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Traditional commercial banking and systemic risk: Evidence from Hungary

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Abstract. Systemic risk reduction in banking is a key component in maintaining financial stability. Even after extensive explorations, the role of nontraditional activites in systemic risk still offers several questions to study. The paper aims to contribute to the literature on the topic by empirically examining whether traditional and nontraditional banking activities differ in terms of systemic risk. To answer this question, traditional commercial banking is assumed to be represented by the loan-deposit interest margin income component. Hungarian banking sector data between 2003 and 2020 are analyzed with principal component analysis and multidimensional scaling. The primary measure in systemic risk quantification is the return covariance-based absorption ratio. Empirical findings suggest that, when compared to a more diverse range of banking activities, traditional commercial banking may be characterized by lower systemic risk. Although in these two cases the most influential components of systemic risk may be considered as similar, the other components exhibit significant differences.

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1. INTRODUCTION

Systemic risk is one of the most frequently studied topics in economics. Since there are several links between the banking, corporate, and household sectors, stability of banking operations is of key economic importance. It could be possible that systemic risk is associated with the non-interest generating banking activities (De Jonghe, 2010), although systemic risk contributions and bank activity diversity are not necessarily positively related (Saunders et al., 2020), and the effect of bank diversification on financial stability may be more complex (Kim et al., 2020). The paper aims to contribute to the literature by empirically examining this topic: systemic risk indicators of general banking activity and traditional commercial banking activity are compared.

The range of banking activities usually varies over time, and such changes can result in income and risk effects. Links between financial intermediaries have evolved over the last decades despite the structural differences that limit the extent of convergence (Beltratti & Corvino, 2008). Regulatory changes may also influence the range of possible cooperation types between the institutions. For instance, the U.S. Gramm-Leach-Bliley Act of 1999 expanded the range of permitted bank activities (Laeven & Levine, 2007), and, in case of bank holding companies, the Dodd-Frank Act reinstated a limited form of Glass-Steagall Act (Acharya & Richardson, 2012). In other countries, universal banking and financial conglomeration have been more widespread phenomena, and the financial architecture characteristics may have several risk effects. For instance, empirical findings of Hryckiewicz and Kozłowski (2017) suggest that during a crisis GDP decline may be smaller in countries with predominantly traditional banking activities compared to countries with systemically important banks relying on investment activities. Kim et al. (2020) have also found that it may be better for banks to concentrate on deposits and loans (traditional intermediation functions) during crisis periods. According to the results of Elyasiani and Jia (2019), factors related to nontraditional activity hypothesis may be associated with the performance and total risk of banks. However, different forms of nontraditional activities may have opposite risk effects. DeYoung and Torna (2013) conclude that pure fee-based nontraditional activities may be associated with smaller bank failure probability, while asset-based nontraditional activities may have a positive relationship with failure probability.

A higher share of non-interest income may be associated with higher profitability (Meslier et al., 2014; Saunders et al., 2020), and bank activity diversity may result in scope economies (Zhang & Malikov, 2022), although this effect can be associated with the composition of the control chain (Saghi-Zedek, 2016). The relationship between activity diversification and risk is complex, and differences between individual and system-wide effects can exist. In certain business models low individual and high systemic risk may be present simultaneously (Hryckiewicz & Kozłowski, 2017). An expansion into non-interest income generating activities may be accompanied by higher individual risk (e.g. Chiorazzo et al., 2018; Lepetit et al., 2008; Williams, 2016) or systemic risk (De Jonghe, 2010), but the relationship between risk and activity diversity depends on several factors. Saunders et al. (2020) found no conclusive evidence about a systemic risk contribution increasing effect of a larger non-traditional income, and retail-oriented banks (as opposed to investment-oriented banks) may be more stable in case of an increasing share of non-interest income (Köhler, 2014). It is also possible that bank size may be among the influencing factors, Kamani (2019) found that an increase in systemic risk exposure may be related to trading activities for small banks, while commission and fees activities may only increase systemic risk exposure of large banks.

The measurement of systemic risk is not straightforward, since it has many aspects. A key point is that systemic risk is a system-wide phenomenon (Zheng et al., 2012), and it should be measured accordingly. Parallel with the development of computation methods, network approaches became widespread (e.g. Huang et al., 2016; Hu et al., 2015), these build a bottom-up model to quantify overall risk. As a consequence, the preciseness of building block details in a network model has a straight relationship with the accurateness of the results. It could be problematic if precise and complete data for network calculations is not available. However, there is an other approach that overcomes this limitation. Common features of banking can be identified and the quantification may result in systemic risk indicators. The absorption ratio (e.g. Kritzman et al., 2011) is one of the measures constructed with this logic. With this approach common factors of return comovement are computed with principal component analysis and the variance explained by the first few of these factors reveals information about systemic risk.

Market or accounting data could be applied to compute the return values for the absorption ratio calculation. For long periods of time only accounting data is available for Hungarian banks, therefore the paper presents accounting-data based results that are computed for selected banks in the time period between 2003 and 2020. The assets of the banks in the analysis represent 69,8 % of total assets of credit institutions in 2020. To find banks with similar commercial banking activities, several data selection criteria are applied. Traditional commercial banking returns are computed based on the interest margin related income values, while total banking activity results are based on the return before taxation. In Hungary, banks may perform certain nonbank activities, therefore the traditional commercial banking and total banking results can exhibit differences. The key research question in the paper is whether the common factors of these two activities differ.

Common factors could be approximated with principal component analysis. However, it should be noted that this methodology has certain requirements regarding database size. To examine validity of results, principal components are also compared with multidimensional scaling results. The research outcomes suggest that these two methodological approaches result in similar findings, and indicate lower systemic risk for traditional commercial banking activities.

The paper is structured as follows. Section 2 reviews systemic risk measurement approaches. Section 3 introduces the data and methodology, and Section 4 presents the empirical results. Section 5 concludes.

2. SYSTEMIC RISK MEASUREMENT

There are several measures for systemic risk, since its concept is quite complex. Probably the simplest principle in the definition is that systemic risk arises as a consequence of the links between financial institutions. Without these linkages the problems of a particular institution could not simply spread among other institutions. However, there is a question what could constitute a link between institutions. It could be a direct financial linkage through the interbank market or an exposure to common economic risks could be possible, and the systemic risk measures reflect how these links are characterized. In whatever way, in short or long run systemic risk is revealed by the common tendencies in returns. This finding is the cornerstone in the following systemic risk analysis.

Previous literature (e.g. Kleinow et al., 2017, Sedunov, 2016; Giglio et al., 2016; Ellis et al., 2014; Eling & Pankoke, 2016) highlighted many aspects of systemic risk. Banking systemic risk can be affected by several factors, for example the interbank relationships, the balance sheet structure of banks, liquidity risk and the operation of the payment system (Thimann, 2014). These risk sources can be incorporated in the systemic risk definitions that exhibit certain similarities. Eling and Pankoke (2016) point out three elements of the concept: the occurrence of a certain event (for example bank insolvency), the effect of the event, and the causal relationship. A precise systemic risk indicator may be advantageous in plentiful applications, for example in forecasting corporate failure over and above the predictions of the traditional accounting-based and market-based factors (Jia et al., 2020). Therefore, the question arises what is the best approach to quantify systemic risk.

With the development of computation techniques, it is possible to illustrate the linkages between financial institutions with detailed network models. This approach is widespread in banking (e.g. de Souza et al., 2016; Huang et al., 2016; Hu et al., 2015). Compared to theoretical models where the assumption of representative banks does not necessarily take into account possible external effects of bank investment decisions on the financial performance of other banks (e.g. Acharya, 2009), network illustration of linkages may capture the links between institutions in detail, and it may result in good quality systemic risk estimations. This preciseness however usually requires in-depth information about banking activities and a large dataset for the computations. It is not always available, and the computations may also be timeconsuming. The application of network approaches may contribute to identify contagion channels, such as for example the risk concentration channel (when banks are exposed to a common risk factor), the balance sheet contagion channel, the contagion through price movements (for example the asset fire sales), and the illiquidity spirals, as pointed out by de Souza et al. (2016). Portfolio correlations between agents may also be considered as one of the major channels of risk contagion in a financial crisis. (Luu, 2021) Systemic risk indicators may be related for example to these risk aspects.

In contrast to the bottom-up modeling approach that characterizes network models an other way for quantification is to focus on the overall consequences of systemic risk that are indicated by the similarity of returns. These consequences may be captured by well-defined indicators. This approach does not necessarily provide a clear explanation about the sources of systemic risk, but it can result in a system-level indicator. It is in line with the view that systemic risk may be associated with the whole financial system (Zheng et al., 2012), although it could be possible to identify the contribution of individual institutions or sectors (e.g. Adrian & Brunnermeier, 2016; Bernal et al., 2014).

Obviously, there are not only these two directions in systemic risk measurement (the network modeling and the return similarity focused approaches). Other indicators may also be relevant when assessing systemic risk, for example volatility, liquidity or loan indicators may also be calculated (Giglio et al., 2016). The paper focuses on that aspect of systemic risk that is revealed by the comovement of returns. There are several ways how it could be measured, possible options range from copula-based methods to correlation-related approaches. Correlation is frequently studied in previous literature when examining systemic risk. For instance, Acharya (2009) measures systemic risk with an endogeneously selected correlation related to the assets held by banks. Wagner (2009) concludes that a smaller correlation is not necessarily advantageous for the financial system if external effects of bank failures depend also on the general features of the banking system, and Civitarese (2016) compares some return correlation related systemic risk measures. Correlation is related to covariance that is applied during the calculation of the absorption ratio (described by Kritzman et al., 2011), that is one of the frequently applied return comovement indicators. The paper presents empirical results related to this systemic risk measure.

3. DATA AND METHODOLOGY

Traditional banking may have several definitions, an example is introduced by Chiorazzo et al. (2018) when identifying relationship loans, core deposit funding, revenue streams from traditional banking services and physical bank branches as basic features. The range of banking activities varies across countries, and the effects of this variation may also be observed in the income structure of banks. In the following the definition of traditional banking takes into account that traditional financial intermediation activities include loan provision and the collection of deposits. Therefore, although there are also other traditional banking activites that are related to non-interest income, it may be assumed that the interest margin describes income from traditional banking activities well. The income before taxation is associated with all banking activities.

Returns for the traditional commercial banking activity and for all banking activities are computed as the ratio between one of these income values and the equity. In previous literature market-based (e.g. Chen et al., 2021; Rodríguez-Moreno & Peña, 2013; Wang et al., 2021; Frattarolo et al., 2020; Choi et al., 2020) and accounting-based calculations (e.g. Ahmad et al., 2021; Duarte & Eisenbach, 2021) are also prevalent. The database for the analysis is associated with accounting-based balance sheet and income statement data that was published by the Magyar Nemzeti Bank (the central bank of Hungary, https://statisztika.mnb.hu/adatok-idosorok). Market based data is not available for several banks in Hungary, therefore the application of accounting-based data may provide a more comprehensive overview about riskiness.

The empirical analysis aims to capture sector-level systemic risk exposure, and it is one of the goals of the analysis to include the largest possible dataset that fits the analysis of the research question. To fulfill this goal, some data selection criteria are defined that aim at including data for a relatively long time period and for banks that have an activity portfolio in which „traditional" commercial banking activities constitute a relatively large part. A panel data set including Hungarian banking sector data between 2003 and 2020 is selected for the analysis.

The analysis aims to provide an insight into the developments of the whole Hungarian commercial banking sector. However, not all banks with commercial banking services in Hungary in 2020 are included in the database. One of the reasons for it is that the analysis is based on a balanced panel data set, and some banks that entered the commercial banking market after 2003 or finished banking activity before the end of 2020 are not included in this database. In addition to this limitation, some further data selection criteria are applied to highlight possible risk effects for commercial banks. Traditional commercial banking activity is predominantly characterized by deposit collection and provision of loans, and two data selection criteria are that (based on the data of the last 5 years in the database) both the average loan-to-assets and deposit-to assets ratio should exceed 40 %. To avoid possibly large effects of outlier data, an additional data selection criteria is that (based on the data of the last 5 years in the database) the ratio between the standard deviation and average of return on equity values (based on before tax profit data) should not exceed one. After taking into account these data selection criteria, data of 10 commercial banks was included in the analysis. The assets of the banks selected for the analysis represent 69,8 % of total assets of credit institutions in 2020. Since there are also credit insitutions with business activities that are not mainly related to traditional commercial banking (because for example mortgage banks are also among the credit institutions) the ratio between total represented assets and assets of banks with activities that are relatively similar to traditional commercial banking activity is even higher than 69,8 % in 2020.

The main systemic risk indicator in the analysis is the absorption ratio that is introduced in detail for example by Kritzman et al. (2011). The absorption ratio is a system-level indicator of financial stability that is related to the comovement of returns. Since individual risk-reducing diversification with similar exposures may be associated with disadvantageous systemic risk effects (Ibragimov et al., 2011; Wagner, 2010; Yang et al., 2020), the comovement of returns may indicate an important aspect of systemic risk.

Theoretically numerous quantitative methods may be adequate when measuring the strength of return comovement. Several of these methods are related to the exploration of common factors in return comovement. A similar and frequently applied method is principal component analysis that aims to maximize the variance of linear combinations of selected variables. Principal component analysis has previously been applied in risk analysis related to several economic topics (e.g. Drake et al., 2017; Rodríguez-Moreno & Peña, 2013; Lux et al., 2020; Zheng et al., 2012). In principal component analysis it can be assumed that the centered return values are represented by the $r_1, \dots r_p$ vectors, then (by assuming that the matrix A is orthogonal) the uncorrelated principal components can be calculated as $x_i=A \cdot r_i$ if the covariance matrix of the variables $x_1, \dots x_p$ is diagonal (Rencher & Christensen, 2012, pp. 406-407.) In case of principal component analysis the diagonal values of this matrix correspond to the eigenvalues of the covariance matrix of the original return vectors. If the original return vectors are standardized before the principal component analysis, then the diagonal values of the diagonal matrix correspond to the eigenvalues of the correlation matrix of the return variables. Since the eigenvalues (indicated by $\lambda_1, \dots \lambda_p$) may be interpreted as the variances of the principal components, it is possible to interpret the proportion of explained variance by the first k components as $\sum_{i=1}^{k} \lambda_i / \sum_{i=1}^{p} \lambda_i$, and if the correlations between the variables are high (in absolute value), then the first few eigenvalues are large, and the essential dimensionality is much smaller than p. (Rencher & Christensen, 2012, p. 408.) This is the logic behind the calculation of the absorption ratio (Kritzman et al., 2011).

The absorption ratio (Kritzman et al., 2011) corresponds to the total variance explained (absorbed) by the first few components in a principal component analysis of the return covariance matrix. Since principal component analysis is a dimension reduction method, the rationale behind the calculation of the absorption ratio as a systemic risk measure is quite straightforward. A relatively high absorption ratio value corresponds to a relatively high level of systemic risk, since then it may be considered that the sources of risk are more unified. (Kritzman et al., 2011) If the variance of the first few components is relatively large compared to the total variance, then the return covariance matrix may be well reproduced with applying a method based on the spectral decomposition theorem, therefore these components may be considered as representing common factors in the comovement of returns. If return comovement emerges as a result of the presence of systemic risk, then the absorption ratio indicates exactly the strength of this type of systemic risk. Previous literature frequently refers to the absorption ratio when discussing systemic risk (e.g. Ahmad et al., 2021; Lux et al., 2020; Frattarolo et al., 2020; Wang et al., 2021), and it has been included in the analysis in several papers (e.g. Chen et al., 2021; Jia et al., 2020; Luu, 2021; Choi et al., 2020).

Similar to principal component analysis, the calculation of absorption ratios is based on the spectral decomposition of a matrix. It is worth noting that there is a database size requirement that is frequently applied in principal component analysis. The database in the analysis does not correspond to this requirement, the number of years in the analysis is relatively small compared to the number of banks (with both types or return data). Therefore, to contribute to the validation of the empirical results, multidimensional scaling results are also presented and compared to the principal component analysis results.

Multidimensional scaling may also be applied in dimension reduction related calculations. This method includes metric and nonmetric scaling with several possibilities for parameter selection. According to Bécavin et al. (2011) principal component analysis and multidimensional scaling results may be strongly related. To contribute to a more straightforward comparison of the results, in the principal component analysis the spectral decomposition of the covariance matrix is analyzed, while in the multidimensional scaling a metric model with interval level of measurement and without the standardization of the variables is applied during the calculations. In principal component analysis it is possible to create components as linear combinations of original variables, and in multidimensional scaling coordinates of dimension variables may be calculated. The Pearson correlation of these variables may contribute to the validation of principal component analysis results that are applied during the calculation of the absorption ratio. The paper aims to contribute to previous literature not only with the analysis of Hungarian banking sector data, but also with this validation step that is not frequently performed by similar empirical studies.

4. RESULTS

The main aim of the analysis is to compare the systemic risk of traditional banking and all banking activities. As a result of the recent changes in the banking industry (for example the evolution of links between banks and other financial intermediaries), and also depending on the regulation, the range of banking activities may be wide. Hungarian banking sector data also illustrates that income from traditional banking activities (approximately measured by the interest margin) and from all banking activities may differ.

When comparing commercial banking and all banking activities, several risk measures could be calculated. For instance, individual bank risk indicators (for example the standard deviation of returns) is one of these measures, however, it does not capture systemic risk adequately. Systemic risk characterizes the whole network of banks, therefore possible measures of individual systemic risk contributions are also not expressing overall risk status. To quantify global systemic risk, the principal component analysis based absorption ratio is applied in the paper.

Table 1

Absorption ratio components (all banking activities)

component	variance (%)	cumulative variance (%)
1	79,782	79,782
2	14,415	94,197
3	2,959	97,156

Source: own calculations based on data published by the Magyar Nemzeti Bank (the central bank of Hungary, https://statisztika.mnb.hu/adatok-idosorok)

When the absorption ratio is calculated, the eigenvalues represent variances of the components. Table 1 presents principal component analysis results about the eigenvalues of the covariance matrix when all banking activities (including traditional commercial banking activities) and the return on equity before taxation is examined. The principal component analysis results are computed based on the return values of the banks in the analysis.The cumulative variance values correspond to the absorption ratios for different components. According to these results, systemic risk is present when all banking activites are taken into account, since already the first component is associated with almost 79,8 % of the total variance. When during the absorption ratio calculation three components are examined, then the systemic risk measure increases to approximately 97%. It indicates that three components describe systemic risk quite well, and may be compared to the three-component solution of traditional (commercial) banking data. Table 2 summarizes the principal component analysis results based on the covariance matrix of interest margin related income measures (belonging to the banks in the analysis).

Table 2

Absorption ratio components (commercial banking)

component	variance (%)	cumulative variance (%)
1	58,915	58,915
2	19,531	78,446
3	14,835	93,281

Source: own calculations based on data published by the Magyar Nemzeti Bank (the central bank of Hungary, https://statisztika.mnb.hu/adatok-idosorok)

A comparison of results in Table 1 and Table 2 reveals that commercial banking related systemic risk exhibits less concentration: the first component has considerably lower variance with commercial banking return data (58,9 % compared to 79,78 %), and a similar difference may be observed also when the solutions with two and three components are compared.

The question also arises, how similar these components are. Table 3 summarizes the (Pearson) correlation values that indicate the strength of the relationship between the components in the two cases in which the results are computed based on the returns belonging to all activities and traditional commercial banking activities, respectively.

Table 3

Component correlations

Correlation	1. component (commercial banking)	2. component (commercial banking)	3. component (commercial banking)
1. component (total)	-0,842*** (0,000)	0,446* (0,063)	-0,202 (0,421)
2. component (total)	0,108 (0,669)	-0,302 (0,222)	-0,791*** (0,000)
3. component (total)	0,249 (0,320)	0,300 (0,227)	-0,234 (0,349)

Source: own calculations based on data published by the Magyar Nemzeti Bank (the central bank of Hungary, https://statisztika.mnb.hu/adatok-idosorok). * indicates significance level at 0.10 level, ** indicates significance level at 0.05 level, *** indicates significance level at 0.01 level.

The empirical findings suggest that the first three components differ when traditional commercial banking activities and all banking activites are compared in terms of systemic risk. The extent of these differences can also be interesting. The first components (that have the highest variance) exhibit similarity, but the second and third components do not correlate significantly. However, the second component for all banking activities is significantly correlated with the third component for the traditional commercial banking activities. On the whole, these results suggest that the sources of systemic risk may be similar, although not completely identical for the wider and narrower (traditional commercial) range of banking activities.

These findings resulted from all available accounting data about the Hungarian commercial banking sector (with the applied definitions outlined previously) between 2003 and 2020. However, it is important to note that the number of return values compared to the number of banks in the analysis is relatively small regarding the usual data requirements of principal component analysis. This constitutes a limitation of interpretation. To mitigate this possible problem, a similar analysis is also performed to validate the principal component analysis outcomes. Metric multidimensional scaling and principal component analysis results may be strongly related (e.g. Bécavin et al., 2011), but database size requirements are less restrictive in multidimensional scaling.

Table 4

Multidimensional scaling results

	all banking activity		commercial banking	
	STRESS	R square	STRESS	R square
1. dimension	0,14848	0,98122	0,25713	0,90746
2. dimension	0,05231	0,99700	0,14804	0,94790
3. dimension	0,02331	0,99915	0,03132	0,99687

Source: own calculations based on data published by the Magyar Nemzeti Bank (the central bank of Hungary, https://statisztika.mnb.hu/adatok-idosorok)

With interval level of measurement and without the standardization of the variables multidimensional scaling and covariance based principal component analysis results are relatively easily comparable. Table 4 summarizes the main indicators of model fit in multidimensional scaling. A STRESS value below 0,05 indicates an excellent model fit, and it is important to note that this result can be observed in case of a three dimensional solution where the R-square values are also large. This finding is in line with the principal component analysis result that indicates a large explained variance with three components. The STRESS values also highlight that the traditional commercial banking activities may be considered as being less characterized by the presence of systemic risk, since all STRESS values are higher for traditional commercial banking activities. It is also similar to principal component analysis outcomes that the one-dimensional solutions are relatively different: commercial banking activities are associated with a substantially higher STRESS value (that indicates lower systemic risk).

A comparison of components and dimensions also reveals a considerable similarity. Table 5 indicates the (Pearson) correlations for all banking activities, while Table 6 summarizes correlation values for traditional commercial banking. The absolute values of correlations between the pairs of components and dimensions (in multidimensional scaling) are close to one, while other pairwise correlations are not significantly different from zero. These results also support the conclusions drawn from the principal component analysis results. It is however important to note that some variables (for example some components) do not follow normal distribution and in some cases autocorrelation is significantly different from zero, therefore the Pearson correlation may not be completely adequate to quantify the strength of relationship of these variables.

Table 5

Comparison of results for all banking activities

Correlation	1. dimension	2. dimension	3. dimension
1. component	1,000*** (0,000)	0,012 (0,964)	0,016 (0,949)
2. component	-0,003 (0,992)	-1,000*** (0,000)	0,026 (0,919)
3. component	-0,001 (0,998)	0,021 (0,935)	0,997*** (0,000)

Source: own calculations based on data published by the Magyar Nemzeti Bank (the central bank of Hungary, https://statisztika.mnb.hu/adatok-idosorok). * indicates significance level at 0.10 level, ** indicates significance level at 0.05 level, *** indicates significance level at 0.01 level.

Table 6

Comparions of results for commercial banking

Correlation	1. dimension	2. dimension	3. dimension
1. component	1,000*** (0,000)	-0,017 (0,948)	0,000 (1,000)
2. component	-0,017 (0,947)	-0,998*** (0,000)	-0,016 (0,951)
3. component	0,001 (0,998)	-0,018 (0,944)	0,999*** (0,000)

Source: own calculations based on data published by the Magyar Nemzeti Bank (the central bank of Hungary, https://statisztika.mnb.hu/adatok-idosorok). * indicates significance level at 0.10 level, ** indicates significance level at 0.05 level, *** indicates significance level at 0.01 level.

Although the results are quite straightforward in indicating lower systemic risk for traditional commercial banking activities and differences across systemic risk influencing factors, some additional details are also relevant when interpreting the results. In addition to deviations from normal distribution and some nonzero autocorrelation values, the statistical significance of the differences could also be tested. However, together with these limitations the difference in systemic risk indicators is quite considerable, thereby suggesting lower systemic risk for commercial banking activities when compared to a wider range of banking activities.

5. CONCLUSIONS

Stable financial intermediation is a key ingredient in a well-functioning economy. Traditional banking activites involved payment services, deposit collection and loan provision, with interest margin being a main income source. However, the latest thorough economic and technological changes also had an impact on the range of banking activities. For instance, strategic alliances between different types of financial intermediaries became increasingly prevalent, with fee-based income emerging as a possible driver of banking profitability. These extensive, ongoing changes may also influence the stability of the financial intermediation sector. This paper aims to explore the systemic risk effects in banking.

Financial stability effects can be measured with systemic risk indicators. To identify global, system-wide risk, a return covariance based measurement approach is applied. The absorption ratio is one of the numerous indicators of systemic risk. It is based on the comovement of returns that expresses joint effects that influence returns, thereby providing an overall measure of systemic risk. Absorption ratio is the amount of variance that the selected return covariance decomposing components explain. Traditional commercial banking related income and total return on equity are compared by means of this indicator. To overcome some data limitation problems and to further validate the findings, multidimensional scaling is also performed. Accounting data between 2003 and 2020 are examined for the Hungarian banking sector. Several data selection criteria are applied to find a panel data set of banks with considerable share of traditional commercial banking within the activities, and the assets of the banks in the analysis represent 69,8 % of total assets of credit institutions in 2020. Traditional commercial banking returns are computed based on the interest margin related income, while total banking activity results are related to the return before taxation.

Both principal component analysis and multidimensional scaling findings suggest that the systemic risk in traditional commercial banking activities, compared to all banking activities, may be lower. The results with these two different methodologies are also similar in indicating the diversity in influencing factors of systemic risk. Although the first components (with the largest variance) are significantly correlated, the other two components related to return covariance are quite different. These findings may add new insights to previous literature about the systemic risk effects of an expanding range of banking activities.

Although data aims to capture all available information for the whole commercial banking sector for a relatively long time period, and a certain form of crossvalidation for the empirical results is possible, there are some limitations of the analysis. Firstly, the application of data selection criteria restricts the dataset. Secondly, in parts of the dataset autocorrelation and nonnormal return distribution is present, these problems could possibly be mitigated by a modified definition of the returns or risk measures. The modification options provide also some avenues for further research.

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