0.12
– Wholesale and retail trade	152	3.7	90	0.13
– Electricity, gas and water supply	81	2.0	209	0.16
– Construction	40	1.0	268	0.18
– Agriculture	37	0.9	134	0.20
– Transport, storage and comms	23	0.6	11	0.17
– Mining and quarrying	14	0.3	86	0.21
– Other	83	2.0	63	0.12
– Debt securities	19	0.5	764	0.18
Households				
– Housing loans	880	21.3	675	0.23
– Consumer loans	264	6.4	455	0.25
Monetary financial institutions	459	11.1	165	0.27
Other financial institutions	122	2.9	93	0.16
Governmental institutions	787	19.0	73	0.20
Rest of the world	740	17.9	89	0.15
Total	4 133	100	155	0.19

In the extreme theoretical case, two different banks can hold all their assets in one of two different (arbitrarily defined) asset categories. These banks are therefore maximally different in terms of cosine similarity. However, the credit risk of the two asset categories may be correlated. Systemic risk can therefore accumulate in the system despite the low measured similarity in the banks' portfolios.

Table 1 provides an overview of the overall structure of the data, including several statistics that are important for the following discussion. It should be noted that for the purposes of our analysis we define credit as all forms of debt, i.e. both loans and debt securities are included. The instruments are summed for each institutional sector, with the exception of households and non-financial corporations, which are further broken down by branches of activity (we use the NACE classification and differentiate between nine industries). However, since we do not have sufficiently granular data to split debt securities issued by non-financial corporations according to branches of activity, we construct a separate quasi-sector where all instruments except loans are summed for all industries in the non-financial corporations sector. However, this category constitutes only a negligible share of the data, so it has only a marginal effect on the results. Banks' exposures to households are divided into two different categories. The first covers credit for housing (i.e. mainly mortgages) and the second contains any other remaining credit, most of which comes in the form of consumer loans.

The data for all sectors except *Rest of the world* include credit to residents, denominated in both Czech koruna and other currencies. Exposure to monetary financial institutions reflects interbank loans and deposits, cross-holdings of debt securities and exposures to credit unions. Cash and central bank balances were not included. Insurance corporations, pension funds and non-bank financial intermediaries constitute the other financial institutions sector. *Government* includes both general government and local governments. Finally, the *Rest of the world* category includes debt to all

Table 2: Level, Variation and Correlation of NPL Ratios

	2003–2013			2008–2013			
Sector	NPL	CV	Corr.	NPL	CV	Corr.	W
Agriculture	4.35	1.50	0.11	3.02	1.60	0.11	2.1
Mining and quarrying	0.39	13.50	0.09	0.34	7.94	0.16	0.1
Manufacturing	8.19	0.97	0.19	9.99	0.66	0.24	17.4
Electricity, gas and water supply	2.78	2.62	0.04	3.42	1.30	0.04	3.2
Construction	10.26	1.43	0.25	15.56	0.70	0.28	27.0
Wholesale and retail trade	7.51	0.94	0.10	8.02	0.78	0.14	12.5
Transport., storage and comms	4.31	1.86	0.04	5.36	1.09	0.05	5.8
Real estate, renting and business	3.61	1.94	0.15	4.53	1.40	0.18	3.8
Other	2.13	1.89	0.09	2.80	1.17	0.10	2.9
Households – housing loans	2.10	0.41	0.43	2.88	0.27	0.56	12.8
Households – consumer loans	6.30	0.65	0.26	7.89	0.68	0.23	12.6

Note: NPL stands for NPL ratio, CV for coefficient of variation, Corr. for Pearson correlation coefficient and W for resulting risk weight. NPL and CV statistics are computed in a weighted form using the stocks of credit supplied by each active bank as weights. Risk weights W are computed for the whole data range as the product of the aggregate NPL level and the coefficient of variation: $W = \mu * V^{-1} = \frac{\mu^2}{s}$.

foreign entities regardless of their type, denominated in any currency. We admit that this sector constitutes a rather heterogeneous group, but the data are not granular enough for us to work with a more detailed breakdown.

It can be seen from Table 1 that the dynamics of the credit supplied by Czech banks have been rather heterogeneous across sectors and industries. Significant growth has been recorded for housing loans provided to households. Correspondingly, the importance of property construction for credit dynamics is reflected in an increase in credit to the real estate industry. Debt securities of NFCs have also recorded high growth, but their share of the total is negligible, underscoring the importance of loan financing. An important feature of the Czech banking sector is its relatively high concentration, especially for exposures to certain sectors and industries (see the last column of Table 1 containing values of the Herfindahl index). High concentration is recorded for housing loans, where a significant proportion of credit has been provided by building societies, which are members of banking groups and offer products with state allowances. In the case of consumer loans, the five largest providers of credit account for almost 90% of the total. Although credit provided to other sectors and industries is split somewhat more evenly among banks, the market is still dominated by several big players – the share of the five biggest creditors was 77% in 2013.

5. Results

5.1 Similarity in Credit Risk Performance

We first provide the statistics that depict basic features of the bank portfolios in terms of credit risk materialisation (NPL ratios). These results will later enter the analysis of portfolio similarity as described in methodological Section 3. Outcomes based on the time series for the NPL ratio as a proxy for credit risk materialisation are provided in Table 2. A detailed view of the evolution of the indicators through the whole period is depicted in Figure 1.

Figure 1: Level and Dispersion of Non-Performing Loans

Note: The statistics were computed in their weighted form, with the gross nominal values of total loans provided by banks serving as the weighting vector. Values exceeding the y-axis scale limit (0, 30) are not depicted in the plot, but the data points are not missing.

It is apparent that several sectors exhibit a relatively high level of non-performing loans. In particular, loans to *Construction*, *Manufacturing* and *Trade* as well as consumer loans to households and the *Real estate* industry represent relatively risky exposures for banks. While some of these sectors have traditionally reported above-average NPL ratios and banks should have incorporated them into their credit risk management, the recession in 2009 and the following economic slowdown have further increased the levels of NPLs in most of these sectors and industries – most notably in *Construction*, *Manufacturing* and *Real estate*. The risk of indirect contagion via these exposures is even more pronounced given the fact that the coefficient of variation is relatively low for most of these asset categories. Likewise, the average correlation tends to be slightly higher than for other asset classes. These sectors thus receive the highest risk weights in the later assessment of risk-adjusted similarity.

By contrast, mortgage loans to households and loans to the residual group of industries (*Other activities*) show very low variation accompanied by a low level of bad loans. This is reflected in relatively high correlations between the performance of individual banking books despite frequent phase shifts among the results of individual banks, which may be a result of different approaches to classifying otherwise similarly performing credit (CNB, 2014, p. 57). This adds noise to the data and the statistics thus tend to be underestimated. Regardless of the current low risk profile of these sectors, the observed correlations and low dispersion across the banking sector may contribute to a higher level of systemic risk.

5.2 Balance-Sheet Similarity

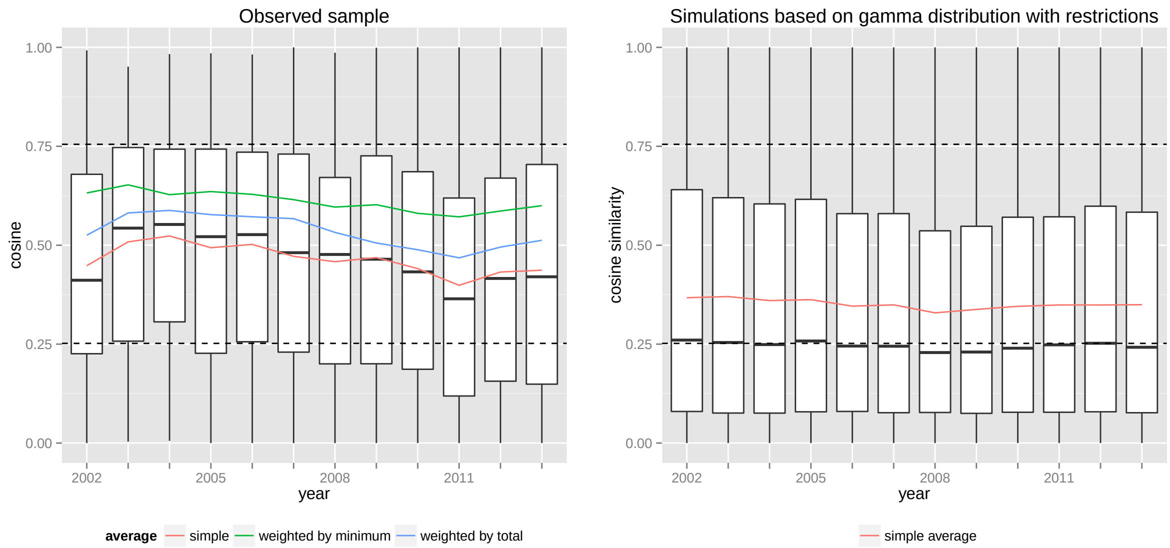
Average Similarity

The average similarity of Czech banks and its evolution over time is depicted in the left-hand chart of Figure 2. Its value has been fairly stable or slightly decreasing (from 0.5 in 2004 to a low of 0.4 in 2011). These values are below the higher benchmark (0.76) implied by highly diversified (uniformly distributed) and therefore very similar portfolios depicted by the upper dashed line, but significantly higher than the lower and more realistic benchmark of 0.25 implied by gamma-distributed portfolios.[7] This applies to the weighted average series as well, although these have been above the simple average values throughout the period. Weighting by banks' total asset value causes a drift in the numbers by up to 10 pp in the case of the first weighting method and 18 pp in the second case. This confirms that the value is driven upwards mostly by large well-established banks with more diversified portfolios. Since 2011, both values have returned near to their original levels. Excluding one of the sectors from the modelled balance sheet (one at a time) does not change the results significantly, except for the *Rest of the world* and *General government* sectors, which significantly contribute to the overall similarity. The boxplot in the background of the figure indicates the 25, 50 and 75 quantiles of the sample distribution of cosine similarity for each of the periods covered in the analysis. We found the resulting similarities to be very evenly distributed over the [0, 1] interval, suggesting the presence of both very similar banks and very dissimilar banks.

The second chart in Figure 2 indicates the properties of the distribution of cosine similarity computed on simulated random banking systems with portfolios drawn from a gamma distribution where the proportions of the hypothetical system were restricted so that they match those of the real one in terms of the total sums in each category (sector and industry) and each bank. It is evident that

[7] 0.76 is the average value resulting from simulations on uniformly distributed random portfolios with 16 asset classes as in the observed sample. The 0.25 value comes from simulations on gamma-distributed portfolios of 16 asset categories with shape and rate parameters estimated at 0.21 and 3.42 respectively. The selection of these benchmarks is discussed in Section 3.

Figure 2: Average Similarity Over Time Compared to Sample and Simulated Random Distributions



Note: The upper dashed line (0.755) represents the average similarity calculated on random portfolios drawn from a uniform distribution. The lower dashed line shows the average similarity calculated on simulated portfolios based on an (unrestricted) gamma distribution. The right-hand chart presents the results for simulated portfolios based on a gamma distribution restricted to fit the observed sample data for sectors' and banks' shares in the total.

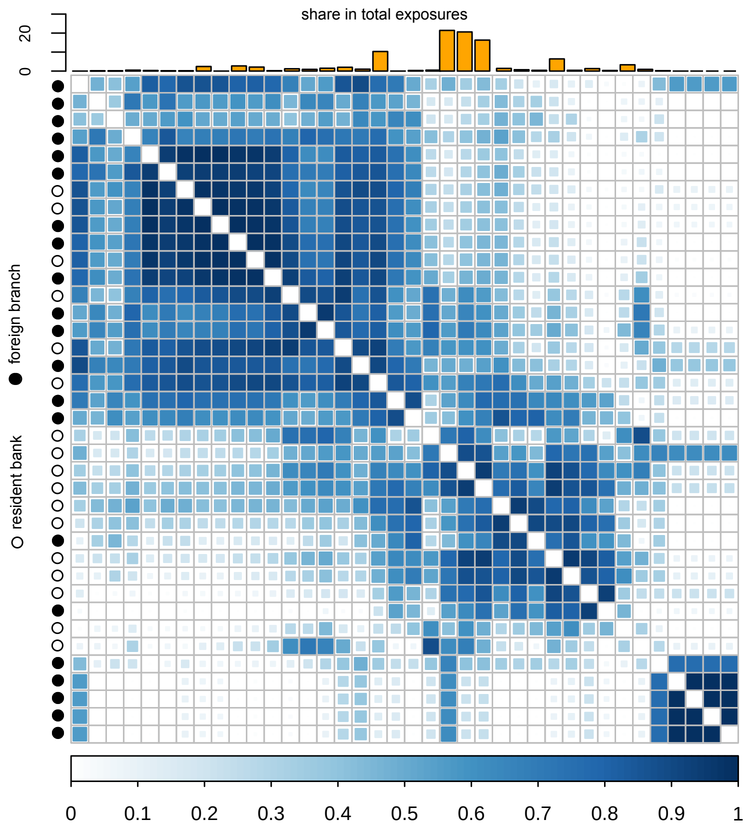
when we restrict the randomly generated systems to match the proportions of the real data, we observe similar patterns in the levels and especially in the evolution over time in the observed (left) and simulated (right) data. This suggests that the deviations in aggregate similarity from the stable level and from the benchmarks given by the simulations on unrestricted random data can be partially attributed to the aggregate structure of the economy and banks' market shares. However, even after taking account of banking sector characteristics on both the individual and aggregate levels, the observed average similarity remains relatively high.

Similarities Between Individual Banks

Although the overall (i.e. average) similarity of banks in the Czech Republic is not excessively high, the aggregate picture may hide some important details. Figure 3 displays the similarity matrix for all pairs of banks active as of the end of 2013. Its rows and columns represent individual banks in the same order. Each cell thus represents the similarity between the two banks of the corresponding row and column. The darker is the cell, the greater is the similarity between the two banks. The diagonal elements of the similarity matrix were omitted, as these would otherwise show the cosine similarity between a bank and the very same bank, which is equal to 1 by definition. Along the upper margin of the similarity matrix, we plot the share of the banks' total assets covered in the analysis in the total value of the banking sector. The left margin of the plot indicates whether the banks are home (or subsidiary) banks or branches of foreign banks.

The diagonal represents a hypothetical spectrum of various business models. The largest banks operating in the system all belong to the central cluster (see the dark blue cloud in the middle), which accounts for 74% of total assets. These banks are located in the middle of the spectrum as

Figure 3: Similarity Matrix of Individual Banks (As of the End of 2013)



Note: Rows and columns represent individual banks in the same order. Each cell thus represents the similarity between the two banks of the corresponding row and column. The darker is the cell, the greater is the similarity between the two banks. The diagonal elements of the similarity matrix were omitted, as these would otherwise show the cosine similarity between a bank and the very same bank, which is equal to 1 by definition.

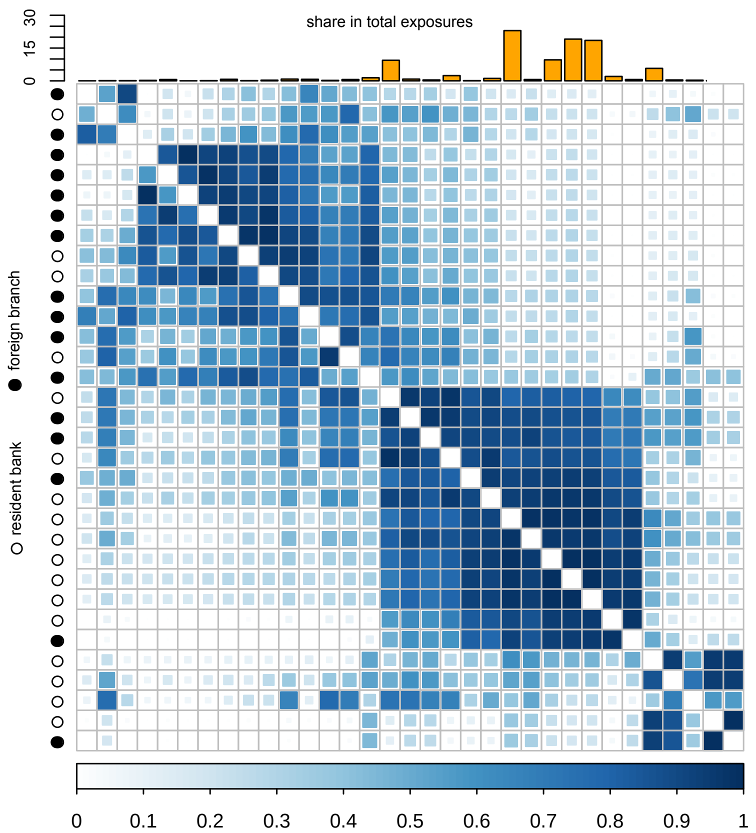
they exhibit above-average similarity compared to most of the remaining banks (see the dark rows and columns coming from the highest values on the diagonal). This result is not surprising. The business model of the large banks is historically focused primarily on residents. Their asset portfolio is quite diverse, with a slight focus on households and domestic government, and the structure of the assets contained in their portfolios is relatively stable. It is evident from the figure that large banks are part of a larger cluster of banks. What they have in common, however, is not the simple concentration of their portfolios on a particular asset or a narrow range of similar assets. Their high cosine similarity lies mainly in the fact that their asset portfolios are similarly diversified into a wide range of assets. Therefore, they are exposed to similar risks, even if this spectrum of risks is broad. Clearly, they are naturally similar. This reflects the fact that these banks operate under the same regulatory framework and that demand for banking services in the Czech Republic is quite concentrated. However, the banks in this cluster differ, for example, in terms of their size, credit history, financial funding or the relative amount of their capital. These additional factors have to be taken into account when assessing the similarity of banks in this cluster.

Going in the upper-left and bottom-right directions from the largest banks we move to the mutually distinct poles of the spectrum. The banks in the upper-left cluster are characterised by high exposures to the *Rest of the world* and *General government* sectors. Even though these are mostly small and medium-sized institutions, together they make up almost 26% of the total banking sector. We would argue that their mutual similarity calls for analysis of their soundness and stability as a group.

The small cluster of banks located in the very bottom-right corner consists of very small branches of foreign banks, whose similarity is driven mainly by their zero-value exposures to many of the categories on the asset side of their balance sheets. Conversely, a large proportion of the credit they provide goes to the *MFI*, *OFI* and *Real estate* sectors.

Risk-Adjusted Similarities Between Individual Banks

Figure 4: Simple (Bottom-Left Area) and Risk-Adjusted (Upper-Right Area) Similarity Matrices Based on Credit Exposures to the Real Economy



Note: Rows and columns represent individual banks in the same order. Each cell thus represents the similarity between the two banks of the corresponding row and column. The darker is the cell, the greater is the similarity between the two banks. The diagonal elements of the similarity matrix were omitted, as these would otherwise show the cosine similarity between a bank and the very same bank, which is equal to 1 by definition.

Based on the analysis in Section 5.1, we eventually get to computing the risk-adjusted similarity matrix, which takes into account the different "risk weights" of different sectors and segments of credit. In this setting, exposures to sectors assigned with low (or zero) weight drive the resulting similarity negligibly (or not at all). Given our choice of NPL ratios as a proxy for credit risk, we could only obtain these weights for exposures to real-economy sectors (non-financial corporations and households) and we therefore limit our focus to these categories from now on. For the sake of comparison, the similarity matrix presented in Figure 4 is not symmetric in this case, as it presents both the similarity matrix without any risk adjustment (the bottom-left triangle) and the risk-adjusted one (upper-right). After controlling for the risk measures, where the highest weights were put on *Construction*, *Manufacturing* and both segments of the *Households* sector, the separation of clusters of similar banks became even more explicit and the mutual similarities in the grouped banks even greater.[8]

Since the underlying data on portfolios are in this case different from the original (there are fewer categories), the ordering of the matrix is different too. However, the banks' membership in the main clusters remains similar. Besides the central cluster described in detail above, it is worth mentioning the main interesting features of the other two clusters.

The upper-left cluster comprises the majority of branches of foreign banks, which together represent about 13% of the total assets covered in the analysis. Their asset portfolio is concentrated mainly on non-residents and hardly engages with domestic households at all. Therefore, this cluster is primarily exposed to cross-country contagion risk. Additionally, banks in this cluster are similar in their sources of financing, as most of them are dependent on wholesale funding. Their vulnerability to potential cross-country shocks is higher, as wholesale funding is generally considered to be a less stable source of financing.

In the setting of risk-adjusted similarity analysis focused on real-economy exposures, a new cluster has separated from the rest of the banks. What distinguishes these mostly domestic banks from the others is their specialisation in consumer lending. This makes them more exposed to risks associated with adverse developments in employment. The cluster is relatively small, as it accounts for less than 5% of the assets of the banking sector. However, its members are relatively young banks with rather short credit histories, and their main source of financing is deposits from households, which makes an argument for monitoring these banks as a group.

6. Conclusion

Although the cross-sectional dimension of systemic risk has recently attracted a lot of attention in the theoretical literature, there are still many gaps in the practical implementation of the outlined principles. This paper has presented several empirical methods to fill some of the gaps in the systemic risk assessment framework and to equip macroprudential policy authorities with a practical monitoring toolkit. The methods has been successfully applied to data on the Czech banking sector in 2002–2013.

In general, the overall similarity of the Czech banks has been found to be quite stable over recent years and significantly below the theoretical benchmark corresponding to the situation where all banks highly diversify their portfolios on the same set of assets. The average similarity, nevertheless, has been found to be considerably higher than the levels of more realistic benchmarks implied by simulations of random banking systems that match the real one in terms of basic statistical properties.

Moreover, the overall similarity measure seems to mute some noteworthy differences observed across the banking sector. Large and well-established banks tend to be more similar to each other and are located in the middle of the spectrum of all business models. Besides that, there are a few other clusters of small and medium-sized banks which are less important individually but which could become systemically important as a group under certain circumstances.

[8] The average similarity, however, was about the same in both cases, which further stresses the importance of the analysis on the individual level.

In a separate empirical analysis of the individual data on non-performing loans, we have shown that the credit provided to some sectors of the real economy represent a relatively risky investment, as banks systematically record poor performance for credit provided to these sectors. The results suggest that holdings of these assets expose multiple banks to common risks. When we adjust the presented similarity metrics for the risk measures obtained from this analysis, the separation of the previously identified clusters of banks becomes even more pronounced. The two empirical approaches prove to be useful complements and demonstrate how credit risk can concentrate in banks with similar credit exposures to the real economy.

The CRD IV directive obliges supervisory authorities to regularly monitor and manage concentration risks. Our findings suggest a need to monitor the diversification of the system as a whole in addition to the regular supervision at the level of individual banks. In particular, clusters of similar banks should be given special attention by supervisors, as the financial soundness of the corresponding banks could be jeopardised simultaneously by common shocks. The results may also help to improve the stress-testing framework by providing the authority with a bigger picture on the concentration of credit risk and allowing for well-tailored scenarios. In the extreme case where the indicators signal high concentration risk, the authority may resort to applying a macroprudential instrument (such as a systemic risk buffer) or a microprudential one (e.g. Pillar II capital requirements) to foster banks' resilience to these types of risks.

In our study, we applied the presented method with a focus on the credit risk of the asset side of banks' balance sheets. Nevertheless, the method is general enough to be applied to any other bank characteristics, such as risk-weighted assets, structure of liabilities, liquidity mismatch, capital structure and trading activity. This could provide authorities with a practical tool for classifying banks by their business models and risk management practices.

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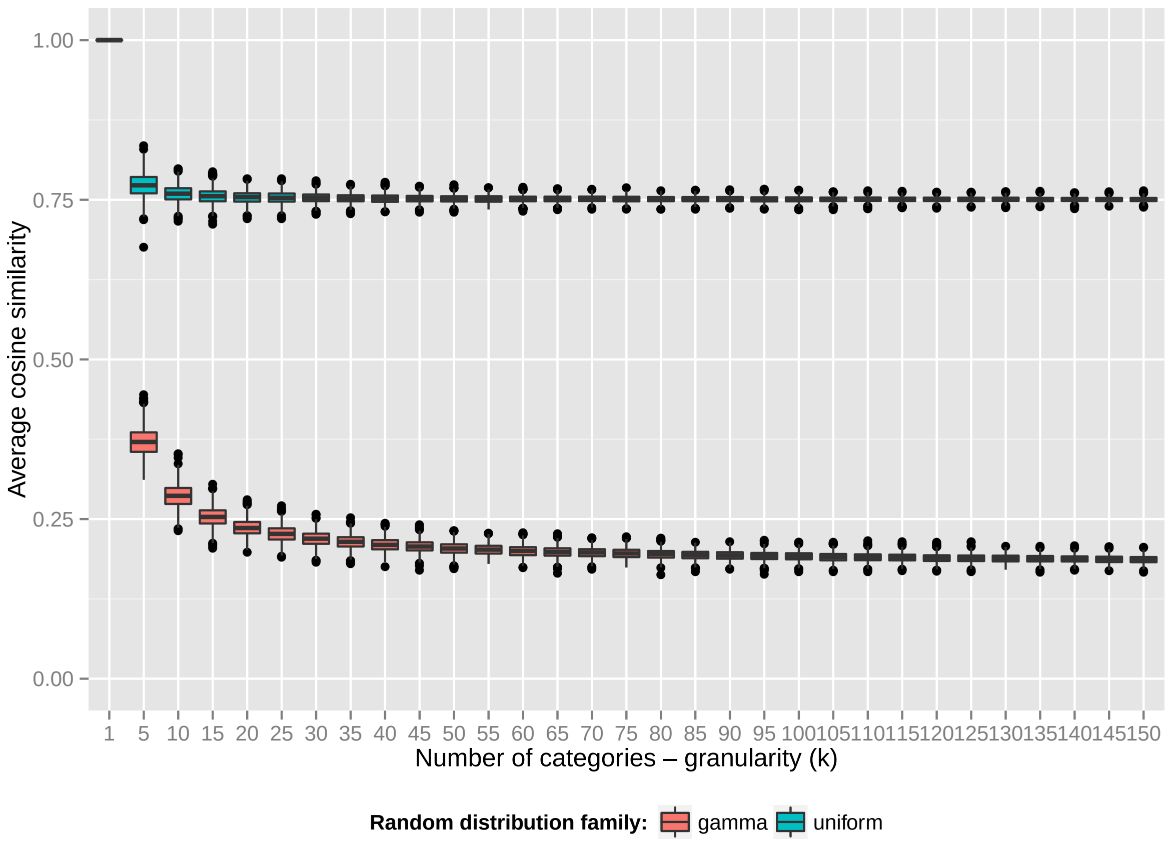
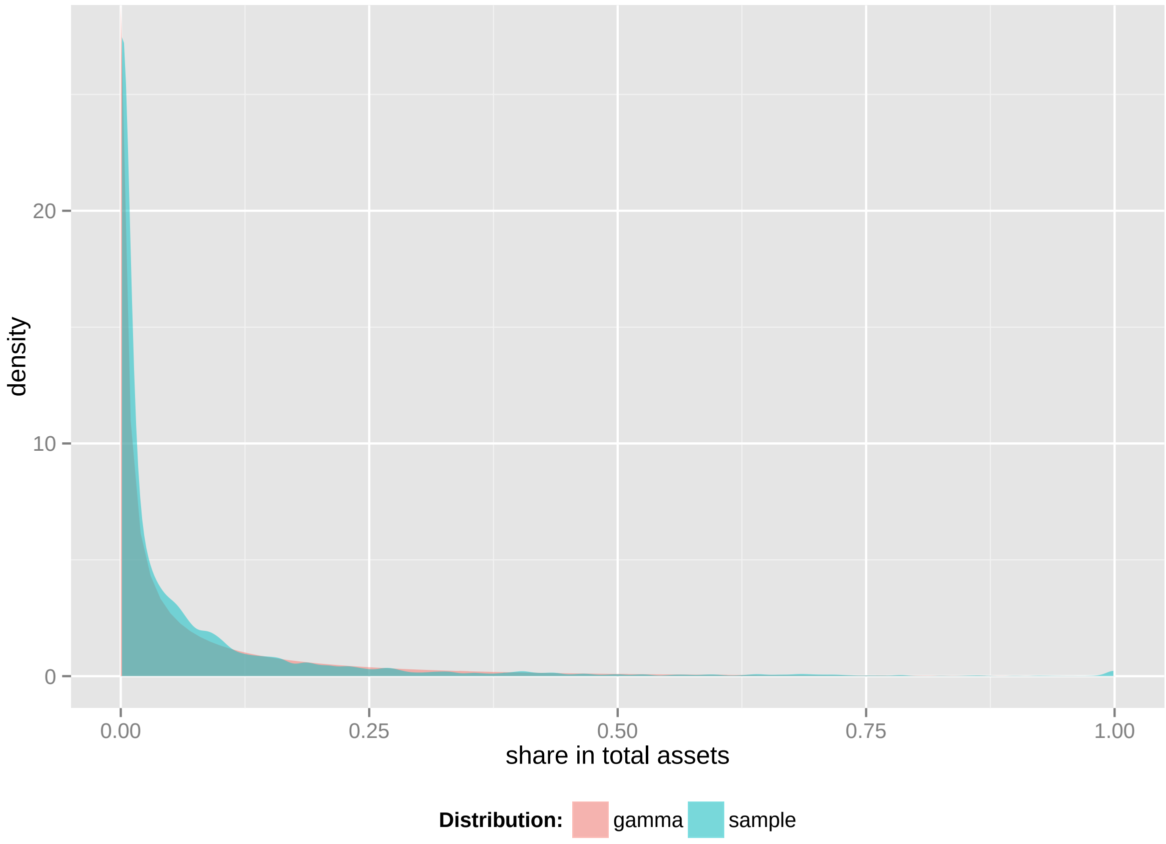
Appendix A: Additional Results

Figure 5: Level of Data Granularity (k) and Its Effect on Average Similarity (Simulated Data)



Note: The chart presents the 25, 50 and 75 quantiles of the mean cosine similarity measured on simulated random banking portfolios. The *shape* and *rate* parameters of the gamma distribution were estimated at 0.21 and 3.42 respectively by the moment matching estimator to fit the data observed for the 2002–2013 period.

Figure 6: Sample and Random Gamma Distributions of Shares of Asset Categories on Banking Portfolios



Note: The chart presents the kernel density of the sample distribution compared to probability density function of a gamma distribution. The *shape* and *rate* parameters of the gamma distribution were estimated at 0.21 and 3.42 respectively by the moment matching estimator to fit the data observed for the 2002–2013 period.

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Czech National Bank
Economic Research Department
Na Příkopě 28, 115 03 Praha 1
Czech Republic
phone: +420 2 244 12 321
fax: +420 2 244 14 278
http://www.cnb.cz
e-mail: research@cnb.cz
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