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Alternative Measures of Risk – Application on the Central European Region

Master Thesis

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Prohlášení

Prohlašuji, že jsem diplomovou práci vypracoval samostatně a použil pouze uvedené prameny a literaturu

V Praze dne   podpis studenta

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Ondřej Vodňanský

ABSTRACT

Increasing volume of research shows that both theoretical assumptions and empirical fit of traditional mean-variance and CAPM frameworks are flawed. Hence, other risk measures are gaining popularity. Downside risk measures not only represent the theory well, they are also significant in explaining variations of stock returns. Most importantly, the definition of risk they provide is more in line with perspectives of investors. We have carried out extensive testing on a sample of companies from the Czech Republic, Germany and Poland. Our results show that Semivariance with respect to zero is the most significant risk measure while CAPM beta by itself has little use. Finally, we also analysed importance of idiosyncratic risk on CEE shares and found out that it is indeed priced on the Czech and Polish stock markets but not in Germany.

JEL Classification: G11, G12, G19
Keywords: Downside risk, Semivariance, Idiosyncratic risk

ABSTRAKT

Stále více výzkumných prací ukazuje, že teoretické předpoklady i empirické výsledky tradičních přístupů, jako je střední hodnota – rozptyl nebo CAPM, jsou chybné. Jiné míry rizika tedy získavají popularitu. Míry, soustředící se pouze na možnost poklesu ceny lépe odpovídají teorii a ukazují se jako signifikantní proměnné pro vysvětlení variace akciových výnosů. Především ale definice rizika, kterou poskytují, je více v souladu s perspektivou investorů. Provedli jsme rozsáhlé testování na vzorku společností z České Republiky, Německa a Polska. Naše výsledky ukazují, že „semivariance" vzhledem k nule je nejvíce signifikantní míra rizika zatímco CAPM beta sama o sobě nemá přiliš využití. Nakonec jsme rovněž analyzovali důležitost idiosynkratického rizika pro středoevropské akcie a zjistili jsme, že má hodnotu na českém a polském trhu, ovšem nikoliv v Německu.

JEL klasifikace: G11, G12, G19
Klíčová slova: Riziko poklesu, semi-rozptyl, idiosynkratické riziko

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Thesis Proposal

Author: Bc.Ondřej Vodňanský

Title:

Alternative Measures of Risk – Applications

Topic Specification:

Ways of measuring risk and its correct pricing has concerned academicians since the creation of the CAPM as well Markowitz general portfolio theory. Scientists have argued over relevance of beta or standard deviation, especially in the environment of emerging markets where CAPM is considered less reliable. This issue also has a practical dimension – ordinary individual investor does not care about theoretical devation but rather the potential downside – loss of invested money is what he really fears. Both the academical and the practical aspects converge in the topic of Alternative measures of risk, which measures exactly the downside risk. Author's motivation is to explore this practical and pragmatic approach to risk measurment and test it on a sample of postcommunist countries in comparison with several western economies.

Main Research Questions:

What are some relevant alternative measures of risk on financial markets? Which of these are the most reliable compared to volatility/s.d.? Is it true that CAPM is more appropriate for developped countries whereas it is the alternative measures in the case of developping and transitive economies? What is the difference in model robustness when using CAPM and alternative methods (such as downside risk, expected shortfall etc.)

Methods

-Comparative study
-Regression model using CAPM
-Regression model using alternative risk measures

Outline

1) Introduction
2) Theoretical overview of the methods
    a. downside risk
    b. expected shortfall
    c. ...etc.
3) Summary of past results in applications
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5) Results and Conclusions

Literature:

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1. INTRODUCTION AND MOTIVATION

How to measure risk and how to correctly price it? Since the advent of finance theory, this one key issue has beleaguered the minds of academicians and practitioners alike. To solve the problem, many have tried to come with tools and concepts. First important paradigm shift was Markowitz's portfolio theory; later came Sharpe's Capital Asset Pricing Model (Sharpe, 1964). They also introduced the most basic measures of risk – variance and beta. The theory built upon those concepts is still used even now but at the same time, it is also debated and questioned more than ever before.

The heat of the debate lies in the adequacy of the theoretical assumptions on the one side and the empirical fit on the other (will be discussed below or see e.g. Fama, French, 2004). However, there is also a more practical, or let's say "down to earth" dimension to this discussion – the level of individual investors – be them mutual funds, insurance companies, sovereign states' governments or regular people. From this practical and intuitive perspective, one can easily see there is something wrong with the definition of risk as used in the original Portfolio theory or in the CAPM framework.

Upside of a stock, the possibility of an upwardly development of the stock price, can hardly be considered "risky" in the original meaning of the word. At least, it is definitely not something negative, yet is understood so under the CAPM theory. What is even more bizarre is that upside is put as equal with the other option – the adverse movement of the security price and negative gain. Incurring losses and losing the invested money, or the downside risk, is what investors really fear and want to avoid. As Estrada (2006, p.2) puts it "…one of the main problems with using standard deviation as a measure of risk: it treats an x% fluctuation above and below the mean in the same way. But investors, obviously, do not. Shouldn't a proper measure of risk capture this asymmetry?"

But the discussion goes beyond this common sense perspective - there is a scientific concern as well: as will be discussed below, empirical tests derived from CAPM often have somewhat dubious results (see Fama, French, 2004). Moreover, the statistical assumption of normal distribution is not met (Hyung, de Vries, 2007). Therefore, we can say that both the academic and the practical aspects conveniently converge on one topic – the downside risk measures. Author's motivation stems from the interest in unifying an intuitively appealing concept with a scientifically correct procedure. A vast strand of literature (see below) suggests that this should be possible, as downside risk measures are reported to be quite reliable and even more so in the environment of emerging markets. Contribution of this paper lies especially in focusing on the level of individual companies, rather cross-sections of country indices which is the prevalent method in literature.

Even though there should be differences between the influence of downside risk measures on developed markets, such as Germany, and emerging or transition economies, we have a found little support for that. Our results show the influence is all-encompassing. However, we found strong evidence that unsystemic or idiosyncratic risk is priced in the Czech Republic and Poland and not in Germany.

The paper is organized as follows. Section 2 provides a literature review including history, theoretical concepts and empirical results. Knowledgeable readers can skip the section 2.2, where we explain the basics of the CAPM. Section 3 gives details about the methods used in the paper and explains the important issue of idiosyncratic risk. Sections 4 to 6 provide the results of empirical tests on the level of individual companies for Germany, Poland and the Czech Republic respectively. Section 7 provides results of the panel data analysis while Section 8 delves deeper into the influence of Idiosyncratic risk on CEE shares. Finally, section 9 concludes.

2. LITERATURE REVIEW

2.1 Historical Background: From Variance to Downside Risk

Returns in finance are inherently connected with risk and, as Sharpe (1964) puts it, it's not realistic to presume that an economic agent merely maximizes expected return - rather, investors maximize return while minimizing total risk. Perold (2004) wonders: “In retrospect, it is striking how little we understood about risk as late as the 1960s.“ Since the emergence of the financial theory, the uncertainty was expressed from the statistical point of view – through Variance.

But this concept had been defined 10 years before. In 1952, two key papers that occupied themselves with investment choice under uncertainty both came out independently in the same year and basically established portfolio theory– they were Markowitz (1952) and Roy (1952). Their principal contribution was in stating several rules of portfolio selection. Building on then-popular Von Neumann-Morgenstern utility functions, Markowitz puts forth the claim that using a rule that only maximizes return is unsatisfactory: “This rule is rejected both as a hypothesis to explain, and as a maximum to guide investment behavior (Markowitz, 1952, p.2)“. Moreover, some went as far as to say that a quantitative utility function of an investor cannot be derived (Roy, 1952).

According to Nawrocki (1998), it was the lesser-known Roy who was on to discovering algorithms for selection of efficient investment sets. He is the author of the so called “safety first“ technique which uses reward-variability ratio:

$$RV = \frac{r - d}{\sigma}$$

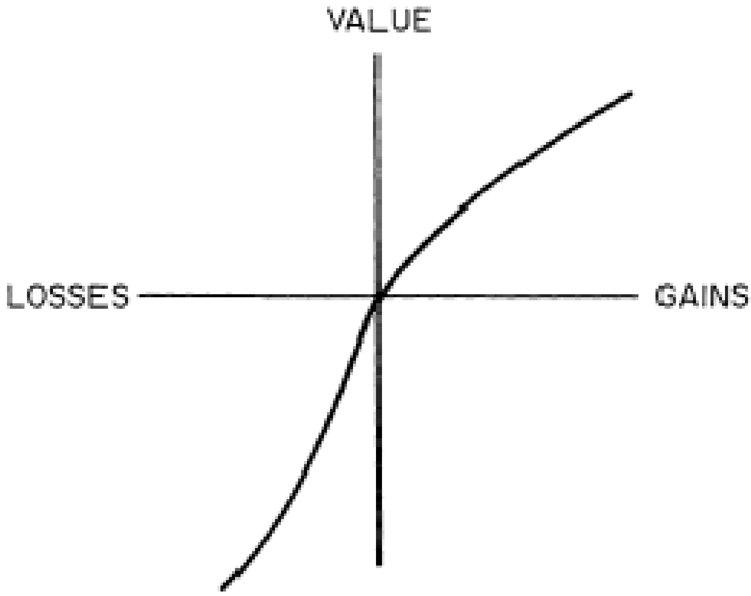
where, as usual, r is the asset return and σ is the standard deviation. However, d is the so called disastrous return (a level of return the investors wants to beat, or simply a benchmark). You can observe that this ratio is in fact a general version of the famous ratio coined by Sharpe (Sharpe, 1966) in which the benchmark return is the risk-free rate. In any case, let us remark, that Roy pioneered the notion of investor being first concerned with risk and then with return which is still valid today. Besides, it lies at the heart of the downside risk measures. After all, it is not hard to see that selecting portfolio with the priority on risk is the same as selecting it using a downside risk measure (Nawrocki notes that it is necessary to select optimal portfolios if the returns are not normally distributed).

However, calculating risk measures in general only started to be possible during the 60s with the advent of the computer, as Perold (2004) observes. So it is no surprise the Capital Asset Pricing Model (Sharpe, 1964, more in detail in section 2.2) emerged at that time as well. Throughout time, there appeared improvements and alterations such as Black's unrestricted shortselling model (Black, 1972), Merton's intertemporal CAPM (Merton, 1973) or international applications of the CAPM (Stulz, 1981).

Even though downside risk measures are now gaining popularity and attention, let us note that even at the time, the notion of downside risk wasn't that foreign. Interestingly, more than one author points out that semivariance has already been used along the variance since the beginning of the portfolio theory. Markowitz himself actually advocated its use but had to reject its use due to heavy computational requirements (see e.g. Estrada, 2000 or Nawrocki, 1999). Nawrocki adds: "As such, there is no basis for labeling the use of downside risk measures 'post-modern portfolio theory' except for marketing 'sizzle' (Nawrocki, 1999, p.1)."

Apart from financial economics, similar themes were explored in other areas. From behavioral perspective, this topic appears for example in Kahneman and Tversky (1979), where they define a value function instead of a utility function which is steeper on the negative side to reflect risk aversion. A more recent paper by the same authors presents another issue in this field. Its results are somewhat in conflict with basic assumptions of the CAPM. They elaborate on the influence of starting conditions (assets in possession of an agent) on decision making. They empirically show that indeed, these conditions can alter choice under uncertainty (Kahneman, Tversky, 1991).

Figure 2-1: Value function reflecting risk aversion. Adapted from Kahneman and Tversky (1991)



Regarding the semivariance concept, its wider following of was also hindered by inadequate computing capabilities in the 50s, but later in the 60s and 70s, this has changed. Even though those were the times of popularity of Beta and CAPM (which we will discuss in a separate section), semivariance has been proven highly advantageous both theoretically and empirically (Nawrocki, 1999). Let us refresh what it actually is here. Semivariance with respect to t (sometimes called downside variance) can be defined as follows:

$$SV_t = \frac{1}{T}\sum_{i=1}^{T} Max(0, t - r_i)^2$$

Where t is the benchmark and return r is the return of the i-th observation - the formula applies both for cross-sectional and time series data. The benchmark can be the mean, target return and also zero. Hogan and Warren (1974) developed a modification the CAPM in the semivariance framework and proved that investment decisions based on it are at least on par with the standard CAPM.

The statistic of Least Partial Moment, introduced by Bawa (1975) was an important milestone in downside risk measures as it gave an all-encompassing view. Nawrocki (1999, p.7), claims that “moving from the semivariance to the LPM is equivalent to progressing from a silent black and white film to a wide screen Technicolor film with digital surround sound.“

$$LPM = \frac{1}{T}\sum_{i=1}^{T} Max(0, t - r_i)^a$$

At the end of 1980s, researchers took the measure of Least Partial Moment which generalizes the semivariance statistic, and developed an alternative version of CAPM, EL-CAPM. The LPM framework can be further generalized to an (a,t) model, where *a* is effectively a degree of risk aversion (low a means risk-loving behaviour) and *t* stands for target return. Typical trait of portfolios with high *a* is higher skewness. However, as *a* increases a various return-to-risk ratios decrease, indicating the insurance against loss becomes more and more costly.

The benefit of the framework was the general view, with different values of *a* having different relevant interpretations. We can see that for *a=0*, the statistic becomes a measure of probability of loss (which is normally used and called shortfall probability, see e.g. Chen and Chen, 2004), for *a=1* it is the expected magnitude of loss. It is also called expected shortfall according to Chen et Chen or “average downside magnitude of failure to meet the target return“ according to Nawrocki (1999, p.7). Values of a higher than 2 might also have interpretations but we will not talk about them here. Higher a generally marks higher degree of risk aversion.

Moreover, any LPM-based measure will obviously tend to be larger for higher value of the benchmark *t* - returns of an asset can easily plunge below mean, but they will fall into negative returns with lower probability. Estrada (2006) illustrates this nicely.

The downside risk framework also has its own portfolio ranking measure, similar to the Sharpe ratio. It is called Sortino ratio and it can be expressed as follows:

$$Sortino\ ratio = \frac{r - t}{\sqrt{SV_t}}$$

with t being the target return or benchmark and SV_t is the semivariance measure with respect to that target. Note that a square root of semivariance is usually called semideviation.

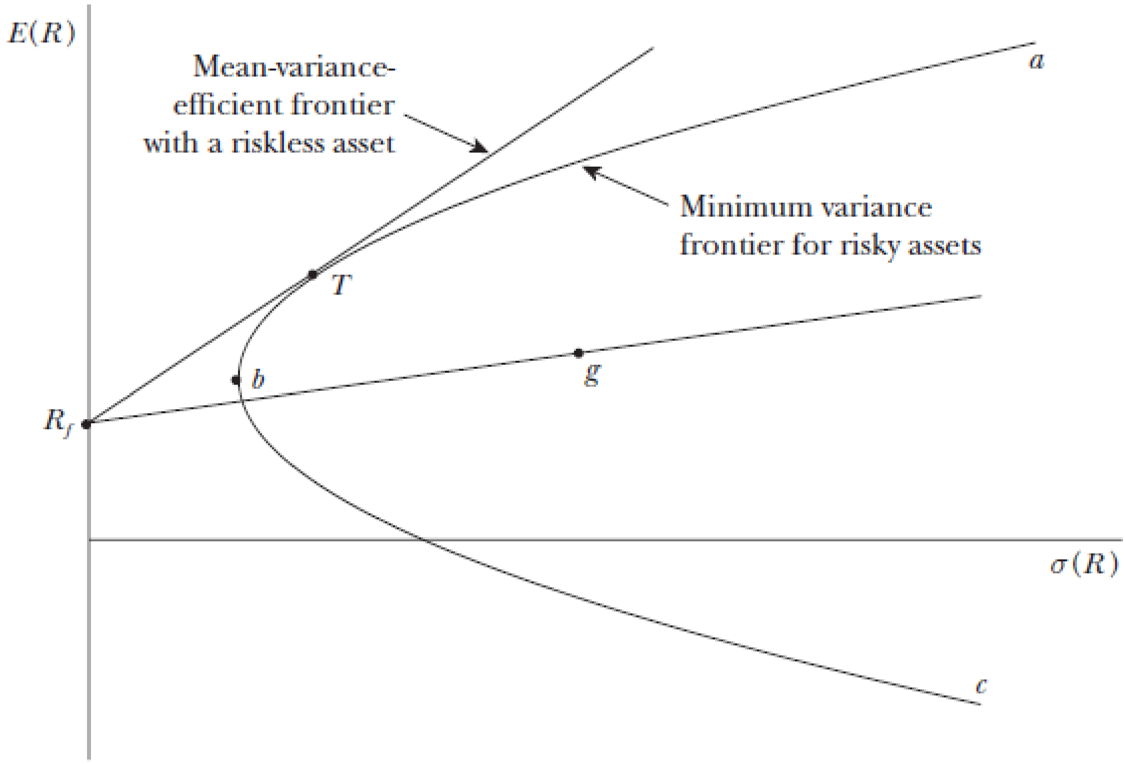
2.2 CAPM explained

CAPM rests on a set of very specific assumptions. Using Perold (2004) and Fama, French (2004) we have come to the following:

1. complete agreement of all agents on the probability distribution of returns
2. perfect capital markets: lending and borrowing at the risk-free rate available for everyone, no transaction costs
3. all the investors have the same quadratic utility function

The picture on Figure 2-2 illustrates the departing point for the theory of capital asset pricing model. The expected return is shown on the vertical axis whilst the horizontal axis measures portfolio risk by standard deviation of returns or “σ”. Let us consider two situations – depending on whether risk-free borrowing and lending is available or not. Both are displayed on the graph. If it is not available, we are moving along the curved line abc. It combines risky portfolios that minimize risk for a given return. That’s why it’s called “The minimum variance frontier“ (Fama, French, 2004). We can observe that various portfolios located on the line have different amounts of risk associated with them – they clearly present a trade-off. Therefore, a risk-seeking investor might gladly enjoy investing in asset *a* as it promises a high return but also higher risk. On the hand, another, more careful, investor would prefer an asset or portfolio *b* with lower return and risk. The curve also shows that not all portfolios are efficient. Only those above point *b* are, since any point on the curve below *b* is unnecessary risky – it can be easily substituted with an asset that provides higher expected return for the same amount of risk.

Figure 2-2: Efficient frontier of risky assets and the risk-free asset. Adapted from Fama and French (2004)



Now, let us lift the restriction on risk-free borrowing and lending. Suppose that you have two investment options - the risk-free asset or some risky portfolio (*g* in the chart) with proportions *s* and *1-s*, respectively. If *s=1*, that is you lend all your money for the risk-free rate, you have portfolio with zero risk and return equal to Rf point on the vertical axis. In the point *g* you invest all your money into that risky asset and in points to right of *g*, you borrow at the risk-free rate and invest the proceeds in *g* again.

The set which includes the risk-free asset becomes an efficient one if the straight line is also a tangency to the minimum-variance set of risky portfolios. One can then observe that all efficient combinations include simply the risk-free asset and one single tangency portfolio, designated by T. The tangency portfolio is our market portfolio of the CAPM. This is assured by the assumption that all investors agree on the expected distribution which also guarantees that they will invest in the same risky portfolio T (Sharpe, 1964). In fact, if it the tangency portfolio wasn't the market portfolio, that would mean there is some other investment opportunity that has higher expected return and/or lower risk. But since the markets disperse information perfectly, investors share the same set of investment opportunities and have homogeneous preferences; they would spot this opportunity immediately and act accordingly. Thus, the composition of the market portfolio would adjust until it becomes the tangency point again.

Individual assets which comprise the market portfolio (let us designate it M) have a certain covariance with the overall portfolio which, when compared to the variance of the portfolio, becomes the key measure of risk in the Capital Asset Pricing Model: beta. Obviously, beta of the market portfolio is 1 because it is a weighted average of all the included assets.

$$\beta_{\mathrm{iM}} = \frac{\mathrm{Cov}(\mathrm{R_i}, \mathrm{R_M})}{\mathrm{Var}\ (\mathrm{R_M})}$$

To proceed to the classical expression of the Sharpe CAPM in an intuitive manner first, we combine the assumption of unified investors' views and preferences with freely available borrowing and lending at the risk-free rate. Then, the rationale is as follows: risk free asset bears no risk by definition but also because it is uncorrelated with the market portfolio. Every risky asset will have some correlation and therefore, will share some risk of the market portfolio M. The investor bearing the risk needs to be compensated by the amount of the return premium of the market portfolio weighetd by the amount of risk of the particular asset. Thus we obtain:

$$E(R_i) = R_f + \beta_i(E(R_M) - R_f)$$

For a more rigorous manner we can use the basic assumptions and the expression of the Sharpe ratio to arrive at the final CAPM equation as can be seen in Perold

(2004). The idea is as follows. If the asset and the market portfolio are negatively correlated (0<ρ<1) then the Sharpe ratio must equal:

$$\frac{E(R_i) - R_f}{\sigma_i} = \rho \frac{(E(R_M) - R_f)}{\sigma_M}$$

Now it's sufficient to observe that $\beta_i = \rho \frac{\sigma_i}{\sigma_M}$ and again, we arrive at the CAPM equation. This is true because we can separate the risk of the asset into two parts – one that is perfectly correlated with the market portfolio and on that is uncorrelated. Since standard deviation of the i-th asset is σ_i, the risk of its perfectly correlated part will be $\rho\sigma_M$. On the other hand, adding a marginal amount of asset *i* adds only a small part of the risk that's uncorrelated with the portfolio, so it can be simply diversified away (Perold, 2004). This is closely connected with the following. What if it were possible to increase the Sharpe ratio of our portfolio, for example by adding such a stock:

$$E(R_i) - R_f > \beta_i(E(R_M) - R_f)$$

that is, a stock with a positive alpha. But then, the markets would be in disequilibrium. Investors would perceive that and the structure of the portfolio would change because we would want more of the asset which has higher Sharpe ratio then the portfolio we hold. Therefore, in equilibrium, it must always hold that:

$$E(R_i) - R_f = \beta_i(E(R_M) - R_f)$$

2.3 The Controversy of the CAPM

We find it is important to discuss the model's imperfections here as a motivation to using the downside risk measures. We have used extensively the work of Fama and French (2004) for this subsection. In short, the authors argue that the classical CAPM is invalidated due to the shortcomings of its functionality. This can be either due to:

- inadequate theoretical basis – one argument here is that perhaps the market portfolio should contain other assets than just stocks such as all securities, real estate or even human capital,
- failure in proper adaptation - badly designed empirical tests etc. (Fama, French, 2004, p.1)

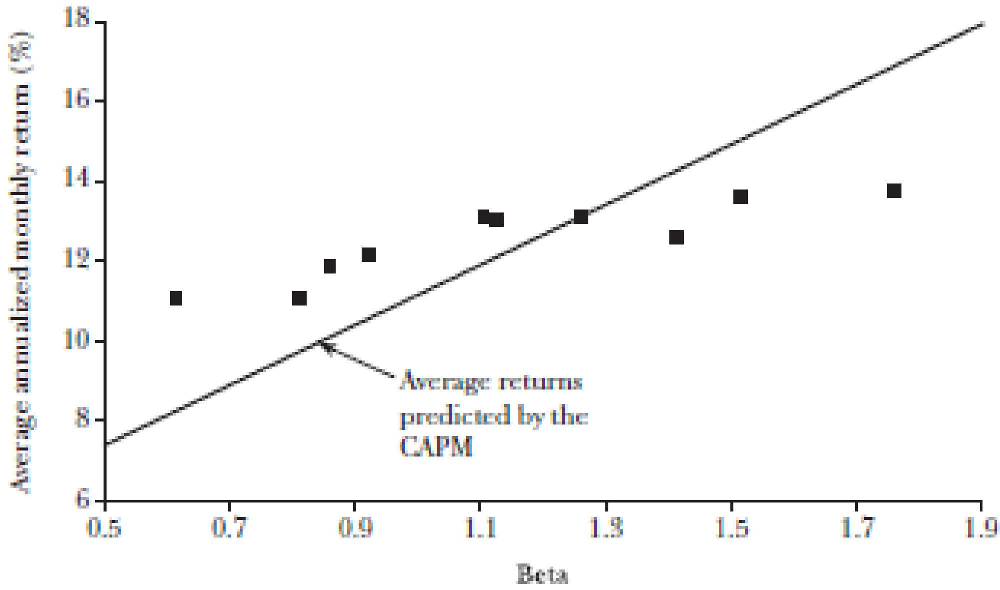
When evaluating these deficiencies, we have to go back to the assumptions of the CAPM we stated at the beginning of 2.2. They do seem restrictive so it is not hard to see what the CAPM opponents have in mind when they claim that the model is not valid. Each of these key assumptions is controversial to say the least. We will not discuss the violations of the first one here. Regarding the second assumption, the authors mention the alternative proposed by Black (1972): unrestricted short-selling of risky assets. It can be proven that the CAPM relationship holds under this assumption. However, if both borrowing and short-selling are forbidden, portfolios of efficient portfolios are no longer efficient and the CAPM relationship is lost (idem, p.5). Finally, concerning the third assumption, later in this section, we will alleviate this restriction when we present the Least Partial Moment formula and framework, which works under any assumption about investor's utility function.

Throughout time, testing of the CAPM framework generally advanced this way: tests of risk premiums, tests if betas sufficiently explain asset returns and tests for market portfolio proxy. Early empirical tests (e.g. Black, Jensen and Scholes, 1972, see Fama, French, 2004 for thorough overview) used simple regression with only one explanatory variable. Oddly, authors in this early stage took assumed beta as an explanatory variable, rather than a market premium. Therefore, the regression had the following form:

$$R_{it} - R_{fit} = \alpha_i + \beta_i \cdot RP_i + \varepsilon_{it}$$

where the intercept alpha was expected to be equal to zero and the slope to equal the prevailing market premium. The results have almost universally rejected the CAPM – the intercept was greater than the risk-free rate (intercept of the regression – the "Jensen alpha" – turned out positive) and the coefficient on beta is less than the average market premium. Also, the relationship between return and beta was reported as “too flat” (means almost a flat straight line, rather than a rising one, see Figure 2-3).

Figure 2-3: Illustration of the implied “flat relationship”, US data from 1928–2003. Adapted from Fama and French (2004)



In the tests of the second wave, focus shifted on the power of beta as an explanatory variable and the general consensus was that it suffices to explain variations in stock returns (Fama, MacBeth, 1972). More recently, researchers concentrated again on the issue of capability of beta as an explanatory variable and there is wide evidence across time periods and countries that rejects the previously accepted hypothesis. Therefore, there are other variables that add significant explanatory power. One strand of literature, among others represented by the authors themselves (e.g. Fama, French, 1992) explores market ratios such as price/earnings (P/E) or book-to-market (B/M) and find these have capability to explain returns variation unexplained by beta. Moreover, these results are consistent across samples outside of the US. Yet another direction of research for example takes into account country-specific variables such as political risk and obtain significant results, confirming that beta is not capable of explaining variation of returns - see Harvey (2004).

One explanation why the market ratios are actually significant includes irrationality of investors, who extrapolate past B/M values to the future (low B/M suggests growth stocks/good times, high B/M suggests bad times). There is also a demand for a more complex model where risk-return relationship is expressed in a better way. This model could generally be a multi-factor model (thus in line with the wave of test rejecting CAPM). Fama and French (1995) propose a three factor model which includes the market premium, the difference of returns between small and big stocks (stocks with low and high market capitalization, respectively) and stocks with high and low B/M ratios. They have proven this model also performs better than CAPM on the international level.

The last hitch in the process of CAPM empirical test is the Market Proxy Problem. Richard Roll (1977) argues that this fundamentally leads to the untestability of the CAPM. This returns to theoretical definition of the market portfolio - what it should include and what it should not. For example, should the market portfolio consist of assets other than financial securities such as real estate or even human capital? Roll says that since nobody can compose the actual market portfolio, neither can they test the CAPM without it. Nevertheless, if CAPM cannot be properly tested does not mean it is empirically adequate.

2.4 Empirical Results Overview

It has been proven in several papers, that downside risk measures are more reliable in the environment of emerging markets than traditional CAPM-based beta or standard deviation (Estrada, 2000 or Chen, Chen, 2004). Estrada focuses on using methods based on downside risk to improve the process of estimation of discount rates for investing companies. Whereas CAPM, despite ongoing academic controversy (see subsection 2.3), tends to hold with some reservations in developed markets, the same is not true for emerging economies. Estrada argues this might be due to segmented markets, where "...in contrast, barriers to arbitrage may allow assets with the same risk characteristics, but traded in different locations, to have different returns (Estrada, 2000, p.3)." He also shows that there is a strong asymmetry in distribution of returns which speaks in favor of downside risk measures.

For his estimations, he uses nine risk variables in total, of which 5 fall under the category of alternative risk measures. In the end, he rejects beta and size as insignificant and keeps the variables of total risk σ, idiosyncratic risk1 and three downside risk measures – semideviation with respect to mean, downside beta and Value-at-Risk. These results are also consistent with the assumption, that emerging markets are only partially integrated. Cost of equity from the regression model using downside risk falls between the one derived from beta (which implies fully integrated markets) and standard deviation (on the other hand, fully segmented markets).

Chen and Chen (2004) take similar departing point like Estrada in his work but use different variables, namely shortfall probability, expected shortfall, downside variance and downside deviation (square of downside variance). They used panel data models on the emerging markets index of the Morgan Stanley Capital Index. They also alter it by testing not only the explanatory but also predictive capacity of the risk measures – that is, regressing future returns on past period estimations of risk measures. They find total variance as most significant for explaining the current period return while semivariance with respect to zero as most suitable for predicting future returns (ex ante significance).

An alternative is a work by Lee, Robinson and Reed (2006), who test downside risk measures on Malaysian listed real estate companies – namely, they compare correlation of size with beta to ascertain their explanatory power. They conclude there is a strong relationship between size and systemic risk (beta) while the link with downside beta is weak. They also provide good insight into the computation of downside beta and its decomposition. They note that semicovariance, necessary for the calculation, is a nonsymmetrical measure and advice how to amend it.

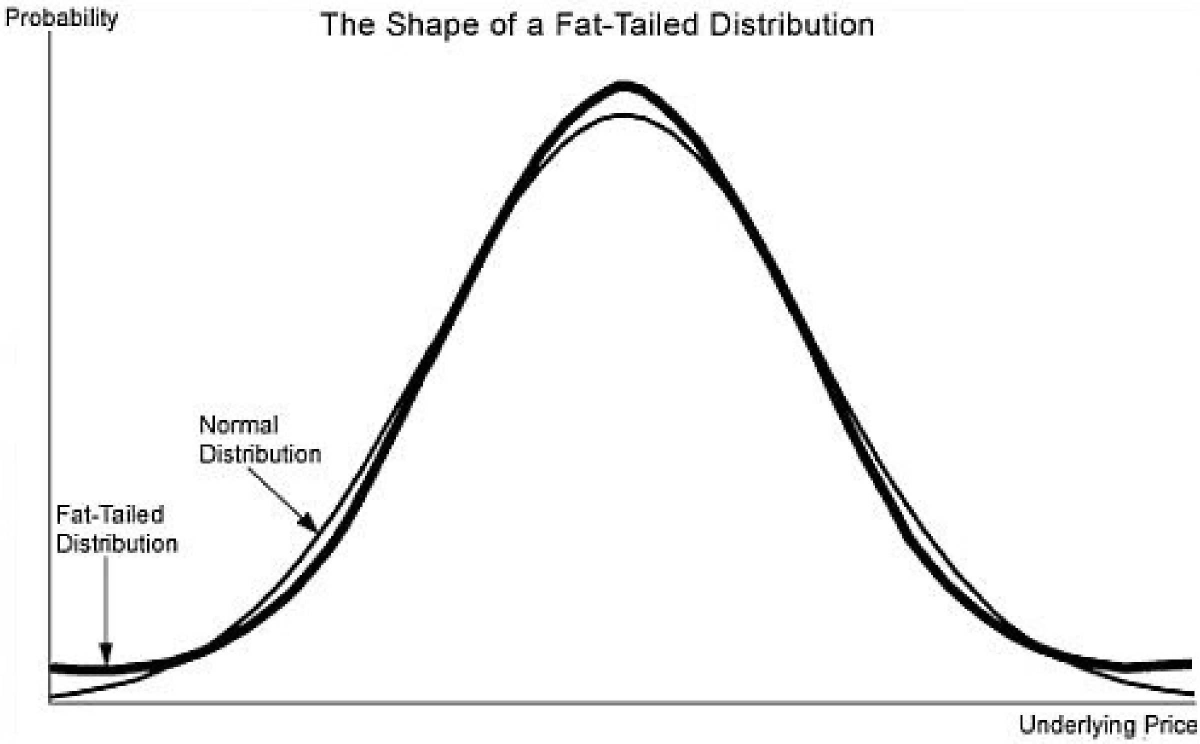
Finally, place where CAPM and mean-variance framework fall short of reality is the statistical dimension. The opposition of the mean-variance framework often cites as a chief problem that returns are not normally distributed which is illustrated in widely spread notion of fat tails – see e.g. Jensen et al. (2000) or Hyung, de Vries (2007).

Egami (2007) also mentions the problem of skewness of returns. “Empirical evidence indicates that returns of financial assets are not normally distributed, and in fact, the

[1] Interesting interpretation of the significance of idosyncratic risk is that, in emerging markets, diversifiable risk is priced (Estrada, 2000, p. 10).

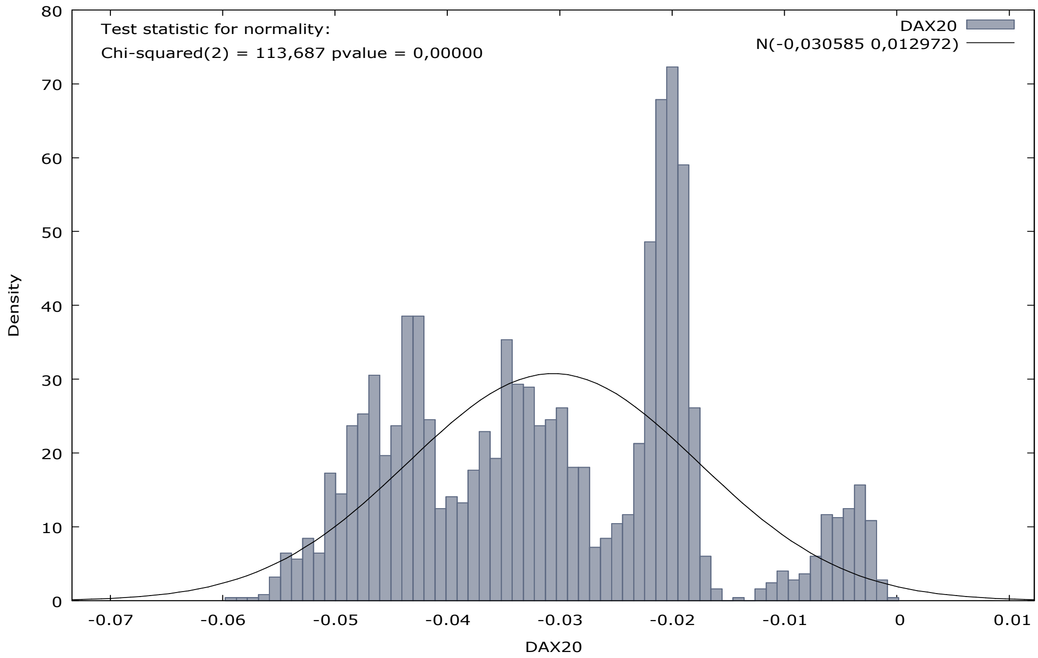
return distribution tends to be fat-tailed and skewed." Harvey and Siddique (2009) also mention the persistent skewness and its link with assymetrical variance.

Figure 2-4: Fat-tail distribution illustrated, source: www.meltlin.org



We have provided a typical textbook example of a fat-tail distribution in the Figure 2-4. But also our data exhibited features of a distribution that cannot be considered normal – both with a mere eyesight as well as by means of Jarque-Berra tests for Normality. For illustration, we enclose this graphical for the German DAX, together with Normality tests reported by gretl, below in Figure 2-5.

Figure 2-5: Distribution of Daily excess returns of the DAX index in 2000-2009



3. RESEARCH HYPOTHESES AND METHODS

The goal of this paper is to build upon previous research and empirical testing which was often focused on emerging markets, but we want to refocus in particular on the Central European region. Sometimes, the tested samples did contain CEE countries but more often; the group encompassed simply too many countries which necessarily made the sample quite heterogeneous. Therefore we will test the suitability of downside risk measures specifically focused on the Central-European and post-communistic countries, namely Czech Republic and Poland. We will also compare these two with Germany, as an immediate neighbour and a representative of a highly developed economy. This should give us a sample of countries that is somewhat varied in size, population, economical structure and development level, while also being a good representative of the regional influences.

See basic quantitative comparison of stock exchanges across the CEE region in the chart.

Table 3-1: Overview of CEE Stock Markets

Country	Index	N.of companies listed	Average Market Cap (EUR mil)	Total Market Cap (EUR mil)
Poland	WIG	379	485,98	184 185,68
Czech Republic	PX	13	2 543,79*	33 069,33*
Germany	Prime All Share	360	1 597,81	575 210,00
Hungary	BUX	21	1 004,29	21 090,00
Slovakia	Listed Market	16	150,75	2 412,00
Austria	Prime Market	48	1 503,49	72 167,67

Sources: pse.cz, gpw.pl, deutsche-boerse.com, bse.hu, bsse.sk, wienerborse.at

* - exchange rate of 26,195 CZK/EUR has been used (www.cnb.cz)

We will be comparing the selected countries using the standard CAPM beta, statistical Variance and mainly a set of downside risk measures. This chapter deals first with the definitions and formulas of the risk measures that were mentioned in the previous chapter and that also constitute the key concern for this paper. Next, we will outline the methodology to compare these measures.

3.1 Definition of employed Downside Risk Measures

They are the following:

Semi-Variance with respect to the mean: $SV_{\mu} = \frac{1}{T}\sum_{i=1}^{T} \mathrm{Max}(0, \mu - r_i)^2$

Semi-Variance with respect to zero: $SV_{0} = \frac{1}{T}\sum_{i=1}^{T} \mathrm{Max}(0, 0 - r_i)^2$

Lastly, we will employ downside beta. Let us stop here though, because this measure needs some adjustment. The standard version of Downside beta with respect to the mean is as follows:

$$\beta_i^{D} = \frac{\frac{1}{T}\sum_{i=1}^{T}(\mathrm{Max}\left(0, \mu_M - r_M\right) \cdot \left(\mu_i - r_i\right))}{\frac{1}{T}\sum_{i=1}^{T} \mathrm{Max}(0, \mu_M - r_M)^2}$$

However, as Lee, Robinson, Reed (2006) point out, this expression of co-semivariance in the numerator suffers from asymmetry. They provide an amendment which yields the symmetrical downside beta written as follows:

$$\beta_i^{D,\mu} = \frac{\frac{1}{T}\sum_{i=1}^{T}(\mathrm{Max}\left(0, \mu_M - r_M\right) \cdot \mathrm{Max}\left(0, \mu_i - r_i\right))}{\frac{1}{T}\sum_{i=1}^{T} \mathrm{Max}(0, \mu_M - r_M)^2}$$

That will the definition used by us. Finally, we will also employ downside beta with respect to zero:

$$\beta_i^{D,0} = \frac{\frac{1}{T}\sum_{i=1}^{T}(\mathrm{Max}(0, 0 - r_M) \cdot \mathrm{Max}(0, 0 - r_i))}{\frac{1}{T}\sum_{i=1}^{T} \mathrm{Max}(0, 0 - r_M)^2}$$

3.2 Framework for the Comparison

Now will define the *general* framework we will use to compare different risk measures among themselves. Note that the framework will vary slightly according to the specific model setup (e.g. panel data etc.). It can be easily expressed according to Estrada (2000, 2006) as follows:

$$E(r_i) = \mathrm{a} + \mathrm{b} \cdot rm_i$$

where $E(r_i)$ is the mean return for the i-th observation over observed period, rm_i is the tested risk measure and *a* and *b* are parameters. Needless to say, we will be focusing exclusively on significance of the slope coefficient.

Of course, we can develop the model further to accommodate for possible comparison of multiple risk measures in one regression, the general model becomes:

$$E(r_i) = \mathrm{a} + \sum_{j=1}^{J} \mathrm{b_j} \cdot rm_{ij}$$

where we have J risk factors.

Once we have settled the theoretical approach, yet another question arises – what specific econometric methods should we use. In previous research, various authors have used time series (Lee et al., 2006), cross-sectional data (Estrada, 2000, Mamoghli and Daboussi, 2008) or panel (Chen and Chen, 2004). One of the contributions this paper strives to make is to resolve this question as well – to enforce the conviction of our conclusions, we will use both time-series and panel data analysis. Moreover, the contribution of this paper to the field is that we will be testing on the level of individual companies, rather than whole countries' indices, which is the case of the papers cited above.

Our hypothesis is that the tests will confirm the significance of downside risk measures, both in absolute terms and also relatively in comparison to CAPM beta. However, we have some reservations particularly about the Czech Republic, since its stock market is very small – both in market capitalization and number of listed companies. Hence the issue shall be to come up with alternative hypothesis should these tests fail.

3.3 Testing on the level of individual companies

In the first part of our empirical testing, we are looking at individual securities on each market and their risk measures *in time*. We wanted to be very specific in our effort, that's why instead of estimating risk measures of a large pool of countries, we chose only a small sample and concentrated in detail on the level of companies. We will refer to this model structure also as "intramarket".

Setting up the model was quite a lengthy process that we will try to describe in detail here. The broad idea was to use data of returns to calculate various risk measures in the first stage, and in the second stage, run a regression on these measures to see which one explains the best the variations of stock returns (slightly similar to Chen and Chen, 2004). The general form for the time series analysis would thus be as follows:

$$R_t = a + b \cdot rm_t$$

where R_t is a stock return at time t, rm_t is a certain risk measure and *a* and *b* are parameters.

Data on the stocks, indices and interbank rates were kindly downloaded by the supervisor mr.Gapko from the Bloomberg© database. The rule for selecting the individual securities was either their market capitalization had to sum up to at least 75% of the entire market or there should be 5 companies minimum (case in point for the Czech Republic). The time period for all three countries has been beginning of 2000 until 5.2.2010 with minor tweaks. The departing point are always data with daily frequency but we made some major adjustments which are described below.

In the first step, we used daily data of the respective index and the companies' returns. Firstly, these had to be synchronized in such a way to make a compact time series because many times, there were cases where certain securities were missing an observation while others were not etc. We then used these daily data to calculate the risk measures that we want wanted to compare. For every security we employ 6 risk measures - they are CAPM Beta, Downside beta with respect to the mean, Downside beta with respect to zero, Variance, Semivariance with respect to the mean and Semivariance with respect to zero. In the model, and sometimes this text, they are designated *Beta, Dbeta u, Dbeta 0, Var, Semivar u and Semivar 0*, respectively. We calculated each of these as a trailing measure over past 30 observations of the respective stock. These are still daily data, that is, we ended up with 30 fewer observations than is the total number of the series of day-to-day returns. The above general equation can then be designated:

$$R_t = a + b \cdot rm_{t-30,t-1}$$

where the subscript of the risk measure rm signifies that it is calculated over the period of past observation up to 30 days back.

Consequently we tried the following: for every individual stock, we regressed the daily returns on a constant and each calculated lagged risk measure. Also, to evaluate the interactions among the risk measures, we ran a separate regression on all of them together (so we had either 2 or 7 explanatory variables). In case of the "all-together" model, we always omitted variables above 0,1 level of significance.

These regressions suffered from a plethora of problems: mainly extremely low goodness of fit (R-squared) and significance of parameters, heteroskedasticity and autocorrelation. Significance, however low, can still be used to compare different variables among them and heteroskedasticity is easily addressed by robust methods of estimation. Autocorrelation (which went as far as 60 observations back) however, cannot be undone so easily.

How to solve this problem? We decided to compute a simple Moving Average of daily returns over the same interval as the risk measures – past 30 days. If we are to modify the equation again, it would appear as follows:

$$\frac{1}{30}\sum_{i=1}^{30} R_{t-i} = a + b \cdot rm_{t-30,t-1}$$

Subsequently, we took two observations that were 30 lags apart and removed all observation in between. Therefore, we kept observation number 1, 31, 61 etc… This somewhat resembles monthly structure of data but obviously, it is not the same. Lastly, with this reduced dataset form, we utilized the same method as with the daily data – regress a time-series of returns on a constant and one or six risk measures in order to evaluate their significance and explanatory power against one another. Voila, the significance of parameters and R-squared improved substantially and what is more, autocorrelation disappeared.

In the end, the final comparison of the risk measures proceeded as follows:

1. For every company, run 6 separate regressions (one for each risk measure) including only the risk measure and a constant.
2. Collect the coefficient of the risk measure, p-value and R-squared and rank them by significance/explanatory power[2].
3. For every company, run a regression including a constant and all the six risk measures as independent variables (the "joint" regression or model).
4. Evaluate heteroskedasticity and use respective robust method (as provided by gretl) if needed.
5. Remove insignificant variables with a cutoff point of 0,1 for p-value.
6. Finally, assess collinearity by using the innate gretl test and common sense and comment.

[2] Ranking according to lowest p-value and highest R-squared was the same. We realize some might think this is a controversial method but it was the most straightforward one and moreover, ranking according to the the Information criteria (Akaike, Hannah-Quinn and Schwarz) was still the same. These criteria are not reported in the text itself but in the appendix with the outputs of the individual regressions for those who are interested.

3.4 Idiosyncratic Risk Explained

As a little digression, we decided to present the notion of idiosyncratic risk. We will need this definition in section 8, where we test the significance of diversifiable risk and find some consistent and significant results.

Stemming from the Portfolio theory by Markowitz (1952) and Sharpe CAPM (1964) and summed for example in Estrada (2000) is the possibility to subdivide risk of an asset into systemic and non-systemic part. To do that, let us start with standard form of CAPM regression:

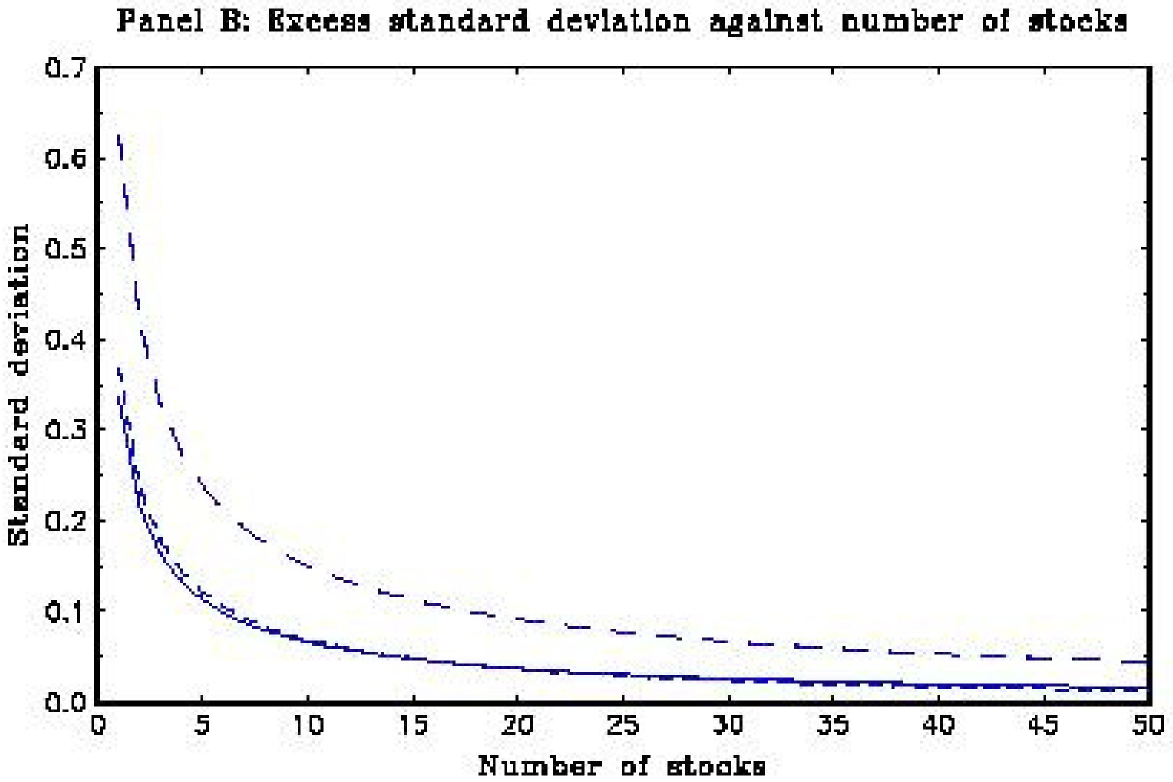
$$R_{it} = \alpha_i + \beta_i \cdot RP_i + \varepsilon_{it}$$

where RPi is the market risk premium in i-th cross section. We then apply the variance operator on both sides of the equation to obtain:

$$\sigma_i^2 = \beta_i^2 \sigma_{RP}^2 + \sigma_\varepsilon^2$$

The left hand side is the total risk of a risky asset – measured by the statistical variance of its returns. The first component on the right is the systemic and undiversifiable risk – in the original Markowitz portfolio selection theory, investors are compensated only for this part of risk. The second term on the right-hand side is the non-systemic (sometimes called idiosyncratic) component. This is the square of residuals from the regression – part unexplained by beta. According to theory (Markowitz, 1952), it can be completely neutralized by diversification and so it doesn't bear any premium.

Figure 3-1: Illustration of decreasing idiosyncratic risk with increasing diversification. Adapted from Markowitz (1952)



In the models for each of the countries in the sections 4 to 6, some results were hard to interpret or simply strange and thus raised our concern that unsystemic risk might be the culprit. We also mentioned that its significance for stock returns in emerging countries has been observed in literature. Therefore, we decided to carry out a detailed test using only idiosyncratic risk as an explanatory variable in the context of separate companies as well as an aggregated panel. Section 8 occupies itself with results of this analysis.

4. INTRAMARKET MODEL FOR GERMANY

4.1 Introduction

We decided to include Germany as a benchmark for our two post-communist countries because it is one of the most developed economies in the world and at the same time belongs to the region of Central and Eastern Europe. Therefore, on the one hand, it still is a part of the same area and subject to similar influences as the Czech Republic and Poland (e.g.: EU-wide policy, mutual trade in the area, etc.), on the other hand, Germany should have a more advanced and established stock market.

The latter point and differences between how stock markets of developing and developed countries work is also explicitly explored in literature. E.g. Estrada (2000) shows, that in general, developing countries have segmented financial markets and downside risk measures tend to have more explanatory power than traditional ones whilst in developed countries, markets are more integrated and governed by traditional indicators, such as beta. Our testing on the level of individual companies shows this is not entirely true for German DAX index –in the sense that downside risk measures bear important explanatory power while beta and variance as single regressor have little use.

Table 4-1: Germany - Overview of selected companies and their average risk measures

Company	Symbol	Excess Return	Beta	Dbeta u	Dbeta 0	Var	Semivar u	Semivar 0
E.ON	EON	0,0335%	0,7532	0,8567	0,8422	0,0412%	0,0183%	0,0185%
Siemens	SIE	0,0075%	1,2675	1,3228	1,3174	0,0666%	0,0304%	0,0316%
Bayer	BAY	0,0247%	0,9015	1,0214	1,0062	0,0540%	0,0231%	0,0239%
Allianz	ALV	-0,0282%	1,1816	1,2302	1,2516	0,0714%	0,0314%	0,0338%
BASF	BAS	0,0332%	0,8713	0,9425	0,9287	0,0423%	0,0188%	0,0190%
Deutsche Bank	DBK	0,0046%	1,1929	1,2355	1,2500	0,0757%	0,0340%	0,0355%
SAP	SAP	0,0137%	1,1166	1,1859	1,1908	0,0806%	0,0346%	0,0354%
Daimler	DAI	-0,0093%	1,0903	1,1577	1,1613	0,0597%	0,0262%	0,0276%
Deutsche Telekom	DTE	-0,0595%	0,9862	1,0456	1,0770	0,0623%	0,0285%	0,0303%
RWE	RWE	0,0311%	0,7071	0,7996	0,7860	0,0346%	0,0161%	0,0162%
Munich Re	MUV	-0,0190%	0,9626	1,0138	1,0368	0,0569%	0,0263%	0,0275%
GRAND AVERAGE		0,003%	1,00	1,07	1,08	0,059%	0,026%	0,027%

The tests were carried out on the DAX index as it is the most liquid part of Frankfurt stock exchange. We have selected the companies according to the rule mentioned in section 3.4. Their overview including averages of returns and trailing risk measures used in the model are provided in Table 4-1. Then, we proceeded with the adjustments that described in. Number of daily observations before the adjustments was 2536 and after all the adjustments, we finished at 82.

4.2 Separate Regressions

Results of separate regression can be seen in Table 4-2. Looking at them, if one thing is clear from the start, it's the absolute dominance of Semivariance with respect to zero. It was significant for all the selected companies and moreover, when used as single slope variable, it managed to explain the most variation of returns for 9 out of 11 stocks. According to our simple ranking procedure, it was rank 2 in only two cases (Deutsche Telekom and RWE) and rank 1 for the rest. This is a very strong and quite surprising result. It indicates that German investors are very much preoccupied with downside risk.

Regarding the sign of the parameter, in all 11 regressions, it was negative. The interpretation here is more statistical than economical and it's derived from Chen and Chen (2004, p.13) – "the relative-to-zero downside risk measures are also measuring the level of return rates, with the negative coefficient being understandable, as it is not reflecting the risk premium, but the return level itself." The coefficients tended to be very high in absolute terms, which is only due to the fact that the time series of *semivar 0* were minuscule in value. Finally, the only economic interpretation that matters here is the explanatory power of Semivariance with respect to zero – it shows that even investors in a highly advanced country such as Germany incorporate concerns of capital loss into their preferences and act accordingly which challenges previous research (for example Estrada, 2000).

Another point which is obvious is the inadequacy of traditional risk measures based on the mean-variance framework (Beta and Variance). The result of CAPM beta is especially surprising. As we explained before, agents in developed economies are usually believed to make their investment decisions according to systemic risk. In spite of these assumptions, beta has proven insignificant in all but one case (Deutsche Telekom) where it unfortunately has a negative sign of its coefficient which is mostly dubious. That would suggest lower return for higher systemic risk which is all but a sensible interpretation.

A similar conclusion applies for Variance. It managed to explain at most 3,3% of stock return variation and otherwise was unambiguously insignificant. Moreover, its coefficients were usually negative as you can see in the table, which should not happen since Variance is a measure of total risk and therefore, we would expect a positive sign. This is probably connected with its insignificance. The outcome for beta and Variance was a concern to us. On the one hand, it is apparent these two risk indicators have little worth for explaining variations of stock returns on the German stock exchange, if used as single slope variables. However, it also raised a question for us whether it is possible that idiosyncratic risk enters evaluation of German investors. Our concerns were dispersed by significance of beta in the joint regression model and by our test aimed specifically at idiosyncratic risk. We present its conclusions further on in the paper in section 8.

The results for the three remaining risk measures were also quite unconvincing. Downside beta with respect to the mean and zero were significant 3 and 2 times out of 11, respectively. We might say that *Dbeta u* had a more reasonable interpretation – in the three significant cases, it also a positive sign of its coefficient, indicating that higher systemic downside risk entailed also higher excess return. Finally, *semivar u* proved significant for only two out of eleven companies but always less than *semivar 0*.

4.3 Joint Regression

To explore different interactions effects between the various risk measures, we included them in one joint regression for every company. Before we start to enlist the particular results, let us ponder on some general issues with the joint models. Firstly, a common denominator for all of the estimations was heteroskedasticity. This is understandable – financial data are by definition very volatile and this translates into the variation of our independent variables. Secondly, collinearity was just as ubiquitous as heteroskedasticity, if not more. Of course, this concerned separately the group of Variance measures (*var, semivar u, semivar 0*) and systemic risk measures (*beta, dbeta u, dbeta 0*). Although each of the definitions is different, they usually share some overlap in each of the two groups. This is especially pronounced for Variance and Semivariance with respect to the mean, since their overlap on the downside part is in fact 100% - *semivar u* explains only the downside volatility, whereas *var* explains the downside and the upside volatility at the same time. Therefore, we can say that Variance carries the same information but adds more, the question is whether this additional information is relevant or not. Our tests indicate that the answer is negative. One way or another we had to reject both Variance and Semivariance with respect to the mean because of the high collinearity and because Semivariance with respect to zero always entertained higher explanatory power.

This leads to the regression results themselves (reported in Table 4-3). We can safely say that *semivar 0* was still highly useful – we kept it in our models in all but one case (Deutsche Telekom) and also and it was most often the variable with the lowest p-value. However, as you can see in the table classic, CAPM Beta and Downside beta with respect to zero were also consistently important in explaining variation of excess stock returns on the German market. This presents an interesting issue. In the previous subsection, we concluded that beta could be rejected as a single regressor. However, a consistent significance of beta suggests it adds some unique information to *semivar 0* and *dbeta 0* which make it significant. This analogously applies to *dbeta 0*.

Regarding quantitative values of the parameters, *semivar 0* still maintains parameters with negative signs and high absolute values. Similarly, in all cases when *dbeta 0* was significant, it had negative parameters – the explanation for this phenomenon was already provided. We would like to stress the results for beta. Not only was it significant for 10 out of 11 German stocks, it also retained positive parameters in all of those cases. This lends itself to a reasonable and expected economic interpretation – when downside risk (expressed either by *semivar 0* or *dbeta 0*) is taken into account, higher systemic risk will lead to higher excess returns.

Overall, results for Semivariance with respect to zero from the separate regressions and for the three risk measures used in the joint model, are reassuring for our decision to carry out a study on the level of companies individually, because a panel data analysis can hardly reveal the nuances and specificities.

4.4 Summary of results

In contrast with literature, we found that downside risk enters firmly into decision making of investors in Germany. This is true especially for Semivariance with respect to zero, which was significant for every company selected in both separate and joint regressions.

Traditional risk measures Beta and Variance did not provide much explanatory power. Variance was insignificant in the separate regressions and too collinear with other variables in the joint regression. CAPM beta however showed interesting feature – it is significant only when used jointly with variables, never by itself. Although this might be also connected with collinearity, it is a notable result which was later confirmed by panel data analysis as well.

Evidence on the three remaining downside risk definitions is mixed but quite surprisingly, the results are worst for Semivariance with respect to the mean. More general conclusions pertaining to the level of the whole market will be drawn out after our panel data analysis.

In Figure 4-1 and Figure 4-2, you can find the comparison of actual and fitted data from regressions that were the most significant. Looking at the one from the regression with only one variable, we can see a pattern. The used variable in that case is of course *semivar 0* and it seems that it's fairly precise in explaining downturns but completely but rather flat for upturns of any other developments. Fortunately, the situation is different for the best fitting joint regression – SAP AG. We can see that in that case, fitted values follow the actual data much more closely even in cases of strong upturns.

Figure 4-1: Best fit from Separate regressions: Bayern

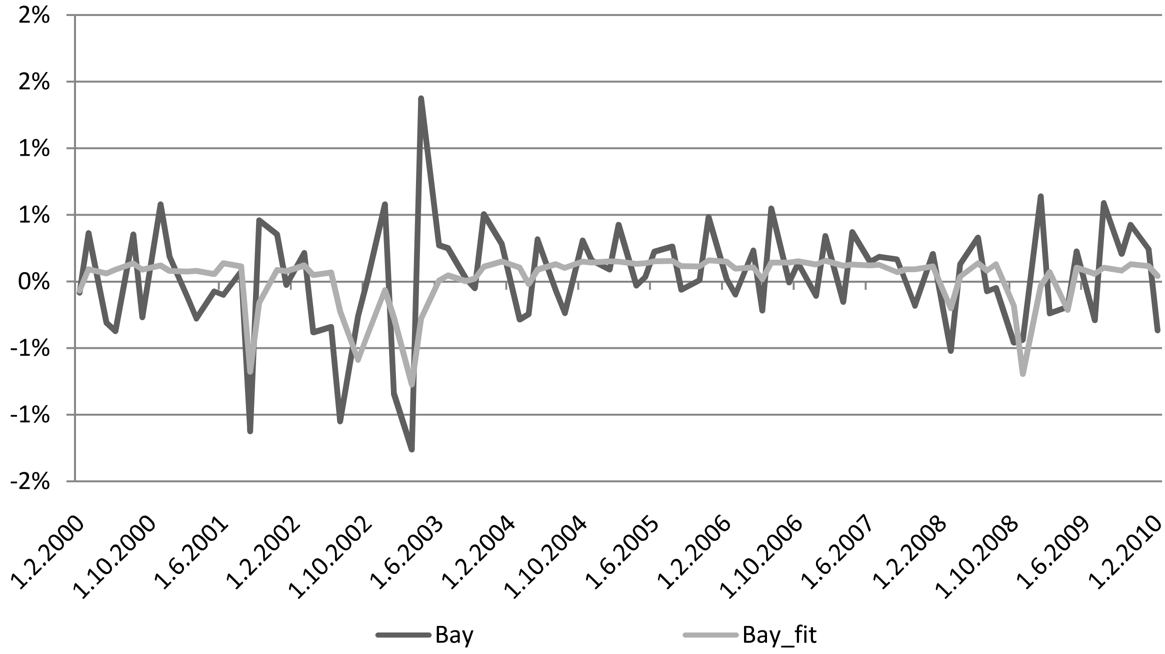


Figure 4-2: Best fit from Join regressions: SAP AG

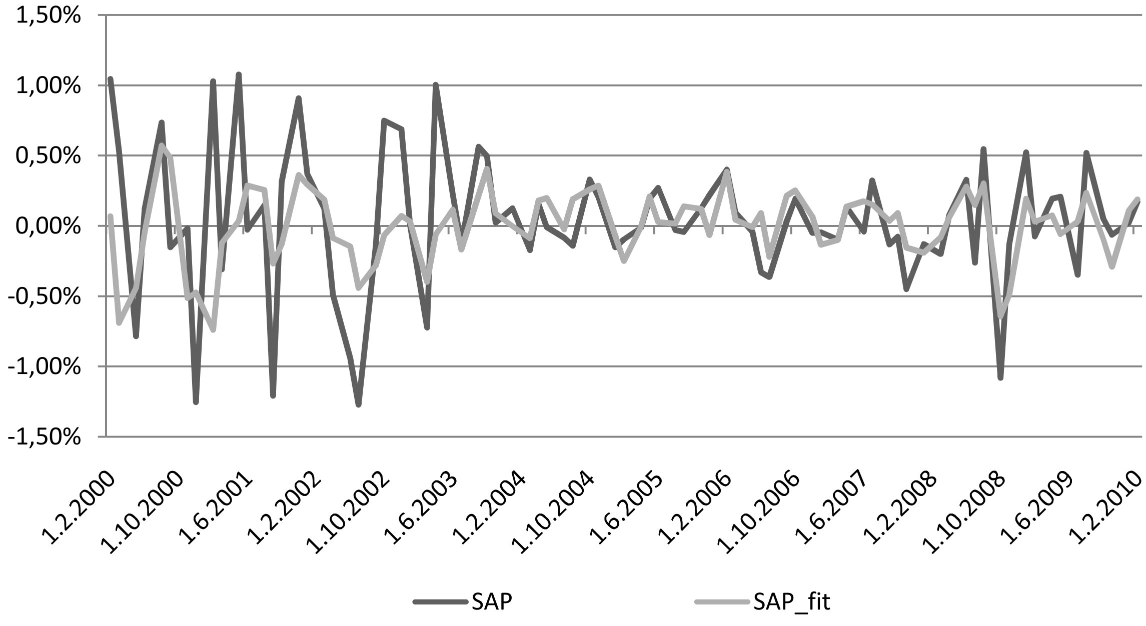


Table 4-2: Results of separate regressions

		Beta			Dbeta u			Dbeta 0		
Company	**Symbol**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**
EON	EON	0,0006	0,4658	0,0066	0,0013	0,1801	0,0221	0,0000	0,9846	0,0000
Siemens	Sie	-0,0009	0,5989	0,0034	-0,0006	0,7049	0,0018	-0,0023	0,0853	0,0361
Bayern	Bay	0,0018	0,2391	0,0171	0,0017	0,3256	0,0119	-0,0018	0,2430	0,0168
Aliianz	Alv	8,75E-05	0,9624	0,0000	0,0003	0,8701	0,0003	-0,0025	0,1671	0,0234
BASF	Bas	0,0020	0,1524	0,0251	0,0017	0,3024	0,0131	-0,0013	0,3919	0,0091
Deutsche Bank	Dbk	0,0023	0,1561	0,0247	0,0026	0,1595	0,0243	-0,0004	0,7989	0,0008
SAP	SAP	0,0015	0,1139	0,0306	0,0016	0,0607	0,0427	0,0005	0,5582	0,0043
Daimler	DAI	0,0015	0,3178	0,0123	0,0017	0,2941	0,0136	-0,0018	0,2458	0,0166
Deutsche Telekom	Dte	-0,0018	0,0681	0,0405	-0,0020	0,0425	0,0498	-0,0033	0,0001	0,1709
RWE	RWE	0,0012	0,2415	0,0169	0,0023	0,0439	0,0492	-0,0005	0,6340	0,0028
Munich Re	MUV	-0,0005	0,6599	0,0024	0,0001	0,9085	0,0002	-0,0006	0,5516	0,0044

		Var			Semivar u			Semivar 0		
Company	**Symbol**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**
EON	EON	-0,3371	0,5136	0,0053	-1,0161	0,4745	0,0063	-3,4992	0,0087	0,0819
Siemens	Sie	-0,5186	0,4117	0,0083	-1,4217	0,3299	0,0117	-4,5525	0,0003	0,1479
Bayern	Bay	0,4673	0,3801	0,0095	-3,0920	0,0544	0,0449	-6,2632	0,0000	0,2422
Aliianz	Alv	-0,7934	0,1001	0,0330	-2,1341	0,096	0,0338	-4,4318	1,34E-05	0,2098
BASF	Bas	-0,4452	0,4528	0,0070	-1,5468	0,2621	0,0155	-3,8073	0,0016	0,1164
Deutsche Bank	Dbk	-0,5071	0,2841	0,0142	-1,0663	0,3507	0,0108	-3,3972	0,0001	0,1640
SAP	SAP	0,7009	0,1761	0,0225	0,9963	0,4499	0,0071	-3,0968	0,0138	0,0726
Daimler	DAI	-0,1759	0,7807	0,0010	-1,1045	0,4938	0,0058	-4,8054	0,0005	0,1399
Deutsche Telekom	Dte	0,3034	0,6084	0,0033	0,5375	0,6814	0,0021	-3,4013	0,0064	0,0884
RWE	RWE	0,2681	0,7217	0,0016	0,7694	0,6563	0,0025	-3,1791	0,0739	0,0389
Munich Re	MUV	-0,1782	0,6784	0,0021	-0,3244	0,7229	0,0016	-1,7059	0,0547	0,0448

Table 4-3: Results of joint regressions

		Beta		Dbeta u		Dbeta 0		Var		Semivar u		Semivar 0			
Company	**Symbol**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**R2**	**H-C[3]**
EON	EON	0,0027	0,0359			-0,0020	0,1019					-6,3115	0,0026	0,1905	*
Siemens	Sie	0,0050	1,85E-02			-0,0048	0,0038					-2,5754	1,16E-01	0,2713	*
Bayern	Bay	0,0071	5,26E-06			-0,0067	0,0001					-8,1152	0,0000	0,3654	*
Aliianz	Alv	0,0049	0,0185			-0,0040	0,0224					-3,8561	1,91E-05	0,3105	*
BASF	Bas	0,0059	0,0007			-0,0070	0,0000					-4,1822	4,70E-02	0,2637	*
Deutsche Bank	Dbk	0,0064	0,0013			-0,0050	0,0119					-3,2717	3,60e-05	0,3429	*
SAP	SAP	0,0090	0,0000			-0,0072	0,0000					-4,6418	0,0113	0,4179	*
Daimler	DAI	0,0089	0,0000			-0,0080	6,00E-06					-7,7139	2,70E-03	0,3514	*
Deutsche Telekom	Dte	0,0087	0,0001			-0,0108	7,51E-07							0,2743	*
RWE	RWE	0,0036	1,88E-02			-0,0032	6,95E-02					-9,7131	0,0011	0,2207	*
Munich Re	MUV			0,0020	0,0964							-4,1491	1,03E-02	0,0858	*

Note: only the significant parameters are reported

[3] Shows whether heteroskedasticity was a serious problem

5. INTRAMARKET MODEL FOR POLAND

5.1 Introduction

Poland is sort of a middle point between Germany and the Czech Republic – this applies both to size and population of the country as well as the structure of the stock market. After all, WIG20 alone, the index of 20 largest companies by market cap, contains more companies than the whole Prague stock exchange. The number of companies listed on the entire Warsaw stock exchange is also very close to Frankfurt (over 300). Nevertheless, Poland is still an economy in transition, so it is probably undergoing some structural adjustments which differentiate it from a large western market, such as Germany. Additionally, emerging and transitive economies tend to have segmented financial markets and systemic risk is a less reliable measure there, as we explained above, mainly in section 2.4. Our tests confirm this hypothesis as beta did not prove to be a very dependable risk measure.

The market index for the case of Poland was the WIG20 and the selected segment of corporate stocks amounted for just under 21 billion EUR in market capitalization. Their overview is provided in Table 5-1. In this case, we had to use a slightly shorter time series – we start only in second half of 2001. This is for two reasons: TPSA was listed at that time and we wanted to keep the number of companies as high as possible. And secondly, the observations of our risk-free rate proxy, overnight Wibor, had increasingly more missing observations in that time period. The starting number of observations was therefore 2164. After adjustments, we received 69 observations.

Table 5-1: Poland - Overview of selected companies and their average risk measures

Company	Symbol	Excess Return	Beta	Dbeta u	Dbeta 0	Var	Semivar u	Semivar 0
Bank Pekao	PEO	0,050%	1,1416	1,1496	1,1492	0,062%	0,028%	0,028%
KGHM	KGH	0,105%	1,2714	1,3884	1,3651	0,086%	0,042%	0,042%
PKN Orlen	PKN	0,035%	1,0486	1,1049	1,1010	0,051%	0,023%	0,023%
TPSA	TPS	-0,003%	0,9911	1,0478	1,0739	0,045%	0,020%	0,021%
Bank Zachodni	BZW	0,082%	1,0142	1,1093	1,0876	0,061%	0,028%	0,027%
Asseco	ACP	0,059%	0,8771	1,0441	1,0231	0,074%	0,035%	0,035%
GRAND AVERAGE		0,055%	1,06	1,14	1,13	0,063%	0,029%	0,029%

5.2 Separate Regressions

To our surprise, the results of the estimations on the Polish market were also very consistent and with even higher goodness of fit than for Germany. We were afraid of one important influence - the extreme values of WIBOR in the first part of the last decade. Although now the rate revolves around 2%, it used to be 19% in 2001 and only slowly decreased (it still exceeded 10% on overnight rates in 2003). This skewed the daily excess returns (returns in excess of the risk-free rate) throughout that period to the negative. Nevertheless, as can be seen in the table above, the market rebound and the average daily return over the observed period were largely positive (except for TPSA).

The results of the separate regressions, summed up in Table 5-2, were somewhat mixed but some tendencies can be extracted. Firstly, the results confirmed Semivariance with respect to zero as the single variable with the most explanatory power by far. Again, the results mirrored the German case both in sign of the parameters (negative) and their magnitude. Likewise, the notion of below-zero returns is the most important risk factor for Polish investors.

Moreover, the results spoke against CAPM beta. As a single slope variable, it was the worst performing one – you can observe in table it was significant for only one company, Asseco, in which case however, every other risk measure had more explanatory power. The maximum variation of the dependent variable that an equation could explain using beta as the slope parameter was 4,91%. This tells us that systemic risk on the Polish stock market is not priced or taken into account at all by investors.

What seems to be a universal result for Poland is an overall high explanatory power of all the variance-type risk indicators: *Var, semivar u* and *semivar 0*. This follows the reasoning of segmented financial markets we mentioned before, where total risk tends to be the governing risk measure (Estrada, 2000). Consequently, unlike CAPM beta, Variance - the other, more “traditional” risk measure - proved to have much more explanatory power on the Polish market. It ended up as marginally insignificant in only case (KGHM) and significant for all the rest.

This has a very important implication from a theoretical perspective. We feel the correct explanation is connected with the notion of idiosyncratic risk (as explained in 3.4). In summary, we already said that variance or total risk is composed of the systemic and unsystemic part. Now, significance of total risk combined with insignificance of systemic risk (beta) would indirectly imply that idiosyncratic risk does have some impact on the variation of Polish stock returns. That, in turn, means that diversifiable risk is priced on the financial market in Poland – this outcome directly confirms a conclusion of Estrada (2000) for his sample of emerging countries. On a final note though, Variance had parameters of negative sign for all 6 companies. This is hard to interpret provided its significance. It might suggest idiosyncratic risk is priced negatively (higher diversifiable risk would entail lower returns). Our calculations that will be presented later in section 8 confirm both our assumptions – idiosyncratic risk is indeed significant and it has a negative sign.

Significance of s*emivar u* was also very high – it was always one of the most significant variables in the model but similarly to Germany, it could never attain the goodness of fit as *semivar 0*. Both downside betas were largely insignificant and with varying parameter signs, therefore we reject their use on Polish market. The exception is Asseco Poland – Downside beta with respect to zero could explain as much as 28% of variation of its stock return.

5.3 Joint Regression

Also the joint models were surprisingly fairly consistent and again, with even higher goodness of fit than Germany. Indeed, R-squared tended to be much higher in case of Poland then in the German one, as

Table 5-3 shows. Furthermore, according to our test we do not disclose, collinearity effects seemed to be even stronger – especially between the “variances” (Variance, Semivariance with respect to the mean and zero). This was most pressing for *Var* and *Semivar u*, which is quite logical because they partially overlap. Other than that, joint regressions show downside risk measures established their significance clearly for Poland.

For starters, Semivariance with respect to zero fared even better than in Germany – it was significant for *every* selected stock. Again, its parameters were universally negative, which is line with explanation we gave in section 4.2. Its value also lies in the fact that is carries more unique information because its overlap with Variance and Semivariance with respect to the mean is lower. Thus it helps reduce collinearity at least a little.

The Polish results also mirrored the German ones with the remaining included variables. You can see that CAPM beta and Downside beta with respect to zero compete – both remained significant in 4 out of 6 cases. An intriguing observation can be made if look at cases where they are in the model together – PKN Orlen and TPSA. In both cases, beta is more significant than *dbeta 0*. So although it is insignificant by itself, it adds some unique information to *semivar 0*. One reason for this phenomenon probably is that *semivar 0* carries partly the same information as *dbeta 0*, so it “steals” some of its explanatory power. Anyhow, coefficients of beta were consistently positive. As you can see, *dbeta u* also ended as significant in 2 cases and with positive parameter values – it is a similar case as beta although with lower consistency.

Variance and Semivariance are little more complicated examples. They were actually almost always significant but we had to drop them because of apparent collinearity issues. We think this also explains their significance in the joint regressions. When estimated separately, they are insignificant, but once put together, they obviously bear some information. It’s almost a textbook example of collinearity. Surprisingly, coefficients of both Variance and Semivariance with respect to the mean also had the desired positive when significant. We would conclude that these two risk measures carry some unique explanatory power but it is hard to discern and we prefer

Semivariance with respect to zero and Downside beta with respect to zero or Beta because they have established their value more clearly.

5.4 Summary of results

Overall, results for Poland very quite similar to Germany. But unlike Germany, this time it wasn't in contrast with previous research – we mentioned before, that downside risk measures are proven to have more explanatory power in emerging and transitive economies. The number one explanatory variable was again Semivariance with respect to zero, which established its position most consistently since it provided the best goodness of fit when used separately as well together with other risk definitions. Therefore, we can conclude with conviction that Polish investors value downside risk more than standard risk measures and the most relevant benchmark for them is zero rather than mean.

Variance, Semivariance with respect to the mean and Downside beta with respect to zero were also significant but not with such consistency as *semivar 0*. Collinearity was also an issue, especially for the former two measures which somewhat takes away their explanatory power. However, if we had to decide, *dbeta 0* would probably be our pick as it added the most significance to *semivar 0* while not inflating indicators of collinearity. The same applies to CAPM Beta which has shown the same tendencies as in Germany – it can be rejected as insignificant when used only by itself but once put into regression with downside risk measures, it proves it has some value. This is an unforeseen result. We would have expected beta to have at least some explanatory power in Germany, but in Poland, which is an example of not yet fully developed financial market, it is suprising.

The charts below illustrate the fact that the Polish regression exhibited better overall fit than German ones. It is already visible in the case of TPSA, which, although using only one explanatory variable provided much more accurate depiction of the real data than we could see for example in the case of Bayern. If we look at results from the joint regressions segment, the company KGHM provided an exceptional fit – we can see that there is a notable deviation only during the sharp rise at the end of 2008, otherwise, the fitted data depict both peaks and bottoms quite precisely.

Figure 5-1: Best fit from Separate regressions: TPSA

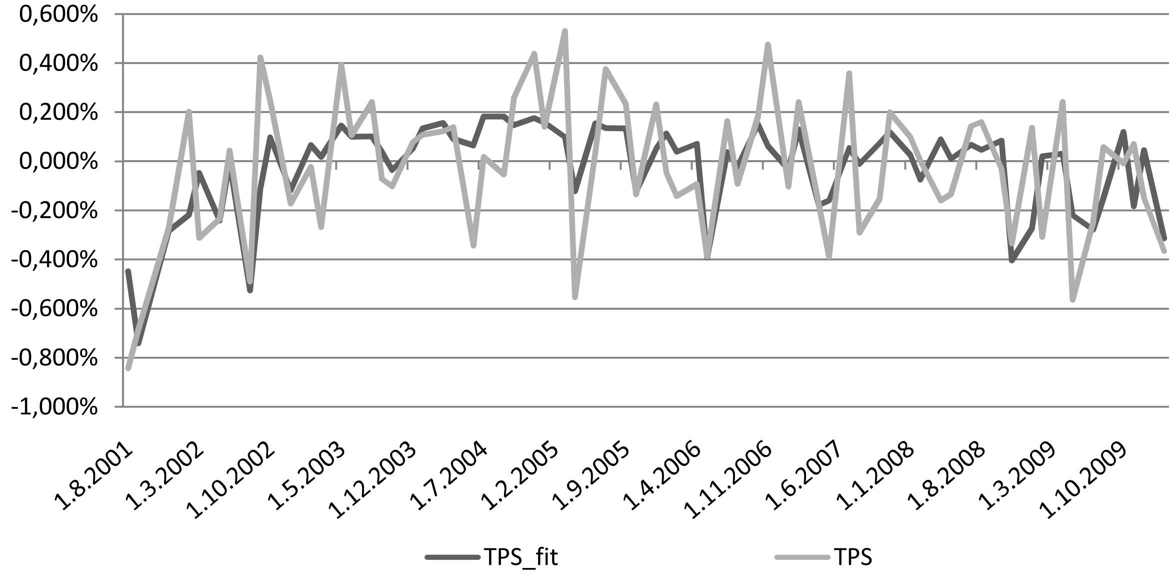


Figure 5-2: Best fit from Joint regressions: KGHM

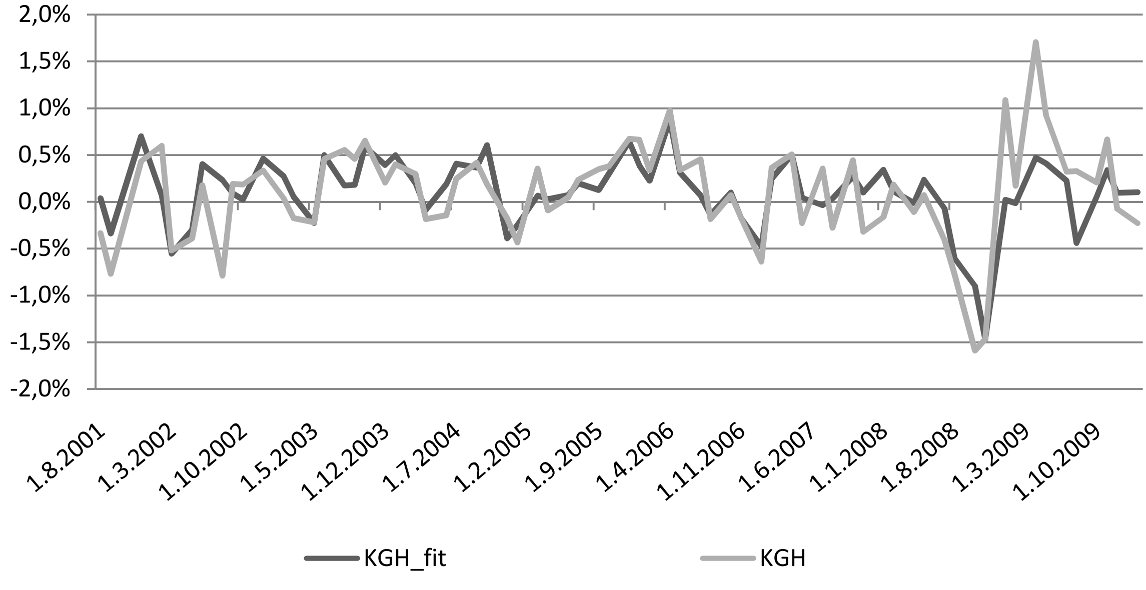


Table 5-2: Results of separate regressions

		Beta			Dbeta u			Dbeta 0		
Company	Symbol	Coeff	P-value	R2	Coeff	P-value	R2	Coeff	P-value	R2
Bank Pekao	PEO	0,0006	0,7709	0,0013	-0,0002	0,9079	0,0002	-0,0016	0,322	0,0146
KGHM	KGH	0,0027	0,2067	0,0237	0,0015	0,4411	0,0089	-0,0022	0,2053	0,0238
PKN Orlen	PKN	0,0030	0,0524	0,0550	0,0023	0,1547	0,0300	0,0000	0,9957	0,0000
TPSA	TPS	-0,0001	0,8962	0,0003	0,0001	0,9497	0,0001	-0,0010	0,2968	0,0162
Bank Zachodni WBK	BZW	0,0001	0,9476	0,0001	-0,0003	0,8615	0,0005	-0,0035	0,0269	0,0710
Asseco	ACP	-0,0026	0,0673	0,0491	-0,0032	0,0416	0,0605	-0,0061	2,48E-06	0,2836

		Var			Semivar u			Semivar 0		
Company	Symbol	Coeff	P-value	R2	Coeff	P-value	R2	Coeff	P-value	R2
Bank Pekao	PEO	-1,7752	0,0262	0,0717	-4,8017	0,0046	0,1140	-6,1687	1,84E-07	0,3355
KGHM	KGH	-1,1397	0,1287	0,0341	-2,4309	0,1536	0,0302	-5,3324	3,18E-05	0,2291
PKN Orlen	PKN	-2,5553	0,0095	0,0961	-6,5181	0,0017	0,1376	-7,8254	1,52E-07	0,3392
TPSA	TPS	-3,9162	0,0029	0,1249	-10,0490	0,0005	0,1689	-12,6017	4,43E-10	0,4428
Bank Zachodni WBK	BZW	-2,0100	0,0986	0,0402	-5,5792	0,0419	0,0603	-9,8219	4,19E-08	0,3636
Asseco	ACP	-2,7097	0,0004	0,1717	-5,3389	9,74E-05	0,2041	-5,7489	4,25E-08	0,3633

Table 5-3: Results of joint regressions

Company	Symbol	Beta		Dbeta u		Dbeta 0		Var		Semivar u		Semivar 0		R2	H-C
		Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value		
Bank Pekao	PEO	0,0095	6,60E-06			-0,0055	0,0001					-8,2591	3,92E-10	0,5151	*
KGHM	KGH			0,0205	0,0000	-0,0160	1,22E-10					-5,5668	2,68E-26	0,8492	*
PKN Orlen	PKN	0,0091	3,59E-07			-0,0053	0,0003					-8,7866	1,12E-06	0,4855	*
TPSA	TPS	0,0044	0,0049			-0,0029	0,0398					-14,3614	3,68E-18	0,7451	*
Bank Zachodni WBK	BZW			0,0028	0,0623							-10,8212	8,96E-09	0,3965	
Asseco	ACP	0,0042	0,0036			-0,0050	0,0037					-5,7579	0,0005	0,3474	*

Note: only the significant parameters are reported

6. INTRAMARKET MODEL FOR THE CZECH REPUBLIC

6.1 Introduction

From the three selected countries, Czech Republic is the smallest one and has the smallest stock exchange, both by market capitalization and by number of companies listed. The effectiveness of its financial market has been questioned before (Kristoufek, 2007). Moreover, according to results of Estrada (2000), Czech Republic was the only country (out of 28 emerging economies) not conforming to the hypothesis of partially integrated financial markets, which would suggest it is still a fully segmented market. We were expecting inconsistent and unreliable results but the opposite was true, actually. However, the results do point out inefficiencies on the Czech market.

Our pool of 5 selected companies amounts to 835 bln.CZK (32 bln.€) in market capitalization. The sample for the Czech Republic was unfortunately the smallest one out of the three countries. The reason for that is that the Erste Group time series was incomplete as it started as late as in November 2002. Therefore, the starting number of daily observations was 1816 and the final number was 59. The statistics of the sample are summarized in Table 6-1.

Table 6-1: Czech Republic - Overview of selected companies and their average risk measures

Company	Symbol	Excess Return	Beta	Dbeta u	Dbeta 0	Var	Semivar u	Semivar 0
Erste Bank	Erst	0,0533%	1,0618	1,1534	0,8713	0,0701%	0,0320%	0,0335%
CEZ	CEZ	0,1404%	1,0651	1,1496	0,5882	0,0455%	0,0214%	0,0210%
Komercni Banka	KB	0,0608%	1,0933	1,1799	0,7172	0,0544%	0,0262%	0,0264%
CME	CETV	0,0426%	0,5663	0,7204	0,3285	0,0330%	0,0162%	0,0161%
Telefonica O2	TO2	0,1180%	0,5300	0,9568	0,7339	0,1844%	0,0890%	0,0930%
GRAND AVERAGE		0,08%	0,863	1,032	0,648	0,08%	0,04%	0,04%

6.2 Separate Regressions

The final outcome of our estimation, which is provided in Table 6-2, was quite consistent and very similar to Poland. In the end *semivar 0* has proven to be a risk measure with the most explanatory power also for the Czech Republic. Not only was it significant for all stocks used, it also explained the most variation of returns when used as a single slope variable – it showed in the R-squared as well as the values of information criteria. Similar to Germany and Poland, its coefficients were always negative, in accord with the explanation we gave in 4.3. At any rate, it is clear that a pure threat of loss (which is after all what Semivariance with respect to zero tells us) has more merit for economic agents on the Czech financial market than any other risk measure. Again, such a result is of course in line with what we previously stated about functioning of financial markets in emerging and transitive economies.

Similarity of the two economies in transition was apparent in other aspects – apart from the explanatory power of *semivar 0*, Czech market seems to display similar traits regarding significance of Variance and possibly idiosyncratic risk. We discussed this empirical phenomenon in the section 5.2, in Czech Republic it was the same. CAPM beta was insignificant for all Czech companies; we can thus conclude plainly that systemic risk bears no significance for investors in the Czech environment. Variance, on the contrary, proved to have some explanatory power in 3 cases and it was only marginally insignificant for Erste Bank. As on the Polish market, Variance also had a negative parameter sign for all stocks. Since the systemic component of the total risk was insignificant, we were again led to the possibility that the significance of Variance is driven by the unsystemic component – diversifiable risk. Our tests confirm that.

Now, let us comment on the remaining three risk measures before moving on to the conclusions of the joint regressions. *Dbeta 0* is apparently a useful for measuring risk on the Prague Stock Exchange. It was significant in 3 out of 5 cases; for CEZ, it managed to explain as much as 25% of variation of the CEZ stock returns, which is definitely impressive. *Dbeta u* was significant in only one case, and it exhibited varying parameter signs, so in our final opinion, its explanatory capability on the level of companies was unconvincing and it can be omitted. Finally, s*emivar u* can be omitted as well. Its levels of significance were similar to *Var* although generally lower (because by definition it always brings less information), while at the same time, it could never match the usefulness of *semivar 0*.

6.3 Joint Regression

Estimations of the joint models for the Czech Republic were somewhat similar to Poland. Heteroskedasticity was less of a problem but we are inclined to say that collinearity was even more prevalent than in the Polish case. Thus, in some cases we had to trade some explanatory power in order to quell collinearity. Obviously this was exclusively an issue for *Var, semivar u* and *semivar 0,* especially for the former two. We didn't detect this problem almost at all for the different definitions of systemic risk (beta, *dbeta u*, *dbeta 0*). Nevertheless, as you can observe in Table 6-3, the tests show some clear-cut tendencies.

As we hinted at in the previous subsection, the reliability of Semivariance with respect to zero in explaining variation of stock returns was confirmed for the Czech Republic as well. With Variance and *semivar u*, we raise the same point as for Poland. They were also strongly significant in more than one case, but showed pronounced signs of collinearity (sharply changing parameter values and R-squared upon including or omitting the variable), which was also confirmed by tests. Beta and the two downside beta definitions were significant in some cases and not in others and their parameter signs were somewhat varied, as can be observed in the table. Overall, it was a very similar story to the joint model for Poland. On the other hand, what is quite novel in the Czech Republic were the cases of Komercni banka and Telefonica O2 – you can see in the table that we kept only one explanatory variable. No other risk measure could add enough useful information to be significant. Of course, it is probably also a sign of slight collinearity, because although other variables (mainly beta, *dbeta u, dbeta 0*) were insignificant, R-squared was much higher when they were included.

6.4 Summary of results

In summary, Czech Republic shows remarkable similarity to Poland, which shouldn't be too surprising. Also in this market, Semivariance with respect to zero was the variable with the most capacity to explain variation of stock returns. Its fundamental importance is especially visible in the results of separate regressions. Interestingly enough, this outcome is a little less clear in joint regression segment. In the cases of CEZ and CME, CAPM beta was the most significant variable. On the other hand, Czech Republic was the only one country, were we retained only one regressor even in the joint regressions (the cases of Komercni Banka and Telefonica O2) which is a result worth noting.

The results for the rest of the variables are somewhat mixed and we cannot draw clear conclusions – we will talk about this more in the panel data analysis.

Now let us evaluate the results graphically. The case of CME, shown on Figure 6-1 is quite unreliable – it is a similar case to Germany, if not worse. Although peaks are represented well by the fitted data, the rest is extremely of the observed period is extremely flat.

Figure 6-1: Best fit from Separate regressions: CME

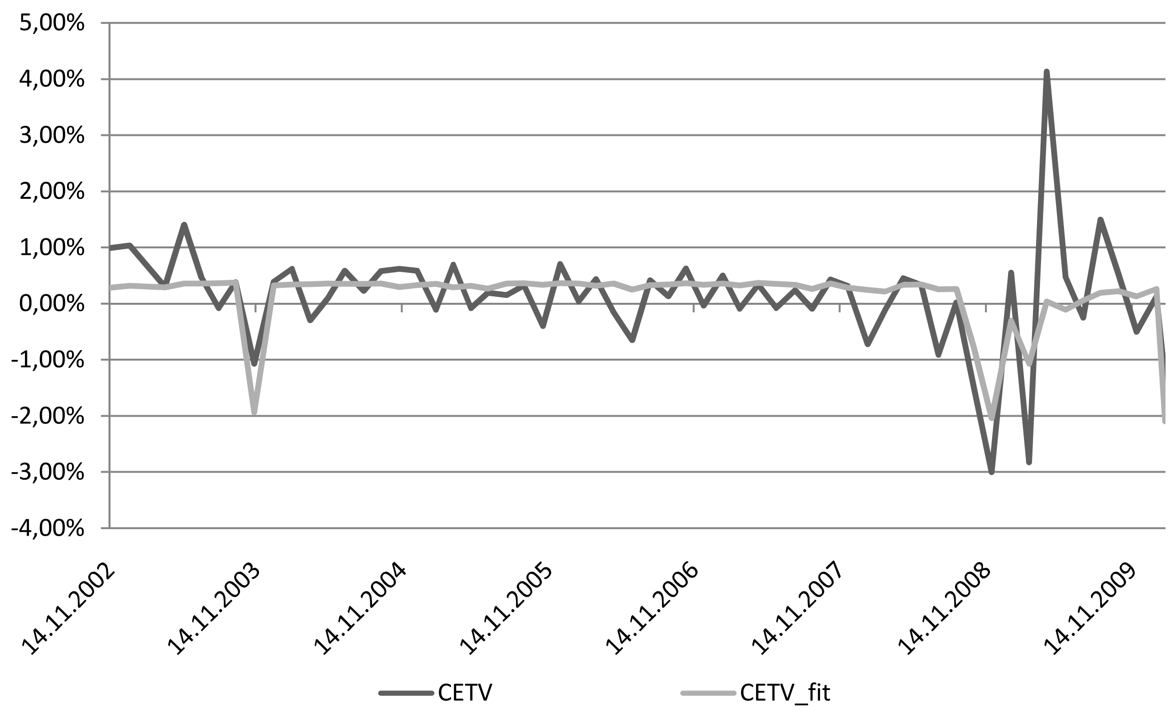


Figure 6-2: Best fit from Joint regressions: Erste Bank

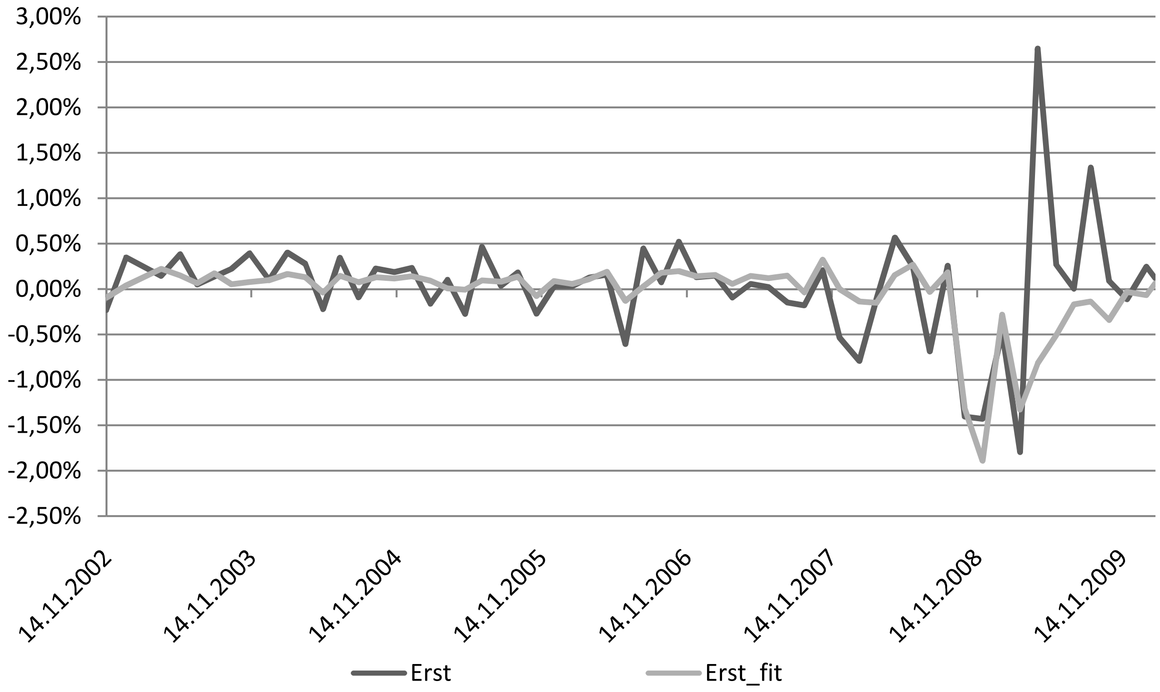


Table 6-2: Results of separate regressions

		Beta			Dbeta u			Dbeta 0		
Company	**Symbol**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**
Erste Bank	Erst	0,0012	0,4774	0,0089	0,0010	0,5675	0,0058	-0,0009	0,7534	0,0017
CEZ	CEZ	0,0018	0,1561	0,0350	0,0025	0,0639	0,0589	-0,0122	0,0001	0,2506
Komercni Banka	KB	-0,0004	0,7720	0,0015	-0,0001	0,9369	0,0001	-0,0052	0,0733	0,0552
Telefonica O2	TO2	0,0000	0,9629	0,0000	-0,0006	0,6396	0,0039	-0,0104	0,0014	0,1661
CME	CETV	-0,0014	0,4696	0,0092	0,0030	0,2352	0,0246	-0,0077	0,0566	0,0623

		Var			Semivar u			Semivar 0		
Company	**Symbol**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**	**Coeff**	**P-value**	**R2**
Erste Bank	Erst	-1,0226	0,1193	0,0420	-1,9732	0,1501	0,0360	-4,2158	0,0001	0,2431
CEZ	CEZ	-1,7020	0,0041	0,1359	-4,4479	0,0008	0,1813	-4,7883	8,25E-06	0,2965
Komercni Banka	KB	-0,9354	0,2298	0,0252	-1,9399	0,1958	0,0292	-3,9665	0,0026	0,1485
Telefonica O2	TO2	-2,25091	0,0263	0,0837	-6,0552	0,0018	0,1587	-7,3731	3,46E-06	0,3169
CME	CETV	-0,77041	0,0571	0,0621	-2,0423	0,0028	0,1459	-2,6485	1,01E-06	0,3440

Table 6-3: Results of joint regressions

		Beta		Dbeta u		Dbeta 0		Var		Semivar u		Semivar 0			
Company	**Symbol**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**R2**	H-C
Erste Bank	Erst	0,0020	0,0735			-0,0059	0,0788					-4,4552	2,17E-05	0,5448	*
CEZ	CEZ	0,0032	0,0030			-0,0100	0,0046					-2,7361	0,0219	0,4369	
Komercni Banka	KB											-5,2857	0,0155	0,0985	*
Telefonica O2	TO2											-7,6059	0,0012	0,1684	*
CME	CETV	-0,0047	0,0017	0,0037	0,0510							-2,3019	0,0053	0,2872	*

Note: only the significant parameters are reported

7. PANEL DATA ANALYSIS OF SELECTED RISK MEASURES

7.1 Model Setup

Detailed analysis on the level of individual stocks helped us gain a more in-depth insight into the workings of selected stock exchanges. Although each company is influenced by a variety of factors, our analysis strongly established that Semivariance with respect to zero is a very reliable risk indicator – across companies as well as countries in our sample. Now we want to use a "bottom-up" approach and verify how these results hold if applied on the sample of companies as a whole. For this we will use panel data analysis. Panel data methods have been used extensively in this context, as we stated before (Estrada, 2000, Chen and Chen, 2004 or Mamoghli and Daboussi, 2008), but always between countries, never on the level of companies.

For the transformed data, we kept only variables that emerged significant in the joint regressions. Since *dbeta u* was significant in merely a handful of cases, we have only retained beta, *dbeta 0* and *semivar 0*. We also included idiosyncratic risk, however we will evaluate separately in the chapter 8. Then, we ran several regressions to assess how the parameter stability and dependability when used on the entire sample of companies. For this end, we primarily employed the "within estimator", or Fixed effects model, which examines how parameters hold within every cross-section. Using the "between estimator" and random effects model to see if the parameters hold also between groups was not a concern to us – such a trait cannot be expected from extremely volatile financial data, nor their risk measures.

The question of course remained whether the data could be estimated together using a Pooled Ordinary Least Squares. To evaluate this, we ran a series of F-tests of poolability/stability of coefficients. To have the maximum of different views, we tested three different variants. To find if the intercept coefficients were common for all companies, we tested the following hypothesis:

H_0: $\mu_i = 0$ for all i against H_0: $\mu_i \neq 0$ for at least one i.

where μ_i indicates the specific fixed effect (a dummy, if you will) for the i-th cross section. The basic formula for the F-test, if we are testing if the intercepts are common for all companies is the following:

$$F_{(N-1),N\cdot(T-1)-K} = \frac{(RRSS - URSS)/(N-1)}{URSS/(N \cdot (T-1) - K)}$$

with *N-1* and *NT-N-K* degrees of freedom, where N is the number of cross sections, in this case, the number of companies; T is the number of time periods and *K* is the number of slope coefficients. RRSS is the residual sum of squares from the restricted model (Pooled OLS) and URSS is the residual sum of squares from the unrestricted model (Fixed Effect).

For the case of the stability of all coefficients, the hypothesis was as follows:

H_0: $\delta_i = \delta$ for all *i* against H_0: $\delta_i \neq \delta$ for at least one *i*.

In that case, δ is the vector of all parameters from the Pooled OLS model while δ_i designates a vector of parameters from a separate estimation for the i-th cross section. The F-test for this hypothesis then compares sum of squared residuals from the Pooled OLS, which is the restricted model, to a sum of squared residuals from separate OLS models for each cross section, added together. It has the following form:

$$F_{(N-1)\cdot(K+1),N\cdot(T-K-1)} = \frac{(RRSS - URSS)/(N-1)\cdot(K+1)}{URSS/N \cdot (T-K-1)}$$

Finally, we also test the stability of slope coefficients only. Our hypothesis will be:

H_0: $\gamma_i = \gamma$ for all *i* against H_0: $\gamma_i \neq \gamma$ for at least one *i*.

where γ is the vector of slope coefficients only. For this final case, the restricted model is the Fixed effect estimator and unrestricted are again separate OLS regressions for every cross section:

$$F_{(N-1)\cdot K,N\cdot(T-K)} = \frac{(RRSS - URSS)/(N-1)\cdot K}{URSS/N \cdot (T-K)}$$

7.2 Germany

Germany was a case remarkable for the homogeneity of its sample – the tests indicated with a very sound statistical significance that intercepts and in some cases also slopes were common. For the German sample, we kept only the variables beta, *dbeta 0* and *semivar 0*. We omitted *dbeta u* because it was significant only in one case. Firstly, we evaluated the market-wide features of Semivariance with respect to zero only. That means we estimated the following equation with the within estimator:

$$Return_{i,t} \ = u_i + \alpha + Semivar\_0_{i,t}$$

The F-statistic for common intercept, as provided by gretl, equaled:

$$F_{10,901} = 0{,}5014$$

with a p-value of *0,8897*, indicating that the fixed effects are statistically insignificant – we can use a common intercept across the sample of selected German companies. Then, we proceeded to separately compute whether the slope of *semivar 0* itself varied across different companies. Our F-test

$$F_{10,902} = 0.984$$

concluded with a p-value *0,4555*. We thus cannot reject the hypothesis the slopes of the variable *semivar 0* are different. Results of the regressions will be provided at the end of the subsection in the Table 7-1.

The story was a little more complicated when we ran a regression for all the selected risk measures – beta, *dbeta 0* and *semivar 0* – together. For starters, tests did indicate that intercept was the same for all companies. Then, the F-test for the stability of all coefficients conluded in favour of the null hypothesis (p-value *0,166*), while the one which examines the stability of slope coefficients only rejected the stability (p-value *0,052*). Therefore the equations in that form are not poolable. However, as you can see in the Table 7-1, the coefficients are fortunately very similar, so it does not make much difference if we use the Pooled OLS or Fixed effect model. The results are also very strongly significant and all variables have expected parameter signs. Interesting is the result for CAPM beta – which again proves that together with *dbeta 0*, it adds statistically important explanatory power to *semivar 0*. Not only was it significant, furthermore, the value of its coefficient is almost identical to the average of coefficients of beta from the joint model on the level of individual companies (refer to Table 4-3). We think this implies that by itself, CAPM beta is still not a dependable risk measure in the German context, only when added to other variables; it becomes a valid indicator of risk to be taken into account by investors.

Table 7-1: Summary of Panel Data Model for Germany

Dependent variable: Return

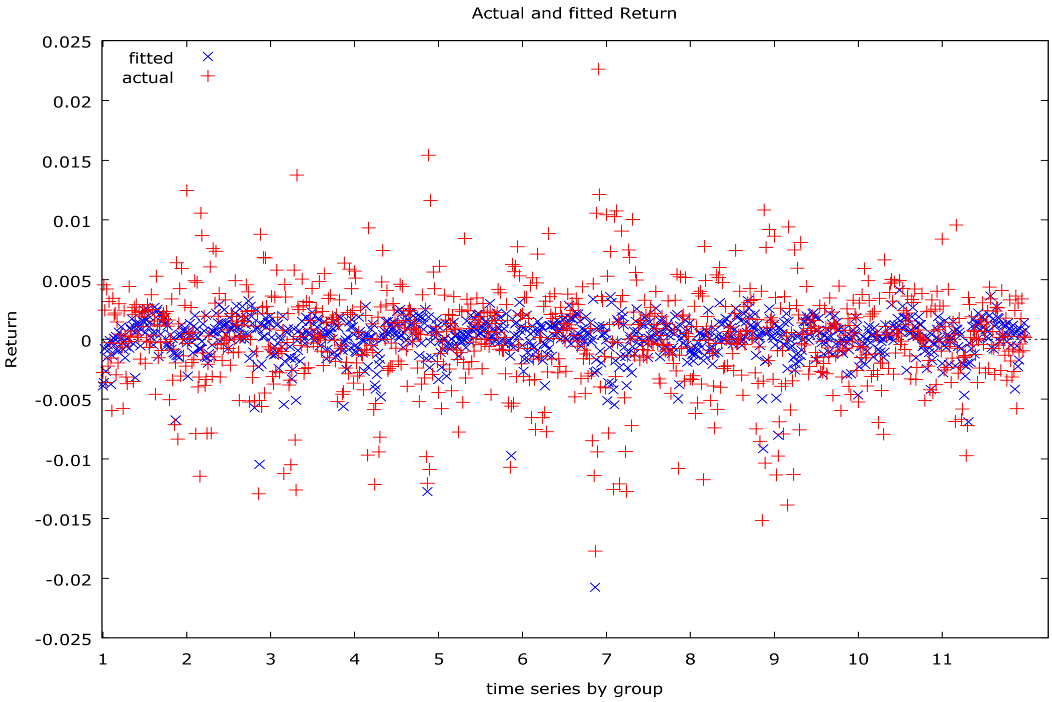
Variable	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
Const	0.001110**	0.001129**	0.0003185	0.0002050
	(0.0001546)	(0.0001558)	(0.0003450)	(0.0003767)
Semivar_0	-3.690**	-3.759**	-3.792**	-3.799**
	(0.3266)	(0.3323)	(0.3389)	(0.3406)
Beta			0.005821**	0.005966**
			(0.0006275)	(0.0006419)
Dbeta_0			-0.004667**	-0.004694**
			(0.0006324)	(0.0006362)
Adjusted R-sq	0.1219	0.1171	0.1973	0.1932
N·T	913			

Standard errors in parentheses

* indicates significance at the 10 percent level

** indicates significance at the 5 percent level

Figure 7-1: Fit of the Pooled OLS model for Germany (horizontal axis are cross-sections)



7.3 Poland

In Poland, we also kept the same variables as for Germany, but we were expecting a less dependable result because the omitted variable *dbeta u* was significant in one third of companies when applying our joint regression models on Polish stocks. The final situation actually provided a better goodness of fit than the German panel regression but it definitely spoke clearly against any pooling – both in terms of common intercept and slopes. We remind that the number of stocks was 6, while number of time observations was 69 and we have used a constant and either one or three regressors.

Let us start with a model using only one regressor – the most significant one – Semivariance with respect to zero. The F-test results for common intercept, stability of all coefficients and stability of slope coefficient only, respectively, were:

$$F_{5,407} = 3.6970$$

$$F_{10,402} = 3{,}2971$$

$$F_{5,408} = 2{,}52713$$

with respective p-values of *0.0027, 0.0004* and *0.0286*. As we said in the above, this rejects poolability on the level of common intercept and also same of the variable *semivar 0*. Nevertheless, in the

Table 7-2, you can see that both Pooled OLS and Fixed Effects/Within estimator provide quite a high goodness of fit, provided that panel data estimation is somewhat restrictive.

How did Poland fare, when we included the remaining two risk measures – beta and *dbeta 0*? Firstly, let us evaluate the relevant F-statistics.

$$F_{5,405} = 5{,}0154$$

$$F_{20,390} = 3{,}2149$$

$$F_{15,396} = 2{,}5594$$

The first one yields that intercepts are not common with a very low p-value of *0.00018*. The remaining two, which test stability of all coefficients and stability of slope coefficients only also reject the null hypothesis with respective p-values of *0.00005* and *0.00117*. Therefore, these results show that Poland is a much less homogeneous market than Germany.

Nevertheless, although this indicates that the models should not be pooled in the reliability of the regressions seems remarkably sound judging by the fit and significance of the parameters (again visible in the last two columns of

Table 7-2). Our doubts about low fit due to omission of *dbeta u* were also dispersed– what is more, R-squared and significance of parameters was even higher than in the case of Germany. Although individual slopes for the risk measures we selected might be different, their market-wide importance in the Polish context is undeniable.

Table 7-2: Summary of Panel Data Model for Poland

Dependent variable: Return

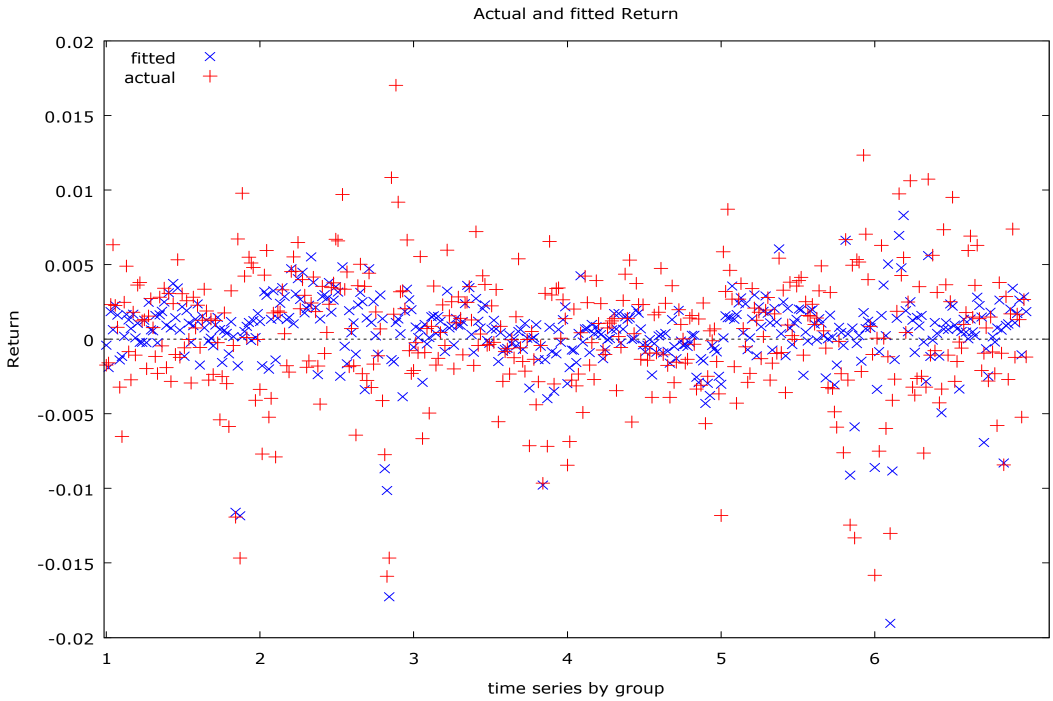
Variable	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
const	0.002164**	0.002275**	0.0005484	0.0006969
	(0.0002268)	(0.0002243)	(0.0005766)	(0.0006022)
Semivar_0	-6.061**	-6.437**	-6.300**	-6.659**
	(0.4796)	(0.4795)	(0.4880)	(0.4848)
Beta			0.006089**	0.006382**
			(0.0007599)	(0.0007714)
Dbeta_0			-0.004217**	-0.004530**
			(0.0007226)	(0.0007117)
Adjusted R-sq	0.2776	0.3031	0.3723	0.4016
N·T	414			

Standard errors in parentheses

* indicates significance at the 10 percent level

** indicates significance at the 5 percent level

Figure 7-2: Fit of the Fixed effect model for Poland (horizontal axis are cross-sections)



7.4 Czech Republic

Since Czech Republic is such a small country and its stock market is composed of only very limited number of listed companies, we would expect a higher degree of homogeneity represented by a better fit of panel data methods. This wasn't entirely true according to the results – they were quite mixed. Measured only by the R-squared obtained, they were better in the case of Germany but worse than for Poland.

Semivariance with respect to the mean has proven to have a fundamental influence on returns of Czech stocks also from the panel data perspective. Firstly again the test on common intercept. According to the statistic

$$F_{4.284} = 3{,}6813$$

we receive a p-value of *0.0062*, so we can reject the hypothesis of common intercept for the sample of companies. If we examine the poolability of slope coefficients, the F-test:

$$\mathrm{F}_{4.285} = 1{,}2415$$

gives a p-value of *0,2935*, so we cannot reject the hypothesis of same slope coefficients. This is interesting and confirms the universal importance of *semivar 0*, even though coefficients varied in the separate regressions. The estimates can be referred to in the Table 7-3. Note how the value of the coefficient is on the lower bound of all *semivar 0* parameter estimates from the separate regressions for individual stocks.

The situation was different for the regression including also beta and *dbeta 0*. A feature worth noting is that in the case of the Czech Republic, the other two added risk measures increased the overall goodness of fit only little, at least compared to both Germany and Poland. Also, they were less significant than the same variables in the other two countries. This was again caused by higher heterogeneity of the Czech sample (recall that in the joint regression section for the Czech Republic, *dbeta 0* was significant only 2 times out of 5). It also evident from the tests of poolability:

$$F_{4.282} = 4{,}0872$$

provides p-value *0,0031* and thus firmly rejects common intercept for the whole panel. For the sake of completeness, let us finish with the test of poolability of slope coefficients only:

$$F_{15,275} = 1{,}9615$$

with low p-value of *0,0182*.

Table 7-3: Summary of Panel Data Model for the Czech Republic

Dependent variable: Return

Variable	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
const	0.001913**	0.002013**	0.0007006	0.0003215
	(0.0003145)	(0.0003101)	(0.0006280)	(0.0006564)

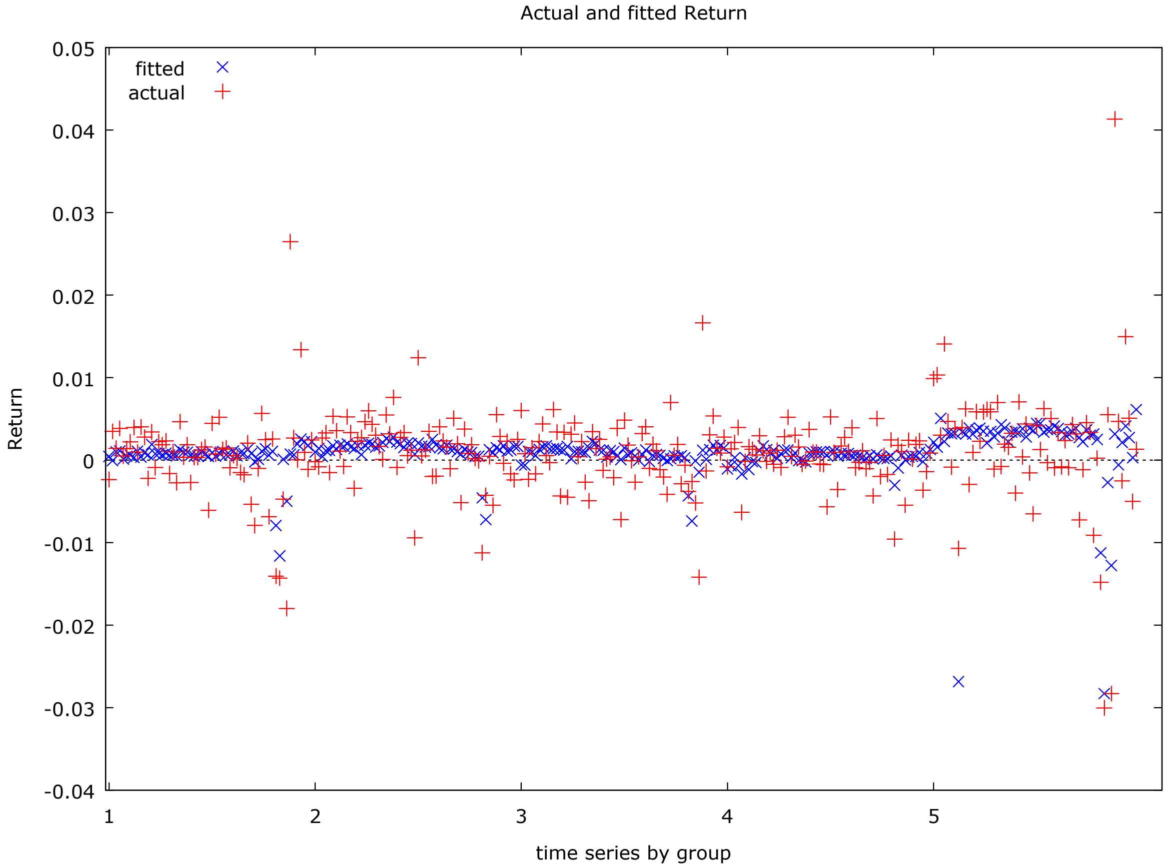
Semivar_0	-3.027**	-3.306**	-3.649**	-3.821**
	(0.3126)	(0.3164)	(0.3952)	(0.3898)
Beta			-0.0001650	0.0009547
			(0.0006335)	(0.0007241)
Dbeta_0			0.004482**	0.002977
			(0.001869)	(0.001889)
Adjusted R-sq	0.2430	0.2702	0.2559	0.2867
N·T	290			

Standard errors in parentheses

* indicates significance at the 10 percent level

** indicates significance at the 5 percent level

Figure 7-3: Fit of the Fixed effect model for the Czech Republic (horizontal axis are cross-sections)



8. ASSESMENT OF IDIOSYNCRATIC RISK

8.1 Germany

In Germany as a developed market, unsystemic risk should not bear any importance for stock returns. Nonetheless, given that both systemic risk and total risk were principally insignificant in separate regressions, we couldn't be quite so sure. Our market-wide panel data assessment validates this assumption in the end, but still, we found some inconsistencies on the level of individual companies.

Table 8-1: Idiosyncratic risk as a single regressor for German stocks

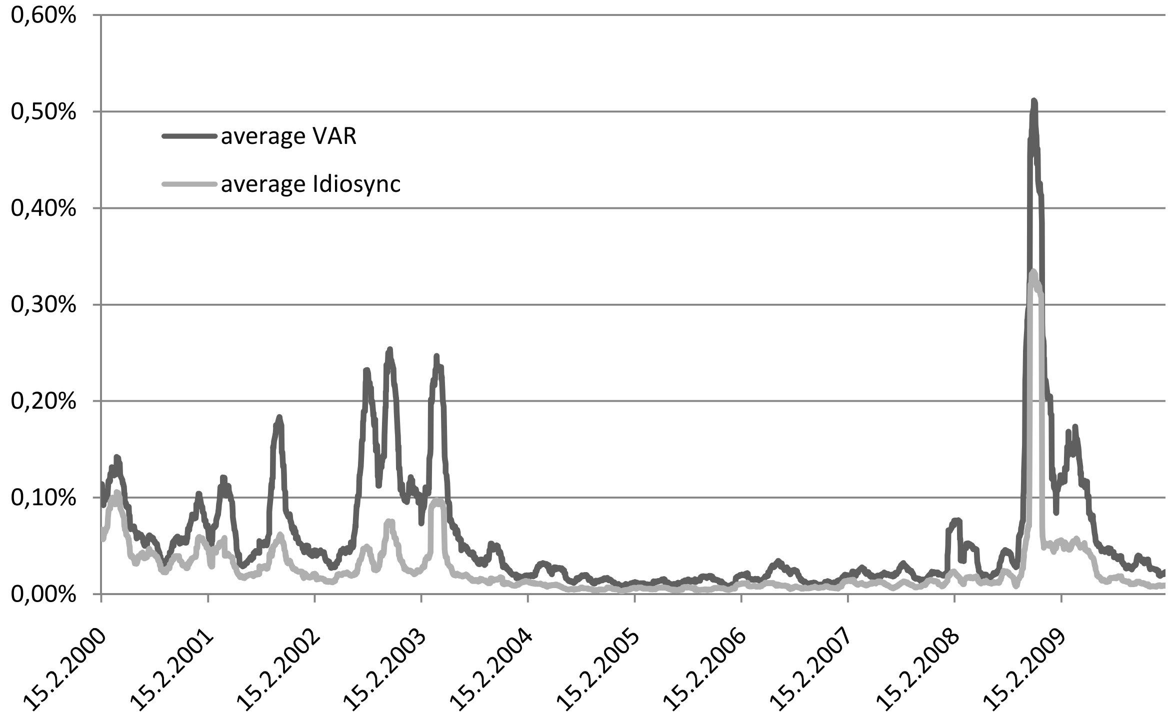
			Idiosync	
Company	**Symbol**	**Coeff**	**P-value**	**R2**
EON	EON	-0,4899	0,5561	0,0007
Siemens	Sie	-0,8717	0,4312	0,0077
Bayern	Bay	1,3101	0,0905	0,0350
Aliianz	Alv	-1,1496	0,1637	0,0238
BASF	Bas	-1,4234	0,2098	0,0193
Deutsche Bank	Dbk	-2,0837	0,0107	0,0777
SAP	SAP	1,0589	0,2047	0,0198
Daimler	DAI	-0,6087	0,6158	0,0031
Deutsche Telekom	Dte	-0,6185	0,6578	0,0024
RWE	RWE	0,2198	0,8632	0,0004
Munich Re	MUV	0,9936	0,3179	0,0123

In Table 8-1, you can see results of a series of estimations which regressed returns of each stock on a constant and its unsystemic risk. In the absolute majority, we find the expected result – insignificance of idiosyncratic risk. However, there are two exceptions – marginal significance for Bayern (at 10% level) and very sound significance in case of Deutsche bank. Even so, the variability of stock returns explained by idiosyncratic risk is often bigger than if we would use CAPM Beta or Variance.

Since idiosyncratic risk is a component of total risk, we decided to compare two. We plotted a time series of averages of these two risk measures in

Figure 8-1 and made an interesting discovery. It is clearly visible that both Variance and *idiosync* move very closely together. That means the unsystemic component of total risk in Germany is very important, which is also in line with the insignificance of beta, or systemic risk, in the separate regressions.

Figure 8-1: Average Variance and Idiosyncratic risk across German stocks



Let us proceed to the outcomes of our panel data model for idiosyncratic risk. F-tests of poolability confirmed again the remarkable trait of German stocks – common intercept, but they logically dismissed the hypothesis of shared slopes. The important outcome of course is the insignificance of unsystemic risk as an explanatory variable on the level of overall market. For comparison, we included the Random effects model which yields very similar results to Pooled OLS but also bears a notable interpretation. Breusch-Pagan test as offered by gretl rejected the use of Random effects only marginally (p-value *0,11*) and Hausman test confirmed it strongly with p-value of *0,65*. After all, this fits perfectly the notion of unsystemic risk – it is a factor specific for every company but it's not time-invariant - an ideal representation of idiosyncratic risk of a stock.

Table 8-2: Panel Data Models using Idiosyncratic Risk for Germany

Dependent variable: Return

Variable	Pooled OLS	Fixed Effects	Random Effects
const	0,0002128	0,0002176	0,0002128
	(0,0001533)	(0,0001543)	(0,0001533)
Idiosync	-0,3965	-0,4152	-0,3965
	(0,2793)	(0,2834)	(0,2793)
Adjusted R-sq	0,0011	-0,0059	
N·T	913		

Standard errors in parentheses

* indicates significance at the 10 percent level

** indicates significance at the 5 percent level

8.2 Poland

Regarding diversifiable risk, our preliminary assumptions about Poland, being a country in transition, were different than for Germany. As we stated in the section 5, results from our separate regressions indicated that total risk is significant while its systemic component beta is not. This would indeed suggest that the unsystemic component carries statistically important information, meaning it is priced on the Polish stock market. This is confirmed very firmly by our tests below.

We present a summary of individual regressions using Idiosyncratic risk as the single slope variable in

Table 8-3. The results signify a very powerful trend present for the selected polish stocks – unsystemic risk was insignificant for returns of all but one company – BZW.

Table 8-3: Idiosyncratic risk as a single regressor for Polish stocks

		Idiosyncratic Risk		
Company	**Symbol**	**Coeff**	**P-value**	**R2**
Bank Pekao	PEO	-6,7063	0,0769	0,0460
KGHM	KGH	-4,4094	0,0207	0,0773
PKN Orlen	PKN	-9,9918	0,0023	0,1308
TPSA	TPS	-8,8825	0,0029	0,1248
Bank Zachodni WBK	BZW	-0,4598	0,9037	0,0147
Asseco	ACP	-3,2956	0,0013	0,1445

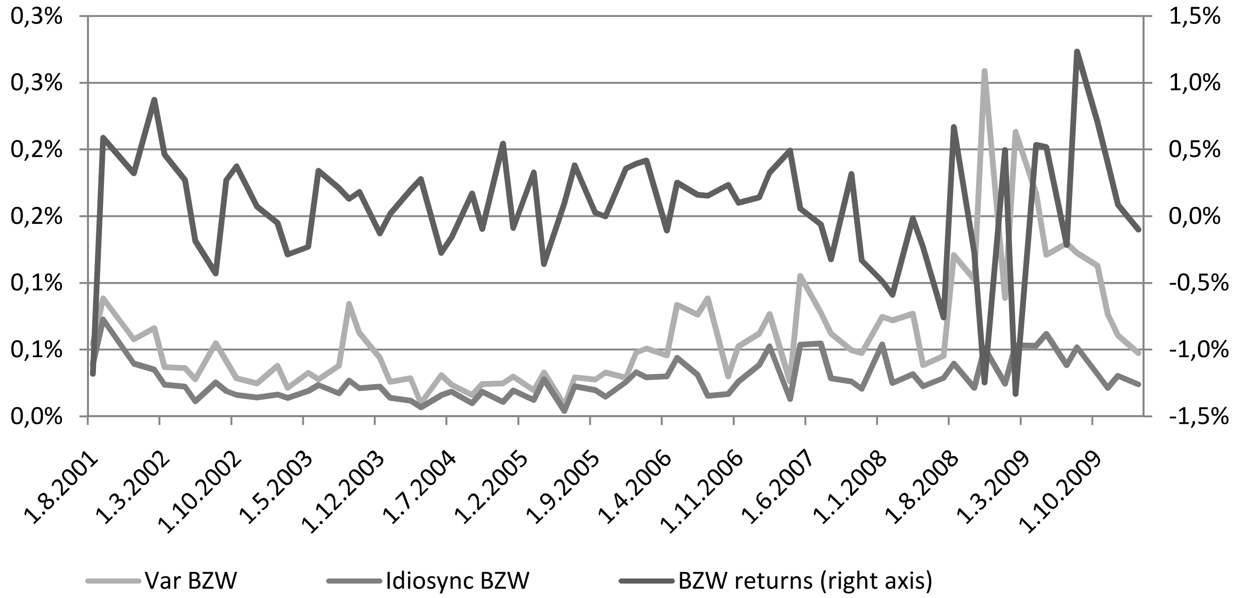
To obtain more insight into why this might be, we inspected the plot of moving averages of returns, together with idiosyncratic and total risk for BZW. For comparison, we have done the same with Asseco Poland, which on the contrary achieved the best significance and R-squared using idiosync as an explanatory variable. You can see the charts for BZW and ACP in Figure 8-2 and

Figure 8-3, respectively.

Indeed, detailed inspection of the graphs gives us a clue. First thing to note about the differences between *ACP* and *BZW* is that in the case of Asseco, idiosyncratic risk moves extremely closely with variance. Their correlation over the period reaches poignant *96%*. This confirms the notion that in transitive and emerging economies, total risk is actually determined by the unsystemic element for the most part. Whilst the correlation between *Var* and *Idiosync* of *BZW* is also fairly high at 71%, the graph itself tells clearly that they are not so closely connected.

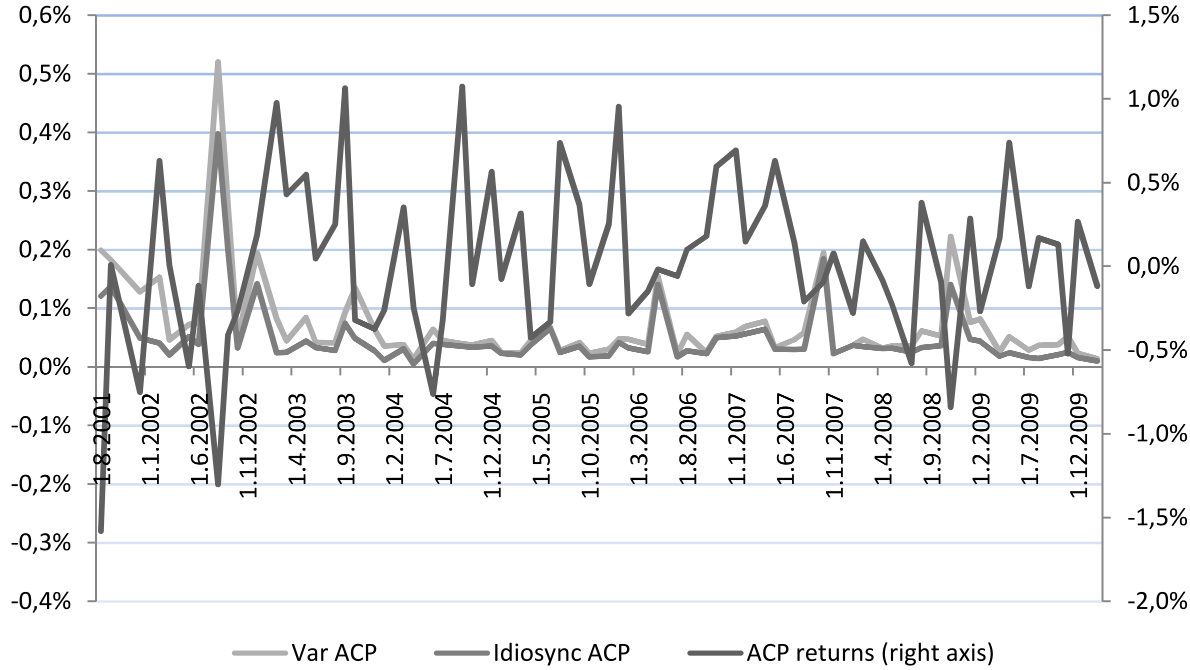
The chart illustrates adequately also another feature – the correlation of the risk measures with the returns themselves. If we look at Asseco again, we can observe the relationship is negative – one can clearly see how dips in returns are almost always connected with sharp spikes of the risk measures. This is much less apparent in the case of Bank Zachodni. Correlation also confirms this, it is *–20%* for *BZW* but *–41%* for *ACP*. However, there is one last issue in this discussion. In case of *BZW*, Variance is significant but Idiosyncratic risk is not – that should leave beta, being the systemic component, as highly significant. However, as our results from the separate regressions for Poland show it is on the contrary strongly insignificant. That means that both systemic and unsystemic components by themselves are insignificant but their sum, the total risk is, which is strange. We were not able to answer this one question.

Figure 8-2: Bank Zachodni WBK – total and unsystemic risk[4]



[4] We remind that in both charts, the returns are moving averages.

Figure 8-3: Asseco Poland - total and unsystemic risk



We move on to the evaluation of unsystemic risk in context of panel data. The results were actually an inverse of the German ones in all aspects. Firstly, test provided by gretl concluded that intercepts are different for different companies – in line with our results for panel data tests of *semivar 0*. However, F-test for stability of the coefficient of *idiosync* had a very low statistic of

$$F_{5,408} = 1,1229$$

and a correspondingly high p-values of *0,3474* implying that the slopes for *idiosync* indeed are the same for all cross-sections. Coupled with the high significance of this coefficient in the panel data regression (see Table 8-4 below) this indicates that the explanatory power and unique information that Diversifiable risk carries is extremely important for the whole Polish market – even the exception of Bank Zachodni was apparently overruled, given the results. For completeness, a random effects estimator was confirmed by Breusch-Pagan test against Pooled OLS but Hausman test concluded against it and in favour of Fixed Effects model (with p-values *0,0076*).

Table 8-4: Panel Data Models using Idiosyncratic Risk for Poland

Dependent variable: Return

Variable	Pooled OLS	Fixed Effects	Random Effects
const	0.001299**	0.001491**	0.001299**
	(0.0002774)	(0.0002848)	(0.0002774)
Idiosync	-3.191**	-3.850**	-3.191**
	(0.6520)	(0.6935)	(0.6520)
Adjusted R-sq	0.0526	0.0653	
N·T :	414		

Standard errors in parentheses

* indicates significance at the 10 percent level

** indicates significance at the 5 percent level

8.3 Czech Republic

Results for Czech Republic were along the lines of its post-communist peer Poland. Based on the results from separate regressions, it also exhibited some signs indicating that idiosyncratic part of Variance possibly might have a correlation with stock returns. These signs were verified with specific calculations.

Table 8-5: Idiosyncratic risk as a single regressor for Czech stocks

		Idiosyncratic Risk		
Company	**Symbol**	**Coeff**	**P-value**	**R2**
Erste Bank	Erst	-7,4867	0,0053	0,1285
CEZ	CEZ	-10,5650	0,0012	0,1685
Komercni Banka	KB	-4,1624	0,1105	0,0441
Telefonica O2	TO2	-2,7179	0,0692	0,0568
CME	CETV	-0,9249	0,0653	0,0508

Table 8-5 sums up results of separate regression of stock returns using only unsystemic risk as an independent variable. We can see that the coefficient ended up as marginally insignificant only for Komercni Banka; otherwise its influence on the dependent variable is undeniable. Even in that case however, it would explain more of the KB's stock returns variation than Total risk itself (compare with Table 5-2).

This is also implied from an inspection of correlation coefficients – the correlation matrix below illustrates it perfectly, including the extremely high correlation between total risk and idiosyncratic risk, which again reinforces our conviction that, apart from maybe extreme events, volatility is almost exclusively driven by risk factors specific to the stock.

KB returns	Var_KB	Idiosync_KB	
1.0000	-0.1587	-0.2099	KB returns
	1.0000	0.9145	Var_KB
		1.0000	Idiosync_KB

Figure 8-4: Komercni Banka – total and unsystemic risk

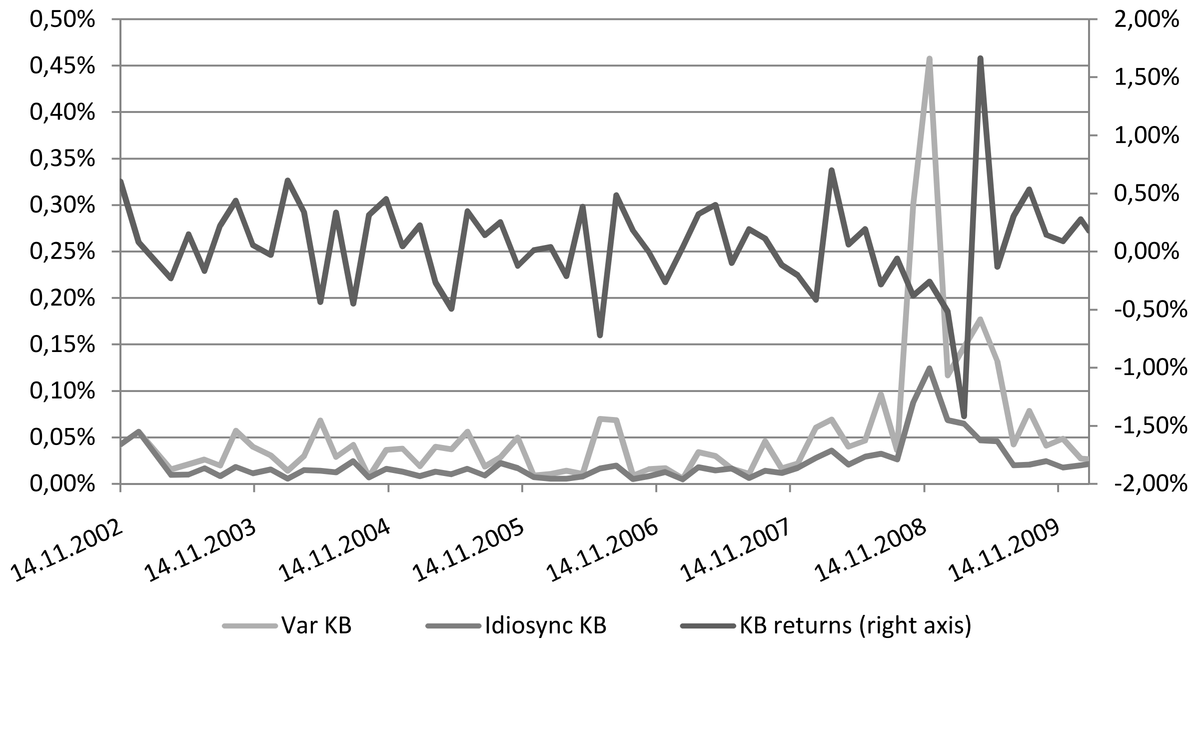
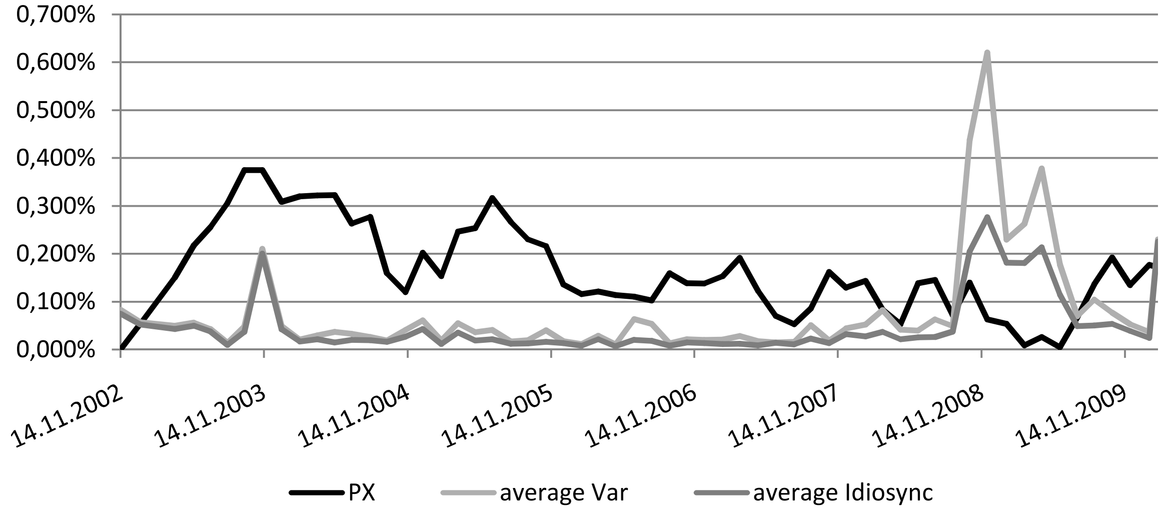


Figure 8-5: PX index – average total and unsystemic risk



Hence, even though Komercni Banka might be a stock the least influenced by some idiosyncratic risk factors among the selected Czech companies, observe Figure 8-4 for a similar pattern we could see with Asseco Poland. Apart from the period in mid-2009, the negative correlation is mayhap less pronounced, but still visible. The trend is actually market-wide – we have done the same with the return of the overall index PX with average total and idiosyncratic risk and plotted them in

Figure 8-5. Also note how the lines of Variance and unsystemic risk tightly follow one another most of time – actually, their correlation on average is 93%.

We will finalize these results in a panel data model. The F-statistic for the test on the issue whether intercepts are the same is equal to

$$\mathrm{F}_{4,284} = 1{,}4667$$

the corresponding p-value is *0,2124* which leads to accept the null hypothesis that the intercept are the same for all cross-sectional units. Regarding the commonness of slopes on the hand, we have to reject it very strongly with a very high statistic of the corresponding F-test.

$$F_{4,285} = 7{,}62297$$

That accounts for a p-value around zero. This result is very decisive, but we still remark that in its spite, the estimations, summed up in

Table 8-6, have shown strong significance of the variable idiosync on the level of panel data. This characteristic obviously might have its nuances from company to company, its general importance, judging also from our analysis of correlation coefficients and charts, is ensured.

Table 8-6: Panel Data Models using Idiosyncratic Risk for the Czech Republic

Dependent variable: Return

Variable	Pooled OLS	Fixed Effects	Random Effects
const	0.001127**	0.001257**	0.001127**
	(0.0003594)	(0.0003632)	(0.0003594)
Idiosync	-0.6437**	-0.9285**	-0.6437**
	(0.2813)	(0.3092)	(0.2813)
Adjusted R-sq	0.0144	0.0208	
N·T : 290			

Standard errors in parentheses

* indicates significance at the 10 percent level

** indicates significance at the 5 percent level

9. CONCLUSIONS

This thesis focused on how various methods of measuring risk financial can explain variations of stock returns. The rationale for this was mainly threefold: violated assumptions of the mean-variance and CAPM frameworks, poor empirical fit of traditional measures such as Beta and finally the intuitive flaw of measuring upside equally as downside and calling it risk in the first place. We have undertaken our assessments on a sample of stocks from three Central European countries – Czech Republic, Germany and Poland. Moreover, what makes this contribution different from other works on the same topic is that we have used time-series data on individual companies, rather than a cross-section of countries, which is the norm.

Our results were quite consistent and also universal – regardless of the country. Key outcome number one is that downside risk measures are indeed highly significant in explaining variations of excess stock returns. Semivariance with respect to zero offered the best fit in most cases – either by itself or even when used with other risk indicators. CAPM Beta was generally insignificant when used as a single regressor but proved it bears some information capacity when used alongside other variables – especially Semivariance with respect to zero. This result was confirmed using both standard time-series OLS on particular stocks and with panel data structure, as well. This challenges previous literature in the way that downside risk measures aren't normally considered influential in developed markets. We have proven the contrary for Germany. However, we found that downside risk measures explain better the downside part while they have trouble fitting the data during peak periods.

We also analysed thoroughly the issue of diversifiable risk (often called idiosyncratic), which is the component of total risk. We estimated whether idiosyncratic risk has any explanatory value in explaining variation of stock returns. In this case, our results are in line with literature – we found it has some importance for stock returns in the Czech Republic and Poland but rejected it as insignificant for Germany.

We think this is a useful contribution to the domain that can be also expanded in several ways. Obviously, the method of running regressions on the level of companies instead of whole countries can be applied on other countries as well.

Moreover, researchers could assess how the risk measures we found significant interact with other variables that are not necessarily risk indicators by themselves – e.g. the Fama-French factors, macro-economical indicators or for example political or social variables. This way, we would obtain a more general multi-factor model that is better suited to modern evidence on investor preferences (given that CAPM beta doesn't provide much explanatory power anymore). Finally, another possible continuation could regard idiosyncratic risk and analyse it even more deeply – for example what are its key factors, how do they interact among each other and how can we adjust our methods to them.

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