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BACHELOR THESIS

Stability of the Banking Sector: Dependence Beyond Correlation

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Declaration of Authorship

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Abstract

We analyze systemic risk of banks in countries of the so-called Visegrad Group (V4). Particularly, we focus on the relationship between a foreign mother and its local subsidiary which we compare to the relationship between subsidiaries in a given V4 country. We find that the systemic risk between two subsidiaries is higher than that between a mother and the respective subsidiary. In our analysis, we employ a technique stemming from a nonparametric multivariate Extreme Value Theory which is distribution free. Thus, our results are robust to heavy tails.

Keywords	Extreme value theory, systemic risk, financial stability, Visegrad Group, mother-subsidiary realtionship

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Abstrakt

V této práci analyzujeme systematické riziko bank v rámci Visegrádské čtyřky (V4). Obzvláště se pak zaměřujeme na vztah mezi pobočkou v dané zemi Visegrádské čtyřky a její zahraniční mateřskou společností, který následně porovnáváme se vztahem mezi lokálními pobočkami. Docházíme k závěru, že systematické riziko mezi pobočkami v rámci jedné země V4 je vyšší než mezi matkou a její pobočkou. Naše analýza je založena na metodě, které vychází z neparametrické vícedimenzionální teorie extrémních hodnot, která není spjata s konkrétním rozdělením; tudíž jsou naše výsledky robustní vzhledem k těžkým chvostům.

Klíčová slova	Teorie extrémních hodnot, systematické riziko, finanční stabilita, Vysegrádská čtyřka, vztah pobočky a mateřské společnosti

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Acronyms

AIB Allied Irish Banks

BIS Bank for International Settlements

BRE Bre Bank Group

BZW Bank Zachodni WBK

CBK Commerzbank

CEE Central and Eastern Europe

CESE Central, Eastern & South-Eastern Europe

CNB Czech National Bank

CS Ceska sporitelna

CSOB Ceskoslovenska obchodni banka

EBRD European Bank for Reconstruction and Development

EBS Erste Group

EUR Euro

FHB FHB Mortgage Bank

HUF Hungarian forint

iid independently and identically distributed

iff if and only if

ING ING Group

ING PL ING Bank Slaski

IPO initial public offering

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

V4 Visegrad Group

VUB Vseobecna uverova banka

Bachelor Thesis Proposal

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Proposed Topic	Stability of the Banking Sector: Dependence Beyond Correlation

The breakdown of financial markets, the collapse of Lehman Brothers and subsequent widespread bail-outs demonstrated the necessity to employ new methods that enable us to process volatile data and to model the dependency of banks' portfolios in the tail area. To address such issues, this work is going to apply the Extreme Value Theory to the empirical study of the banking system in the countries of the so-called Visegrad Group which is known for high foreign ownership of banks. Moreover, it is characteristic for a significant concentration of the banking market. Such a structure may hide interconnections not apparent under normal conditions, thus it is ideal for this study. In order to assess the interdependence on the market, I will avail the linkage measure employed by de Vries (2005). Furthermore, I will assess the dependence of the branches on their mother banks.

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4. Modelling Systemic Risk
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Chapter 1

Introduction

Is the threat of contagion from a mother bank higher than from the bank's peers? Such a question is at the centerpoint of this paper. Knowing the answer is important especially for the regulators. Should the threat of contagion from peers be higher, then they need to focus on mitigating the threat within the local market. On the other hand, evidence of threat from mostly foreign mother banks would push the regulators towards ring–fencing the local market, active cooperation or towards a creation of a supranational body. In this paper, we present an analysis for the Visegrád Group (V4) countries: the Czech Republic, Hungary, Poland and Slovakia.

The European Bank for Reconstruction and Development (EBRD) reports that almost 92% of the Slovak banking sector is owned by foreign investors. The proportion in the other countries is also relatively high with Poland showing the lowest degree of foreign ownership of 69%.[1] The owners are almost unexceptionally international multi-bank holding companies. Does that mean that banks in the V4 countries can purely enjoy the safety of mother companies and profit from higher efficiency at the same time? What are the adversities?

During 2008 Ceskoslovenska obchodni banka (CSOB), the Czech subsidiary of KBC Group, paid CZK 17 bn. or 30% of its capital[2] to its mother company, since the mother company itself was in a desperate situation (Zelezny 2012). This type of transaction was not unique to CSOB, as other Czech banks exhibited similar behaviour. Such a situation, as it is discussed below, contradicts most of the present literature, which mostly acknowledges positive effects of ownership by a mother bank: a healthy subsidiary – in the middle of the cri-

[1] EBRD: Share of foreign owned banks. Downloadable from `www.ebrd.com/downloads/research/economics/macrodata/Share_of_foreign_banks.xlsx`.

[2] Own computation based on information in Zelezny (2012) and CSOB (2009)

sis – provides a capital injection to its mother bank, thus decreasing its own financial stability.

The costs of unsound policies of the foreign mother banks were thus transferred onto domestic subsidiaries, i.e., the risk of a systemic crisis increased. To our best knowledge, so far no one has examined the effects of foreign mothers on domestic subsidiaries, especially with respect to potential systemic breakdowns. Furthermore, no one has estimated the probability of a systemic crash neither in V4 nor in CEE countries. In this paper, we examine this effect based on the methodology availed by Slijkerman et al. (2005; 2013). Most notably, this methodology does not hinge on the correlation measure and allows for heavy-tailed distributions (Hartmann et al. 2004). Therefore, our analysis is robust to extreme situations characteristic of stock markets.

We organize the paper as follows: An overview of current research is presented in Chapter 2. The economic reasoning underlying the availed model can be found in Chapter 3. The argumentation why correlation is not a measure fitting to systemic risk management, review of the tail dependence measure as well as the systemic risk model are all presented in Chapter 4. The estimation is explained in Chapter 5 and the dataset in Chapter 6. Our empirical analysis of the dependence between banks is demonstrated in Chapter 7. The last section concludes.

Chapter 2

Literature Overview

In this section we present what differentiates our paper from the current literature as well as an overview of the recent literature in systemic risk. Our paper is unique in three aspects. First, by its focus on the relationship between a domestic subsidiary and its foreign mother. Second, due to its geographical concentration on the V4 countries. Third, by its techniques which examine dependence in tails.

Firstly, the literature acknowledges the positive effects of the mother-to-subsidiary relationship. Based on US data, Ashcraft (2004) finds that "a bank affiliated with a multi-bank holding company is significantly safer than either a stand-alone bank or a bank affiliated with a one-bank holding company", since "affiliated banks are more likely to receive capital injections and recover more quickly than other banks." Using simulation techniques Klein and Saidenberg (1997) conclude that diversification within the holding-company structure enables higher efficiency, i.e., holding less capital and doing more lending than the benchmark. Deng et al. (2007) highlight the positive effects of "geographic diversification of deposits and diversification of assets". De Haas and Van Lelyveld (2010) find positive effects of a strong mother on the expansion of subsidiaries. Moreover, due to the support of the mother bank "foreign bank subsidiaries also do not need to rein in their credit supply during a financial crisis, while domestic banks need to do so", which suggests counter-cyclical effects on the domestic economy. However, they do not discuss what happens if the mother is weakened.

The potential downsides are less pronounced in the literature. Only Keeton (1990) discusses three situations which result in adverse effects. Firstly, the mother may decide to let its subsidiary fail if the expected earnings are lower than potential earning. Secondly, the mother company may transfer the resources from a troubled subsidiary in mispriced transactions. Thirdly, a low capitalized mother may force its healthy subsidiaries to take big risks in order to earn enough to pay for the mother's debt. However, Keeton's paper is based on the US reality in the 1980s, which is remote from the situation in the V4 countries in these days.

Regarding the foreign ownership, the results are mostly positive. Goldberg et al. (2000) conclude that foreign ownership of banks in Argentina and Mexico had contributed to a greater stability during a crisis. On the other hand, Lensink et al. (2008) find that "foreign ownership negatively affects bank efficiency". Nevertheless, they agree that inefficiency is reduced in the presence of sound institutions. Specifically in the case of Central and Eastern Europe (CEE), Bonin et al. (2003) conclude that "majority foreign ownership generate[s] higher efficiency scores". Using a sample of ten CEE countries, Dinger (2009) finds stabilizing effect of foreign-owned banks on emerging economies. Brissimis et al. (2008) ascertain significantly positive effects of foreign ownership on the productive efficiency of banks in the so-called new EU member states. Focusing only on Hungary, Hasan and Marton (2003) show that "[f]oreign banks and banks with higher foreign bank ownership involvement were associated with lower inefficiency". Ábel and Siklos (2004) than argue that "the policy of searching for foreign strategic partners to take over existing domestic institutions . . . has created [in Hungary] a stable and well-functioning banking sector". Thus, it seems that foreign bank ownership yields positive effects on efficiency at least in the V4 countries, which are relevant for this study.

Secondly, only a few studies concerning the systemic risk of banks that are concentrated on some of the CEE countries exist. However, they are conceptually different from ours. The closest paper is that of Arvai et al. (2009). On BIS country-level data they study the exposures between Western European and Central, Eastern & South-Eastern European countries (CESE). They conclude that "[t]he financial interlinkages with Europe are economically significant" and that most CESE countries are dependent on banks in Austria, Germany and Italy stating that "the exposures are fairly concentrated". The exposure in the opposite direction is said to be "far smaller". Focusing only on the Czech Republic, Cihak et al. (2007) conclude that the Czech banking sector is "relatively resilient to the shocks". These results suggests there is a downside from a high exposure to Western Europe, although some countries may be more resilient than others.

Festić et al. (2011) then assess the vulnerability of the banking sector in terms of its relationship with macroeconomic variables in the Baltic states plus Bulgaria and Romania. Examining the relationship between non-performing loans and a set of macro variables they conclude that “strong economic growth and a decelerating non-performing-loan ratio” can be understood as a “threat to banking sector performance.”

A comparatively larger literature is devoted to stock market comovements. Focusing only on stock indices of banks in the Czech Republic, Hungary and Poland, Jokipii and Lucey (2007) find a presence of a considerable comovement. Examining the whole stock markets, Horvath and Petrovski (2013) conclude that stock markets in the Czech Republic, Hungary and Poland are heavily correlated with those in Western Europe. In another study, Gjika and Horvath (2013) find high level of market integration between the three countries and the euro area. The analysis of Syllignakis and Kouretas (2011) which involves all V4 countries shows similar results. Should the comovements exist also in the tails of return distributions of banks, in terms of our technique, it would hint at a higher level of systemic risk.

Thirdly, focusing more on the methodological aspect,[3] Chollete et al. (2012) employ both the correlation and the tail dependence measure, which is similar to ours, to data from G5 countries, east Asia and Latin America. They find that “correlations and extreme dependence sometimes deliver different or ambiguous risk management signals”. Thus, the authors conclude that “the finding of correlation complexity and potential heavy tails bolsters extant theoretical reasons for using robust dependence measures in risk management”, which is exactly what we do. Empirically, they find that “regions exhibit downside risk at different times” and “[l]eft dependence is also the only measure that is always largest for the region with largest returns.”

Furthermore, examining data from the US and Western Europe, Rodríguez-Moreno and Peña (2012) conclude that the CDS-based measures are superior to measures based on stock market prices. In particular, the model of Lehar (2005) and $\Delta CoVaR$ model of Adrian and Brunnermeier (2008). However, these two models differ from our technique substantially. Lehar's model is based on option pricing. $\Delta CoVaR$ then measures the “contribution of a particular institution . . . to the overall systemic risk”, whereas our technique does

[3] As it was stressed in the introduction, we use methodology of Slijkerman et al. (2013). Their paper is however focused on economically different issues.

not condition on the fall of a specific institution, i.e., ours captures the overall fragility. Moreover, $\Delta CoVaR$ suffers from disadvantages inherent to VaR models, see for example Kuester et al. (2006) or Daníelsson (2002).

Girardi and Tolga Ergün (2013) then use Multivariate GARCH to estimate modified CoVaR. On the US data, they find that “depository institutions were the largest contributors to systemic risk, followed by broker-dealers, insurance companies, and non-depository institutions” and that “[s]ystemic risk of all industry groups increased substantially prior to the crisis.”

Finally, there is a vast literature on other geographic areas which uses correlation to capture the dependence between banks. Most recently, Patro et al. (2013) use “stock return correlations among financial institutions as an indicator of systemic risk.” On a sample of twenty two largest bank holding companies and investment banks in the US they find “an increasing trend in stock return correlation among banks” which leads them to conclude that “the systemic risk in the banking system has increased”. Similarly, Huang et al. (2012) examine twenty two major banks in Asia and the Pacific using a method hinging on correlation, and Puzanova and Düllmann (2013) who study “a panel of 54–86 of the world’s major commercial banks” which does not contain any CEE bank.

Chapter 3

Economic Background

In this section we elaborate on the economic relationships underlying our paper. In particular, we examine the linkages through which the systemic breakdown can spread. In the first section, we show that the systemic risk stems from the mutual similarity of banks' balance sheets. In the second section, we explain how the systemic crash can spread between a mother bank and its subsidiary. These relationships are then reflected in the (joint) stock returns.

3.1 Subsidiary-to-subsidiary linkages

The linkages between subsidiaries can be explained from the mutual similarity of banks' balance sheets. Following de Vries (2005), banks' balance sheets contain similar entries on both sides. This similarity then creates potential for a systemic breakdown, since banks face comparable risks.

The asset side of the balance sheets contains a wide range of akin 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, thus, 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 (de Vries 2005). Banks in the V4 countries are financed mostly by deposits. Thus, they rely heavily on the people's trust in the banking sector; any disruption of the trust would lead to systemic breakdown. de Vries (2005) also quotes interest rate as a major risk driver.

Apart from the linkages described above, banks enter into mutual deals on the interbank market. These interactions enter respective balance sheets two times, since an asset of one bank is liability to the other and vice versa. The interbank market therefore creates direct exposures between banks.

3.2 Mother-to-subsidiary linkages

We derive the dependence between a mother and its subsidiary from mutual interconnectedness of their balance sheets which in turn usually stems from the mother's ownership rights. However, 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 other 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 2) over the period of three years prior to 2012 (CNB 2012). In response, the Czech National Bank (CNB) 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 the bank portfolios, i.e., the argument from the previous section applies. Even though the geographical area is different, banks still hold similar assets like mortgages. Another example are Greek bonds which were held by banks across Europe; only the extent of involvement was different.

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, like in the case of CSOB and KBC. On the other hand, subsidiaries have to comply with regulatory requirements like Basel Accords as well as local laws and decrees which are deemed to secure financial stability.

Like in the case of two subsidiaries, mothers and subsidiaries are linked together indirectly via deposits in the similar way as discussed above, and also directly via interbank markets. Focusing on the interbank markets, some mothers provide loans to their subsidiaries that are redeemable on a short notice (a bank manager who prefers to stay anonymous). These loans provide mothers with a quick access to liquidity, while at the same time they pose a liquidity threat for the subsidiaries. On the other hand, banks have to withstand stress tests required by regulators to ensure bank stability.

To sum up, mother banks have numerous ways to drain capital and liquidity from their subsidiaries, but regulators like central banks set limits on the outflow from banks under their jurisdiction that would threaten local financial stability; this factor influences our analysis.

Chapter 4

Modelling Systemic Risk

Systemic risk modelling is concerned with extreme shocks that endanger the whole banking sector.[4] This risk, however, originates at the level of individual institutions which 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). Systemic event in its 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, one usually works with data on individual institutions and the dependence among them[5] if one wants 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 an example see Lehar (2005) or Acharya (2009); which is closely associated with the normal distribution (de Vries 2005). However, this approach is known for its pitfalls.

As argued by Hartmann et al. (2004), "crash correlation can be zero even if there is a high spillover probability". This issue stems form the close link between correlation and the normal distribution. Under the normal distribution assumption, correlation captures all the dependence between variables. Generally, this is not true for the other distributions and *only* in the case of

[4]Systemic risk is not unique to the banking sector only. For example, Schwarcz (2008) suggests that a "greater focus should be devoted to financial markets and the relationship between markets and institutions". However, the method availed in our paper is not necessarilly limited to banks only.

[5]We are aware that some authors like Acharya (2009) go even deeper, on the level of bank asset holdings. This approach has a great disadvantage that such data is usually kept secret. Moreover, these holdings "are sooner or later also reflected in the value of bank equity" (de Vries 2005).

a multivariate normal distribution it is permissible to interpret zero correlation as implying independence (Embrechts et al. 2002).

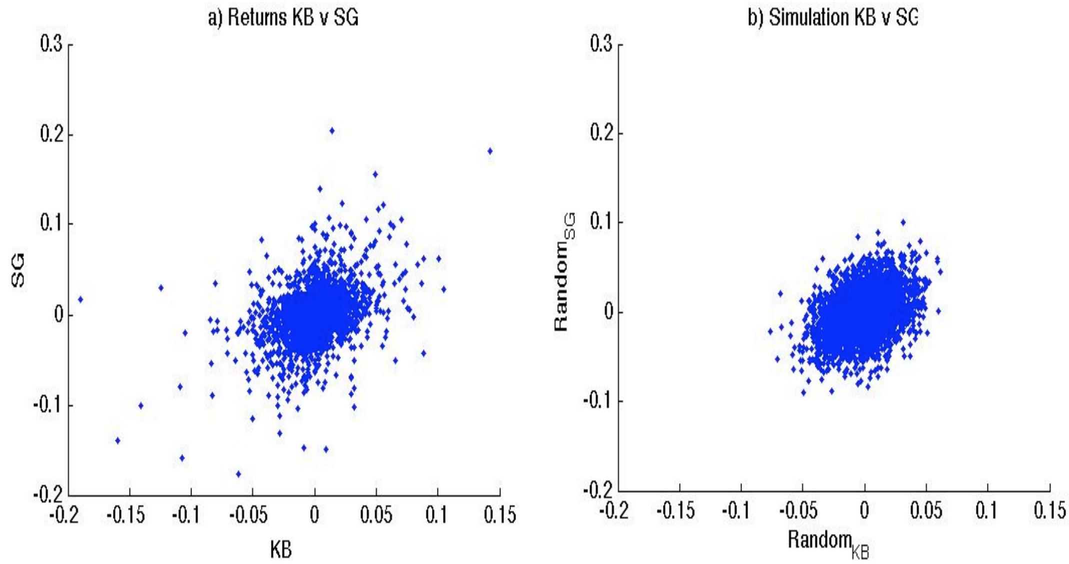
We support this notion by an example carried out by Slijkerman et al. (2013). Suppose that X and Y are two appropriately defined random variables that in this example represent two asset returns. Now, construct two portfolios based on these assets, $X - Y$ and $X + Y$. If both X and Y are identically and independently distributed (iid), then the portfolios are uncorrelated. Furthermore, if the two variables are normally distributed, then the two portfolios are independent. On the other hand, for fat-tailed distributed variables following, e.g., a Student t distribution with more than two degrees of freedom, the two portfolios are dependent. Thus, if one wants to capture the dependence by correlation, one needs to assume that variables are normally distributed.

However, quite an extensive literature exists suggesting that asset returns are characterized by distributions with heavier tails than normal, see Cont (2001), Ibragimov et al. (2011), etc. We illustrate this fact in Figure 4.1a where we have plotted asset returns of Komercni banka (KB) 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 (KB 2002) and ending on March 8, 2013 when the data was acquired, which gives us 2921 observations. In Figure 4.1b, 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 does not exhibit nearly as many extreme observations as the empirical data do. The most extreme observations in the simulation reach barely 10% in absolute value. In contrast, extremes as large as 20% had been observed, 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, i.e., returns of KB and SG seem to be moving in tandem. This suggest that dependence between the two exists.

Finally, we are primarily interested in the “downside dependence” (Slijkerman et al. 2013). Correlation tries to capture the overall dependence where the large number of observations around the center overweight the extreme ones. However, we are rather interested in the dependence in extremes, since we need to capture contemporaneous extreme losses. An appropriate measure is introduced in the following section.

Figure 4.1: Empirical returns v simulated returns drawn from a multivariate normal distribution.



4.1 Dependence beyond correlation

As discussed above, the techniques based on the normal distribution and the correlation measure impose severe limitations on modelling dependencies. Since risk management is concerned with modelling downside extreme movements, we need a measure that is able to cope with distributions that exhibit heavier tails than normal. This requirement also makes it impossible to employ correlation which is closely linked to normal distribution and – as discussed above – 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

$$E(\kappa|\kappa \geq 1) = \frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)}. \tag{4.1}$$

where κ stands for the number of simultaneous crashes; random variables A and B represent stock returns and are defined on some probability space $(\Omega, \mathcal{F}, P)$ whereby Ω is a sample space, $\mathcal{F}$ is a set of events and P is a probability measure, and t denotes a common bankruptcy threshold.[6]

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 behaviour of correlated bank portfolios". Zhou (2010) uses the measure to show that "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 the Western currencies] to the dollar" compared to the other currencies. Finally, Slijkerman et al. (2005; 2013) avail the measure to study the interdependence between the insurance and banking sector.

The cause for such popularity stems from the measure's favourable properties. First of all, it is not associated with any type of distribution, which allows us to use heavy-tailed distributions. Second, the measure "can allow for non-linear relationships". (both Hartmann et al. 2004) Therefore, it can seize the dependency that correlation cannot capture. Third, the measure can easily be extended into a higher dimension if desirable. Fourth, "one does not need to condition on a specific bank failure, whereby one would look only into one direction in the plane of failures." (both de Vries 2005) Finally, in a two-dimensional setting the measure minus one can be interpreted as "the conditional probability on a systemic crisis" (Slijkerman et al. 2013), because it is equal to the probability that two bank crash, given that one is already bankrupt (originally in Hartmann et al. (2004)).

$$E(\kappa|\kappa \geq 1) - 1 = \frac{P(A > t, B > t)}{1 - P(A \leq t, B \leq t)} = P(\kappa = 2|\kappa \geq 1). \tag{4.2}$$

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 (4.1)

$$SR(\kappa) := \lim_{t \to \infty} E(\kappa|\kappa \geq 1). \tag{4.3}$$

Geluk et al. (2007) point out that "[o]ne reason to take the limit, rather than using a finite loss level [t], is that economics does not say what the critical level is at which systemic failure sets in. Taking the limit thereby removes

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

some arbitrariness." Moreover, "[e]xtreme value theory then shows that even though the measure is evaluated in the limit, it nevertheless provides a reliable benchmark for the dependency at high but finite levels of t" (Slijkerman et al. 2013).

4.2 Statistical modelling

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

Assuming 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 very weak assumption, since "the distribution of returns seems to follow a power-law or Pareto-like tail" (Cont 2001).

Definition 4.1. *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 abovementioned risk components and for $x_m = 1$, we can write

$$P(G > t) = P(H > t) = P(F > t) = P(X_i > t) = t^{-\alpha}. \tag{4.4}$$

Should the tail indices differ, please consult Slijkerman et al. (2013, p. 10) on the appropriate transformation.

Function $\bar{F}(t) = P(X > t)$ is known as a *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 the Approach where losses are modelled as positive numbers a survival function needs to be interpreted as the probability that a bank goes bankrupt once the threshold is surpassed.

Note, however, that the Pareto distribution assumption can be weakened further. As pointed out by Slijkerman et al. and as we show, it would be sufficient to assume that the risk components follow a distribution with regularly varying tails.[7] This stems from a lemma as given by Feller (1971, p. 275) which states every converging function resembles some power function in its tail.

Lemma 4.1. *Let U be a positive monotone function on $(0, \infty)$ such that*

$$\lim_{t\to\infty} \frac{U(tx)}{U(t)} = \psi(x) \leq \infty \tag{4.5}$$

at a dense set A of points. Then

$$\psi(x) = x^{\alpha} \tag{4.6}$$

where $-\infty \leq \alpha \leq \infty$.

Feller accompanies the lemma by an important note that "[t]he senseless symbol x^{∞} is introduced only to avoid exceptions" and is should be interpreted as "∞ for $x > 1$ and as 0 for $x < 1$." The expression $x^{-\infty}$ is to be interpreted similarly.

Before formulating the proposition, we need to define slowly and regularly varying functions. We use the definition of Feller (1971).

Definition 4.2.

i. *A positive (not necessarily monotone) function L defined on $(0, \infty)$ varies slowly at infinity iff*

$$\lim_{t\to\infty} \frac{L(tx)}{L(t)} = 1. \tag{4.7}$$

ii. *A function U varies regularly with exponent α $(-\infty < \alpha < \infty)$ iff it is of the form*

$$U(x) = x^{\alpha} L(x) \tag{4.8}$$

with L slowly varying.

We highlight that "[t]he property of regular variation depends only on the behaviour at infinity" Feller (1971, p. 276).

[7] See Definition 4.2.

Now, we prove that the tail behaviour of any regularly varying distribution function and that of a Pareto survival function is asymptotically equivalent. From this follows that outcomes under Pareto distribution assumption hold also for any regularly varying distribution function, and vice versa.

Proposition 4.1. *Let a random variable X follow a distribution function with regularly varying tails $U(x)$. Also assume that a random variable Y follows Pareto distribution with $x_m = 1$ and the survival function $\bar{F}(x)$, $x \in [1, \infty)$. Then for a constant $k \in \mathbb{R}^+$ holds*

$$\lim_{x \to \infty} U(x) = k \lim_{x \to \infty} \bar{F}(x). \tag{4.9}$$

Proof. Let $x \in [1, \infty)$ so that all functions are defined and let U be a regularly varying distribution function. By definition of a regularly varying function it holds that

$$U(x) = x^{\alpha} L(x) \tag{4.10}$$

where $L(x)$ is a slowly varying function, i.e.,

$$\lim_{t \to \infty} \frac{L(tx)}{L(t)} = 1.$$

This means that for a very large t the expression $L(tx)$ is almost the same as $L(t)$. Therefore, for a very large t, we can write

$$L(tx) \simeq L(t). \tag{4.11}$$

Such a result implies that for large values of an argument a tail of the slowly varying function can be approximated by a constant. Thus, for $c > 0$ we end up with

$$L(x) \simeq c \tag{4.12}$$

for x very large.

Since $U(x)$ is also a distribution function, it must be true that

$$U(x) \leq 1 \tag{4.13}$$

Combining the results of the equation (4.13) with the equations (4.10) and (4.12) we get

$$x^{\alpha} c \leq 1 \tag{4.14}$$

for large x. For the sake of clarity we rewrite the last equation as follows:

$$x^{\alpha} \leq \frac{1}{c} \tag{4.15}$$

From the last expression it is already clear that $\alpha \leq 0$, since for $x \geq 1$, any $\alpha > 0$ would result in a function going to infinity which contradicts equation (4.13).

At this point, we show that α cannot even equal zero. We begin the argumentation by writing the equation (4.15) for the case when $\alpha = 0$:

$$1 \leq \frac{1}{c} \tag{4.16}$$

Since the inequality must hold also for c greater than one, this case is not valid either. Thus, there only remains the case when α is smaller than zero, because the equation (4.15) holds for large x.

From the definition of regular variation we can now compute how the function behaves in its tail, i.e., we take its limit. For $c \simeq L(x)$ and $\alpha < 0$

$$\lim_{x\to\infty} U(x) = \lim_{x\to\infty} x^{\alpha} L(x) = x^{\alpha} c. \tag{4.17}$$

Replacing $\alpha < 0$ by $\beta > 0$ we have

$$\lim_{t\to\infty} U(x) = c x^{-\beta} = k\bar{F}(x) \tag{4.18}$$

whereby $k = c$.

□

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

$$A_i = G + H + X_i \text{ and } B_j = G + F + X_j \tag{4.19}$$

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

4.2.1 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 4.1. *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

$$\lim_{t\to\infty} \frac{P(A+B>t)}{2t^{-\alpha}L(t)} = 1 \tag{4.20}$$

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" (Slijkerman et al. 2013).

For finite t we can, therefore, write

$$P(A_i > t) = P(G + H + X_i > t) = 3t^{-\alpha} + o(t^{-\alpha}). \tag{4.21}$$

Note also that $P(B_j > t)$ would yield the same result.[8]

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

$$P(A_k > t, A_l > t) = P(G + H + X_k > t, G + H + X_l > t). \tag{4.22}$$

When investigating what the probability that the two inequalities hold simultaneously is, we need to realize that "only the probability mass along the axis

[8] Slijkerman et al. (2013) discuss cases for a varying tail index α, we therefore refer an interested reader to their paper.

counts" (Slijkerman et al. 2013). Because only the G and H axes are common to the banks and the "points along the X_k or the X_l axes larger than t cannot simultaneously satisfy both inequalities",[9] (Slijkerman et al. 2013) it follows that

$$\lim_{t\to\infty} \frac{P(G+H+X_k > t, G+H+X_l > t)}{P(G+H>t)} = 1. \tag{4.23}$$

The equation (4.23) already ensues that

$$P(A_k > t, A_l > t) = P(G+H>t) + o(t^{-\alpha}) = 2t^{-\alpha} + o(t^{-\alpha}). \tag{4.24}$$

Next, we move to mother – subsidiary dependence.

4.2.2 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

$$P(A_k > t, B_l > t) = P(G+H+X_k > t, G+F+X_l > t) = t^{-\alpha} + o(t^{-\alpha}). \tag{4.25}$$

The reasons why it is so 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.

4.2.3 Systemic risk

In this subsection[10] we utilize the results we derived in the equations (4.21), (4.24) and (4.25) to compute the systemic risk measure $SR(\kappa)$ from the equation (4.3).

Before proceeding further, we compute the future denominator of the mea-

[9] Slijkerman et al. (2013) use different notation for the variables.
[10] Technically, we still follow the Approach of Slijkerman et al. (2013).

sure. Realizing that

$$1 - P(X \leq t, Y \leq t) = P(X > t) + P(Y > t) - P(X > t, Y > t) \tag{4.26}$$

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

$$1 - P(A_k \leq t, A_l \leq t) = P(A_k > t) + P(A_l > t) - P(A_k > t, A_l > t) \tag{4.27}$$

for a pair of domestic banks A_k and A_l. By utilizing equations (4.21), (4.24), and (4.27) to compute the systemic measure, we get

$$SR(\kappa) = \lim_{t\to\infty} \frac{P(A_k > t) + P(A_l > t)}{1 - P(A_k \leq t, A_l \leq t)} = \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - 2t^{-\alpha}} = \frac{6}{4}. \tag{4.28}$$

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 a framework of de Vries (2005) this result implies that the potential for the sytemic breakdown is strong, as the linkages do not vanish asymptotically.

Based on equation (4.26), we derive the denominator for the case of a foreign mother B_l and domestic subsidiary A_k:

$$1 - P(A_k \leq t, B_l \leq t) = P(A_k > t) + P(B_l > t) - P(A_k > t, B_l > t) \tag{4.29}$$

Analogously, from the equations (4.21), (4.25), and (4.29) we compute the systemic measure for the mother-to-subsidiary dependence

$$SR(\kappa) = \lim_{t\to\infty} \frac{P(A_k > t) + P(B_l > t)}{1 - P(A_k \leq t, B_l \leq t)} = \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - t^{-\alpha}} = \frac{6}{5}. \tag{4.30}$$

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 asigned 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 cases in the empirical section and test whether the difference is statistically significant. If it is not the case, it would mean that the country risks are "similar or unimportant"

(Slijkerman et al. 2013). If they differ, it would suggest that the model gives a reasonable prediction.

4.2.4 A remark on normality

It can be shown[11] that if the risk components G, H, F, X_k and X_l are standard normally distributed, which implies that A_k, A_l and B_l are correlated, then the individual failure in the economy remains isolated, i.e., $SR(\kappa) = 1$. In other words, "[e]ven though there is positive correlation if the returns of both $[A_k]$ and $[B_l]$ follow a bivariate normal distribution . . . all dependence between the firms disappears as t increases" (Slijkerman et al. 2013).

[11] For a full derivation see Slijkerman et al. (2013).

Chapter 5

Estimators

In this chapter we introduce a non-parametric estimator for the linkage measure in the equation (4.1); we use the version presented in Slijkerman et al. (2013). Following their work, we accompany the estimator by examples based on a simulation as well as on empirical data.

5.1 The linkage measure estimator

The estimator of the measure in equation (4.1) is truly simple. Indeed, it is sufficient only to count the number of times when $\min[A, B]$ and $\max[A, B]$ are greater than a threshold t. The estimator is therefore given as follows

$$\widehat{E(\kappa|\kappa \geq 1)} = 1 + \frac{\sum_{i=1}^{n} \mathbb{1}_{\{\min[a_i,b_i]>t\}}}{\sum_{i=1}^{n} \mathbb{1}_{\{\max[a_i,b_i]>t\}}} \tag{5.1}$$

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:

$$\frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)} = 1 + \frac{\min[A, B] > t}{\max[A, B] > t} \tag{5.2}$$

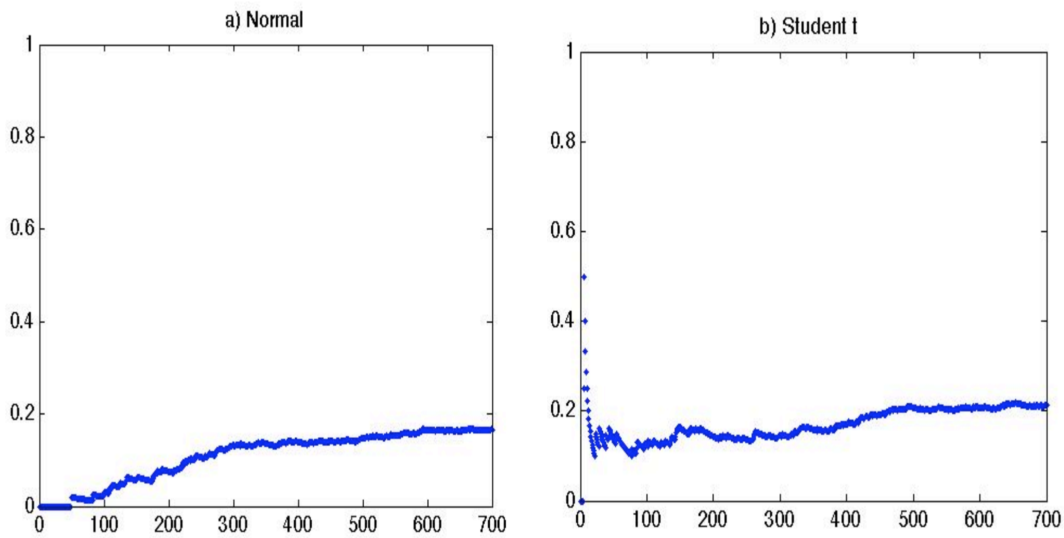
However, we do not go deeper into the derivation of the estimator, because it is already presented in Slijkerman et al. (2005).

The estimator described above has two favourable 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 the Extreme Value Theory (Slijkerman et al. 2013).

5.2 Simulation

To understand better how the estimator behaves depending on the choice of the threshold, we run a simulation. We draw 2921 realizations – which is exactly the same number as 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 were rescaled so that the means, variances and correlation is the same as it had been observed for SG and KB.

Figure 5.1: 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 the equation (5.1) we know that this number is actually the conditional number of failures minus one:

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

In the Figure 5.1, this number is depicted on the y axis.

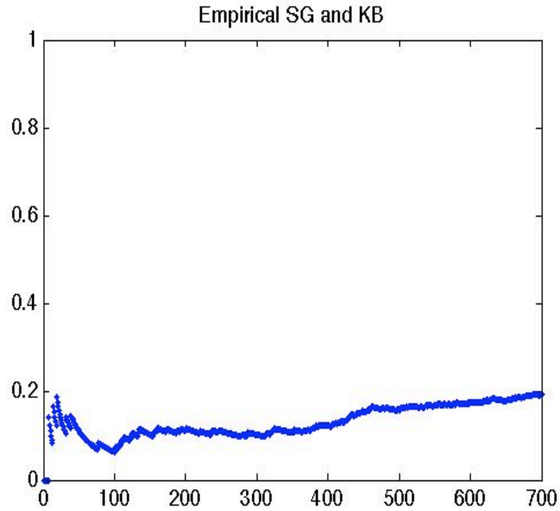
On the x axis, various bounds (related, but not equivalent to the threshold t) are depicted whereby the numbers are denoting the position of the threshold; the thresholds are taken from the order statistics. Let us accompany this description by a clarifying example: A value of 100 on the x axis means 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 exceedances increases as well.

This 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. However, 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 availed by Slijkerman et al. which corresponds to the lower number of realizations.

Finally, we comment on the Figure 5.1. In part (a), we have plotted the results drawn from the normal distribution. In the beginning, the estimator is at zero, since no realization was extreme enough to approximately surpass the first fifty thresholds. As the threshold is gradually decreased, more and more observations exceed the given threshold. Thus, the curve begins to increase.

The result of simulation based on the student t distribution is depicted in part (b). 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. Meaning that if the bank returns followed a student t distribution, we can expect that on average two tenths of a bank fail or inversely, we can expect that the other bank bank crashes once out of five times a crash happens. It is worth noting that Slijkerman et al. (2013) also ended up with approximately 0.2. Thus, it would be interesting to verify whether this is a general property of the estimator. Nevertheless, such an investigation is beyond the scope of this paper.

Figure 5.2: Conditional number of failures (minus one) estimated from the returns of SG and KB.



5.3 Empirical example

We also investigate the estimator using SG and KB returns, i.e., the same data as in the beginning of Chapter 4. We present our results in Figure 5.2; the axes are to be understood in the same way 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 neatly visible that the initial instability stems from a low number of threshold exceedances whereas as the number of threshold exceedances increases, the estimator becomes stable. Ultimately, we can move to the confidence intervals.

5.4 Confidence intervals

We use the Jackknife method similarly to Slijkerman et al. (2013). For each estimated pair, we create twenty clusters of observations. Next, we drop one cluster and estimate the linkage measure (5.1) each time. Then we line up the estimates. The second-largest and second-smallest ones demarcate the 90% confidence interval.

Chapter 6

Data

We use daily stock prices of the banks in V4 countries, namely the Czech Republic, Hungary, Poland and Slovakia. We focus on banks that are among the five largest, are included in the local stock marktet index, and have a mother bank. 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 its subsidiary. Our longest time series begins in January 1994 and ends in March 2013. However, some series are considerably shorter due to different dates of IPOs and acquisitions. Following Slijkerman et al. (2013), we compute daily *loss* returns that are "the empirical counterparts" of A_i and B_j from the chapter 4. The data was downloaded from Bloomberg in March 2013.

Table 6.1: Analysed 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

We point out some exceptions to the general rule above which is due to the low availability of data. In the Czech Republic, we also consider Ceska sporitelna (CS), even though the company has been delisted in August 2002, after its sale to Erste Group, Austria (EBS). Furthermore, we add two banks due to the lack of large listed banks. Thus, 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 also consider a local branch of OTP Bank as it is a component of SAX, the Slovak stock index. In Hungary we include FHB Mortgage Bank (FHB) into the sample, since it is in the base of the main stock index BUX of the Budapest Stock Exchange. Next, we highlight that none of the listed Hungarian banks has a mother. We can therefore only estimate subsidiary-to-subsidiary dependence, which effectively somewhat changes the focus of our analysis in favour of the triplet of Slavic countries.

There are also some caveats to beware of. In Poland, BZW has been sold by Allied Irish Banks (AIB) as late as February 2, 2011 to Santander (SAN) (BZW 2013). In our analysis, we examine only the relationship with AIB, since the time series is roughly five times longer. We emphasize that our results may be influenced by the lower number of observations for the pair CS & EBS.

In Table 6.1 we summarize the analyzed banks. In the end, we have two banks per country with the exception of Poland, which is known for its well-developed stock market, represented by four banks. We also present national rank according to the book asset value and the asset value itself. In the last column, we present the mothers of the given banks, where 'N/A' means that no one posseses more than 50% of shares. The complete overview of the five largest banks according to their assets is in the Appendix in Table A.1.

Chapter 7

Empirical Analysis

We estimate the systemic risk measure (5.1) for the subsidiary-to-subsidiary and mother-to-subsidiary dependence. Subsidiary-to-subsidiary dependence estimates the downside dependence between two banks in one V4 country. Mother-to-subsidiary dependence then involves a bank from a V4 country and its foreign mother, defined as a bank holding at least a 50% share in the subsidiary. Our results are summarized in Table 7.1.

We conclude that systemic risk between banks in one country is higher than the systemic risk between a mother and its subsidiary, and is significantly different. The probability that the other bank fails given that one is bankrupt then hoovers around 15% and 7%, respectively.[12] A detailed discussion of our results is provided below. Further details are provided in Tables 7.4 and 7.6, confidence intervals are tabulated in Appendix B. Summary statistics of individual time series data are to be found in Table 7.2.

Table 7.1: 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, see Figure 5.1b or 5.2. 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. We also use "stability checks" at 5% and 7% to

[12] We would like to remind the reader that $SR(\kappa) - 1$ can be interpreted in a bivariate setting as a conditional probability.

see the robustness of our results. We emphasize that we model *loss* returns, i.e., the losses are modelled as positive numbers.

7.1 Summary statistics

The summary statistics in Table 7.2 display key characteristics of continuously compounded loss return series for banks in our sample. Thereby, the extreme nature of our data is revealed. 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 down from 5.643 EUR to 1.992 EUR. More surprisingly, these two are neighbouring observations. We belive that this break can be attributed to the difficulties of an economy in transformation. Disregarding this observation, further extreme losses are 44% in the case of AIB and 32% for ING.

Table 7.2: Summary statistics of 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%, it virtually eliminates the possibility that the loss returns are normally distributed. Regarding the distribution of returns, we hint at the discussion regarding normal distribution in Chapter 4. For completeness, we report a cross-bank summary in Table 7.3.

Table 7.3: Summary of Table 7.2

Avg mean	-0.0001
Avg st. dev	0.0237
Min min	-0.4984
Max max	0.7129
Max, 2nd high.	0.7129
Max, lowest	0.1165

Remark We advise other researchers to check the time series of FHB downloaded from Datastream, which is ten times the true price up to June 8, 2005. There is a drop in price from 13400 HUF to 1360 HUF on the following day. However, this drop conflicts with the official records of the Budapest Stock Exchange which show an increase from 1340 to 1360 HUF.

7.2 Subsidiary-to-subsidiary estimates

Being interested in the systemic risk among banks within individual countries, we estimate 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 pair per country lies in poorly developed capital markets. Indeed, the majority of banks in respective countries is not listed. For listed banks, we use the maximal possible length of respective time series.

In Table 7.4 we present the estimates for all four levels of the threshold t. We highlight the stability of the measure with respect to the lower threshold. The averages are within a narrow range of only 0.0003. Even though we report $SR(\kappa)$ which denotes the expected conditional number of failures, we remind the reader that $SR(\kappa) - 1$ can be interpreted as the conditional probability of an extra crash, given that one bank is 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

Table 7.4: 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

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 terminology of de Vries (2005), it means that the potential for systemic breakdown 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; still in the area of volatility. Decreasing the threshold then stabilizes the estimator, see Figure 5.2. The Hungarian banks are excluded from the average for the sake of consistency. (They are also excluded from the mother-to-subsidiary analysis, because none of them has a mother.) The last column in the Table 7.4 contains the number of observations.

7.3 Mother-to-subsidiary estimates

For each analysed bank in a V4 country, we compute the dependence between the bank (subsidiary) and its mother, whereby mother is defined as holding at least 50% of the subsidiary. We only use the data after the subsidiary has been acquired. Dates of acquisition were determined from annual reports and other official sources of information. For BZW which changed its mother in 2010, we consider the longer period which is that under AIB. The overview is provided in Table 7.5. 'N/A' denotes that the bank does not have a mother; this excludes Hungarian banks form the mother-to-subsidiary analysis.

The average probability that the other bank fails, given that one is already bankrupt is roughly 7%. The number is also relatively stable across different

Table 7.5: Dates of acquisition of analysed banks.

Country	Bank	Acquired on	Source
Czech Rep.	CS	1.3.2000	CS (2001)
Czech Rep.	KB	12.7.2001	KB (2002)
Slovakia	VUB	21.11.2001	VUB (2002)
Slovakia	OTP SK	4.4.2002	OTP-SK (2003)
Poland	PEO	3.8.1999	PEO (2000)
Poland	BRE	17.10.2000	BRE (2000)
Poland	ING PL	24.7.1996	ING-PL (2013b)
Poland	BZW	23.6.2001	BZW (2013)
Poland	BZW	10.9.2010	BZW (2011)
Hungary	OTP	N/A	BSE (2013b)
Hungary	FHB	N/A	BSE (2013a)

levels of the threshold t. Going down to pairs, we find the highest probability for PEO & UCG at approx. 13%, followed by SG & KB and CBK & BRE. The weakest realtionship is to be found for EBS & CS with probability of zero which suggests weak potential for systemic breakdown. However, the result is highly probably influenced by the short time series of the pair. The second lowest is then to be found for OTP SK & OTP with the probability of only 2.5%. Overview of our results is in Table 7.6.

Table 7.6: 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	

7.4 Testing for the difference

We test for systemic differences 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. The null hypothesis is rejected 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 p-value is 0.0547, 0.0156, 0.0234 and also 0.0156, respectively. We therefore conclude that the difference is significant at the 10% confidence level.

Should we use the sign test, see e.g. King and Mody (2010, p. 289), we conlude that the subsidiary-to-subsidiary and mother-to-subsidiary probabilities are significantly different for all thresholds t at the 10% confidence level, since the p-values are 0.0703 for all thresholds t.

7.5 Interpretation of results

We have found that the potential for a systemic breakdown between a mother and its subsidiary is on average smaller and significantly different than that between subsidiaries within a country. The explanation is twofold. Firstly, we attribute this outcome to successful attempts of central banks and regulators to protect subsidiaries under their jurisdiction from capital and liquidity outflows. Secondly, this result suggests that investors perceive some risks as specific to V4 countries. However, it is a question to which proportion of this effect is attributable to regulatory policies or to the country specific risks.

In this respect, we highlight that the model from Chapter 4 is able to capture the difference by taking the country specific risk component into account, see equations (4.28) and (4.30). Yet, the model gives a reasonable prediction only with respect to the ordering of the events, since it failed to predict the particular numbers accurately – 50% as opposed to 15%, and 20% versus 7% in reality. Still, the model predicted correctly that there is a difference, that the difference is large and that the dependence between two subsidiaries is larger than between a mother bank and its subsidiary. Thus, the model seems to be well suited for qualitative analysis, however, more research in this respect is necessary.

Chapter 8

Conclusion

We analysed the systemic risk dependence between a mother bank and its subsidiary and compared it with the dependence between two subsidiaries within the same country. The analysis is conducted on the sample of banks from the countries of the so-called Visegrad Group which includes the Czech Republic, Hungary, Poland and Slovakia. We conclude that the threat of a systemic breakdown between subsidiaries is significantly different and higher than between a mother and its subsidiary.

In our analysis, we employed a systemic risk measure that originates in the extreme value theory. This measure is distribution-free, which allows for heavy tails typical for financial time series, and captures also the non-linear dependence. Moreover, it is suited for capturing the extreme dependence in tails which allows us to focus on the dependence between large losses only. The measure minus one is equal to the probability of the joint crash given that one of the banks is already bankrupt; we use this fact in our interpretation.

The probability that the other bank fails given that one is bankrupt hoovers around 15% in the case of two subsidiaries and 7% for the mother-to-subsidiary dependence. The results imply that regulators in the V4 countries should focus their attention to domestic systemic risk and try to lower the risk of a systemic breakdown at least to a level comparable with the mother-to-subsidiary relationship. Thus, this thesis sets grounds for improving the current regulatory framework.

We emphasize that our analysis is novel in three ways. Firstly, it focuses on the relationships between mothers and their subsidiaries which are subsequently compared with the relationships between subsidiaries. Secondly, the analysis focuses on V4 countries which are barely covered in the current literature;

the existing studies do not focus on the systemic risk issues we cover in this paper. Thirdly, we employ techniques well-suited for the systemic risk analysis.

Limitations of our approach stem from its focus on the dependence among stock returns. Banks are not always listed in countries with a lower degree of stock market development. This approach also disregards other determinants like banking variables or a central bank policy.

Possible extensions of our paper include larger or other geographical areas, for example the whole Central and Eastern Europe. For countries with well-developed capital markets it would be interesting to utilize the multidimensionality of the measure, e.g., to examine the expected number of failures in the whole economy. Finally, one can conduct a similar study but control for the policy of the central bank.

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Appendix A

Largest Banks in V4

This table presents the largest banks in V4 countries plus some smaller ones that are examined in our analysis. CS is denoted as not listed, since the company is not public anymore. Assets are in billions of euro.

Table A.1: Largest banks in V4 countries

Country	Rank	Bank	Assets.	Listed	Source
Czech Rep.	1	CSOB	36.8	No	CSOB (2012)
Czech Rep.	2	CS	35.1	No	CS (2012)
Czech Rep.	3	KB	29.6	Yes	KB (2012)
Czech Rep.	4	UCB CZ	11.3	No	UCB-CZ (2012)
Czech Rep.	5	RB CZ	8.0	No	RB-CZ (2012)
Hungary	1	OTP	32.4	Yes	OTP (2012)
Hungary	2	ERT HU	10.3	No	Erste-HU (2012)
Hungary	3	MKB	9.3	No	MKB (2012)
Hungary	4	KHB	9.1	No	KHB (2012)
Hungary	5	CIB	8.0	No	CIB (2012)
Hungary	9	FHB	2.6	Yes	FHB (2012)
Poland	1	PKO	42.7	Yes	PKO (2012)
Poland	2	PEO	32.8	Yes	PEO (2012)
Poland	3	BRE	22.1	Yes	BRE (2012)
Poland	4	ING PL	15.6	Yes	ING-PL (2013a)
Poland	5	BZW	13.4	Yes	BZW (2012)
Slovakia	1	SlSp	11.3	No	SlSp (2012)
Slovakia	2	VUB	11.1	Yes	VUB (2012)
Slovakia	3	TB	9.2	No	TB (2012)
Slovakia	4	CSOB SK	5.2	No	CSOB-SK (2012)
Slovakia	5	UCB SK	3.9	No	UCB-SK (2012)
Slovakia	10	OTP SK	1.2	Yes	OTP-SK (2012)

Appendix B

Confidence Intervals

This appendix accompanies the empirical analysis in Chapter 7. In particular, it provides 90% confidence intervals for the estimates in Tables 7.4 and 7.6. 'L' denotes the lower bound of the interval, 'E' is the estimate and 'U' denotes the upper bound.

Table B.1: 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 B.2: 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