Conditional Volatility Exposures in Asset Pricing in the Downside and Classical Framework

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Abstract

In this paper the variance in the residuals of the market model or downside market model is time-varying and has an association with the conditional volatility of the market. This paper empirically models conditional volatility exposures for log-daily returns on assets listed on the Warsaw Stock Exchange. For this purpose, a Factor-ARCH type process is adopted where the exposure of asset volatility to market portfolio (WIG) volatility is estimated in the variance equation. All analyses are made in the downside and standard asset pricing frameworks. This article provides evidence that the conditional volatility of returns on assets (portfolios) has a statistically significant contemporaneous association with market portfolio volatility. The downside volatility beta is statistically higher than its classical equivalent. There is evidence of a significant relationship between classical systematic risk and the average returns on individual assets and portfolios. The results of cross-sectional regressions show that both volatility betas are also priced.

JEL classification codes: C21, C22, G12
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1. Introduction

The Capital Asset Pricing Model (CAPM) continues to be one of the basic tools describing the relationship between a rate of return and risk. One of the assumptions of classical finance, to which the aforementioned theory belongs, is the assumption of variance as the key measure of risk. Investors treat very high and very low returns as equally undesirable. It is, however, widely argued that investors usually do not perceive returns above a threshold as bad, giving rise to the downside risk framework. Therefore, given the evidence of asymmetry in return distributions, the use of a classical pricing model to explain volatility of returns, and thereby, to treat the beta as a measure of systematic risk, is questionable. Taking the foregoing into account, an alternative measure of systematic risk––the downside beta––is considered here (Galagedera, 2007). In this research three measures of the downside beta widely discussed in the literature are considered. In the CAPM with downside beta, the risk premium is always positive and in many cases statistically significant. Many studies showed that downside measures particularly downside beta is a better risk measure than CAPM beta in explaining high average stock returns (Post, van Vliet, 2006). Many studies of emerging markets reveal that different downside measures are better for explaining variability in the cross-section of returns than classical measures (Estrada, 2002, 2007). Studies using individual securities traded on the London Stock Exchange, Paris Stock Exchange or in the Asia Pacific region also demonstrate that downside risk measures explain a greater proportion of securities returns than the beta coefficient (Pedersen, Hwang, 2007; Artavanis et. al., 2010, Alles, Murray, 2013). They found evidence that downside beta is priced by investors. It should be pointed out that bearing a downside risk is not simply compensation for the CAPM beta risk or for the risk expressed in other economic measures or categories, such as co-skewness, co-kurtosis, liquidity or capitalization (Ang. et al., 2006), (Markowski, 2013).

The standard versions of the CAPM model are often insufficient for describing the relationship between risk and return. The foregoing does not result from the erroneous specification of the model, but from the ineffectiveness of the market portfolio's approximation, or from erroneous or insufficient market model specification. In addition, yet another aspect of risk is brought up here. Residual variances in both classical and downside market model equations are time-varying and have an association with the conditional volatility of the market as a whole. The reason for this is the relationship between price volatility and turbulence in financial markets. Investors may be more perceptive to news in periods of relatively high market volatility, and such sentiments may result in price volatility of individual assets increasing (Veronesi, 1999). In other words, it may hypothesize that market volatility provides additional information, which in return may result in the volatility of returns on securities changing. In addition, market volatility affects the volatility of stock returns contemporaneously. The nature of the processes typical for financial markets, such as irregularity of news about companies or macroeconomic variables, suspension of trading, or correlations between the dynamics of various instruments causes volatility to be a time-varying process, whose prominent feature is a clustering of variances. Hence, stock return volatility should be modelled as a conditional volatility process that is a function of the conditional volatility of market portfolio returns. Such an approach provides a new measure of sensitivity to market volatility, referred to as the conditional volatility beta (Cai et al., 2006). This measure is determined using the equation for the conditional volatility of stock returns. It is therefore appropriate to examine the statistical relevance and co-existence of a return beta and return volatility beta. Studies conducted using conditional volatility series show that the estimated volatility betas are positive and significant. Cai et. al. (2006) suggest that for daily returns, systematic volatility exposures are significant variables in the cross-sectional regression of market returns. Other analyses reveal that the volatility beta is not priced (Li and Galagedera, 2008).

Previous attempts at modelling equity market volatility conditionally refer to the association between country-specific exposure and that of the world market. The results were compared in the developed and emerging capital markets. The contribution of this paper is that this methodology was used to search the co-movement of company-specific conditional volatility and that of the Polish market. It is pointed out that the level of return exposure and volatility exposure in the conventional and downside frameworks depends on the size of the company or belonging to a particular sector of the economy and in the consequence that the risk is priced.

The joint estimation of beta and conditional volatility beta requires that ARCH type models be applied, and in particular, the Factor-ARCH type models. They are used to co-estimate the classical or downside beta and the conditional volatility beta. They also demonstrate that the multidimensional models of conditional volatility may be significantly simplified through the determination of the common source of volatility, which in this case is the market (Bollerslev, Engel, 1993). Therefore, in order to estimate the level of exposure of conditional volatility for a given stock to the conditional volatility of the market, the conditional volatility of the market (stock exchange) portfolio is regarded as the exogenous variable in the variance equation. This volatility is estimated first using a GARCH model.

The empirical analysis of volatility exposure is carried out under the conditions of the Polish capital market. The analysis covers single companies listed on the WSE and equally weighted portfolios based on their stocks. This paper aims at estimating return betas and conditional volatility betas, with special consideration given to the downside framework in risk measurement and to the verification of whether these variables have an effect on the pricing of capital assets.

2. Methodology

A downside risk framework in the pricing of capital assets is based on the lower partial moments (Galagedera 2009). The application of such measures means that investors perceive a set of investment opportunities not through the prism of a mean-variance (m-s2) combination, but as a relationship between the mean and the lower partial moment (m-lpm). The key term for this type of measure is the threshold. The lower partial moment may be formulated as follows:

$$LMP_i^k = \frac{1}{T-1} \sum_{t=1}^{T} lpm_{it}^k \ , \tag{1}$$

where:

$$lmp_{it} = \begin{cases} 0 & dla \ \ R_{it} \geq 1 \\ R_{it} - l & dla \ \ R_{it} < 1 \end{cases} \ , \tag{2}$$

where: R_{it} is the return in time t for company I, T is the length of the time series, and 1 is the threshold or return assumed by an investor. The downside betas may be expressed as follows (Price et al. 1982):

$$\beta_i^D = \frac{CLMP_i^2}{LPM_i^2} \quad , \tag{3}$$

where $CLMP_i^2$ means the asymmetric mixed lower partial moment squared for company i calculated as follows (Rutkowska-Ziarko 2013):

$$CLMP_i^2 = \frac{1}{T-1} \sum_{t=1}^{T} (R_{it} - 1) lpm_{Mt} \ , \tag{4}$$

where:

$$lmp_{Mt} = \begin{cases} 0 & dla \ R_{Mt} \geq 1 \\ R_{Mt} - l & dla \ R_{Mt} < 1 \end{cases} , \tag{5}$$

and R_{Mt} is the market portfolio return in time t.

In the theory, there have been many varieties of downside beta β^D distinguished with different formulas and reference points l (Estrada 2002, 2007). Bawa and Lindenberg, as well as Hogan and Waren, developed the CAPM model in which the measure of systematic risk is the downside beta (BL-beta) expressed as follows (Hogan and Warren, 1974), (Bawa and Lindenberg, 1977), (Chow, Denning, 1994):

$$\beta_i^{BL} = \frac{E[(R_{it} - R_f) min(R_{Mt} - R_f; 0)]}{E[min(R_{Mt} - R_f; 0)]^2} \ , \tag{6}$$

where R_f is the risk-free rate. When there is no appropriate risk-free rate, zero may be considered the threshold. Then, equation (6) becomes (Li, Galagedera, 2008):

$$\beta_i^D = \frac{E[R_{it} \, min(R_{Mt};0)]}{E[min(R_{Mt}; 0)]^2} \ . \tag{7}$$

The downside beta β_i^D is estimated in the following mean equation[1]:

$$R_{it} = \beta_i^D min(R_{Mt},0) + \xi_{it} \tag{8}$$

where $\xi_{it} \sim N(0,\sigma^2_{it})$.

The variance equation in the ARCH model with the exogenous variable is then given by (Cai et al., 2006):

$$\sigma^2_{it} = \gamma_{i0} + \gamma_{i1}\xi^2_{i,t-1} + \beta^D_{iv}\hat{\sigma}^2_{Mt} \ , \tag{9}$$

where σ^2_{it} is the conditional variance of a given sector index , $\hat{\sigma}^2_{Mt}$ is the conditional variance of the market portfolio, and β^D_{iv} is the conditional volatility beta. For the classical market model, the estimated equations are as follows:

$$R_{it} = \alpha_i + \beta_i R_{Mt} + \xi_{it} \text{ , where } \xi_{it} \sim N(0,\sigma^2_{it}) \tag{10}$$

$$\sigma^2_{it} = \gamma_{i0} + \gamma_{i1}\xi^2_{i,t-1} + \beta_{iv}\hat{\sigma}^2_{Mt} \tag{11}$$

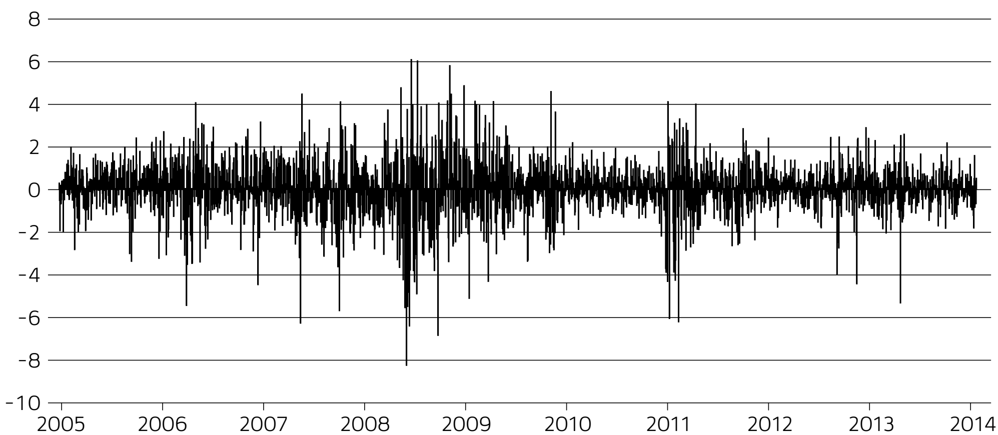
[1] Where the constant is included in the mean equation $R_{it} = \alpha_i^d + \beta_i^d (min(R_{Mt};0)) + \xi_{it}$, the downside beta is calculated according to the following formula: $\beta_i^D = \beta_i^d + \alpha_i^d \, E[min(R_{Mt};0)]/E[min(R_{Mt};0)]^2$ (Galagedera, 2007).

The conditional volatility betas measure the response of contemporaneous co-movements in a given stock, and the volatility of market index returns. Low (high) values of this measure indicate that the volatility of a given stock is less (more) receptive to movements in market index volatility. These measures are estimated using the two-step maximum likelihood method (MLM). The first step involves determining the conditional variance of a stock market index using the GARCH(1.1) model with a constant. The second step consists in estimating the conditional volatility of stocks, where the main equation is the market model (equation 8 and 10), and the variance equation (equations 9 and 11) includes the market index conditional variance estimated in the first step.

3. Data

The dataset comprises a time series of log-daily returns on companies listed on the WSE[2]. The sample period covers the years from 2005 to 2014 and includes 2,502 observations. The analysis comprises all the companies listed on the WSE in the aforementioned period for at least 8 years. Based on the aforementioned assumptions, the analysis covers 195 companies, including 49 large, 55 medium and 91 small companies. The names of the companies are given using a three-letter abbreviation form in accordance with their naming adopted on the WSE. The WIG index is used as the market portfolio approximation. Figure 1 presents daily returns on the WIG index. This illustrates series of periods of the increased and decreased variance of returns on the WIG index, which means that the variance clustering effect is present. The theories explaining the reasons for such a phenomenon, as referred to in the introduction, are associated with the inflow of information to the market. Investors base their decisions on actual information, which is a key factor that determines their choices. The inflow of information is very often irregular, serial, and its impact on the market pricing of given assets varies. Such situations result in periods of increased and decreased price volatility.

Figure 1. Daily Return from WIG Index for 2005–2014



Source: Author's calculations

[2] The closing prices of shares are taken from the WSE quotation database available at www.gpw.pl.

The clustering of variances may primarily be observed in periods of strong increases and, in particular, decreases in stock prices, which result from market distortions caused by relevant news. Such news causes changes in prices and leads to an increase in their volatility. Such an event took place at the end of 2008 with the start of the global crisis. The above arguments fully justify the empirical application of the ARCH models.

4. Results

4.1. Estimation of Risk Factors

The conventional betas and conditional volatility betas in the context of total and downside risk and the corresponding t-statistics are estimated according to equations 8 to 11. The summary results for analysed individual assets quoted on the WSE are reported in Table A1 in the Appendix. The results demonstrate that in the majority of cases there is a systematic and contemporaneous relationship between the conditional volatility of stock returns and the conditional volatility of the market. The conventional betas both classical and downside are positive and statistically significant (significance level of 1%). The only exception is WST. Approximately 90% of stocks have positive, both classical and downside, conditional volatility betas, and approximately 75% of these are statistically significant (significance level of at least 10%).

It should be noted that at the same level of systematic risk expressed by β_i and β^D_i, companies may vary considerably in terms of conditional volatility exposure. In addition, differences in the individual pairs of measures in the whole sample were confirmed, due to the absence of a normal distribution of such measures, through two non-parametric tests, namely the Wilcoxon rank-sum test and the signed-rank test. The test results indicate that there is no relationship between the two types of beta, either in the classical or downside frameworks. In addition, there is no evidence of any significant correlation between these two types of measure. The Pearson Correlation Coefficient for the classical measures is (-0.03), and for the downside measures 0.12. The analyses confirm, therefore, that information provided by conditional volatility betas, when assessing the market risk of a given stock, is unconventional.

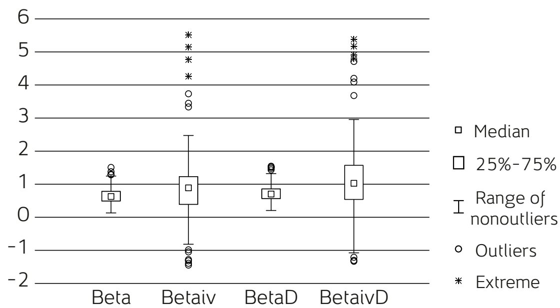
Table 1 reports the summary distribution statistics for all types of beta. The graphical presentation is provided in Figure 2. The estimated volatility betas are on average higher than the conventional betas. However, it should be added that the downside betas of both types are for the majority of companies on average higher than the betas determined in the classical framework. The foregoing suggests that the downside volatility betas indicate that the companies are more receptive to the contemporaneous volatility of the market than demonstrated by the classical volatility betas. In addition, the volatility beta distributions are characterized by higher diversity, skewness and kurtosis than the conventional betas, which results in higher deviations of such distributions from the normal distribution. This results from outliers being present in the volatility beta population. Another issue, which is not included in this analysis, is the stability of volatility betas in the periods of various market portfolio conditional volatility levels. As demonstrated by the results obtained by Li and Galagedera (2008), the higher the value of the conditional volatility of the market, the lower the values of volatility betas.

Table 1. Descriptive Statistics of Daily Return and Classical and Downside Beta Coefficients

Coefficient	Mean	Median	Min	Max	S.D.	Skewness	Kurtosis	J-B test
β_i	0.664	0.615	0.143	1.508	0.262	0.757	0.254	19.194
β_{iv}	0.935	0.894	-1.370	5.531	1.021	1.377	4.338	214.513
β^D_i	0.741	0.696	0.203	1.522	0.266	0.685	0.174	15.501
β^D_{iv}	1.117	1.021	-1.329	5.391	1.085	1.210	3.284	135.181
$\bar{R}_i$	0.016	0.017	-0.160	0.155	0.053	-0.222	0.331	2.487

Note: β_i, β_{iv}, classical return beta and conditional volatility beta; β^D_i, β^D_{iv}, downside return beta and conditional volatility beta, $\bar{R}_i$ – mean daily return.
Source: Author's calculations

Figure 2. Box Plot of Classical and Downside Return and Volatility Beta Coefficients



Source: Author's calculations

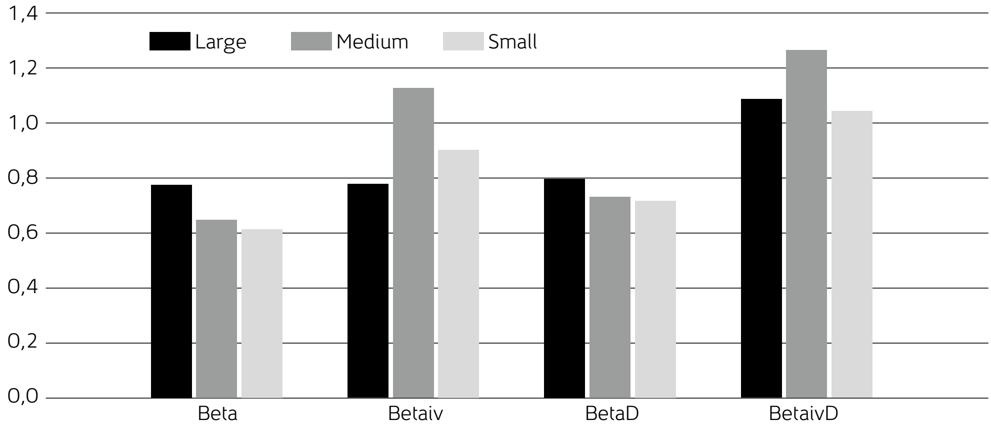
As far as the size of a company is concerned, the volatility betas display greater variations than the conventional betas. The highest average values of these measures are observed for medium companies (1.127 and 1.265). The foregoing is presented in Table 2 and Fig. 3. The return betas are the highest for large companies and the lowest for small enterprises. These values correspond to the average returns, which are 0.032% and 0.001%, respectively for large and small companies. To sum up, stocks with average capitalization, as opposed to stocks of marginal-size companies, with a relative low level of response to changes in stock exchange trends (conventional beta) are highly perceptive to movements in the conditional volatility of the market (volatility beta).

Table 2. Mean Daily Return and Classical and Downside Beta Coefficients in Regard to Size of Company

Coef-ficient	Large			Medium			Small		
	Median	Min	Max	Median	Min	Max	Median	Min	Max
β_i	0.775	0.180	1.508	0.648	0.211	1.277	0.613	0.143	1.280
β_{iv}	0.778	-0.410	1.833	1.127	-1.309	5.531	0.903	-1.370	5.174
β^D_i	0.796	0.203	1.522	0.731	0.225	1.446	0.717	0.325	1.489
β^D_{iv}	1.087	-0.341	2.601	1.265	-1.329	4.920	1.044	-1.301	5.391
$\bar{R}_i$	0.032	-0.046	0.122	0.026	-0.068	0.123	0.001	-0.160	0.155

Note: β_i, β_{iv}, classical return beta and conditional volatility beta; β^D_i, β^D_{iv}, downside return beta and conditional volatility beta, $\bar{R}_i$ – mean daily return.
Source: Author's calculations

Figure 3. Plot of Classical and Downside Return and Volatility Beta Coefficients in Regard to Size



Source: Author's calculations

In the end, the similarity between conditional volatility of industries and sectors is analysed. For this purpose, Table 3 reports estimated betas and volatility betas for various branches of the economy. The downside betas for all sectors, excluding the banking sector, are on average higher than the classical betas. In general, companies operating in service sectors are characterized by the lowest return risk and conditional volatility exposure.

Table 3. Mean Daily Return and Classical and Downside Beta Coefficients in Regard to Sector

Coefficient	Finance			Industry			Service		
	Banks	Developer	Financial services	Chemical	Fuel and primary products	Heavy industry	Trade	IT, media	Energy
β_i	0.921	0.967	0.805	0.583	1.110	0.657	0.591	0.577	0.487
β_{iv}	0.707	0.715	1.515	1.532	0.997	0.791	0.928	0.789	0.663
β^D_i	0.911	1.077	0.924	0.658	1.127	0.733	0.670	0.652	0.539
β^D_{iv}	1.272	1.056	1.602	1.688	1.470	0.965	1.043	0.927	0.789
$\bar{R}_i$	0.030	0.007	0.022	0.046	0.010	0.017	0.004	0.001	0.025

Note: β_i , β_{iv} , classical return beta and conditional volatility beta; β^D_i, β^D_{iv}, downside return beta and conditional volatility beta, $\bar{R}_i$ – mean daily return.
Source: Author's calculations

The fuel sector is the most perceptive, in the general and downside framework, to fluctuations in market trends. This sector also has high volatility betas. Another figure of interest is the chemical sector, where on average the sensitivity to index movements is low, but the response to conditional volatility exposure is strong. The aforementioned analysis may give indications that there are common sector-specific information factors in the Polish capital market.

4.2. Cross-Sectional Analysis, Risk Pricing

In light of the pricing of capital assets, it is appropriate to examine the relevance of a systematic risk premium. The analysed conventional betas and conditional volatility betas are risk sources in the expanded versions of the CAPM model. The application of downside measures falling within an asymmetric risk measure group means that the proposed versions of the model may be considered an alternative to the three-factor and four-factor CAPM models (Kraus and Litzenberger, 1976). These models use such measures as skewness, co-skewness and co-kurtosis. The equations subject to cross-sectional regression analysis are as follows:

$$\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_{iv} + \lambda_3 D_i + \varepsilon_i\,, \tag{12}$$

$$\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_{iv} + \varepsilon_i\,, \tag{13}$$

$$\bar{R}_i = \lambda_0 + \lambda_1\beta_i^D + \lambda_2\beta^D{}_{iv} + \lambda_3 D_i + \varepsilon_i\,, \tag{14}$$

$$\bar{R}_i = \lambda_0 + \lambda_1\beta_i^D + \lambda_2\beta^D{}_{iv} + \varepsilon_i\,, \tag{15}$$

where $\bar{R}_i$ means the average return on asset *i*. The model also takes into consideration the size of a company and includes the dichotomous variable D_i, whose value equals one for large companies and zero for other companies. Table 4 reports the estimated results of equations (12 to 15) for individual companies.

Table 4. Cross-sectional Analysis of Expected Returns and the Betas for Individual Assets

	λ_0	λ_1	λ_2	λ_3	$\bar{R}^2$	F-statistic (p-value)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_{iv} + \lambda_3 D_i + \varepsilon_i$						
Estimate	-0.0179[c]	0.0236[c]	0.0136[a]	0.0203[b]	0.094	7.698
t-value	-1.672	1.676	3.787	2.326		(0.000)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_{iv} + \varepsilon_i$						
Estimate	-0.0174	0.0318[b]	0.0130[a]	—	0.073	8.642
t-value	-1.621	2.247	3.562	—		(0.000)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i^D + \lambda_2\beta^D{}_{iv} + \lambda_3 D_i + \varepsilon_i$						
Estimate	-0.0075	0.0067	0.0117[a]	0.0209[b]	0.073	6.115
t-value	-0.660	0.451	3.394	2.433		(0.000)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i^D + \lambda_2\beta^D{}_{iv} + \varepsilon_i$						
Estimate	-0.0051	0.0109	0.0114[a]	—	0.050	6.057
t-value	-0.446	0.769	3.279	—		(0.003)

Note: β_i , β_{iv} , classical return beta and conditional volatility beta; $\beta^D{}_i$, $\beta^D{}_{iv}$, downside return beta and conditional volatility beta, $\bar{R}_i$ - mean daily returnn for asset *i*; D_i, dummy variable whose valueequals one for large companies and zero for other companies; ε_i - random variable; a, b, c indicates significance respectively at the 1%, 5%, 10% level.

Source: Author's calculations

The results demonstrate that the statistical significance of a risk premium related to the overall situation in the market is 10%. The volatility exposure, both in the classical and downside framework, is priced at the significance level of 1%. These risk premiums are positive and higher in the classical framework. In addition, investors are rewarded for investments in large companies, which means that the company's size effect is present. The equations explain between 5% and 9.4% of the volatility of the average returns on companies. It seems that the estimates of the conventional conditional volatility beta are significant, according to results received from empirical investigations in emerging and developed markets (Cai et. al., 2006). As distinct from other studies mentioned here that use country indices (Li, Galagedera, 2008), these results provide strong empirical evidence that the co-movement of asset-specific conditional volatility (conditional volatility beta) and that of the market may be a factor of asset pricing. Furthermore, what is also important for portfolio theory, volatility exposure is equally valuable risk measure as return exposure.

It has been decided that the pricing for individual sources of risk be analysed for investments aggregated in portfolios. For that purpose, when ranking companies in view of a given risk measure and average rate of return, there have been 20 equally weighted portfolios constructed that comprise 10 stocks each, except for the last portfolio, which is based on 5 companies with the highest values of a given measure. The average returns have been made dependent on individual measures and on the pair of conventional and volatility betas. The results are reported in Table 5 (see also Table A1 in the Appendix).

Table 5. Cross-sectional Analysis of Expected Returns and Betas for Equally Weighted Portfolios

	λ_0	λ_1	λ_2	Adjusted $\bar{R}^2$	F-statistic (p-value)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \varepsilon_i$ Portfolios sorted by β_i					
Estimate	-0.0059	0.0331[a]	–	0.458	17.101
t-value	-1.009	4.135	–		(0.000)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_{iv} + \varepsilon_i$ Portfolios sorted by β_{iv}					
Estimate	0.0035	0.0136[a]	–	0.344	10.947
t-value	0.551	3.309	–		(0.004)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i^D + \varepsilon_i$ Portfolios sorted by β_i^D					
Estimate	0.0023	0.0188	–	0.053	2.066
t-value	0.251	1.437	–		(0.167)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_{iv}^D + \varepsilon_i$ Portfolios sorted by β_{iv}^D					
Estimate	0.0033	0.0112[a]	–	0.341	10.840
t-value	0.571	3.292	–		(0.004)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_{iv} + \varepsilon_i$ Portfolios sorted by $\bar{R}_i$					
Estimate	-0.2046[b]	0.3334[a]	0.0557[b]	0.388	7.044
t-value	-2.711	2.988	2.271		(0.006)
Model: $\bar{R}_i = \lambda_0 + \lambda_1\beta_i^D + \lambda_2\beta^D_{iv} + \varepsilon_i$ Portfolios sorted by $\bar{R}_i$					
Estimate	-0.1533[c]	0.2299[c]	0.0665[b]	0.333	5.742
t-value	-1.809	2.048	2.701		(0.012)

Note: β_i, β_{iv}, classical return beta and conditional volatility beta; β^D_i, β^D_{iv}, downside return beta and conditional volatility beta, $\bar{R}_i$ – mean daily returnn for asset i; D_i, dummy variable whose valueequals one for large companies and zero for other companies; ε_i – random variable; a, b, c indicates significance respectively at the 1%, 5%, 10% level.

Source: Author's calculations

The aggregation of individual stocks in portfolios indicates that the role of systematic risk measures in the pricing of securities is significant. Except for the downside betas, other risk factors determine the average returns at the significance level of 1%. The highest risk premium is obtained in the model with the classical beta (0.0331). This model explains the average returns at the level of 45.8%. The portfolios ranked according to conditional volatility betas are characterized by a systematic increase in the average returns, giving the risk premiums respectively of 0.0136 and 0.0112. The pricing models using these betas explain the returns of 34%. The last two models of the expanded CAPM versions are estimated for the portfolios sorted according to the returns. The results indicate that both the classical risk measures and the volatility exposure measures are factors that affect returns on assets. The models describing the analysed relationships in the context of a downside risk explain asset pricing in the Polish capital market to a lesser extent.

The significance of a systematic conditional risk, in particular a downside measure, may also be useful in developing portfolio optimization methods in the context of sectoral and company size investing.

5. Conclusion

This paper presents an analysis of conditional volatility exposure by modelling the returns and volatility of companies listed on the WSE with the use of ARCH type models. The analysis takes into account not only the classical framework, but also the downside aspect of risk. The systematic measures of risk are the classical and downside betas obtained in the market model, and the volatility betas, which assess the common impact of the conditional variance specific for a given company, and such a variance of the market index as a representative of the market portfolio.

In the vast majority of cases, the classical and downside betas, both return and conditional volatility, are positive and statistically significant in the entire 10-year period. The downside betas of both types are on average higher than their classical equivalents. The conventional betas of both types are characterized by higher relative diversity. The risk measures discussed here are also significantly varied as far as company size and sector of the economy are concerned. The highest volatility exposure is observed for medium companies and companies operating in the chemical and financial sectors, whereas the highest sensitivity to the risk of changes in economic trends is observed for large companies and companies operating in the fuel sector.

The cross-sectional analyses demonstrate that conditional volatility exposure is subject to statistically significant pricing. The models describing the analysed relationships in the context of a classical risk exposure explain asset pricing in the Polish capital market to a greater extent than the models using downside measures.

As the analyses carried out indicate that the systematic measures of volatility exposure are significant in the processes generating such measures, they may be helpful in creating investment portfolios that include not only national but also international assets. The calculation of volatility betas for various companies may be used to discover a common sector-specific factor connecting companies that operate in various sectors.

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Appendix

Table A1. Estimates of Classical and Downside Return Beta and Volatility Beta Coefficients

Asset	Classical beta		Classical volatility beta		Downside beta		Downside volatility beta	
	β_i	t_{β_i}	β_{iv}	$t_{\beta_{iv}}$	β_i^D	$t_{\beta_i^D}$	$\beta^D{}_{iv}$	$t_{\beta^D{}_{iv}}$
ABE	0.627[a]	13.71	1.750[a]	5.82	0.628[a]	9.59	1.916[a]	5.91
ACP	0.682[a]	20.03	0.997[a]	3.26	0.698[a]	15.00	1.264[a]	4.70
ACS	0.288[a]	7.40	1.119[b]	4.39	0.337[a]	6.05	1.149[a]	4.43
ACT	0.604[a]	10.53	2.469[a]	3.58	0.667[a]	8.12	2.54[a]	3.51
AGO	0.809[a]	19.45	0.945[a]	5.45	0.894[a]	14.32	1.129[a]	5.86
ALC	0.458[a]	5.31	-0.104	-0.51	0.496[a]	4.25	-0.196	-0.86
ALM	0.598[a]	13.79	0.915[a]	3.94	0.713[a]	11.75	1.032[a]	4.24
AMB	0.663[a]	15.50	1.833[a]	5.79	0.751[a]	12.34	2.000[a]	6.07
AMC	0.711[a]	15.73	1.499[a]	3.99	0.771[a]	13.17	1.757[a]	4.11
APL	0.936[a]	13.14	0.306	0.52	1.072[a]	9.83	0.692	1.09
APT	0.495[a]	13.19	0.964[a]	5.51	0.541[a]	9.89	1.022[a]	5.73
AST	0.715[a]	12.39	1.619[a]	3.96	0.814[a]	10.21	1.832[a]	4.29
ATG	0.497[a]	8.79	1.443[a]	3.73	0.616[a]	8.60	1.472[a]	3.67
ATM	0.484[a]	8.73	1.237[a]	3.91	0.549[a]	6.48	1.295[a]	4.13
ATP	0.501[a]	8.93	0.780[b]	2.12	0.518[a]	6.87	1.016[b]	2.49
AWB	0.615[a]	10.81	-1.011[a]	-6.71	0.671[a]	9.31	-0.988[a]	-4.88
BAK	0.576[a]	11.72	0.327[c]	1.83	0.650[a]	9.67	0.409[b]	2.06
BCM	0.451[a]	9.90	0.628[a]	2.76	0.567[a]	8.77	0.653[a]	2.84
BDL	0.895[a]	9.47	-1.37[a]	-3.74	1.035[a]	6.92	-1.301[a]	-3.35
BDX	0.591[a]	16.66	0.654[a]	3.06	0.581[a]	11.09	0.803[a]	3.55
BHW	0.810[a]	23.42	0.474[a]	3.11	0.793[a]	15.40	0.847[a]	4.68
BLI	0.720[a]	1.53	0.013	0.04	0.767[a]	9.18	0.166	0.43
BMP	0.589[a]	12.30	0.128	0.73	0.706[a]	10.88	0.124	0.64
BNP	0.290[a]	4.50	0.240	0.45	0.443[a]	4.04	0.244	0.46
BOS	0.308[a]	7.22	0.531[a]	2.79	0.388[a]	5.48	0.518[a]	2.83
BPH	0.765[a]	17.07	1.143[a]	2.64	0.820[a]	15.98	1.361[a]	3.29
BRE	1.176[a]	35.71	1.064[a]	8.55	1.104[a]	24.29	1.934[a]	9.51
BRS	0.955[a]	4.44	1.701[a]	2.58	0.958[a]	15.63	2.037[b]	2.10
BSK	0.723[a]	24.07	0.925[a]	6.87	0.692[a]	15.52	1.337[a]	8.74
BTM	0.761[a]	10.33	0.369	0.46	0.829[a]	9.65	0.610	0.65
BZW	1.048[a]	27.35	0.750[a]	6.20	0.942[a]	17.73	1.739[a]	8.24
CAR	0.532[a]	12.03	1.716[a]	5.73	0.558[a]	8.07	1.879[a]	6.11
CCC	0.569[a]	14.96	0.766[a]	3.99	0.581[a]	10.35	0.894[a]	4.31
CCI	0.462[a]	9.48	0.791[a]	3.52	0.447[a]	7.81	0.932[a]	3.66
CEZ	0.490[a]	11.37	1.000[a]	7.29	0.539[a]	7.88	1.119[a]	7.81

CFL	0.584[a]	6.59	-0.454[b]	-2.04	0.755[a]	8.59	-0.479[b]	-2.08
CIE	0.742[a]	19.17	0.676[a]	3.41	0.846[a]	15.18	0.803[a]	3.72
CMP	0.321[a]	8.51	0.535[a]	3.54	0.331[a]	6.42	0.591[a]	3.58
CMR	0.658[a]	17.89	0.736[a]	4.44	0.728[a]	14.13	0.892[a]	4.88
CNG	0.464[a]	10.48	0.248[c]	1.66	0.584[a]	8.83	0.246	1.50
COG	1.101[a]	12.22	0.360	0.32	1.206[a]	13.14	0.656	0.52
CPA	0.905[a]	8.07	1.087[c]	1.68	1.012[a]	13.61	1.366[c]	1.79
CST	0.905[a]	19.27	0.986[a]	3.83	0.920a[a]	14.70	1.579[a]	4.71
DBC	0.417[a]	11.45	1.030[a]	4.77	0.518[a]	9.55	1.039[a]	4.75
DCR	0.449[a]	8.16	1.565[a]	4.00	0.601[a]	6.91	1.602[a]	3.93
DGA	0.707[a]	11.97	-0.261	-0.66	0.731[a]	9.39	-0.154	-0.33
DOM	0.702[a]	14.65	1.131[a]	5.17	0.816[a]	13.50	1.425[a]	5.18
DPL	0.912[a]	16.36	0.402	0.77	1.031[a]	14.50	1.011[a]	1.66
DUD	0.936[a]	14.05	2.434[a]	2.78	1.116a[a]	15.63	2.79[a]	2.98
EAT	0.633[a]	16.30	0.935[a]	5.25	0.656[a]	12.49	1.174[a]	5.42
ECD	0.729[a]	10.21	0.680	1.06	0.848[a]	9.48	0.669	0.98
ECH	0.857[a]	20.46	1.251[a]	6.24	0.854[a]	13.52	1.562a[a]	6.77
EEF	0.656[a]	11.26	0.949[b]	2.49	0.787[a]	8.85	1.079[a]	2.62
EFK	0.600[a]	12.17	1.496[a]	4.21	0.613[a]	8.16	1.708[a]	4.31
EFR	0.452[a]	7.67	2.336[c]	1.77	0.651[a]	7.29	2.356[c]	1.80
ELB	0.472[a]	12.00	0.094	0.76	0.527[a]	9.81	0.139	1.03
ELZ	0.332[a]	6.97	0.594[c]	1.81	0.543[a]	6.03	0.655[c]	1.82
EMC	0.452[a]	3.93	0.774[b]	2.06	0.572[a]	2.78	0.796[b]	2.16
EMP	0.416[a]	10.90	0.615[a]	3.25	0.452[a]	9.18	0.700[a]	3.47
ENP	0.655[a]	8.64	0.271	0.70	0.798[a]	7.48	0.182	0.52
EPL	0.596[a]	7.66	1.141	1.38	0.666[a]	7.18	1.595[c]	1.71
EUR	0.584[a]	15.22	0.579[a]	3.62	0.590[a]	10.83	0.694[a]	3.93
FAM	0.696[a]	13.31	-0.122	-0.58	0.821[a]	11.88	0.007	0.03
FCL	0.491[a]	11.99	0.708[a]	5.11	0.573[a]	9.56	0.769[a]	5.29
FER	0.556[a]	8.99	1.343[c]	1.74	0.681[a]	7.30	1.318	1.57
FOT	0.504[a]	7.54	0.102	0.22	0.515[a]	6.36	0.115	0.23
FSG	0.609[a]	10.29	1.315[a]	2.96	0.684[a]	8.34	1.591[a]	3.36
FTE	0.432[a]	10.65	1.199[a]	5.05	0.460[a]	7.57	1.317[a]	5.11
GCN	0.924[a]	15.87	1.244[b]	2.42	1.163[a]	13.79	1.633[a]	2.63
GNT	1.277[a]	16.26	-1.309[a]	-4.47	1.446[a]	14.92	-1.223[a]	-3.56
GRI	0.688[a]	11.85	2.201[a]	2.94	0.844[a]	11.25	2.128[a]	2.92
GRJ	0.727[a]	14.17	1.207[a]	4.65	0.790[a]	12.13	1.335[a]	4.75
GRL	0.632[a]	14.54	1.378[a]	4.55	0.741[a]	12.31	1.425[a]	4.45
GTC	1.187[a]	28.13	1.045[a]	5.62	1.174[a]	20.45	1.855[a]	6.59
GTN	1.262[a]	32.35	0.308[b]	2.42	1.224[a]	22.84	1.039[a]	3.94
GZU	1.116[a]	19.01	0.379	0.95	1.206[a]	18.44	1.076[c]	1.72

HDR	0.393[a]	8.85	1.066[a]	3.74	0.447[a]	6.67	1.165[a]	3.98
HGN	0.976[a]	15.89	4.310	1.19	1.191[a]	13.21	4.793	1.37
HOP	0.391[a]	5.16	1.055[c]	1.86	0.525[a]	3.82	1.004[b]	2.06
HTM	0.835[a]	10.10	4.805[a]	3.04	0.982[a]	12.34	5.186[a]	3.59
HYP	0.432[a]	7.73	0.891[b]	2.47	0.569[a]	7.85	0.948[a]	2.75
IDM	1.118[a]	16.19	-1.271[a]	-4.28	1.157[a]	12.43	-1.329[a]	-3.93
INC	0.600[a]	9.39	0.142	0.53	0.722[a]	8.02	0.195	0.62
IND	0.344[a]	7.85	2.029[a]	6.41	0.400[a]	5.56	2.077[a]	6.57
INF	0.369[a]	6.13	0.313	1.02	0.444[a]	5.95	0.393	1.16
INK	0.604[a]	13.36	1.01[a]	3.62	0.658[a]	10.22	1.226[a]	3.78
IPL	0.462[a]	10.89	0.833[a]	3.04	0.491[a]	7.86	0.980[a]	3.55
IPO	0.310[a]	5.22	1.286[a]	2.96	0.452[a]	5.27	1.236[a]	2.85
IPX	0.987[a]	21.69	2.022[a]	3.13	1.079[a]	20.41	2.442[a]	3.76
JPR	0.789[a]	13.00	1.178	0.85	0.994[a]	9.76	1.470	1.10
JTZ	0.729[a]	15.05	2.078[a]	5.27	0.771[a]	12.72	2.241[a]	5.41
KFL	0.391[a]	5.16	1.055[c]	1.86	0.525[a]	3.82	1.004[b]	2.06
KGH	1.508[a]	35.45	1.574[a]	5.34	1.522[a]	26.16	2.601[a]	8.56
KGN	0.425[a]	12.02	0.571[a]	3.22	0.476[a]	9.09	0.653[a]	3.58
KLR	0.522[a]	11.25	0.964[a]	3.42	0.616[a]	8.89	1.021[a]	3.51
KMP	0.481[a]	7.99	-0.516[a]	-3.03	0.578[a]	6.71	-0.531[b]	-2.41
KPX	1.003[a]	18.25	0.879[a]	3.00	1.001[a]	15.28	1.435[a]	4.21
KSW	0.441[a]	10.53	0.936[a]	4.64	0.544[a]	9.32	1.024[a]	4.72
KTY	0.666[a]	19.23	0.618[a]	4.78	0.694[a]	14.13	0.762	4.79
KZS	0.741[a]	7.58	5.174[a]	2.88	0.836[a]	7.63	5.391[a]	2.91
LBW	0.860[a]	13.87	-0.042	-0.16	0.975[a]	12.39	0.102	0.29
LEN	0.602[a]	12.93	1.206[a]	4.24	0.664[a]	10.09	1.331[a]	4.41
LPP	0.545[a]	13.75	0.560[a]	3.68	0.579[a]	10.95	0.606[a]	4.17
LTS	1.117[a]	32.39	0.604[a]	4.25	1.165[a]	24.14	0.985[a]	5.39
LTX	0.533[a]	10.81	3.442[a]	3.32	0.620[a]	9.14	3.691[a]	3.72
LZP	0.685[a]	10.25	0.027	0.04	0.757[a]	8.76	-0.045	-0.07
MCI	1.222[a]	23.66	2.259[a]	3.69	1.333[a]	21.09	2.971[a]	5.20
MCL	0.314[a]	7.35	1.718[a]	4.96	0.388[a]	6.43	1.738[a]	5.00
MDS	1.004[a]	7.29	5.531[a]	2.58	1.109[a]	6.52	4.920[b]	2.37
MIL	1.121[a]	26.19	1.431[a]	4.86	1.125[a]	20.90	1.912[a]	5.93
MIT	1.113[a]	17.83	-0.040	-0.07	1.125[a]	16.66	0.397	0.67
MNC	0.225[a]	7.00	0.009	0.07	0.227[a]	5.07	0.025	0.19
MNI	0.695[a]	15.96	0.097	0.38	0.773[a]	12.09	0.559[c]	1.65
MOL	0.846[a]	18.93	1.833[a]	6.13	0.873[a]	13.27	2.083[a]	6.45
MSO	0.626[a]	15.15	0.894[a]	3.55	0.686[a]	11.97	1.044[a]	4.17
MSP	0.622[a]	13.39	-0.188	-1.18	0.631[a]	11.00	-0.070	-0.34
MSW	0.636[a]	11.81	-0.410[a]	-2.90	0.718[a]	9.37	-0.341[b]	-2.16

MSX	1.277[a]	13.27	-0.817	-1.51	1.417[a]	9.67	-0.202	-0.24
MSZ	1.022[a]	20.64	0.660[a]	2.59	1.150[a]	16.16	1.142[a]	3.23
MTL	0.543[a]	6.95	0.226	0.41	0.575[a]	6.32	0.248	0.42
MZA	0.408[a]	6.85	0.951[b]	1.97	0.515[a]	5.93	1.062[b]	1.98
NCT	0.642[a]	9.57	0.275	0.82	0.718[a]	8.40	0.259	0.78
NEM	0.507[a]	10.54	0.853[b]	2.52	0.633[a]	9.28	0.923[a]	2.66
NET	0.484[a]	15.40	0.395[a]	2.73	0.514[a]	11.01	0.432[a]	2.88
NEU	0.347[a]	9.84	0.839[a]	5.61	0.392[a]	8.15	0.841[a]	5.34
NVT	0.489[a]	6.96	1.650	1.56	0.552[a]	6.62	1.613	1.34
O2O	0.801[a]	10.55	-0.147	-0.33	0.905[a]	9.35	-0.065	-0.16
ODL	0.573[a]	7.01	1.885[c]	1.92	0.756[a]	7.91	2.048[b]	2.16
OPT	1.034[a]	16.10	1.912[c]	1.76	1.164[a]	13.42	2.501[c]	1.77
ORB	0.539[a]	13.01	1.241[a]	5.41	0.603[a]	9.89	1.301[a]	5.55
PBF	0.651[a]	8.65	2.250[a]	2.94	0.716[a]	6.67	2.237[a]	2.98
PBG	0.827[a]	14.18	-0.363[a]	-3.71	0.877[a]	10.26	-0.310[c]	-1.94
PCE	0.766[a]	16.23	0.942[a]	3.03	0.850[a]	12.98	1.125[a]	3.55
PEK	0.386[a]	8.29	0.419[c]	1.67	0.438[a]	6.28	0.526[c]	1.86
PEO	1.381[a]	46.11	0.490[a]	6.33	1.293[a]	30.01	1.675[a]	9.76
PEP	0.545[a]	14.18	0.417	1.35	0.603[a]	10.90	0.595[c]	1.66
PGD	0.542[a]	9.27	3.743[a]	4.87	0.574[a]	7.22	4.092[a]	5.10
PGF	0.612[a]	15.33	1.578[a]	5.61	0.667[a]	12.38	1.669[a]	5.11
PGM	0.375[a]	5.02	-1.046[a]	-7.24	0.439[a]	3.73	-1.075[a]	-6.87
PGN	0.790[a]	24.53	0.530[a]	4.97	0.788[a]	16.97	0.728[a]	5.48
PGS	0.211[a]	4.96	0.954[a]	4.54	0.225[a]	3.77	0.915[a]	4.32
PJP	0.529[a]	9.86	0.251	1.10	0.732[a]	9.06	0.266	1.17
PKN	1.290[a]	46.69	0.444[a]	5.94	1.286[a]	34.46	0.953[a]	7.31
PKO	1.247[a]	51.82	0.420[a]	6.72	1.202[a]	37.32	1.381[a]	10.28
PLA	0.592[a]	6.85	3.727[c]	1.69	0.696[a]	6.05	4.216[c]	1.65
PLX	0.419[a]	8.39	1.247[a]	2.94	0.553[a]	8.82	1.133[a]	2.66
PMG	0.291[a]	5.11	-0.486[b]	-2.49	0.339[a]	4.39	-0.471[b]	-2.39
PMP	0.637[a]	9.99	2.400[a]	2.95	0.832[a]	8.66	2.660[a]	3.12
PND	1.201[a]	13.02	1.971[a]	2.87	1.438[a]	8.39	2.245[a]	3.14
PPS	0.529[a]	8.33	0.919	0.93	0.569[a]	5.55	1.081	1.09
PPW	1.113[a]	17.83	-0.040	-0.07	1.245[a]	16.66	0.397	0.67
PRC	0.830[a]	15.33	-0.447[c]	-1.78	0.991[a]	13.06	-0.202	-0.57
PRM	0.516[a]	11.52	1.046[a]	4.21	0.532[a]	8.88	1.145[a]	4.03
PRT	0.685[a]	10.25	0.027	0.04	0.757[a]	8.76	-0.044	-0.065
PUE	0.500[a]	10.76	1.315[a]	3.13	0.520[a]	8.42	1.425[a]	3.28
PXM	1.173[a]	9.31	-0.294[c]	-1.76	1.258[a]	6.29	-0.106	-0.37
QSM	0.528[a]	12.09	0.970[a]	4.59	0.590[a]	8.92	1.047[a]	4.99
RDN	0.791[a]	13.08	0.236	0.68	0.958[a]	11.31	0.307	0.74

RFK	0.734[a]	15.23	0.378	0.78	0.845a	11.03	0.496	1.04
RLP	0.718[a]	12.99	1.070[a]	3.29	0.802[a]	11.47	1.376[a]	3.84
RMK	0.561[a]	9.22	1.336[a]	3.15	0.643[a]	7.57	1.432[a]	3.26
RPC	0.497[a]	10.18	1.988[a]	4.41	0.593[a]	8.85	2.015[a]	4.34
SFS	0.569[a]	8.37	0.139	0.34	0.720[a]	6.74	0.085	0.21
SGN	0.707[a]	17.44	1.085[a]	3.97	0.827[a]	16.32	1.282[a]	4.57
SKA	0.308[a]	7.79	1.231	2.95	0.354[a]	5.92	1.275[a]	3.01
SKT	1.280[a]	12.61	0.926	0.83	1.489[a]	15.87	0.493	0.74
SME	0.456[a]	8.28	1.704[b]	2.34	0.556[a]	7.00	1.835[a]	2.58
SNK	0.419[a]	10.10	0.801[a]	3.29	0.464[a]	7.22	0.749[a]	2.85
SNS	0.854[a]	20.82	1.425[a]	5.91	0.878[a]	15.38	1.826[a]	6.43
STF	0.681[a]	14.56	0.745[b]	2.03	0.747[a]	11.65	0.952[b]	2.27
STP	0.679[a]	16.35	0.595[a]	3.05	0.709[a]	12.19	0.737[a]	3.57
STX	0.723[a]	12.26	2.390[a]	3.45	0.810[a]	11.38	2.966[a]	4.13
SUW	0.337[a]	7.30	0.551[b]	2.40	0.402[a]	6.14	0.619[a]	2.62
SWD	0.868[a]	12.28	0.394	1.23	0.990[a]	11.67	0.817[c]	1.93
TEL	0.301[a]	7.91	0.441[a]	2.64	0.359[a]	6.91	0.445[a]	2.71
TIM	0.545[a]	11.27	0.933[c]	1.69	0.659[a]	9.19	1.013[c]	1.89
TLX	0.278[a]	5.48	0.959[a]	3.71	0.382[a]	4.95	0.948[a]	3.73
TPS	0.745[a]	24.85	0.138	1.52	0.734[a]	17.01	0.264[b]	2.28
TRI	0.756[a]	10.48	1.107[c]	1.69	0.890[a]	9.34	1.578[b]	2.03
TUP	0.792[a]	12.52	-0.189	-0.30	0.920[a]	11.07	-0.052	-0.07
TVL	0.320[a]	4.59	1.081[c]	1.69	0.516[a]	5.09	0.885	1.41
TVN	0.998[a]	25.37	1.160[a]	5.36	0.975[a]	17.74	1.596[a]	7.04
U2K	0.488[a]	8.67	2.026[a]	6.31	0.609[a]	7.07	2.081[a]	6.26
ULM	0.579[a]	10.12	0.559	1.35	0.682[a]	9.18	0.643	1.31
VRT	0.506[a]	10.48	0.839[b]	2.09	0.631[a]	9.09	1.001[b]	2.34
VST	0.726[a]	14.52	2.153[a]	5.11	0.842[a]	11.26	2.291[a]	5.13
WAS	0.830[a]	13.87	0.005	0.02	0.934[a]	10.40	0.129	0.38
WDX	0.574[a]	10.46	0.465	1.41	0.694[a]	9.22	0.594[c]	1.68
WLB	0.634[a]	12.74	-0.560[b]	-2.08	0.673[a]	9.07	-0.551[c]	-1.86
WST	0.143	1.52	3.352[c]	1.75	0.325[a]	2.30	4.743[b]	2.24
WWL	0.355[a]	10.32	0.964[a]	3.74	0.322[a]	6.27	1.037[a]	4.04
YWL	0.664[a]	11.25	0.445	1.22	0.772[a]	8.69	0.524	1.32
ZAP	0.557[a]	15.39	0.734[a]	4.82	0.593[a]	11.50	0.831[a]	4.95
ZKA	0.491[a]	10.26	1.127[a]	3.43	0.536[a]	7.47	1.051[a]	3.11
ZWC	0.180[a]	6.4	0.549[a]	5.13	0.203[a]	4.84	0.556[a]	4.96

Note: β_i, β_{iv}, classical return beta and conditional volatility beta; β^D_i, β^D_{iv}, downside return beta and conditional volatility beta; t_β denotes respective to the beta t statistics; a, b, c indicates significance respectively at the 1%, 5%, 10% level.
Source: Author´s calculations