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Ailing Mothers, Healthy Daughters? Contagion in the Central European Banking Sector*

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Abstract

Foreign-dominated banking sectors, such as those prevalent in Central and Eastern Europe, are susceptible to two major sources of systemic risk: (i) linkages between local banks and (ii) linkages between a foreign mother bank and its local subsidiary. Using a nonparametric method based on extreme value theory, which accounts for fat-tail shocks, we analyze interdependencies in downward risk in the banking sector of the Czech Republic, Hungary, Poland, and Slovakia during 1994–2013. In contrast to the presumptions of the current regulatory policy of these countries, we find that the risk of contagion from a foreign mother bank to its local subsidiary is substantially smaller than the risk between two local banks.

JEL Classification: F23, F36, G01, G21
Keywords: systemic risk, extreme value theory, financial stability, Central Eastern Europe, banking, parent-subsidiary relationship

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1 Introduction

In many emerging markets, especially in Central and Eastern Europe, a significant portion of banks are owned by foreign multi-bank holdings. Until the global financial crisis of the late 2000s, the high level of foreign presence in the banking sector of these countries was mostly viewed favorably: foreign owners were thought to reduce the inefficiency of local banks, often state-owned in the past. These expectations were corroborated by researchers examining the drivers of bank efficiency in Central and Eastern Europe, who showed that foreign-owned bank outperformed other local banks (for example, Bonin et al. 2005; Brissimis et al. 2008; Hasan and Marton 2003). The positive view changed when the financial crisis spread from developed to emerging markets, and regulators began to worry that mother banks would drain liquidity from their local subsidiaries and began to consider foreign ownership as a potential source of risk (see, for instance, CNB 2012; NBP 2011).

In contrast to the change in the perception of foreign ownership of local banks, the research literature traditionally focuses on the positive effects of the ownership of local banks by multi-bank holdings. For example, Ashcraft (2004) argues that banks affiliated with multi-bank holdings are safer than stand-alone banks, because the affiliated banks can receive capital injections in bad times and are thus able to recover more quickly. De Haas and Van Lelyveld (2010) suggest that foreign ownership of banks can have counter-cyclical effects, since affiliates of foreign banks do not have to reduce credit supply in times of financial crisis idiosyncratic to the domestic economy. Goldberg et al. (2000) conclude that foreign ownership of banks in Argentina and Mexico contributed to greater stability of the financial system during crises in emerging markets.

In this paper we focus on the threat of contagion from foreign owners to local banks in Central and Eastern Europe (the Czech Republic, Hungary, Poland, Slovakia). We compare these risks with those stemming from systemic interdependencies among individual banks in the local market. To the best of our knowledge, this paper is the first to examine the transmission of risks from multi-bank holdings in advanced countries to healthy local subsidiaries in emerging countries. We investigate these issues using stock market data and the methodology of Slijkerman et al. (2013), which we adjust so that it can be employed to examine the relationship between a foreign mother bank and a domestic subsidiary or the relationship between banks in the domestic market. This non-parametric methods builds on extreme value theory and accounts for fat-tailed distributed shocks, which constitute a characteristic feature of financial markets.

We find that the threat of contagion between local banks and their foreign owners is much weaker than the risk between the local banks themselves. The estimated probability that a local bank fails after a failure of another bank in the local market is 15%, while the probability of default of a bank is only 7% if the bank's foreign owner crashes. Therefore, our results suggest that foreign ownership does not substantially contribute to systemic risk in the local banking sector.

The remainder of the paper is organized as follows: Section 2 provides the economic rationale of our analysis, Section 3 explains the model based on extreme value theory, Section 4 describes estimation methods and data, and Section 5 discusses the results. Section 6 concludes the paper. Appendix A provides additional simulation results, Appendix B provides confidence intervals around our central estimates, Appendix C reports summary statistics of the data, and Appendix D shows acronyms of bank names used in the paper.

2 Economic Background

In this section we elaborate on the economic relationships motivating our paper. To be specific, we examine the linkages through which systemic breakdown can spread. In the first subsection we describe how systemic risk stems from the mutual similarity of banks' balance sheets. In the second subsection we explain how systemic failures can spread from a mother bank to its subsidiaries. These relationships are then captured by the (joint) stock returns.

2.1 Subsidiary-to-subsidiary linkages

The linkages between subsidiaries can be explained by the mutual similarity of banks' balance sheets. As noted by de Vries (2005) and Slijkerman et al. (2013), among others, banks' balance sheets contain similar entries on both sides. The similarity creates potential for a systemic breakdown, since banks face comparable risks. The asset side of the balance sheets contains a wide range of similar products or direct linkages. For example, mortgages or credit card debt are subject to the same type of risk, as the default rates are driven to a large extent by macroeconomic conditions. Direct linkages then include large corporate loans or government bonds. Large corporate loans tend to be syndicated; therefore, a default of a large corporate customer as well as that of a sovereign would lead to a joint shock.

The liability sides of the banks' balance sheets resemble each other even more. Banks in the Central European countries are financed mostly by deposits. Thus, they rely heavily on people's trust in the banking sector; any abrupt disruption of the trust could lead to systemic breakdown. Interest rates serve as another major risk driver. Apart from these linkages, banks are also involved in mutual deals on the interbank market. These interactions enter respective balance sheets two times, since an asset of one bank is a liability to the other, and vice versa. The interbank market therefore creates direct exposures between banks.

2.2 Mother-to-subsidiary linkages

We derive the dependence between a mother bank and its subsidiary from mutual interconnectedness of their balance sheets, which in turn usually stems from the mother bank's ownership rights. Nevertheless, these rights are limited by regulators who impose restrictions to protect financial stability. We approach the issue from the perspective of a subsidiary.

On the asset side the subsidiary is linked to its mother by both direct and indirect exposures. The direct exposure is limited by the central bank or another regulatory body. For example, the exposure of the five largest Czech banks to their mother companies was about 60% of their regulatory capital (according to the definition of Basel II) over the period of three years prior to 2012. In response, the Czech National Bank has taken steps that imply a decrease in the gross exposure limit from 100% of regulatory capital to 50% (CNB 2012).

Indirect exposures originate in the similarities of bank portfolios; that is, the argument from the previous subsection applies in the relation between foreign owners and local banks as well. Even though the geographical area is different, banks still hold similar assets like mortgages. Another example concerns Greek government bonds which were held by banks across Europe; only the particular extent of involvement differed. Further interconnections stem from the liability side of the balance sheet. Most importantly, mother banks hold a controlling share in the equity of subsidiaries, which enables them to pay themselves dividends when they need to pile up their own capital. On the other hand, subsidiaries have to comply with regulatory requirements like Basel Accords as well as local laws and decrees which guard local financial stability.

As in the case of two subsidiaries, mothers and subsidiaries are linked together indirectly via deposits in a way similar to what was discussed above, and also directly via interbank markets. Concerning interbank markets, some mother banks provide loans to their subsidiaries that are redeemable on a short notice. These loans provide mothers with a quick access to liquidity, but at the same time they pose a long-term liquidity threat for the subsidiaries.

3 Modelling Systemic Risk

The modeling of systemic risk is concerned with extreme shocks that endanger the whole banking sector. This risk, however, originates at the level of individual institutions that are usually linked via the interbank deposit market, mutual equity holdings, and other linkages to be found in their portfolio holdings, like syndicated loans (de Vries 2005). A systemic event in a narrow sense then happens when a release of 'bad news' about a financial institution leads to considerable adverse effects on other financial institutions, e.g., to one or more crashes (de Bandt and Hartmann 2000).

Therefore, researchers usually work with data on individual institutions and dependences among them if they want to gain information on the possibility of a systemic breakdown. Conclusions are subsequently drawn based on these two pieces of information. Such an analysis is mostly conducted using methods based on correlation—for example, Lehar (2005) or Acharya (2009)—which is closely associated with the normal distribution.

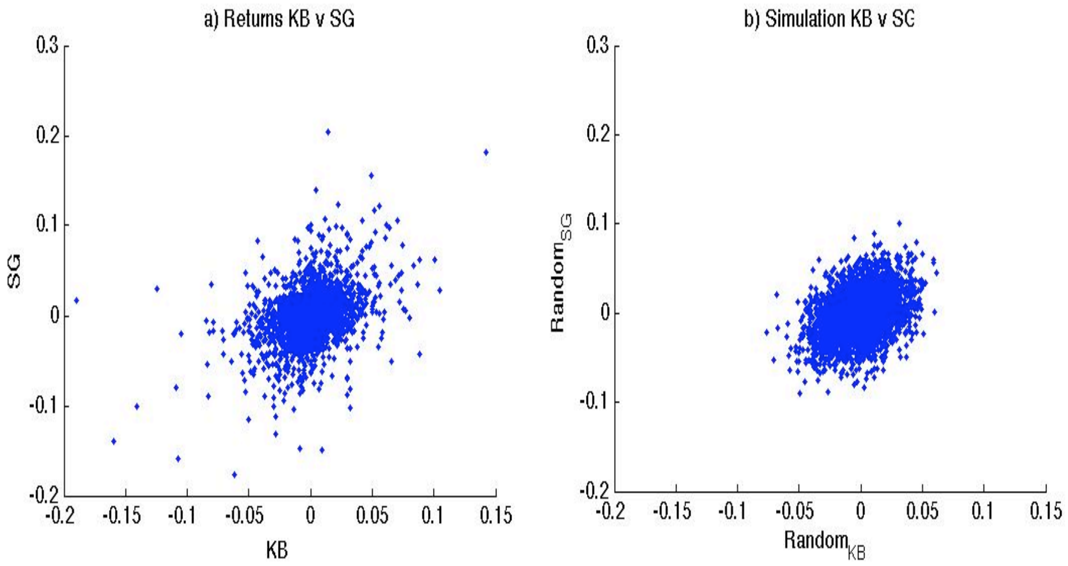
As argued by Hartmann et al. (2004), crash correlation can be zero even if there is a high spillover probability. This problem stems form the close link between correlation and the assumption of normal distribution of returns. Under the normal distribution assumption, correlation captures all the dependence between variables. Generally, however, this is not true for the other distributions and *only* in the case of a multivariate normal distribution it is permissible to interpret zero correlation as implying independence (Embrechts et al. 2002).

Nevertheless, quite an extensive literature exists suggesting that asset returns are characterized by distributions with heavier tails than normal; see, for example, Cont (2001) and Ibragimov et al. (2011). We illustrate this fact in Figure 1a where we plot asset returns of Komercni banka (KB), one of the largest Czech banks, and its mother bank Societe Generale (SG). The returns stem from a time series beginning on July 12, 2001, when KB was sold to SG, and ending on March 8, 2013, when the data was acquired, which gives us 2921 observations. In Figure 1b we present a simulation consisting of the same number of realizations drawn from a multivariate normal distribution using the means, variances and correlation as it was estimated from the empirical data.

It is apparent that the simulation based on normal distribution does not exhibit nearly as many extreme observations as the actual data do. The most extreme losses in the simulation reach barely 10% in absolute value. In contrast, extremes as large as 20% are observed in the data, meaning that normal distribution unambiguously underestimates day-to-day risks in reality. Note also there is a pattern in returns between both of the firms. The returns are elongated along the axes of the first and third quadrant; that is, returns of KB and SG seem to be moving in tandem. This suggest that dependence between the two exists.

Finally, we note that we are primarily interested in the dependence between downside risks, following Slijkerman et al. (2013). Correlation tries to capture the overall dependence, and the large number of observations around the center overweight the extreme ones. Nevertheless, in order to analyze systemic risk we need to focus on contemporaneous extreme losses. An appropriate measure is introduced in the following subsection.

Figure 1: Empirical returns vs. simulated returns drawn from a multivariate normal distribution.



3.1 Dependence beyond correlation

As discussed above, the techniques based on the normal distribution and the correlation measure impose severe limitations on the modeling of dependencies. Since risk management is concerned with modeling downside extreme movements, we need a measure that is able to cope with distributions that exhibit heavier tails than the normal distribution. This requirement also makes it impossible to employ correlation which is closely linked to normal distribution and does not necessarily capture the dependence between random variables in tails.

For these reasons we use the measure developed by Huang (1992), which satisfies the stated requirements. It is a conditional expected value $E(\kappa|\kappa \geq 1)$ that can be interpreted as the expected number of bank failures in the whole economy, given that one bank is already bankrupt. Suppose for simplicity that we are dealing with a two-bank economy. The measure is then given by

$$E(\kappa|\kappa \geq 1) = \frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)}. \tag{1}$$

where κ stands for the number of simultaneous crashes; random variables A and B represent negative stock returns, and t denotes a common bankruptcy threshold.[1]

[1]Note that the analysis can be extended so that it accounts for individual thresholds a and b, see Hartmann et al. (2004).

The measure was applied for the first time by Hartmann et al. (2004) to examine linkages between stock and bond markets and has gained in popularity ever since. For example, de Vries (2005) shows how the dependence is linked to the shape of the underlying distribution. Similarly, Geluk et al. (2007) study the joint loss behavior of correlated bank portfolios. Zhou (2010) uses the measure to show that economic size should not be considered as a proxy of systemic importance. Hartmann et al. (2010) then use it to study dependencies between exchange rates, and uncover a higher joint connection of Western currencies to the dollar compared to other currencies. Finally, Slijkerman et al. (2005) and (Slijkerman et al. 2013) employ the measure to study the interdependence between the insurance and banking sector.

The measure is popular because of its favorable properties. First of all, it is not associated with any type of distribution, which allows us to account for fat-tail returns. Second, the measure can allow for non-linear relationships (Hartmann et al. 2004). Therefore, it can describe the dependency that correlation cannot capture. Third, the measure can easily be extended into a higher dimension if desirable. Fourth, as noted by de Vries (2005), researchers do not need to condition the estimation on a specific bank failure. Finally, in a two-dimensional setting the measure minus one can be interpreted as the conditional probability on a systemic crisis, because it is equal to the probability that two bank crash, given that one is already bankrupt.

$$E(\kappa|\kappa \geq 1) - 1 = \frac{P(A > t, B > t)}{1 - P(A \leq t, B \leq t)} = P(\kappa = 2|\kappa \geq 1). \tag{2}$$

Due to this flexibility we employ the measure in our analysis.

Following Slijkerman et al. (2013), we define the systemic risk measure as the limit of the expected value in equation (1)

$$SR(\kappa) := \lim_{t\to\infty} E(\kappa|\kappa \geq 1) = \lim_{t\to\infty} \frac{P(A > t, B > t)}{1 - P(A \leq t, B \leq t)} + 1. \tag{3}$$

3.2 Statistical model

This section builds on the approach developed by Slijkerman et al. (2005; 2013) for modeling linkages between European banks and insurance companies. Nevertheless, we reshape their approach so that it can be used to model the relationship between a foreign mother and a domestic subsidiary or the subsidiary-to-subsidiary relationship.

We assume that the banking sector is subject to the three following risk components: The banks have to face the global (macro) risk G, the risk related to an individual country—here, we differentiate between home H and foreign F country risk—, and the bank-specific risk X_i. Finally, we also use the assumption that the risk components follow the Pareto distribution, which is a relatively weak assumption, since the distribution of returns seems to follow a power-law or Pareto-like tail (Cont 2001).

Definition 3.1. *Let $\alpha, x_m \in \mathbb{R}$. Let X be a random variable defined on some probability space $(\Omega, \mathcal{F}, P)$. We say that X follows the Pareto distribution, if the probability that X is greater than a real number t is*

$$P(X > t) = \left(\frac{x_m}{t}\right)^{\alpha}$$

for $t \geq x_m$ and 1 otherwise. The shape parameter $\alpha > 0$ is the tail index determining the number of finite moments.

Thus, for a random vector (G, H, F, X_i) of the above-mentioned risk components and for $x_m = 1$, we can write

$$P(G > t) = P(H > t) = P(F > t) = P(X_i > t) = t^{-\alpha}. \tag{4}$$

Function $\bar{F}(t) = P(X > t)$ is known as the *survival function.* We refer to a survival function of a Pareto-distributed random variable as to the *Pareto survival function.* We emphasize that in the set up of our approach where losses are modeled as positive numbers the survival function needs to be interpreted as the probability that a bank goes bankrupt once the threshold is surpassed.

Finally, we can define "the equity loss returns" (Slijkerman et al. 2013) A_i and B_j for a domestic and foreign bank, respectively. Keeping in mind that both A_i and B_j consist of three different risk components, we can write

$$A_i = G + H + X_i \text{ and } B_j = G + F + X_j \tag{5}$$

where $i \neq j$, and where we keep the original assumption of our approach that the weights of the individual components are equal to one.

3.2.1 Subsidiary-to-subsidiary dependence

Under this setting the risk profile of each bank A_i is composed of the same risk components with the exception of the bank-specific factor X_i. Being interested in computing the probability that A_i is greater than t, we need to compute the probability that $G+H+X_i$ is higher than t. To achieve that we need the corollary formulated by Slijkerman et al. (2013) based on the Feller's convolution theorem (1971, p. 278).

Corollary 3.1. *Suppose that two independent random variables A and B follow Pareto distribution with $x_m = 1$, i.e., they satisfy*

$$P(A > t) = P(B > t) = t^{-\alpha}.$$

Then their convolution satisfies

$$\lim_{t\to\infty} \frac{P(A + B > t)}{2t^{-\alpha}L(t)} = 1 \tag{6}$$

where $L(t)$ is a slowly varying function and $\alpha > 0$.

The corollary implies that for large failure levels t, the convolution of A and B can be approximated by the sum of the marginal distributions of A and B.

For finite t we can, therefore, write

$$P(A_i > t) = P(G + H + X_i > t) = 3t^{-\alpha} + o(t^{-\alpha}). \tag{7}$$

Note also that $P(B_j > t)$ would yield the same result.

At this point, we need to determine what the probability of a parallel crash in the domestic banking sector is. This is given by the probability that two domestic subsidiaries crash simultaneously. Thus, for k other than l the probability of a simultaneous crash is given by

$$P(A_k > t, A_l > t) = P(G + H + X_k > t, G + H + X_l > t). \tag{8}$$

It follows that

$$\lim_{t\to\infty} \frac{P(G + H + X_k > t, G + H + X_l > t)}{P(G + H > t)} = 1. \tag{9}$$

The equation (9) already ensues that

$$P(A_k > t, A_l > t) = P(G + H > t) + o(t^{-\alpha}) = 2t^{-\alpha} + o(t^{-\alpha}). \tag{10}$$

3.2.2 Mother-to-subsidiary dependence

In particular, we are interested in the relationship between a *foreign* mother and its domestic subsidiary. This results in a slight difference in comparison to the former case discussed above. The risk profile of the domestic subsidiary is still the same $G + H + X_k$. On the other hand, the risk the foreign mother is facing is somewhat different: $G + F + X_l$. Being interested in the joint probability, we get

$$P(A_k > t, B_l > t) = P(G + H + X_k > t, G + F + X_l > t) = t^{-\alpha} + o(t^{-\alpha}). \tag{11}$$

The reasons why it is the case are very similar to the previous case. The probability mass is concentrated along the axes, but this time there is only one factor (global risk G) that the two banks have in common. Therefore, their joint risk is driven by this component only and the resulting joint probability is equivalent to the probability that G is greater than t.

3.2.3 Systemic risk

In this subsection we utilize the results we derived in equations (7), (10) and (11) to compute the systemic risk measure $SR(\kappa)$ from the equation (3).

Before proceeding further, we compute the future denominator of the measure. Realizing that

$$1 - P(X \leq t, Y \leq t) = P(X > t) + P(Y > t) - P(X > t, Y > t) \qquad (12)$$

for some random variables X and Y. Thus, we can write

$$1 - P(A_k \leq t, A_l \leq t) = P(A_k > t) + P(A_l > t) - P(A_k > t, A_l > t) \qquad (13)$$

for a pair of domestic banks A_k and A_l. By using equations (7), (10), and (13) to compute the systemic measure, we get

$$SR(\kappa) = \lim_{t\to\infty} \frac{P(A_k > t) + P(A_l > t)}{1 - P(A_k \leq t, A_l \leq t)} = \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - 2t^{-\alpha}} = \frac{6}{4}. \qquad (14)$$

This means that in a two-bank economy we expect that on average one and a half bank fail, given that one is bankrupt. In other words, if one bank is already bankrupt then the second one is expected to fail in one out of two cases. In the framework of de Vries (2005) this result implies that the potential for the systemic breakdown is strong, as the linkages do not vanish asymptotically.

Based on equation (12), we derive the denominator for the case of a foreign mother B_l and domestic subsidiary A_k:

$$1 - P(A_k \leq t, B_l \leq t) = P(A_k > t) + P(B_l > t) - P(A_k > t, B_l > t) \qquad (15)$$

Analogously, from the equations (7), (11), and (15) we compute the systemic measure for the mother-to-subsidiary dependence

$$SR(\kappa) = \lim_{t\to\infty} \frac{P(A_k > t) + P(B_l > t)}{1 - P(A_k \leq t, B_l \leq t)} = \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - t^{-\alpha}} = \frac{6}{5}. \qquad (16)$$

The systemic measure suggests that the dependence between a foreign mother and a domestic subsidiary is lower than that between two domestic subsidiaries. The difference between the two cases stems form the varying country risk component. This effect can be assigned to the diversification possibilities resulting from the multinational structure. Although the systemic risk is somewhat lower, it does not vanish completely. In the perspective of the de Vries' system, there still exists a strong potential for a systemic breakdown. As in Slijkerman et al. (2013), we estimate the two models in the empirical section and test whether the difference between the models is statistically significant.

4 Estimation and Data

4.1 Estimation

In this subsection we introduce a non-parametric estimator for the linkage measure in equation (1); we use the version presented in Slijkerman et al. (2013). Following their work, we accompany the introduction of the estimator with sensitivity examples based on a simulation as well as on actual data (available in Appendix A).

The estimator of the measure in equation (1) is straightforward. It is sufficient only to count the number of times when $\min[A, B]$ and $\max[A, B]$ are greater than a threshold t. In this set up, A and B are empirical negative stock returns, the joint co-movements of which approximate for systemic risk. The estimator is therefore given as follows

$$\widehat{E(\kappa|\kappa \geq 1)} = 1 + \frac{\sum_{i=1}^{n} \mathbb{1}_{\{\min[a_i,b_i]>t\}}}{\sum_{i=1}^{n} \mathbb{1}_{\{\max[a_i,b_i]>t\}}} \tag{17}$$

where $\mathbb{1}_x$ is to be understood as an indicator function which equals one whenever the expression x holds and zero otherwise. The ith observations, denoted as a_i and b_i, are realizations of random variables A and B, respectively. The number of observations is given by n.

To understand where the minimum and maximum function comes from, one needs to realize that:

$$\frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)} = 1 + \frac{\min[A, B] > t}{\max[A, B] > t} \tag{18}$$

Nevertheless, we do not go deeper into the derivation of the estimator, because it is already presented in Slijkerman et al. (2005).

The estimator described above has two favorable features. First, for a fixed threshold t the estimator is asymptotically normally distributed as $n \to \infty$. Second, we can let $t \to \infty$ which stems from extreme value theory (Slijkerman et al. 2013).

For the construction of confidence intervals we use the Jackknife method. For each estimated pair, we create twenty clusters of observations. Next, we drop one cluster and estimate the linkage measure (17) each time; then we order the estimates. The second-largest and second-smallest ones demarcate the 90% confidence interval.

4.2 Data

We use daily stock prices of banks in the countries of the Visegrad group, namely the Czech Republic, Hungary, Poland, and Slovakia. We focus primarily on banks that belong among the five largest in the country, are included in the local stock market index, and have a foreign majority owner. The largest banks are chosen according to the value of their assets as reported in the respective annual reports in 2012. The mother bank is defined as holding at least 50% of shares in the local bank. Our longest time series begins in January 1994 and ends in March 2013. Nevertheless, some series are considerably shorter due to different dates of initial public offerings and acquisitions. Following Slijkerman et al. (2013), we compute daily *loss* returns. The data were downloaded from Bloomberg in March 2013.

Table 1: Analyzed banks and their mother companies.

Country	Rank	Bank	Assets EUR bn.	Mother bank
Czech Rep.	2	CS	35.1	Erste Group
Czech Rep.	3	KB	29.6	Societe Generale
Hungary	1	OTP	32.4	N/A
Hungary	9	FHB	2.6	N/A
Poland	2	PEO	32.8	UniCredit Group
Poland	3	BRE	22.1	Commerzbank
Poland	4	ING PL	15.6	ING Group NL
Poland	5	BZW	13.4	Santander
Slovakia	2	VUB	11.1	Intesa Sanpaolo
Slovakia	10	OTP SK	1.2	OTP Hungary

Due to the low availability of data in some cases we have to make a few exceptions to the selection rule described above. In the Czech Republic we also consider Ceska sporitelna (CS), even though the company was delisted in August 2002, after its sale to the Erste Group, Austria (EBS). Furthermore, we add two other banks due to the lack of large listed banks. These banks are smaller; nevertheless, we believe they are of systemic relevance, since their shares are included in the local stock indices. In Slovakia we consider a local branch of OTP Bank as it is a component of the Slovak stock index. In Hungary we include FHB Mortgage Bank (FHB) into the sample, since it is a part of the base of the main stock index of the Budapest Stock Exchange. Next, none of the listed Hungarian banks has a foreign majority owner. Therefore in the case of Hungary we can only estimate subsidiary-to-subsidiary dependence in downside risk.

Other caveats concerning data are worth mentioning. In Poland, BZW bank was sold by Allied Irish Banks (AIB) as late as February 2, 2011 to Santander (SAN). In our analysis, we examine only the relationship with AIB, since the corresponding time series is roughly five times longer. We also realize that we only have a few observations for the pair CS & EBS.

In Table 1 we summarize some basic information concerning the analyzed banks. In the end, due to data availability, we have two banks per country with the exception of Poland, which is represented by four banks. We also report the national rank of each bank according to the book asset value and the book asset value itself. In the last column, we present the mothers of the given banks, where 'N/A' means that no one possesses more than 50% of shares. Summary statistics of stock market data used in our analysis are available in Appendix C.

5 Results

We estimate the systemic risk measure (17) for the subsidiary-to-subsidiary and mother-to-subsidiary dependence. Subsidiary-to-subsidiary dependence estimates the downside risk dependence between two local banks in the country. Mother-to-subsidiary dependence then involves a local bank and its foreign mother, defined as a bank holding at least a 50% share in the subsidiary. Our results are summarized in Table 2.

We conclude that systemic risk between banks in one country is higher than the risk of contagion between a mother and its subsidiary, and these two sources of risk are significantly different. The probability that the other bank fails given that one is bankrupt then hoovers around 15% (in the case that a local bank crushes) and 7% (in the case that the foreign owner crushes), respectively. A detailed discussion of our results follows in the next paragraphs. Further details are provided in Tables 3 and 5, confidence intervals are tabulated in Appendix B. Summary statistics of individual time series data can be found in Table 8.

Table 2: SR(κ) averages for different levels of threshold t.

	t=0.075	t=0.07	t=0.055	t=0.05
Avg, mother-to-subsidiary	1.0703	1.0637	1.0614	1.0647
Avg, subsidiary-to-subsidiary	1.1387	1.1699	1.1493	1.1496

For the estimation we use two levels of the threshold t. One is at 5.5% loss return in a day, which reflects the level at which the estimator becomes stable, as depicted in Figure 2b and Figure 3. The other threshold is at 7.5%, so that our results can be compared with the study on the largest European banks and insurers which are based in Western Europe (Slijkerman et al. 2013). We also use additional values at 5% and 7% to evaluate the robustness of our results. We emphasize that the model works with *loss* returns; that is, the losses are modeled as positive numbers.

5.1 Subsidiary-to-subsidiary estimates

We estimate the potential of contagion for all possible pairs for each country. Thus, we have one estimate for the Czech Republic, six for Poland, and also one for Slovakia. For completeness, we report the results also for the pair from Hungary. The reason for only one available pair for some countries is the insufficient development of stock markets in Central and Eastern Europe; indeed, the majority of banks in respective countries are not listed. For listed banks we use the maximal possible length of the respective time series.

Table 3: Subsidiary-to-subsidiary dependence.

Country	Subs.	Subs.	$SR(\kappa)$				Obs.
			t=0.075	t=0.07	t=0.055	t=0.05	
Czech R.	CS	KB	1.2308	1.2083	1.2500	1.2436	1744
Poland	PEO	BRE	1.1538	1.2143	1.1778	1.1739	3695
	PEO	ING PL	1.2258	1.2571	1.1486	1.1489	3696
	PEO	BZW	1.1333	1.1765	1.1731	1.1622	2947
	BRE	ING PL	1.1200	1.1852	1.1679	1.1686	4688
	BRE	BZW	1.1905	1.2174	1.1404	1.1410	2945
	BZW	ING PL	1.0556	1.1000	1.1364	1.1475	2947
Slovakia	OTP	VUB	1.0000	1.0000	1.0000	1.0111	2049
Average			1.1387	1.1699	1.1493	1.1496	
Hungary	FHB	OTP	1.1379	1.1389	1.1406	1.2069	2454

In Table 3 we present the estimates for all four levels of threshold t. We highlight the stability of the measure with respect to the lower threshold. The averages lie within a narrow range of only 0.0003. Even though we report $SR(\kappa)$, which denotes the expected conditional number of failures, we repeat that $SR(\kappa) - 1$ can be interpreted as the conditional probability of a crash given that one bank goes bankrupt; the average probability reaches approximately 15%. Focusing on individual pairs, we find the strongest dependence between CS & KB in the Czech Republic, which exceeds 20% regardless of the threshold. The lowest systemic risk is found for the Slovak banks VUB & OTP SK with the probability of an extra crash equal to 0% for the first three levels of t.

In the terminology of de Vries (2005), the latter result implies that the potential for systemic breakdown in Slovakia is weak, since the crash of one of the banks is likely to remain isolated. We can also see that the threshold of 7.5% is for the estimator in cases like BZW & ING PL too high to stabilize. This instability means that the threshold is located at the beginning of the potential range, still in the area of increased volatility. Decreasing the threshold stabilizes the estimator, which is apparent from Figure 3. Hungarian banks are excluded from the average reported in the table for the sake of consistency. (They are also excluded from the mother-to-subsidiary analysis, because none of them has a foreign majority owner.) The last column in the Table 3 reports the number of observations.

5.2 Mother-to-subsidiary estimates

For each local bank we compute the dependence between the bank (subsidiary) and its mother bank. We only use the data for the period after the subsidiary was acquired by the foreign owner. The dates of acquisition are determined based on annual reports and other official sources of information. For BZW, which changed its mother in 2010, we consider the period when it was owned by AIB. An overview of the dates of foreign acquisition is provided in Table 4. 'N/A' denotes that the bank does not have a mother; this excludes Hungarian banks form the mother-to-subsidiary analysis. Sources for the dates of acquisition are annual reports of the corresponding local banks.

Table 4: Dates of acquisition of analysed banks.

Country	Bank	Acquired on
Czech Rep.	CS	1.3.2000
Czech Rep.	KB	12.7.2001
Slovakia	VUB	21.11.2001
Slovakia	OTP SK	4.4.2002
Poland	PEO	3.8.1999
Poland	BRE	17.10.2000
Poland	ING PL	24.7.1996
Poland	BZW	23.6.2001
Poland	BZW	10.9.2010
Hungary	OTP	N/A
Hungary	FHB	N/A

The average probability that a bank fails, given that another has already crashed, is roughly 7%. The number is relatively stable across different levels of threshold t. Focusing on specific pairs of banks, we find the highest probability of contagion for PEO & UCG at 13%, followed by SG & KB and CBK & BRE. The weakest relationship concerns EBS & CS with estimate equal to zero, which suggests weak potential for contagion. Nevertheless, the result is probably influenced by the short data series available for the pair. The second lowest intensity of potential contagion is found for OTP SK & OTP with the probability of only 2.5%. An overview of our results is available in Table 5.

Table 5: Mother-to-subsidiary dependence.

Mother	Subsidiary	$SR(\kappa)$				Obs.
		t=0.075	t=0.07	t=0.055	t=0.05	
EBS	CS	1.0000	1.0000	1.0000	1.0000	589
SG	KB	1.1282	1.1020	1.0645	1.1026	2921
UCG	PEO	1.1389	1.1364	1.1395	1.1193	3401
CBK	BRE	1.1154	1.1167	1.1028	1.1007	3087
ING	ING PL	1.1094	1.0930	1.0979	1.0889	4148
AIB	BZW	1.0380	1.0330	1.0467	1.0629	2504
ISP	VUB	1.0000	1.0000	1.0233	1.0172	2572
OTP	OTP SK	1.0323	1.0286	1.0161	1.0260	1973
Average		1.0703	1.0637	1.0614	1.0647	

We test for systemic differences between contagion among local banks and contagion from foreign owners to local banks using the non-parametric Wilcoxon (1945) signed rank tests. The null hypothesis is that the mean difference as well as median difference is zero; the alternative is that they are different from zero. We reject the null hypothesis for all levels of t at the 10% significance level and for the three lowest levels of t even at the 5% significance level. The resulting p-value of the test is 0.0547, 0.0156, 0.0234, and 0.0156, respectively. We therefore conclude that the difference between the two sources of risk is statistically significant. Should we use the sign test (see, for example, King and Mody 2010), we would conclude that the subsidiary-to-subsidiary and mother-to-subsidiary probabilities of contagion are significantly different for all thresholds t at the 10% confidence level, since the p-values are 0.0703 for all thresholds t.

We find that the potential for a systemic breakdown between a mother and its subsidiary is on average approximately half compared to that between subsidiaries within a country, and that the difference is statistically significant. The result has two potential explanations. First, the finding can be attributed to successful attempts of regulators to protect local banks under their jurisdiction from capital and liquidity outflows. Second, the result suggests that investors perceive some risks as specific to Central and Eastern European countries. Nevertheless, it is unclear what proportion of this effect is attributable to regulatory policies and what to country specific risks.

6 Conclusion

In this paper we analyze the interdependencies in downside risk between local banks in Central and Eastern Europe (the Czech Republic, Hungary, Poland, and Slovakia) and between local banks and their foreign owners. We find that the risk of contagion is much stronger between local banks than between foreign parent banks and their local subsidiaries. In the analysis we use a measure of systemic risk which builds on extreme value theory. The measure is non-parametrical, which allows us to account for potentially fat-tailed distribution of shocks in financial markets, and also captures non-linear dependencies and enables us to focus on the interdependencies between large losses of local and foreign banks.

Our results suggest that the probability that a default of a local bank causes a default of another local bank is about 15%. In contrast, contagion from foreign owners is much less pronounced: a default of a foreign owner bank leads to the default of its local subsidiary with the probability of only 7%. Therefore, our analysis suggests that the worries of regulators in Central and Eastern Europe concerning the danger of increased systemic risk due to high foreign ownership of local banks might be exaggerated. In contrast, integration of local banks into multi-bank holdings may help alleviate systemic risk.

The contribution of our analysis in comparison with previous research is threefold. First, our paper is the first to focus on the relationship between foreign mother banks and their local subsidiaries and compare contagion risks from ailing mothers to healthy daughters with the relationships between individual banks in the local market. Second, few studies have analyzed systemic risk in Central and Eastern Europe (the rare examples include, for instance, Arvai et al. 2009; Cihak et al. 2007). Third, we employ modern techniques well-suited for the examination of interdependencies in downside risk between banks (Slijkerman et al. 2013). The main limitation of our analysis is the reliance on stock returns, because some stock markets in Central and Eastern Europe are not particularly liquid (especially the Slovakian stock exchange). On the other hand, stocks of the large banks that we select for our analysis typically rank among the most traded ones at the individual stock exchanges.

Our results also point to much weaker co-movement of extreme losses in stock prices between a local bank and its foreign owner than between local banks. This finding seems to contrast with a relatively large literature on stock market co-movements in Central and Eastern Europe. For example, Horvath and Petrovski (2013) conclude that stock markets in the Czech Republic, Hungary and Poland are heavily correlated with those in Western Europe. Gjika and Horvath (2013) report a high level of market integration between the Czech Republic, Hungary, and Poland and the euro area. The analysis of Syllignakis and Kouretas (2011) shows similar results. Our findings are different because we use a more flexible, non-parametric method that focuses on large outlying shocks in financial markets.

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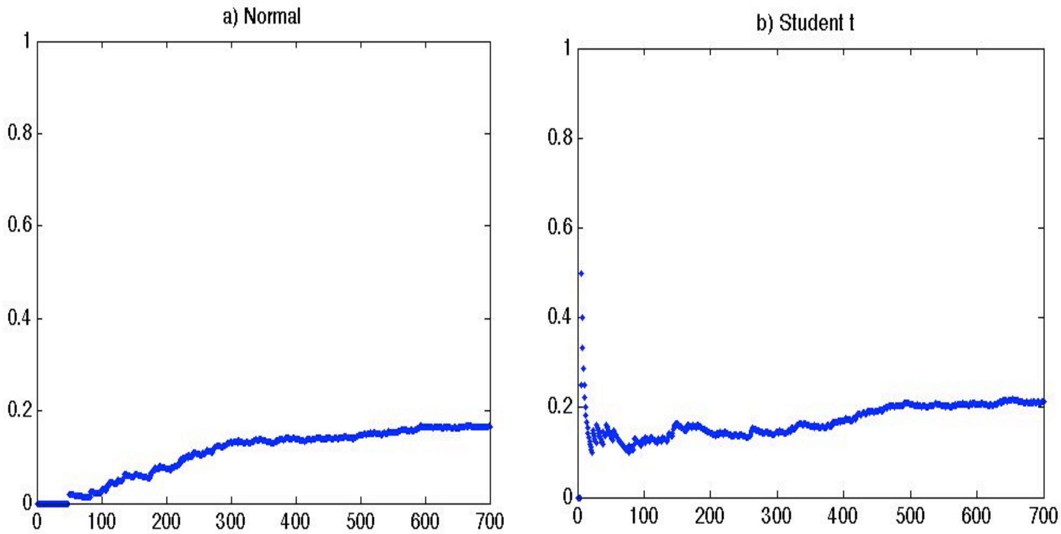
A Additional Simulation and Example

To illustrate how the estimator is sensitive to the choice of the threshold, we run a simulation. We draw 2921 realizations—which equals the number of observed returns between SG (Societe Generale) and KB (Komercni banka)—from the bivariate normal and student t distributions with three degrees of freedom. The realizations are rescaled so that the means, variances, and correlations are the same as what is observed for actual data on SG and KB.

Figure 2: Simulated conditional number of failures (minus one) drawn from a bivariate normal and student t distributions.



We compute the ratio of the times when the minimum and maximum of the two variables exceeds the threshold t. From equation (17) we know that this number is actually the conditional number of failures minus one:

$$E(\widehat{\kappa|\kappa \geq} 1) - 1 = \frac{\sum_{i=1}^{n} \mathbb{1}_{\{\min[a_i,b_i]>t\}}}{\sum_{i=1}^{n} \mathbb{1}_{\{\max[a_i,b_i]>t\}}}$$

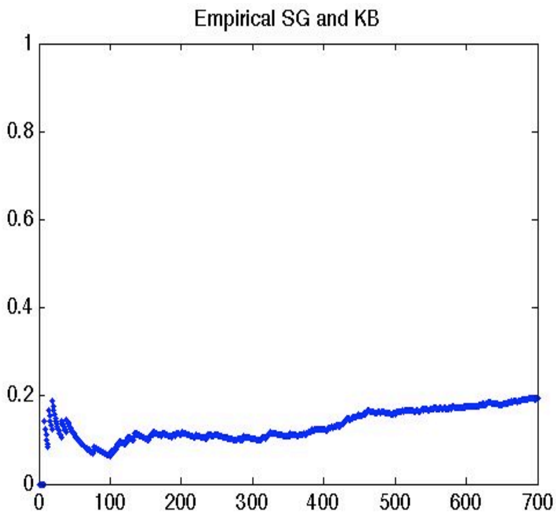
In Figure 2 this number is depicted on the y axis.

On the x axis, various boundaries (related, but not equivalent to the threshold t) are depicted, and the numbers denote the position of the threshold; the thresholds are taken from the order statistics. For example, a value of 100 on the x axis means that the threshold t is equal to the 100th *highest* order statistic, a value of 200 then represents a threshold equal to the 200th highest order statistic. As the value on the x axis increases, the threshold t decreases and the number of threshold violations increases as well.

This observation also implies that for $x = 2921$ it holds that $\widehat{E(\kappa|\kappa \geq 1)} - 1 = 1$, because the threshold is then at its lowest and t is equal to the lowest order statistic. Nevertheless, as Slijkerman et al. (2013) point out, "this is not a relevant area, since $SR(\kappa) = \lim_{t\to\infty} E(\kappa|\kappa \geq 1)$ should be judged from using a low number of order statistics only." Therefore, we present only the 700 highest order statistics whereby 700 is somewhat lower than 750 employed by Slijkerman et al. and corresponds to the lower number of realizations in our case.

Finally, we comment on Figure 2. In part (a) of the figure we show the results drawn from the normal distribution. In the beginning the value is zero, since no realization was extreme enough to surpass the first fifty thresholds. As the threshold is gradually decreased, more and more observations exceed the given threshold.

Figure 3: Conditional number of failures (minus one) estimated from the returns of SG and KB.



The result of the simulation based on the student t distribution is depicted in part (b) of the figure. We can see that the estimator is very volatile at the beginning, because only a few observations exceed the threshold level $\min[a_i, b_i] > t$. The value of the estimator therefore changes with every additional realization above that level. As the threshold decreases, the estimator stabilizes around 0.2. This means that if bank returns followed a student t distribution, we could expect that the other bank crashes once out of five times. It is worth noting that Slijkerman et al. (2013) also ended up with the value of approximately 0.2 in his estimation.

Furthermore, we investigate the behavior of the estimator using SG and KB returns; that is, the same data as in the beginning of Chapter 3. We present our results in Figure 3; the axes denote the same values as in the previous case. Resembling the case of simulated student t series, the estimator is unstable at the beginning before it stabilizes approximately at 0.2. Furthermore, it is clearly visible that the initial instability stems from the low number of threshold violations. As the number of threshold violations increases, the estimator stabilizes.

B Confidence Intervals

This appendix accompanies the empirical analysis in Section 5. In particular, it provides 90% confidence intervals for the estimates in Tables 3 and 5. 'L' denotes the lower bound of the interval, 'E' is the estimate and 'U' denotes the upper bound.

Table 6: Mother-to-subsidiary dependence. Estimates, and 90% confidence interval lower and upper bounds.

Subsidiary	Mother		$SR(\kappa)$			
			t=0.075	t=0.07	t=0.055	t=0.05
CS	EBS	L	1.0000	1.0000	1.0000	1.0000
		E	1.0000	1.0000	1.0000	1.0000
		U	1.0000	1.0000	1.0000	1.0000
KB	SG	L	1.1282	1.1000	1.0513	1.1019
		E	1.1282	1.1020	1.0645	1.1026
		U	1.1389	1.1111	1.0698	1.1101
PEO	UCB	L	1.1389	1.1212	1.1053	1.0769
		E	1.1389	1.1364	1.1395	1.1193
		U	1.1515	1.1463	1.1481	1.1275
BRE	CBK	L	1.1064	1.0909	1.0824	1.0870
		E	1.1154	1.1167	1.1028	1.1007
		U	1.1224	1.1273	1.1100	1.1091
ING PL	ING	L	1.0984	1.0875	1.0794	1.0759
		E	1.1094	1.0930	1.0979	1.0889
		U	1.1167	1.0988	1.1037	1.0943
BZW	AIB	L	1.0380	1.0330	1.0405	1.0577
		E	1.0380	1.0330	1.0467	1.0629
		U	1.0429	1.0375	1.0534	1.0688
VUB	ISP	L	1.0000	1.0000	1.0130	1.0094
		E	1.0000	1.0000	1.0233	1.0172
		U	1.0000	1.0000	1.0267	1.0196
OTP SK	OTP	L	1.0323	1.0286	1.0161	1.0156
		E	1.0323	1.0286	1.0161	1.0260
		U	1.0357	1.0313	1.0179	1.0282
CS&RBAG	EBS	L	1.1613	1.1714	1.2301	1.2283
		E	1.1719	1.1867	1.2458	1.2411
		U	1.1930	1.2154	1.2727	1.2689

Table 7: Subsidiary-to-subsidiary dependence. Estimates, and 90% confidence interval lower and upper bounds.

Country	Subs.	Subs.		$SR(\kappa)$			
				t=0.075	t=0.07	t=0.055	t=0.05
Czech R.	CS	KB	L	1.2105	1.1957	1.2157	1.2206
			E	1.2308	1.2083	1.2500	1.2436
			U	1.2500	1.2273	1.2778	1.2639
Poland	PEO	BRE	L	1.1250	1.1875	1.1594	1.1553
			E	1.1538	1.2143	1.1778	1.1739
			U	1.1667	1.2250	1.1905	1.1835
	PEO	ING PL	L	1.2069	1.2258	1.1385	1.1325
			E	1.2258	1.2571	1.1486	1.1489
			U	1.2414	1.2727	1.1618	1.1591
	PEO	BZW	L	1.1333	1.1765	1.1667	1.1594
			E	1.1333	1.1765	1.1731	1.1622
			U	1.1429	1.1875	1.1875	1.1739
	BRE	ING PL	L	1.1127	1.1711	1.1453	1.1497
			E	1.1200	1.1852	1.1679	1.1686
			U	1.1250	1.1923	1.1756	1.1779
	BRE	BZW	L	1.1905	1.2174	1.1346	1.1370
			E	1.1905	1.2174	1.1404	1.1410
			U	1.2105	1.2381	1.1538	1.1528
	BZW	ING PL	L	1.0556	1.1000	1.1190	1.1379
			E	1.0556	1.1000	1.1364	1.1475
			U	1.0625	1.1111	1.1463	1.1607
Slovakia	OTP	VUB	L	1.0000	1.0000	1.0000	1.0111
			E	1.0000	1.0000	1.0000	1.0111
			U	1.0000	1.0000	1.0000	1.0122
Hungary	FHB	OTP	L	1.1200	1.1290	1.1270	1.1905
			E	1.1379	1.1389	1.1406	1.2069
			U	1.1481	1.1471	1.1500	1.2143

C Summary Statistics

The summary statistics reported in Table 8 display the key characteristics of continuously compounded loss return series for the banks in our sample. The highest loss incurred, equal to 71%, occurred in the case of OTP SK. Such a high number is to some extent a result of continuous compounding. We checked the original data containing prices; indeed, the price of OTP SK dropped between July 29, 1998 and August 14, 1998 from 5.643 EUR down to 1.992 EUR. More surprisingly, these two prices are neighboring observations. We believe that this break can be attributed to the specifics of a transition economy and low liquidity of the Slovakian stock exchange. If we dropped this observation, however, results would not change significantly. Other extreme losses are 44% in the case of AIB and 32% for ING.

Table 8: Individual loss return series, continuous compounding.

Bank	Mean	St. Dev.	Min	Max
CS	-0.0004	0.0271	-0.1886	0.2753
EBS	-0.0003	0.0234	-0.1703	0.2000
KB	-0.0002	0.0230	-0.2005	0.2409
SG	-0.0003	0.0227	-0.2033	0.1771
PEO	0.0001	0.0214	-0.1356	0.2059
UCG	0.0000	0.0222	-0.1755	0.1895
BRE	-0.0002	0.0237	-0.1290	0.1415
CBK	0.0002	0.0234	-0.2048	0.1640
ING PL	-0.0002	0.0206	-0.0953	0.1165
ING	0.0000	0.0233	-0.1925	0.3214
BZW	-0.0003	0.0195	-0.1103	0.1214
SAN	-0.0002	0.0193	-0.1339	0.1955
AIB	0.0005	0.0323	-0.3610	0.4383
VUB	-0.0007	0.0226	-0.1086	0.2757
ISP	-0.0002	0.0216	-0.1614	0.1846
OTP SK	0.0008	0.0345	-0.4984	0.7129
OTP	-0.0005	0.0247	-0.2092	0.2513
FHB	0.0001	0.0213	-0.2089	0.1972

The most extreme gain reaches 50% in the case of OTP SK, but again, there is a break of almost two months in trading. The other maxima include 36% for AIB and 21% for OTP. Combined with an average mean of -0.01% and average standard deviation of 2.37%, these numbers virtually eliminates the possibility that the loss returns are normally distributed, which we discuss in Section 3.

D Acronyms of Bank Names

AIB Allied Irish Banks

BRE Bre Bank Group

BZW Bank Zachodni WBK

CBK Commerzbank

CS Ceska sporitelna

CSOB Ceskoslovenska obchodni banka

EBS Erste Group

FHB FHB Mortgage Bank

ING ING Group

ING PL ING Bank Slaski

ISP Intesa SanPaolo

KB Komercni banka

OTP OTP Bank, Hungary

OTP SK OTP Bank, Slovakia

PEO Bank Pekao

PKO PKO Bank Polski

SAN Banco Santander

SG Societe Generale

UCG UniCredit Group

VUB Vseobecna uverova banka

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