Explaining Asymmetric Volatility around the World*

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Abstract

Based on the APARCH model and two outlier detection methods, we compute reliable time series of volatility asymmetry for 49 countries with relatively few observations. Results show a steady increase in the asymmetry over the years for most countries. We find that economic development and market capitalization/GDP are the most important factors that increase volatility asymmetry. We also find that higher participation of private investors and coverage by financial analysts increases the asymmetry, suggesting investor sentiment as a driving force. Leverage and feasibility of short-selling increase volatility in falling market conditions, although only to a smaller extent.

JEL classification: D490, G150, G190

Keywords: Volatility asymmetry, leverage effect, short-selling, APARCH model

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1. Introduction

The effect that volatility in equity markets appears to be asymmetric: i.e. volatility is larger in bear than in bull markets, is well documented. For an overview see Bekaert and Wu (2000). The phenomenon was first documented by Black (1976) and Christie (1982) who explained the asymmetry with the leverage effect, meaning that a drop in the value of the stock increases financial leverage, which makes the stock riskier and increases its volatility. More recent studies have proposed a positive feedback effect of volatility (Bekaert and Wu, 2000), a possible effect of short selling restrictions (Jayasuriya, Shambora and Rossiter, 2005) and behavioral preferences (Hens and Steude, 2009) as an explanation for the asymmetry. Despite various different hypotheses, the effect has still remained largely unexplained.

The aim of this article is to test various explanations that have been suggested as a cause for asymmetric volatility on a large data set covering a large number of countries and a relatively large time span. Once we have generated this data, we test various hypotheses concerning the cause of asymmetric volatility by regression and panel data analysis methods, propose new explanations for the effect and document policy making consequences.

To obtain time series dataset on volatility asymmetry for a large number of countries, we first need to improve the existing methods for the measurement of volatility asymmetry based on daily stock market returns, since higher frequency data would only be available for a small number of countries. Our method is based on the asymmetric power GARCH (APARCH) model of Ding, Granger and Engle (1993) using a skewed student's t-distribution. To increase the reliability of our results and to reduce the amount of necessary data for each single computation, two methods for jump detection are implemented. A time series of volatility asymmetry is then generated by using a rolling time window with smooth input weighting. Equipped with this method we are in a position to compute reliable time series of volatility asymmetry for 49 countries worldwide.

Using the unique data set of generated asymmetry measures, we can check various potential causes of asymmetric volatility. Whereas previous studies have used data for a rather limited number of countries, averaged over time, we can use a much wider cross-sectional analysis and even panel data analysis. This helps to distinguish the influences of factors which are highly correlated in the time-average.

In particular, we demonstrate that the original leverage effect explanation can only be a small contribution to the overall effect and also the effect of short-selling is significant, but small. Instead we find a strong effect of general market development and participation of private investors: the better developed a financial market, and the more individual investors take part, the larger the volatility asymmetry. It is therefore not surprising that we find a general increase in volatility asymmetry over time. We identify furthermore analyst coverage as a significant factor: the more the stock market is covered by analysts, the larger the volatility asymmetry.

The rest of the paper is organized as follows: in Section 2 we provide an overview of previous studies concerning asymmetric volatility, both empirical and theoretical. Section 3 describes our method to compute the volatility asymmetry. We summarize the data used in this paper briefly in Section 4. In Section 5 we present the results for the volatility asymmetry across 49 countries and for the years 1980–2007. In Section 6 we examine several potential explanations for asymmetric volatility, where we consider various macroeconomic and cultural factors. Conclusions and further areas of research are presented in Section 7.

2. Previous Results

The first explanations of the asymmetric volatility as a leverage effect (Black, 1976; Christie, 1982) have their roots in Miller and Modigliani (1958): for a firm with a mix of issued liabilities as stocks and bonds, its debt to equity ratio, ceteris paribus, changes when its stock price moves. The decrease in the stock price decreases the value of the equity more than the value of debt; thus the debt to equity ratio increases which increases the risk associated with the firm and results in the increase of volatility. The same principle applies to rising stock prices which may lead to a decrease in future volatility. However, Schwert (1989) points out that although aggregate leverage is significantly correlated with volatility, it explains only a small part of the movements in volatility.

The effect of financial leverage is not the only explanation in the literature for the asymmetric volatility. Another well documented theoretical hypothesis explains the effect by the existence of a time-varying risk premium (Pindyck, 1984; Engle, Lilien and Robins, 1987). The time-varying risk premium theory explains return shocks by changes in conditional volatility.

However, Bekaert and Wu (2000) and Li, Yang, Hsiao and Chang (2005) point out that the negative relationship between market volatility and expected market return immediately implies that the time-varying risk premium theory cannot explain the stock market behavior. This is also supported by Glosten, Jagannathan and Runkle (1993) and Nelson (1991), who argue that across time there is no theoretical agreement about the relationship between returns and volatility. Accordingly, both a positive and a negative relationship between current stock returns and current volatility are possible within a fixed period of time.

Among papers investigating volatility asymmetry, Bekaert and Harvey (1997) provide some evidence that the effect is also present on emerging markets. Fraser and Power (1997) find evidence of asymmetric volatility for the United Kingdom, Japan, and Malaysia. Brooks, Faff, McKenzie and Mitchell (2000) find evidence of volatility asymmetry in equity indices for ten mature markets (using an APARCH model). Jayasuriya et al. (2005) (also using APARCH) report asymmetry in both mature and emerging markets. Selçuk (2005) (using a Markov Chain Monte Carlo method) finds significant negative correlation between shocks to the stock market index and shocks to volatility implying a "leverage effect". Brooks (2007) reports that the degree of volatility asymmetry appears to vary across the set of emerging markets.

As pointed out by Bollerslev, Chou and Kroner (1992), early studies may not be reliable because variance modeling in these studies did not make efficient use of the data. More recent studies have typically used some type of GARCH models to allow for time-varying volatility. GARCH type models include a variance term in the conditional mean equation, as well as modifications of the model which include an asymmetric term in a conditional standard deviation or conditional variance equation. Bekaert and Wu (2000) provide an overview of the methods and models used.

Among papers investigating the causality behind asymmetric volatility, Sentana and Wadhwani (1992) propose stop-loss orders and portfolio insurance as trading practices which are consistent with positive feedback trading. They also discuss the effect of margin positions which may have to be liquidated due to price declines and thus lead to higher volatility.

Figlewski and Wang (2001) (finding a strong asymmetry for falling stock prices but a very weak or even nonexistent asymmetry for rising prices) argue that a firm's leverage is staying near a certain level rather than changing constantly. When the stock price changes along with its financial leverage, volatility should change permanently, too. However, volatility changes are not permanent but die out quickly. In conclusion they propose to use the term "down-market effect" instead of "leverage effect". The lack of causality from leverage is supported by Bekaert and Wu (2000) who find more support for volatility feedback than leverage.

McQueen and Vorkink (2004) develop a theoretical preference-based equilibrium asset pricing model that explains both volatility clustering and asymmetry by a feedback effect. In the case of a negative shock the volatility-driven drop in price amplifies the effect of the negative shock itself, making the market even more volatile. In the case of a positive shock, the volatility-driven drop in price offsets the effect of the positive shock, so volatility increases, but less than after the negative shock.

Aydemir, Gallmeyer and Hollfield (2005) quantify the asymmetry effect by using an equilibrium asset pricing model and find that financial leverage is economically not significant at market level and only partially explains variations in volatility at firm level. However, the magnitude of the effect of a decline in current prices on future volatilities appears to be too large to be explained solely by changes in financial leverage (Figlewski and Wang, 2001). Further, contrary to a leverage based explanation, the asymmetry is generally larger for aggregate market index returns than for individual stocks (see, e.g. Tauchen, Zhang and Liu (1996), and Andersen, Bollerslev, Diebold and Ebens (2001)). Further, Hens and Steude (2009) show in a financial market experiment that asymmetry effect seems to exist even when there is no financial leverage present. Instead they suggest that the asymmetry is caused by behavioral preferences of the investors.

3. Methodology

3.1. ASYMMETRY CALCULATIONS

To estimate the possible asymmetric volatility, we use the asymmetric power GARCH (APARCH) model of Ding et al. (1993). There is a wide choice of models (see e.g. Poon and Granger (2003)) that could be used for the task when using daily returns. Current focus in the volatility literature has shifted more to using realized volatility from intraday returns (see e.g. works of Andersen, Bollerslev and Diebold (2003)). However, for most financial markets only daily data is available and this limits the choice of possible models among which GARCH type models are most commonly and successfully used (see e.g. Bekaert and Wu (2000) for overview of different studies, Poon and Granger (2003) for overview of different models and Hansen and Lunde (2005) for GARCH type model comparison).

APARCH is chosen to estimate volatility in the current study. The model is supplemented with the use of a skewed t-distribution and a kernel weighting function for the model inputs. An APARCH model is also used in similar works of Brooks et al. (2000), Brooks (2007) and Jayasuriya et al. (2005). Although Brooks (2007) finds that non-normal conditional error distributions appear to fit the data well for developed countries whereas normal distribution appears to be a better option for emerging markets when using a similar APARCH model, we do not impose any restrictions on the skewness nor kurtosis of the distribution and the shape of the distribution is let to be determined by the input data. Neither of the previous studies has used skewed t-distribution nor weighting function which enables us to obtain more reliable results.

Our choice is supported by Mittnik and Paolella (2000) and Giot and Laurent (2004) who show that the APARCH model (coupled with a generalized asymmetric Student's t distribution) delivers in comparison with other models very accurate VAR forecasts relying on volatility out of sample forecasting.

Hansen and Lunde (2005) find (when analyzing IBM stock data) that the best overall performing model was the APARCH(2,2) model with t-distributed errors and mean zero; among other models, also V-GARCH specification (which is less sensitive to outliers) did quite well contrary to some other GARCH type (e.g. E-GARCH) models. It should be noted that realized intraday returns were used for calculations in that study.

The general form of an APARCH model is given as:

$$y_t = x'_{1,t}\mu + \varepsilon_t, \tag{1}$$

$$\varepsilon_t = \sigma_t z_t, \tag{2}$$

$$\sigma_t^\delta = x'_{2,t}\omega + \sum_{i=1}^{q} a_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta, \tag{3}$$

where $x_{1,t}$ and $x_{2,t}$ are two vectors of respectively n_1 and n_2 weakly exogenous variables (including the intercept), μ, ω, a_i, γ_i, β_i and δ are parameters to be estimated. δ

(where $\delta > 0$) plays the role of a Box-Cox transformation of the conditional standard deviation σ_t, and γ_i reflect the volatility asymmetry. A positive value of the γ_i means that past negative shocks have a larger impact on current conditional volatility than positive shocks.

In our APARCH model estimations, we do not use ARMA orders in the conditional mean Equation (1) nor constants (intercepts) in either Equation (1) or (3). This enables us to get more stable results with smaller standard errors for parameter estimations when using rolling time windows for our empirical data. As our focus is on the measure of asymmetric volatility which is impacted by the parameters δ and especially γ from Equation (3), we use an APARCH (1,1) model to estimate all parameters for all countries.

Although Hansen and Lunde (2005) found APARCH(2,2) to outperform APARCH(1,1) with their data, our choice is motivated by an effort to obtain γ_t and δ_t estimates with higher statistical reliability which would be negatively impacted by using higher order APARCH models and including ARMA orders in a conditional mean equation. We tested various combinations or different ARMA and APARCH orders (also including constants in equations) with our data. Based on the results, APARCH(1,1) without constants and ARMA orders proved to give more stable and reliable estimates for the parameters of interest. With this method we obtained results with quite a small number of observations (1000 observations for each rolling time window) of returns. This resulted in higher standard errors for the estimates than it would have been with wider time windows. However, using outlier detection methods (as described below), we are nevertheless able to get sufficiently small standard errors.

Another advantage of using APARCH(1,1) without constant terms over higher order APARCH models is the simpler interpretation of the estimated parameters as Equation (3) becomes

$$\sigma_t^{\delta} = a_1 \left(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1}\right)^{\delta} + \beta_1\sigma_{t-1}^{\delta}, \tag{4}$$

where γ is the volatility asymmetry parameter.

As the APARCH parameters cannot be derived analytically, they are estimated using the maximum likelihood method. We use standardized skewed Student log-likelihood (Lambert and Laurent, 2000; Lambert and Laurent, 2001) expressed as:

$$\begin{aligned} L_{SkSt} = & \left\{ \log \Gamma \left(\frac{v+1}{2} \right) - \log \Gamma \left(\frac{v}{2} \right) - 0.5 \log \left[\pi - (v-2) \right] \right. \\ & \left. + \log \left(\frac{2}{\xi + \frac{1}{\xi}} \right) + \log(s) \right\} \\ & - 0.5 \sum_{t=1}^{T} \left\{ \log \sigma_t^2 + (1+v) \log \left[1 + \frac{(sz_t + m)^2}{v-2} \xi^{-2I_t} \right] \right\}, \end{aligned} \tag{5}$$

where

$$I_t = \begin{cases} 1, & z_t \geq -\frac{m}{s} \\ -1, & z_t < -\frac{m}{s}, \end{cases}$$

ξ is the asymmetry parameter, v is the degree of freedom of the distribution,

$$m = \frac{\Gamma\left(\frac{v+1}{2}\right)\sqrt{v-2}}{\sqrt{\pi}\,\Gamma\left(\frac{v}{2}\right)} \left(\xi - \frac{1}{\xi} \right)$$

and

$$s = \sqrt{\left(\xi^2 + \frac{1}{\xi^2} - 1 \right) - m^2}.$$

Note that $\log \xi$ is estimated instead of ξ to facilitate inference about the null hypothesis of symmetry. See Lambert and Laurent (2001) and Bauwens, Laurent and Rombouts (2006) for more detail. Despite using skewed Student's distribution and imposing no restrictions on the parameters in Equation (4), which should give better results than other setups for the model, GARCH type models do not fit all samples of data. On occasion there is no stable solution for the parameters using the maximum likelihood method. In these cases the model is said to be non-convergent or unstable. Mostly non-convergent estimates occur when data includes one or more uncharacteristically large jumps or falls in the prices or the sample size is too small.

As our sample size for a rolling time window is quite small (1000 observations) compared to typical applications of GARCH type models, we utilize three different approaches to deal with jumps in the price data. First we use two different outlier detection methods (see Section 3.2) for MSCI index data for all countries. After removing all captured jumps, we use a Gaussian kernel (see Section 3.3) with the size of 4 standard deviations as a weighting function for the input data to each rolling time window.

The outlier detection methods and the kernel weighting function improve the stability of our estimations of the APARCH parameters significantly. For further analysis, we are only interested in estimates of γ from Equation (4). Gamma represents the asymmetry parameter and by definition:

$$-1 \leq \gamma \leq 1. \tag{6}$$

As the APARCH Equation (4) also includes the power parameter $\delta > 0$, similarly to Jayasuriya et al. (2005) and Brooks (2007) we compose a metric τ to capture the relative contribution of negative versus positive unit shocks to volatility by

$$\tau = \left(\frac{1+\gamma}{1-\gamma}\right)^{\delta}. \tag{7}$$

Our further analysis focuses on time dynamics and variation of the calculated asymmetry parameter γ and the asymmetry metric τ is used for cross checking the obtained results although results are not presented.

3.2. OUTLIER DETECTION METHODS

As GARCH type models cannot properly handle jumps frequently present in market returns (Barndorff-Nielsen and Shephard, 2006), it is important to have methods that could automatically detect the jumps. We use a wavelet method by Fan and Wang (2007) along with a method by Lee and Mykland (2006). We apply both of the methods to our data and eliminate all outliers detected by both methods. The methods are able to detect most problematic outliers in returns and the number of eliminated observations is not significant considering the data amount (see Appendix E). Thus the improved results of APARCH estimates clearly outweigh the loss of some data.

With a wavelet based approach as proposed by Fan and Wang (2007) jump locations and sizes are estimated and then removed from the observed data, resulting in jump adjusted data. See Wang (2006) for further details about the wavelet methods.

The second outlier detection method by Lee and Mykland (2006) uses local volatility in a predefined time window to test for jump components in returns. If returns contain a jump component, it should be observable among other data points. This is captured studying the volatility condition prevailing at the time of the tested return. In times of high volatility, an abnormal return is bigger than an abnormal return in times of low volatility. Hence, Lee and Mykland (2006) study the properties of the ratio of the tested return over a measure of local volatility. They derive an asymptotic theory for the statistic and a rejection region under the null of no jump at the tested time, proposing a powerful, parsimonious methodology that allows testing whether any return contains a jump component, its location and size.

Both outlier detection methods (Fan and Wang, 2007; Lee and Mykland, 2006) were designed for use on intraday data and have shown superior results compared to other methods on intraday data. Although both methods have been reported by authors not to work as efficiently on daily data (as used in our study), combining the methods (removing all outliers reported by both methods) has clearly helped to detect outliers resulting in a better fit of the APARCH model. The average number of eliminated observations amounts to 1-2% for most countries (see Appendix E for detailed results).

3.3. DATA SMOOTHING METHODS

As the focus of this study is on time dynamics and causes of asymmetric volatility, we are particularly interested in asymmetry measures in as small a time window as possible. This enables us to better isolate possible factors influencing the asymmetry. GARCH type models require quite a large number of observations (usually at least 2000 observations) for reliable and convergent parameter estimation. By method improvements, we were able to bring the number of needed observations down to 1000 (meaning about 4 years of trading data) for quite stable results. As 1000 observations is an arbitrary choice and to focus the measurement on an even smaller time span, we use the Gaussian kernel weighting function for the input data to the APARCH model with the size of 4 standard deviations defined as:

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}, \tag{8}$$

where

$$-2 \leq u \leq 2.$$

The weighting function reduces the negative impact from previously still non-captured outlying returns as well as the impact from data points on the boundary of the time window. The stability of the estimates for our APARCH model parameters remains quite similar with and without using the kernel weighting function.

4. Data

We use Morgan Stanley Capital International (MSCI) index daily stock market return data for 49 countries to calculate volatility asymmetry measures for each country. Data is obtained from Thomson's Datastream. The choice of countries is limited only by data availability. To estimate the APARCH model, we needed at least 1000 daily returns (approx. 4 years of daily index data). Moreover, three countries (out of originally 52) were excluded, since their number of trading days per week was too low. The minimum inclusion criteria was 7 years of data. By their composition, MSCI indices are free float adjusted market capitalization indices calculated similarly for each country. All returns are measured as the log difference of price in U.S. dollars of MSCI country index which makes them comparable at international level.[1]

We study the largest time period available for each country. For most developed countries, MSCI daily data starts from 1980. Emerging market data starts the earliest from 1987. Greece is included with the shortest time period starting from 2001, other countries have data starting the latest from 1995. Please see Appendix A for the list of countries and starting data points for each country.

The data used in testing the causes of the asymmetry includes variables of: economic structure and development; stock market structure and efficiency; corporate environment; and cultural indicators. See Appendix B for details.

Examples of variables capturing the economic structure and the development of the country include GDP per capita, total GDP and the level of private debt. There is quite a high correlation present between different variables of this class. Therefore we choose only a few of them for testing. The reason for including this class of variables is to capture the possible influence from the economic environment on the volatility asymmetry. We also include variables describing stock market structure and characteristics of practices and laws (including short selling feasibility and enforcement of insider trading laws) concerning stock market. For example the feasibility of short selling could have an effect on volatility asymmetry whereas other variables are of more descriptive nature and we can basically only test correlations with volatility asymmetry measures. Cultural indicators include 4 variables from Hofstede (2001). We use them to test the hypothesis that cultural differences in risk attitudes can also drive the behavior of investors and are

[1] As a robustness check, we repeated the calculation procedure with MSCI indices denominated in local currencies.

one of the explanations for volatility asymmetry.

5. How Big is the Volatility Asymmetry across Time and Space?

5.1. COMPARISON BETWEEN COUNTRIES

To compare asymmetric volatility in different countries, we estimate the time series of the APARCH model parameters for each country. As proxy for the volatility asymmetry, we use the time series of gamma from Equation (3). We also calculate the volatility metric as defined in Equation (7).

If the approximation by the APARCH model was perfect, we would not find any relation between the gamma and the stock market return at a given point of time. This is unfortunately not the case: the estimated parameters from the APARCH model are still correlated with the input data to the model, thus market returns affect the estimated asymmetry measures. This might become a possible problem when comparing results across the sample as stock market return patterns of countries differ enormously, in particular when measured over relative short time periods as in the case of emerging markets. To eliminate this effect, we regress cumulative returns for each rolling time window of the time series of the estimated gamma. As it turns out, correlations between cumulative returns and estimated gammas are quite significant (44 out of 49 countries have p-values less than 0.01). For 44 countries the correlation is negative meaning that higher cumulative returns result in a lower estimate for gamma. The same result holds when using the metric τ instead of gamma.

As we want to eliminate the effect of the input data (returns) on the APARCH model to study other causes of the asymmetry, we use the intercepts from time series regression between the estimated gamma and the corresponding cumulative return of each country, to define an adjusted measure of gamma for each country. We ignore residuals as possible noise and hence the intercept represents the base value of asymmetry. The intercept from the returns ("adjusted gamma") still takes into account the time dimension of the data and is also comparable across countries.

As a robustness check, we still use median values of the non-adjusted gamma for each country in our regressions and find that the behavior is similar as in the case of the adjusted gamma. We also calculate the volatility metric derived from Equation (7) for each rolling time window for each country and adjust it in the same way as the gamma. Non-linearity of the metric causes the correlation between the metric and the returns from such regressions not to be as significant as for gammas but the influence is still present.

For another robustness check and comparability with previous studies we also estimate the APARCH model for each country, using all observations without any weighting function. As we use all the data points in such estimations, we obtain only one estimate for the APARCH parameters for each country. We call the asymmetry estimates obtained in such a way the "whole period gamma" and the "whole period metric". Using such an approach for calculations implies that results in estimates of volatility asymmetry will not be directly comparable as we use different time spans for different countries.

To save space we present only the estimates for the median of gamma, the "adjusted gamma", the "whole period gamma" and the "whole period metric" (see Appendix C and Figure 2 for results). Regression details for obtaining the "adjusted gamma" can be found in Appendix D.

Using the "adjusted gamma" value results in higher estimates for the volatility asymmetry compared to using the median of gamma or the "whole period gamma". In general, the different gammas are in comparable ratio across countries (see Figure 1) where the "adjusted gamma" shows the highest asymmetry and the "whole period gamma" is the lowest. This is quite an expected result as the time fluctuations of the asymmetry level fade away in large datasets when using a single longer period estimate.

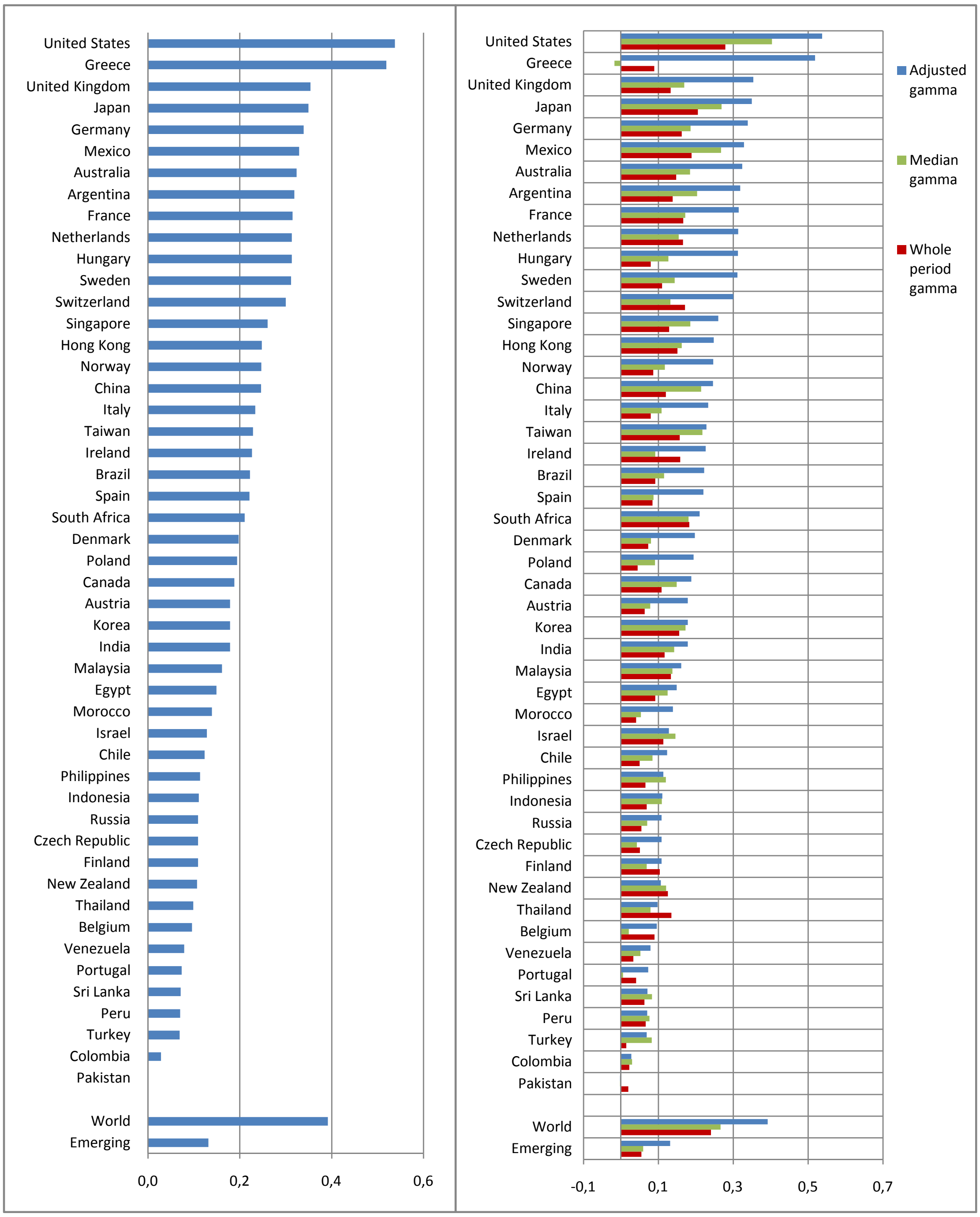

Figure 1. The adjusted gamma for all included countries (left panel). Comparison between the adjusted gamma, the median gamma and the whole period gamma (right panel) for the sample.

As the different gamma estimates confirm each other in most cases, we can conclude that developed countries tend to have a higher level of volatility asymmetry. The United States rank first by all measures. Japan, Germany and France rank among the first 10 in all categories. The United Kingdom has the forth rank with the median gamma. The only emerging market with a relatively high level of asymmetry is Mexico that ranks second or third in all gamma measures. The mixed results for Greece are caused by the fact that its time series is the shortest of all countries and the return of the market during this short period was very high.

The tendency of developed markets to have higher volatility asymmetry comes out in the aggregate data for country groups as well. We have repeated the same estimation procedure on MSCI World and MSCI Emerging Markets Index and calculated both simple and market capitalization weighted averages of all asymmetry measures. In all cases developed market (classification by MSCI) measures are higher than emerging market measures. As market capitalization weighted averages are largely influenced by the USA that has the highest measures in all categories, measures for the world rank either in the top or the middle of the sample, depending on the averaging methodology.

5.2. TIME DYNAMICS OF VOLATILITY ASYMMETRY

All previous studies have looked at the volatility asymmetry from a static point in time. Such estimations do not take into consideration possible changes in asymmetry over time. In addition to static asymmetry estimation, we also use the rolling time window estimation of the APARCH model. This enables us to capture the changes in the asymmetry in time. Results of repeatedly calculating the asymmetry for each country give us time series of the asymmetry estimation. Here we present the time series of gammas from Equation (3) for each country (see Figure 2). P-values for single point estimates are in the range of 0.01-0.20 during most of the time for all countries, however, standard errors and p-values become clearly larger when jumps can be observed in the series of gamma estimates.[2] As we use a weighting function for the APARCH input data, for an input data range of 01.1980–12.2007, we get estimates for a period 01.1982–12.2005.

Results show that the level of asymmetry changes in time quite remarkably. Part of the fluctuations can be explained by the correlation between the gamma estimation and the market returns as shown in Section 5.1. The strong influence from the returns could be a model imperfection or a behavioral tendency connected with the market direction. The impact of model input returns becomes smaller (but still present) when using the asymmetry metric from Equation (7) instead of the gamma. Still, this would not explain any trends that could be found in the asymmetry measures.

Some of the major fluctuations of the estimated gammas are caused by extreme fluctuations of the market prices which the APARCH model is incapable of capturing. It should be noted that the presented results are obtained by using outlier detection methods as described in Section 3.2 to minimize the effect of extreme fluctuations (and still use as short time windows as possible). Further smoothing functions (in addition to the input weighting) could be used on estimated time series or a wider time window could be used to obtain more stable estimations. As we use the data in further adjustment procedures for testing different causes and want to keep the time window as small as possible to study a possible influence of various factors, we do not use any smoothing function and keep the time window size small (see description in Section 3.1 and 3.3).

To study the time dynamics more closely, we firstly conduct a trend analysis of the time series of gammas. We run a regression for each country time series of gammas, using a trend dummy as the explanatory variable. Results of the regressions are reported in Table I. At the 1% confidence level we find a positive trend in asymmetry for 36 countries and a negative trend for 8 countries. The positive trend is especially apparent for developed countries where our dataset is larger.

[2]Standard errors for the series of gamma estimates are presented in Appendix C.

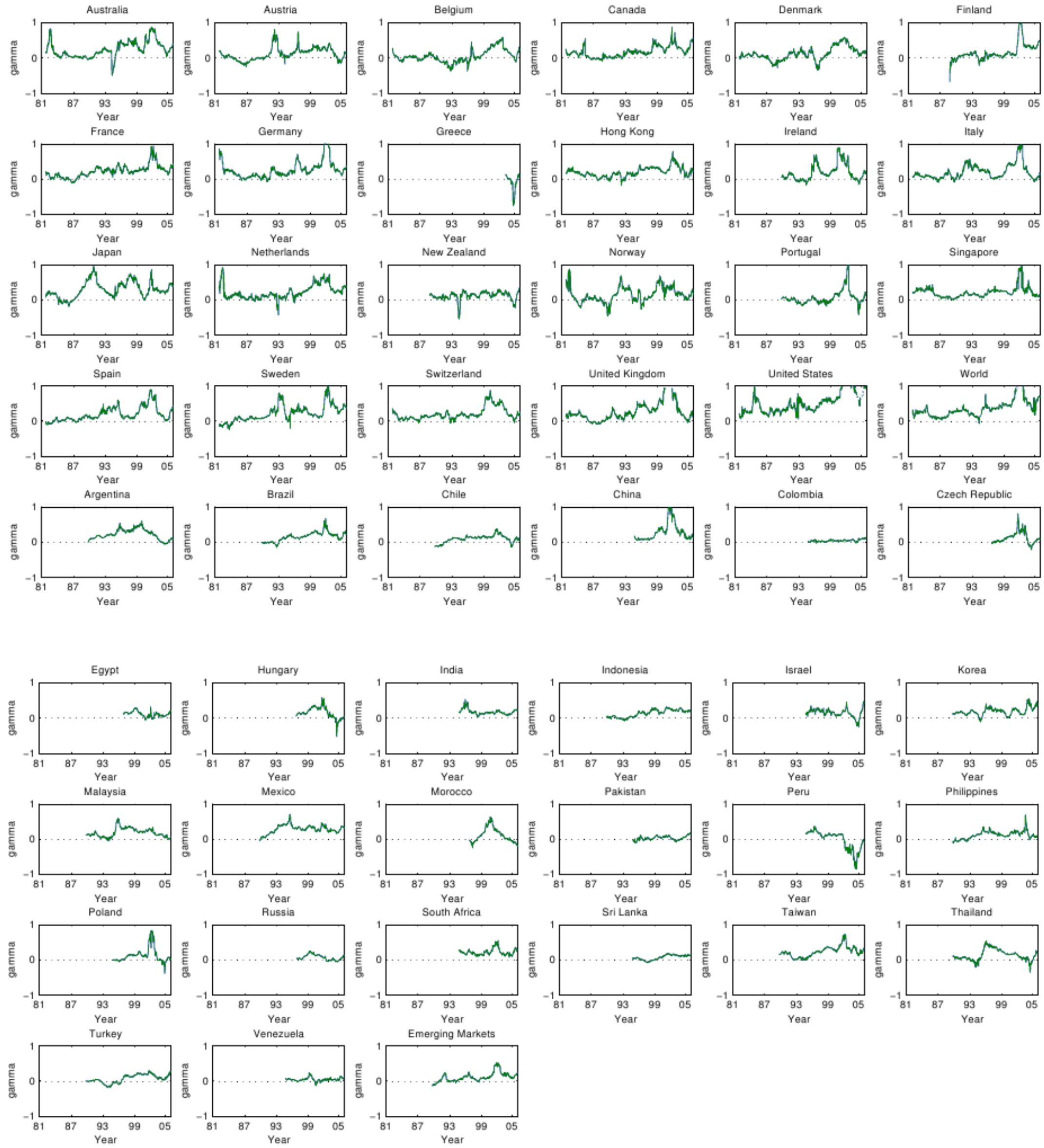

Figure 2. Time dynamics of volatility asymmetry (gamma) for all countries. Values over zero indicate asymmetry where volatility is higher when prices fall, values below zero mean that volatility is higher when market goes up. The value on the time axis denotes the midpoint of the time window used for the computation.

Table I. Regressions with the trend variable show a significant increase of volatility asymmetry over time in most countries – developed and developing alikepar The table presents direction of the trend in volatility asymmetry along with corresponding regression statistics where the gamma is the left hand side variable and a dummy trend variable is used as the right hand side variable for each country. A positive trend in volatility asymmetry is present for all but 9 countries.

Country	R^2	F-stat	T-stat	
Australia	0.21	334.6	18.29	***
Austria	0.16	230.2	15.17	***
Belgium	0.21	331.2	18.2	***
Canada	0.39	784.9	28.02	***
Denmark	0.27	456.7	21.37	***
Finland	0.43	665.5	25.8	***
France	0.46	1056.5	32.5	***
Germany	0.11	153.8	12.4	***
Greece↓	0.02	3.3	-1.82	*
Hong Kong	0.21	333.7	18.27	***
Ireland	0.07	63.6	7.97	***
Italy	0.13	179.2	13.39	***
Japan	0.11	158	12.57	***
Netherlands	0.18	270.3	16.44	***
New Zealand	0.02	21	4.58	***
Norway	0.05	64	8	***
Portugal	0.1	90.3	9.5	***
Singapore	0.06	81	9	***
Spain	0.34	654.3	25.58	***
Sweden	0.45	1021.5	31.96	***
Switzerland	0.25	420.9	20.51	***
United Kingdom	0.23	355.2	18.85	***
United States	0.45	915.4	30.26	***
Emerging Markets	0.35	456.7	21.37	***
World	0.49	1134.9	33.69	***

Country	R^2	F-stat	T-stat	
Argentina↓	0.01	8.7	-2.96	***
Brazil	0.48	775	27.84	***
Chile	0.2	205	14.32	***
China	0.1	66.5	8.16	***
Colombia	0.31	250.4	15.82	***
Czech Republic	1.8	1.34		
Egypt↓	0.16	85.3	-9.23	***
Hungary↓	0.2	118.8	-10.9	***
India↓	0.14	93.1	-9.65	***
Indonesia	0.67	1699	41.22	***
Israel↓	0.12	75.1	-8.66	***
Korea	0.18	186.8	13.67	***
Malaysia	2.2	1.49		
Mexico	0.07	58.8	7.67	***
Morocco↓	0.02	7.6	-2.76	***
Pakistan	0.16	108.1	10.4	***
Peru↓	0.61	879.4	-29.65	***
Philippines	0.24	265	16.28	***
Poland	0.02	8.9	2.98	***
Russia↓	0.18	104.3	-10.21	***
South Africa	0.02	10.4	3.22	***
Sri Lanka	0.52	622.6	24.95	***
Taiwan	0.35	451.3	21.24	***
Thailand	2	1.43		
Turkey	0.43	618.3	24.87	***
Venezuela	0.01	5.3	2.3	**

* Coefficient significant at the 10% level
** Coefficient significant at the 5% level
*** Coefficient significant at the 1% level
↓ Slope of the trend is negative

Although volatility asymmetry might be considered a market inefficiency and should be fading in time, our results show the opposite: the asymmetry is increasing in time for 40 countries and for the MSCI World as well as the MSCI Emerging Market Index.[3] When we look at the time series of the asymmetry measures, the increase in asymmetry seems to be facilitated especially during turbulent market situations as can be seen around the Asian crises and the bursting of the technology bubble.

The negative correlation with market efficiency is confirmed by our analysis of various factors on cross section level (see results of Section 6) and is implied by results of Section 5.1 where developed countries seem to have higher asymmetry measures.

Finally, when controlling for several factors (average return, GDP/capita, market capitalisation/GDP, short selling) by a panel data analysis (see results of Section 6) the non-explained part of the time dynamics for the gamma becomes visible (see Fig. 3).

5.3. COMPARISON OF OUR RESULTS WITH PREVIOUS STUDIES

The most recent comparable work in the area is done by Brooks (2007) and Jayasuriya et al. (2005). As they have not concentrated on time dynamics of the asymmetry effect, only cross sectional results can be somewhat comparable. Although our focus is not on all parameters of Equation (3), our estimates of delta are in a similar range that has been found by Hentschel (1995), Brooks et al. (2000), Jayasuriya et al. (2005) and Brooks (2007). Slight differences come from extending the dataset and using a more flexible approach of estimating APARCH model parameters.

Our estimates of the volatility asymmetry differ more from previous studies especially considering a subset of emerging markets. We present the correlation matrix between our estimated gammas and results from Jayasuriya et al. (2005) and Brooks (2007) in Table II.

[3] As a robustness check, we also repeated the calculation procedure with MSCI indices denominated in local currencies. Correlation between gamma estimates based on MSCI indices denominated in US dollars and local currencies is 0.87 whereas asymmetry estimates tend to be slightly higher when indices in local currencies are used.

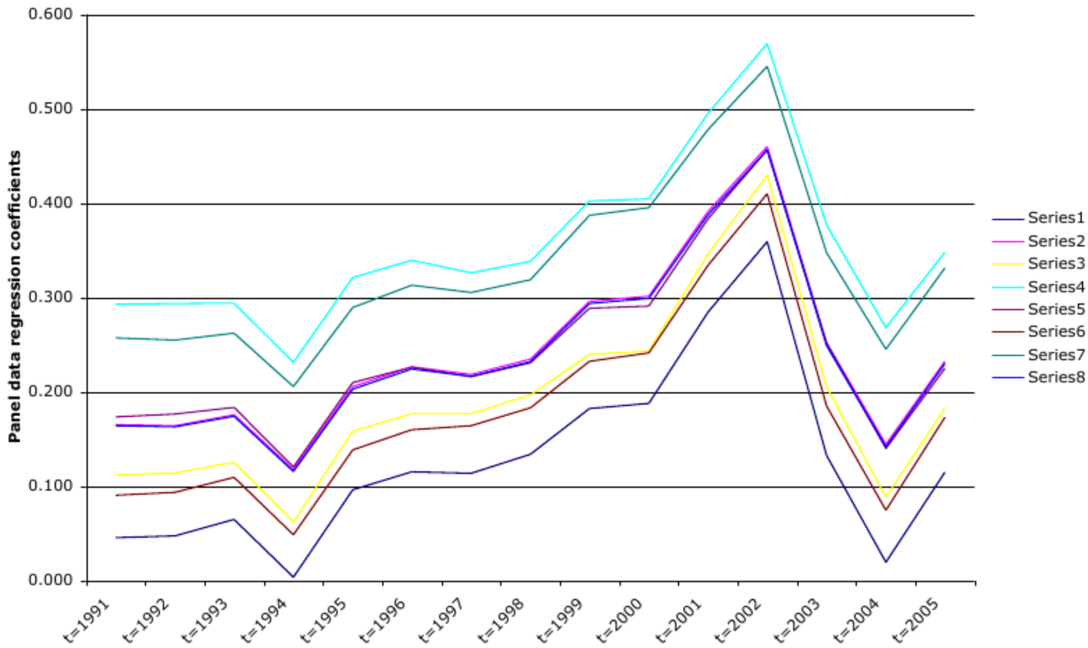

Figure 3. Coefficients of the year dummies in the panel data analysis of the gamma (see Appendix F) for 8 different regression models using data from 1991 to 2007. In all cases the underlying trend is very similar. Series 1 to 8 represent corresponding models. Model 1 uses GDP (gross domestic product) per capita as the right hand side variable; Model 2 uses GDP (gross domestic product) per capita and cumulative returns; Model 3 uses market capitalization per GDP and GDP per capita; Model 4 uses market capitalization per GDP and cumulative returns; Model 5 uses market capitalization per GDP, cumulative returns and GDP per capita; Model 6 uses a dummy variable for short selling feasibility; Model 7 uses a dummy variable for short selling feasibility and cumulative returns; Model 8 uses a dummy variable for short selling feasibility, cumulative returns and GDP per capita as right hand variables.

Also note that some of their estimates can be largely driven by turbulent times concerning the economies of Latin-America. As we have eliminated single large outliers from the data, our model and estimates are not negatively affected by such extreme events that could have been the case for Jayasuriya et al. (2005). Surprisingly our results indicate less asymmetry for the whole dataset as compared to Jayasuriya et al. (2005) even when using adjusted gamma values that are generally larger than the "whole period gammas". The difference is not very significant when considering the list of lower asymmetric volatility countries.

Our estimates of both the gamma and the volatility metric also tend to be lower than the results by Brooks (2007). Even considering that dataset and the APARCH model specification vary between our approach and Brooks' specification, the correlations between the estimated gamma parameters are surprisingly low (see Table II). The differences between our and Brooks (2007) metric estimates are lower (see Table II and Figure 4). However, the correlation between the results of Brooks (2007) and Jayasuriya et al. (2005) is even lower, indicating that there might be unknown factors having an impact on the measurement in Brooks (2007).

6. What Causes Volatility Asymmetry?

After calculating the time series of volatility asymmetry for a large number of countries, we use this data to test various hypotheses regarding factors that could potentially influence asymmetric volatility and explain why volatility is asymmetric at all. To test these hypotheses we use regression analysis of our volatility asymmetry measurements with various factors. Depending on data availability, we either use regressions at the cross section level or whenever sufficient data is available, we also use time series and panel data analysis to take advantage of the time dimension of the volatility asymmetry estimates.

Table II. Correlation of our results with previous studies (using the respective country subsamples that are included in both studies).

The table presents correlation coefficients between our asymmetry estimates and estimates of Jayasuriya et al. (2005) and Brooks (2007).

	Adjusted gamma	Whole period gamma	Jayasuriya gamma	Brooks gamma
Adjusted gamma	1			
Whole period gamma	0.70	1		
Jayasuriya gamma	0.82	0.67	1	
Brooks gamma↑	0.17	0.38	0	1
Brooks gamma↑↑	0.11	0.25	0.03	0.81

↑ calculated by using the same time period for all countries
↑↑ calculated by using the whole available dataset for each country

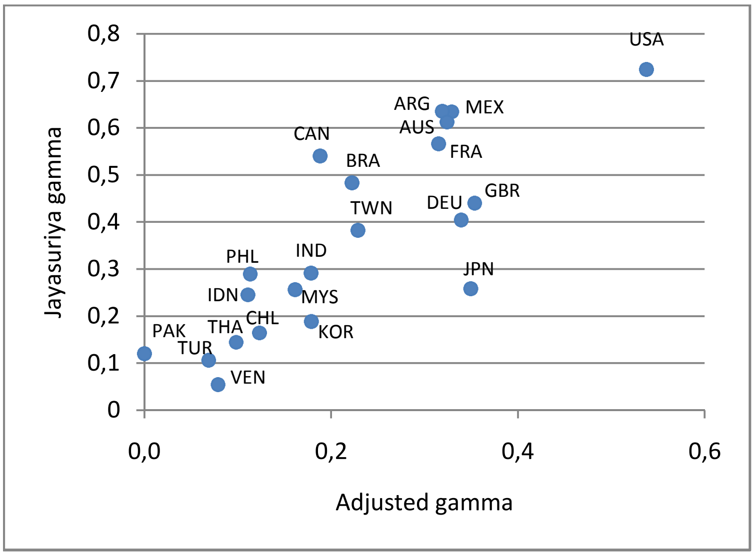

Figure 4. Scatter plot of adjusted gamma vs. Jayasuriya gamma.

In the next subsections, we test a number of factors that should drive volatility asymmetry based on the findings and prepositions in the literature and present and interpret the results of our analysis. As a robustness check, we used different volatility measures (the adjusted gamma and the metric, the whole period gamma and the metric as well as the median over the time period of both the gamma and the metric). In addition to OLS estimates, we also used iteratively reweighted least squares estimates as a more robust method to avoid the distorting effect from outliers in the data. In panel data regressions, we used different setups (fixed effect, random effect and dynamic models) including also a trend variable and year dummies to account for possible autocorrelation as well as adding average returns as an independent variable.

For conciseness we present only select results from different regressions on the adjusted gamma (our choice of the best asymmetry estimate) or the median gamma (panel data regressions). Regressions using different variables for the asymmetry measure (i.e. the whole period gamma and the metric; the median and the adjusted metric) have confirmed the findings presented in this subsection. All the presented statistically significant independent variables in the regressions are also economically significant.

6.1. VOLATILITY ASYMMETRY AND THE LEVERAGE EFFECT

The first studies on volatility asymmetry (Black, 1976) suggested that the effect might be caused by the increase in financial leverage due to a drop in market prices. To test this explanation, we use two different variables. We find a positive significant relationship (see the select results for cross section regressions and panel data regressions in Table III and IV and Appendix F) between a country's private debt level to GDP and the asymmetry. This finding supports the "leverage effect" explanation. However, the explanation is somehow contradicted by the fact that we did not find any significant impact of the average debt to equity ratio of a countries' listed companies to the volatility

Table III. Summary fit for regressions using a single explanatory variable for the adjusted gamma as the dependent variable.

The table presents summary fit for different regressions that all use a single right hand side variable where the gamma (asymmetry measure) is the left hand side variable. The results are presented for 4 different regression setups. Upper left panel reports OLS regression results with no transformation of explanatory variables. Upper right panel reports robust regression results with no transformation of explanatory variables. Lower left panel reports OLS regression results with log transformation of explanatory variables. Lower right panel reports robust regression results with log transformation of explanatory variables. Regressions use cross section data.

	No transformation of X-variable OLS				ROBUST			
	Adj. R^2	Coef.	T-stat		R^2	Coef.	T-stat	
Analyst coverage	0.454	0.011	5.854	***	0.092	0.011	6.190	***
Debt to Equity 2007	-0.010	0.011	0.719		0.125	0.013	0.860	
Developed	0.231	0.122	4.041	***	0.109	0.127	4.191	***
GDP per capita	0.306	0.000	4.847	***	0.106	0.000	4.744	***
Individuality	0.224	0.002	3.782	***	0.109	0.002	3.696	***
Media	0.202	0.003	3.331	***	0.117	0.003	3.475	***
Ownership concentration	0.155	-0.392	-2.948	***	0.116	-0.444	-3.337	***
Private debt/GDP	0.209	0.129	3.704	***	0.109	0.134	3.801	***
Relative efficiency	0.277	-1.537	-4.400	***	0.106	-1.539	-4.293	***
Risk premium	0.182	-2.203	-3.383	***	0.110	-2.354	-3.594	***
Short selling allowed	0.085	0.099	2.219	**	0.120	0.105	2.347	**
Short selling feasible	0.160	0.109	3.190	***	0.112	0.112	3.248	***
Stock market capitalization to GDP	0.217	0.001	3.779	***	0.110	0.001	3.694	***
Uncertainty Avoidance	0.022	0.001	-1.427		0.121	0.001	-1.537	

	Log transformation of X-variable OLS				ROBUST			
	Adj. R^2	Coef.	T-stat		R^2	Coef.	T-stat	
Analyst coverage	0.428	0.117	5.560	***	0.093	0.117	5.770	***
Debt to Equity 2007	0.037	0.025	1.684	*	0.118	0.031	2.043	**
Developed								
GDP per capita	0.310	0.057	4.887	***	0.107	0.055	4.573	***
Individuality	0.224	0.096	3.780	***	0.109	0.094	3.628	***
Media								
Ownership concentration	0.182	-0.157	-3.213	***	0.118	-0.167	-3.296	***
Private debt/GDP								
Relative efficiency	0.321	-0.186	-4.864	***	0.103	-0.187	-4.752	***
Risk premium	0.222	-0.198	-3.800	***	0.107	-0.204	-3.900	***
Short selling allowed								
Short selling feasible								
Stock market capitalization to GDP	0.341	0.083	5.081	***	0.098	0.081	4.964	***
Uncertainty Avoidance	0.024	-0.052	-1.454		0.122	-0.053	-1.442	

* Coefficient significant at the 10% level
** Coefficient significant at the 5% level
*** Coefficient significant at the 1% level

Table IV. Panel data analysis with the gamma as the dependent variable investigating the influence of three factors that potentially drive the volatility asymmetry: GDP/capita, market capitalisation/GDP and short selling feasibility. In all cases $N = 35$ countries have been studied from 1991–2007 including year dummies. The complete regression results can be found in Appendix F.

	Model 1			Model 2		
	Coef.	Stdv.	p	Coef.	Stdv.	p
GDP/cap.	5.90E-06	6.81E-07	< 0.001	4.84E-06	-1.50E-05	< 0.001
Return				-0.088	0.024	< 0.001

	Model 3			Model 4			Model 5		
	Coef.	Stdv.		Coef.	Stdv.		Coef.	Stdv.	
MC/GDP	0.048	0.012	***	0.053	0.011	***	0.032	0.012	***
Return				-0.154	0.023	***	-0.098	0.024	***
GDP/cap.							4.17E-06	7.75E-07	***

	Model 6			Model 7			Model 8		
	Coef.	Stdv.		Coef.	Stdv.		Coef.	Stdv.	
Short	0.079	0.016	***	0.064	0.015	***	0.017	0.017	
Return				-0.134	0.023	***	-0.089	0.024	***
GDP/cap.							4.41E-06	8.55E-07	***

* Coefficient significant at the 10% level
** Coefficient significant at the 5% level
*** Coefficient significant at the 1% level

asymmetry, which should be a better measure of leverage. In conclusion, we cannot find support for the pure leverage effect with our data.

6.2. VOLATILITY ASYMMETRY AND RISK PREMIUM

Numerous other earlier works (Pindyck (1984), Campbell and Hentschel (1992) and others) propose an explanation based on time varying risk premia. To check this, we test the correlation between the risk premium of the country (derived from S&P ratings for the country) and the volatility asymmetry. We find a significant negative correlation (see the select results for cross section regressions and panel data regressions in Table III and IV and Appendix F) between the volatility asymmetry and the risk premium of the country at the cross section level. This would mean that in case of higher risk premium, the volatility asymmetry would be lower – opposite to what the theory predicts.[4] The correlation becomes insignificant in the panel data analysis. We conclude that there is no evidence supporting an explanation of volatility asymmetry based on the level of risk premium.

6.3. VOLATILITY ASYMMETRY AND MARKET EFFICIENCY

Our findings in Section 5 show that the level of volatility asymmetry can differ significantly across countries, so it is natural to wonder whether the economic development or structure can be a factor explaining the asymmetry. The reasoning behind such a test is that the volatility asymmetry could be connected with market inefficiency where more developed countries tend to have more efficient capital markets.

As the level of economic development might only loosely be connected with stock market efficiency, we also test more direct measures of market efficiency (Appendix B). As the different variables have quite a significant correlation within the category, we

[4]The time-varying risk premium theory has been criticized also in later works by Bekaert and Wu (2000) and Li et al. (2005).

use the level of GDP per capita as our main proxy for the level of economic development. (Regressions with other parameters of market efficiency and development yield similar results, see below.) Both cross section and panel data regressions (see the select results for cross section regressions and panel data regressions in Table III and IV and Appendix F) show a significant *positive* impact of the level of GDP per capita of the country on the volatility asymmetry.

To check this effect, we included the total level of GDP and population as separate variables. The results indicate that population does not have a significant effect on the asymmetry measure. The positive impact found for the total GDP in the single regressions is outweighed by the level of GDP per capita in multiple regressions including both variables. We also find confirming results from panel data regressions for the significant impact of the level of GDP per capita.

To confirm the findings that countries with a higher level of GDP per capita (thus a higher level of economic development) have a higher volatility asymmetry, we also used variables from the Global Competitiveness Report and the variables describing economic openness and economic freedom instead of GDP per capita. These different variables are correlated within the group, including other variables of economic development, which confirms the rejection of the proposed hypothesis and enables to reach a conclusion that a higher level of economic development leads to a higher level of volatility asymmetry.

Results from Sections 5.2 and economic development testing indicate that the level of asymmetry is not positively connected with the level of market efficiency. To further test the finding, we use results from different recent studies (Marshall, Cahan and Cahan (2008), Griffin, Kelly and Nardari (2007)) of market efficiency and run regressions with their findings on our estimated volatility asymmetry. In both cases we find significant negative correlation between excess returns of the studied markets and the level of asymmetric volatility. This confirms the finding that the level of market efficiency is coupled with a higher level of volatility asymmetry and a positive trend in the level of asymmetry can be found for most countries. In particular, our results are strong evidence that volatility asymmetry is not a mere artefact caused by market inefficiencies: very much to the contrary, it is stronger on higher developed financial markets.

6.4. VOLATILITY ASYMMETRY AND SHORT-SELLING

Sentana and Wadhwani (1992) propose that stop-loss orders and margin call liquidations could affect the asymmetry which means that more intensive selling is present in case of price drops than under normal circumstances. The same principle applies to the ability to short-sell securities that could lead to a higher level of volatility asymmetry as proposed by Jayasuriya et al. (2005).

To test the influence of short-selling on the level of asymmetry we use three different variables derived from the works of Bris, Goetzmann and Zhu (2007) and Charoenrook and Daouk (2005). We find a significant positive relationship between the level of asymmetric volatility and a dummy variable for availability of short selling for all instances at the cross section level. As the feasibility of short selling captures the possibility of shorting the stock market most precisely, we use the same variable in various panel data regressions to confirm the finding. The positive influence of short selling is present in random effect panel data regressions as well as in dynamic models of panel data, allowing for autocorrelation of the endogenous variable (in our case, the gamma) and different instrumental variables.

The influence of short selling is not so evident at the cross section level when including GDP per capita as an additional variable in the regressions; and in the fixed effect panel data model when including multiple variables as GDP per capita, the trend dummy and average returns. Although short selling is generally feasible in more developed countries, the correlation between GDP per capita and the feasibility of short selling does not bias the positive impact of short selling on the asymmetric volatility in other regression setups.

A graphical representation of the relation between the feasibility of short selling and the gamma can be seen in Figure 5. The results enable us to conclude that the asymmetry of volatility is indeed influenced by the feasibility of short selling, meaning that the ability to short-sell stocks (or buy put options) makes markets more volatile during falling market prices. However, short selling cannot be the main factor influencing the volatility asymmetry as most of the fluctuations in the asymmetry measures cannot be explained by changing conditions for short selling.

As by itself the positive correlation between the feasibility of short selling and volatility asymmetry does not tell us whether short selling increases volatility in down market conditions or decreases volatility in up market conditions (both cases would increase the asymmetry), we study the changes in other parameters of the Equation (4). As the overall level of volatility is also positively influenced by parameter β, we repeat similar regressions, also on the panel of estimated β. We find a positive correlation of the feasibility of short selling on β in cross section and panel data regressions. As the ability to short-sell increases both parameters γ and β in the Equation (4), the results indicate that short selling increases volatility in down market conditions when $\varepsilon_{t-1} < 0$. The same cannot be said about up market conditions where the effect from a larger γ has a negative impact on the volatility but a larger β increases the volatility. So our findings do not indicate that short-selling makes markets more volatile in general but does cause a higher volatility when prices are falling.

6.5. VOLATILITY ASYMMETRY AND INDIVIDUAL INVESTORS

As a result of a financial markets experiment where there were no fundamental market factors present (including the leverage), Hens and Steude (2009) suggest that volatility asymmetry can be caused by behavioral preferences of the investors. Alternatively, bias in expectations has been suggested as a possible cause (Shefrin, 2005).

To test behavioral factors as a potential direct cause of volatility asymmetry we

Figure 5. Time dynamics of gamma (blue line) and short selling feasibility (red line) across countries.

Table V. Summary of fit for multiple regressions for the adjusted gamma

The table presents summary fit for regressions where the adjusted gamma (asymmetry measure) is the left hand side variable and all regressions use logarithm of GDP per capita as one independent variable and other possible factors such as ownership concentration; analyst coverage; media; and individualism as the second right hand side variable. Regressions use cross section data.

Variable	**Coefficient**	**T-stat**		**Adj.** R^2	**N**
Log(GDP per capita)	0.054	3.97	***	0.38	43
Ownership concentration	-0.176	-1.39			
Log(GDP per capita)	0.038	2.89	***	0.54	41
Analyst coverage	0.008	4.18	***		
Log(GDP per capita)	0.100	1.61		0.33	40
Media	-0.002	-0.59			
Log(GDP per capita)	0.041	2.76	***	0.32	47
Individualism	0.001	1.65			

* Coefficient significant at the 10% level
** Coefficient significant at the 5% level
*** Coefficient significant at the 1% level

would need to quantify at least some of the underlying behavioral aspects. Instead we rely on an indirect approach: since individual investors are more prone to bias than institutional investors, we would expect large volatility asymmetry on markets where the impact of individual investors is higher. The first hint that this might be indeed an important effect is one observation we have already made, namely that more developed markets tend to have larger volatility asymmetry. It is, however, possible to measure the impact of individual investors more directly: two parameters that capture this impact are ownership concentration and market capitalization/GDP.

We find a significant negative impact of ownership concentration on volatility asymmetry. Although the coefficients for the ownership concentration become less significant in multiple regressions, the sign for the direction of the variable remains clearly negative. The finding indicates that countries where the ownership concentration of the listed companies is low (implying the presence of more individual investors or at least smaller institutional investors who are likely to be less experienced and/or informed), have a higher level of asymmetry.

That would mean that in case of bad news, there would be a higher absolute number of investors selling and pushing the prices down more quickly, thus increasing the volatility during falling prices. This could be the explanation for a different behavior of investors after falling and rising prices, which would be consistent with the ideas of Hens and Steude (2009) and Shefrin (2005).

We also used market capitalization divided by GDP as a proxy for the percentage of private investors on the market. This has a significantly positive effect on the volatility asymmetry, even when controlling for GDP/capita (Table V). The effect becomes even more significant in the panel data analysis (Table IV), which further supports the theory that behavioral effects, mainly in individual investors are a key source of volatility asymmetry.

6.6. VOLATILITY ASYMMETRY, MEDIA AND ANALYSTS

As media has been argued to influence the sentiment of investors and thus prices of the stock market (Tetlock, 2007) and media penetration can be quantifiable, we test the hypothesis that media accentuates especially the negative information flow, thus contributing to the volatility asymmetry. Our analysis, however, does not show a significant impact of media penetration when controlling for GDP/capita. The likely reason is that both variables are too closely correlated. We could not use a panel data analysis, since media penetration was not available as panel data.

Instead of general media penetration, we can test a more direct measurement of stock market related news, namely the number of financial analysts. They are an important source of information for investors and could potentially influence their sentiment. Since big news are typically bad news, one would expect their volatility increasing influence to be larger in bear markets, thus increasing volatility asymmetry. In fact, we find a significant positive correlation between asymmetric volatility and the measure of analyst coverage. The effect is still present when using the analyst coverage variable in multiple regressions along with the level of GDP/capita (Table V). This indicates that better coverage of the listed firms helps to draw more attention to the possible shortcomings in the operations of the firms and in case of bad news, to react more quickly and decisively to the news. The finding is supported by Hong, Lim and Stein (2000) who argue that low analyst coverage stocks tend to react less especially to bad news compared to high coverage stocks.

6.7. OTHER POSSIBLE FACTORS

Other potential influencing factors have been suggested in the past, e.g. cultural differences can influence investor behavior, as has been demonstrated by Chui, Titman and Wei (2008) for the momentum effect. We therefore tested whether cultural dimensions influence volatility asymmetry and included the four variables of Hofstede (2001) into our analysis. Our results indicate that a higher level of individualism (reliance on oneself) might indeed result in a higher volatility asymmetry. Higher level of individualism is commonly associated with a higher level of confidence (which could lead to overconfidence). When adding GDP/capita to the regression, however, the effect becomes insignificant. We therefore conclude that individuality might be rather a property of (most) highly developed countries which have, as we demonstrated above, large volatility asymmetries. The one country in our sample that has a very high level of development and yet has a low individuality score is Japan. Japan, however, shows a large volatility asymmetry, which is in line with the development hypothesis rather than with the individuality hypothesis.

As market capitalization and the level of trading were mentioned by Brooks (2007), we tested similar variables. Contrary to Brooks (2007), we find a positive correlation between market capitalization and the asymmetric volatility as well as between the level of trading and the asymmetric volatility at the cross section level. However, the effect disappears in the panel data analysis and in conclusion we cannot report a clear positive relationship (nor causality) from market capitalization or the level of trading.

Brooks (2007) briefly tested the influence of corporate environment on volatility asymmetry. To repeat the analysis, we tested a number of variables extracted from the works of Bushman and Smith (2003) and Djankov, La Porta, Lopez-de Silanes and Shleifer (2008). We did not find any significant correlation between the estimated volatility asymmetry measures and the variables of the corporate environment category.

7. Conclusions

Based on a refined method for measuring volatility asymmetry we have obtained time series data for a large number of countries. Cross-sectional and panel data analysis demonstrated that there are common factors that seem to increase volatility asymmetry:

- **GDP/capita** as a proxy for economic development increases volatility asymmetry. This shows that volatility asymmetry cannot be caused by a lack of market development. It might, however, be related to the *proportion of non-professional investors* on the market. This proportion is likely to be higher in wealthier countries. The hypothesis is further supported by our next finding:
- **Market capitalisation/GDP** shows a significant positive correlation with volatility asymmetry, also in the panel data analysis.
- **Analyst coverage** also increases volatility asymmetry.
- **Short selling** seems to increase volatility in bear markets, but the effect was not visible in the panel data analysis.

On the other hand we find only little evidence of the validility of the original explanation of the "leverage effect" in our study. The evidence therefore points clearly to the behavioral sentiment of non-professional investors as a driving force for volatility asymmetry.

It would be an interesting task for further studies to find a more direct relation between behavioral bias and its effect on volatility asymmetry. Moreover, it would be interesting to further investigate the time dynamics of volatility asymmetry, since we observed a large fluctuation over the years, besides a general increasing trend. The methodology to generate sufficient data for such studies has been developed in this article.

A. Included Markets

The table presents included markets in the study with corresponding starting dates for used MSCI index data.

Developed markets		
Country	*Code*	*Starting date*
Australia	AUS	1.01.1980
Austria	AUT	1.01.1980
Belgium	BEL	1.01.1980
Canada	CAN	1.01.1980
Denmark	DNK	1.01.1980
Finland	FIN	1.01.1987
France	FRA	1.01.1980
Germany	DEU	1.01.1980
Greece	GRC	1.06.2001
Hong Kong	HKG	1.01.1980
Ireland	IRL	1.01.1988
Italy	ITA	1.01.1980
Japan	JPN	1.01.1980
Netherlands	NLD	1.01.1980
New Zealand	NZL	1.01.1987
Norway	NOR	1.01.1980
Portugal	PRT	1.01.1988
Singapore	SGP	1.01.1980
Spain	ESP	1.01.1980
Sweden	SWE	1.01.1980
Switzerland	CHE	1.01.1980
United Kingdom	GBR	1.01.1980
United States	USA	1.01.1980
World Index	WOR	1.01.1980

Emerging markets		
Country	*Code*	*Starting date*
Argentina	ARG	1.01.1988
Brazil	BRA	1.01.1988
Chile	CHL	1.01.1988
China	CHN	1.01.1993
Colombia	COL	1.01.1993
Czech Republic	CZE	2.01.1995
Egypt	EGY	2.01.1995
Hungary	HUN	2.01.1995
India	IND	1.01.1993
Indonesia	IDN	1.01.1988
Israel	ISR	1.01.1993
Korea	KOR	1.01.1988
Malaysia	MYS	1.01.1988
Mexico	MEX	1.01.1988
Morocco	MAR	2.01.1995
Pakistan	PAK	1.01.1993
Peru	PER	1.01.1993
Philippines	PHL	1.01.1988
Poland	POL	1.01.1993
Russia	RUS	2.01.1995
South Africa	ZAF	1.01.1993
Sri Lanka	LKA	1.01.1993
Taiwan	TWN	1.01.1988
Thailand	THA	1.01.1988
Turkey	TUR	1.01.1988
Venezuela	VEN	1.01.1993
Emerging Markets	EME	1.01.1988

B. Data Used in Testing Volatility Asymmetry Causes

Analyst coverage: Number of analysts following the largest 30 companies in each country in 1996. Data was extracted from Chang, Khanna and Palepu (2000).
Average return: Average returns were calculated from a country specific MSCI index. Data was obtained from Thomson's Datastream.
Corp. Disclosure index: Index measuring the level of corporate disclosure. Data was extracted from Bushman and Smith (2003).
Corporate transparency index: Index measuring corporate transparency. Data was extracted from Bushman and Smith (2003).
Debt to Equity 2007: Average debt to equity ratio of publicly traded firms at the end of 2007. Source: Bloomberg, Value Line. Data was downloaded from A. Damodaran's website: http://pages.stern.nyu.edu
Developed: A dummy variable for developed countries according to MSCI Index classification.
GDP billion$\uparrow$: Total GDP for each country. Source: World Bank World Development Indicators. Data was downloaded from: http://www.ers.usda.gov/Data/Macroeconomics/
GDP per capita$\uparrow$: GDP per capita for each country. Source: World Bank World Development Indicators. Data was downloaded from: http://www.ers.usda.gov/Data/Macroeconomics/
Index of shareholder rights: The index measuring the level of shareholder rights. Data was extracted from La Porta, Lopez-de Silanes, Shleifer and Vishny (1998).
Individualism: Individualism Index measures the degree to which individuals are integrated into groups. Constructed by Hofstede (2001). Data was downloaded from G. Hofstede's website: http://www.geert-hofstede.com/
Market Cap 2007: Market Capitalization of publicly traded firms at the end of 2007. Source: Bloomberg, Value Line. Data was downloaded from A. Damodaran's website:
http://pages.stern.nyu.edu/
Masculinity: Masculinity refers to the distribution of roles between the genders. Constructed by Hofstede (2001). Data was downloaded from G. Hofstede's website: http://www.geert-hofstede.com/
Media: Average rank of the countries' media development (print and television) between 1993 and 1995. Source: World Development Indicators
Ownership concentration: Average percentage of common shares owned by the top three shareholders in the ten largest non-financial, privately-owned domestic firms in a given country. Data was extracted from La Porta, Lopez-de Silanes and Shleifer (2006).
Power Distance: Power Distance Index measures the extent to which the less powerful members of organizations and institutions accept and expect that power is distributed unequally. Constructed by Hofstede (2001). Data was downloaded from G. Hofstede's website: http://www.geert-hofstede.com/
Private debt/GDP$\uparrow$: Private debt as a share of GDP for each country. Source: World Development Indicators. Data was downloaded from A.Shleifer's web site:
http://www.economics.harvard.edu/faculty/shleifer/data.html
Relative efficiency: Measure of relative efficiency of the stock market. Data was extracted from Griffin et al. (2007).
Revised Anti-director Index: Anti-director index measures the protection of the investors. Data was extracted from (Djankov et al., 2008).
Risk premium$\uparrow$: Risk premium estimates based upon the country ratings assigned by Standard and

Poors'. Data downloaded from A. Damodaran's website: http://pages.stern.nyu.edu/

Short selling allowed↑: A dummy variable for countries where short selling is allowed by regulation. Data extracted from Bris, Geotzmann and Zhu (2003).

Short selling feasible↑: A dummy variable for countries where short selling or put option trading is feasible. Data was extracted Charoenrook and Daouk (2005).

Short selling practiced↑: A dummy variable for countries where short selling is practiced. Data was extracted from Bris et al. (2003).

Stock Market Capitalization / GDP↑: Value of listed shares to GDP. Data was obtained from World Bank's Financial Development and Structure database.

Stock Market Total Value Traded / GDP↑: Total shares traded on the stock market exchange to GDP. Data was obtained from World Bank's Financial Development and Structure database.

Stock Market Turnover Ratio↑: Ratio of the value of total shares traded to average real market capitalization. Data was obtained from World Bank's Financial Development and Structure database.

Technical analysis daily return: Average daily return from technical analysis strategies. Data was extracted from Marshall et al. (2008).

Uncertainty Avoidance: Uncertainty Avoidance Index measures the tolerance for uncertainty and ambiguity. Constructed by Hofstede (2001). Data downloaded from G. Hofstede's website: http://www.geert-hofstede.com/

↑ Cross section and time series data was available, in other cases only cross section data was used.

C. Asymmetry Measures

The table presents median of gamma (volatility asymmetry measure) series; standard error of the time series of gammas; 'Adjusted gamma' where the impact from returns is regressed out; 'Whole period gamma' where the estimation is done only once, using all available data points for each country; 'Whole period metric' (volatility asymmetry measure) where estimation is done only once, using all available data points for each country.

Country	Median gamma	SE of gamma series	Adjusted gamma	Whole period gamma	Whole period metric
Argentina	0.203	0.211	0.319	0.139	1.652
Australia	0.185	0.111	0.324	0.148	1.612
Austria	0.079	0.219	0.179	0.064	1.223
Belgium	0.022	0.058	0.096	0.090	1.353
Brazil	0.116	0.177	0.222	0.092	1.439
Canada	0.149	0.175	0.188	0.109	1.424
Chile	0.084	0.241	0.123	0.050	1.207
China	0.215	0.166	0.246	0.120	1.500
Colombia	0.030	0.114	0.028	0.022	1.086
Czech Republic	0.043	0.151	0.109	0.051	1.132
Denmark	0.081	0.253	0.197	0.073	1.211
Egypt	0.125	0.191	0.149	0.092	1.651
Finland	0.069	0.201	0.109	0.104	1.406
France	0.172	0.181	0.315	0.167	1.856
Germany	0.186	0.137	0.339	0.163	1.754
Greece	-0.017	0.105	0.519	0.089	1.280
Hong Kong	0.162	0.087	0.248	0.151	1.676
Hungary	0.127	0.113	0.313	0.080	1.318
India	0.143	0.120	0.179	0.117	1.561
Indonesia	0.109	0.233	0.111	0.069	1.225
Ireland	0.092	0.159	0.226	0.158	1.639
Israel	0.146	0.176	0.128	0.113	1.489
Italy	0.109	0.254	0.233	0.080	1.354
Japan	0.269	0.207	0.350	0.206	1.650
Korea	0.173	0.244	0.179	0.156	1.662
Malaysia	0.138	0.204	0.161	0.133	1.587
Mexico	0.268	0.172	0.329	0.189	1.842
Morocco	0.054	0.093	0.139	0.041	1.097

Country	Median gamma	SE of gamma series	Adjusted gamma	Whole period gamma	Whole period metric
Netherlands	0.155	0.203	0.313	0.166	1.819
New Zealand	0.121	0.197	0.107	0.125	1.352
Norway	0.117	0.072	0.247	0.086	1.294
Pakistan	-0.002	0.157	-0.003	0.020	1.073
Peru	0.077	0.115	0.070	0.066	1.197
Philippines	0.120	0.166	0.113	0.065	1.261
Poland	0.091	0.244	0.194	0.045	1.172
Portugal	0.006	0.058	0.073	0.041	1.142
Russia	0.070	0.090	0.109	0.055	1.231
Singapore	0.186	0.124	0.260	0.129	1.561
South Africa	0.181	0.179	0.210	0.183	1.640
Spain	0.087	0.118	0.221	0.085	1.281
Sri Lanka	0.083	0.208	0.071	0.063	1.236
Sweden	0.144	0.133	0.312	0.110	1.538
Switzerland	0.133	0.172	0.300	0.172	1.923
Taiwan	0.218	0.194	0.229	0.158	1.750
Thailand	0.079	0.148	0.098	0.135	1.570
Turkey	0.083	0.115	0.069	0.014	1.053
United Kingdom	0.169	0.193	0.354	0.133	1.671
United States	0.404	0.136	0.538	0.279	2.973
Venezuela	0.052	0.063	0.079	0.033	1.096
World [a]	0.266	0.241	0.392	0.241	2.073
Emergingmarkets [b]	0.060	0.027	0.132	0.055	1.181
Average [c]	0.125	0.160	0.205	0.107	1.464

a MSCI World Index
b MSCI Emerging Markets Index
c Average of all countries

	Median gamma	Adjusted gamma	Whole period gamma	Median metric	Adjusted metric	Whole period metric
World†	0.290	0.437	0.241	2.238	1.099	2.073
Emerging markets†	0.087	0.143	0.055	1.168	2.664	1.181
Developed markets††	0.313	0.485	0.229	2.138	1.656	2.468

† calculated using APARCH estimations for MSCI World and MSCI Emerging Markets index
†† calculated by market capitalization weighted average (2007) of MSCI defined developed countries in current study

D. Regressions for Gamma Adjustment

The table presents regression statistics for the gamma (volatility asymmetry measure) adjustment, where the gamma is the left hand side variable and cumulative return is the right hand side variable. The adjusted gamma is the intercept of such regressions representing a long term base value for volatility asymmetry where the impact of market returns is eliminated.

Country	Adjusted gamma	T-stat		Adj. R^2	F-stat	
Argentina	0.319	60.158	***	0.458	689.221	***
Australia	0.324	38.861	***	0.178	271.295	***
Austria	0.179	33.152	***	0.286	501.142	***
Belgium	0.096	15.996	***	0.125	179.429	***
Brazil	0.222	48.910	***	0.472	739.761	***
Canada	0.188	25.828	***	0.004	6.053	**
Chile	0.123	33.957	***	0.420	601.972	***
China	0.246	24.373	***	0.120	79.164	***
Colombia	0.028	24.041	***	0.028	17.438	***
Czech Republic	0.109	9.591	***	0.015	8.013	***
Denmark	0.197	28.440	***	0.253	422.690	***
Egypt	0.149	21.217	***	0.006	3.444	*
Finland	0.109	15.529	***	0.019	17.619	***
France	0.315	51.892	***	0.382	760.967	***
Germany	0.339	41.789	***	0.239	392.842	***
Greece	0.519	7.135	***	0.369	82.264	***
Hong Kong	0.248	58.768	***	0.365	713.010	***
Hungary	0.313	30.907	***	0.488	448.040	***
India	0.179	47.630	***	0.178	124.241	***
Indonesia	0.111	33.367	***	0.000	0.882	
Ireland	0.226	20.728	***	0.091	84.220	***
Israel	0.128	22.242	***	0.005	3.849	**
Italy	0.233	37.788	***	0.220	352.967	***
Japan	0.350	80.764	***	0.574	1683.745	***
Korea	0.179	45.055	***	-0.001	0.203	

Country	Adjusted gamma	T-stat		Adj. R^2	F-stat	
Malaysia	0.161	50.471	***	0.460	693.971	***
Mexico	0.329	79.337	***	0.441	649.964	***
Morocco	0.139	40.292	***	0.859	2848.419	***
Netherlands	0.313	51.579	***	0.361	705.144	***
New Zealand	0.107	26.456	***	0.001	1.917	
Norway	0.247	30.717	***	0.222	356.644	***
Pakistan	-0.003	-1.003		0.000	0.977	
Peru	0.070	8.689	***	0.365	327.037	***
Philippines	0.113	34.756	***	0.227	243.517	***
Poland	0.194	22.984	***	0.268	209.020	***
Portugal	0.073	11.247	***	0.147	144.370	***
Russia	0.109	25.581	***	0.274	174.387	***
Singapore	0.260	57.126	***	0.244	402.057	***
South Africa	0.210	44.417	***	0.000	1.191	
Spain	0.221	30.704	***	0.086	118.765	***
Sri Lanka	0.071	31.399	***	0.176	120.407	***
Sweden	0.312	31.614	***	0.145	212.364	***
Switzerland	0.300	66.111	***	0.546	1506.501	***
Taiwan	0.229	53.244	***	0.191	195.337	***
Thailand	0.098	32.846	***	0.741	2354.612	***
Turkey	0.069	16.794	***	0.043	38.168	***
United Kingdom	0.354	47.768	***	0.332	592.164	***
United States	0.538	63.454	***	0.164	229.459	***
Venezuela	0.079	26.060	***	0.123	79.049	***
World	0.392	65.233	***	0.274	464.297	***
Emerging	0.132	23.804	***	0.179	181.541	***

* Coefficient significant at the 10% level
** Coefficient significant at the 5% level
*** Coefficient significant at the 1% level
† MSCI World Index
†† MSCI Emerging Markets Index

E. Outlier Detection Statistics

Country	Total observ.	Total eliminated jumps	Eliminated jumps %
Argentina	5216	131	2.51%
Australia	7304	57	0.78%
Austria	7304	58	0.79%
Belgium	7304	66	0.90%
Brazil	5216	70	1.34%
Canada	7304	84	1.15%
Chile	5216	61	1.17%
China	3911	51	1.30%
Colombia	3911	81	2.07%
Czech Republic	3390	32	0.94%
Denmark	7304	65	0.89%
Egypt	3390	122	3.60%
Finland	5477	84	1.53%
France	7304	56	0.77%
Germany	7304	57	0.78%
Greece	1716	16	0.93%
Hong Kong	7304	102	1.40%
Hungary	3390	38	1.12%
India	3911	56	1.43%
Indonesia	5216	200	3.83%
Ireland	5215	43	0.82%
Israel	3911	77	1.97%
Italy	7304	60	0.82%
Japan	7304	62	0.85%
Korea	5216	73	1.40%
Malaysia	5216	150	2.88%

Country	Total observ.	Total eliminated jumps	Eliminated jumps %
Mexico	5216	88	1.69%
Morocco	3390	32	0.94%
Netherlands	7304	69	0.94%
New Zealand	5477	58	1.06%
Norway	7304	73	1.00%
Pakistan	3911	109	2.79%
Peru	3911	62	1.59%
Philippines	5216	83	1.59%
Poland	3911	69	1.76%
Portugal	5216	54	1.04%
Russia	3385	78	2.30%
Singapore	7304	94	1.29%
South Africa	3911	53	1.36%
Spain	7304	63	0.86%
Sri Lanka	3911	109	2.79%
Sweden	7304	72	0.99%
Switzerland	7304	48	0.66%
Taiwan	5216	84	1.61%
Thailand	5216	98	1.88%
Turkey	5216	81	1.55%
United Kingdom	7304	47	0.64%
United States	7304	60	0.82%
Venezuela	3911	113	2.89%
World †	7304	56	0.77%
Emerging Markets ††	5216	61	1.17%

† MSCI World Index
†† MSCI Emerging Markets Index

F. Panel Data Regressions for Gamma

The table presents year dummies and other independent variables for 8 different panel data regressions where the gamma (asymmetry measure) is the left hand side variable. 'GDP/cap.' stands for gross domestic product per capita; 'Return' is cumulative index return over the observed period; 'MC/GDP' is market capitalization per GDP; 'Short' is a dummy variable representing short selling feasibility.

	Model 1			Model 2		
	Coef.	Stdv.		Coef.	Stdv.	
t=1991	0.046	0.029		0.165	0.043	***
t=1992	0.048	0.029		0.164	0.043	***
t=1993	0.065	0.029	**	0.176	0.042	***
t=1994	0.004	0.029		0.118	0.042	***
t=1995	0.096	0.029	***	0.206	0.041	***
t=1996	0.116	0.029	***	0.227	0.042	***
t=1997	0.114	0.030	***	0.219	0.041	***
t=1998	0.134	0.030	***	0.235	0.040	***
t=1999	0.183	0.030	***	0.296	0.042	***
t=2000	0.188	0.030	***	0.302	0.043	***
t=2001	0.285	0.030	***	0.391	0.041	***
t=2002	0.359	0.030	***	0.460	0.040	***
t=2003	0.133	0.030	***	0.252	0.044	***
t=2004	0.020	0.030		0.145	0.045	***
t=2005	0.115	0.030	***	0.233	0.044	***
GDP/cap.	5.90E-06	6.81E-07	***	4.84E-06	-1.50E-05	***
Return				-0.088	0.024	***

	Model 3			Model 4			Model 5		
	Coef.	Stdv.		Coef.	Stdv.		Coef.	Stdv.	
t=1991	0.112	0.029	***	0.293	0.039	***	0.174	0.044	***
t=1992	0.114	0.029	***	0.294	0.038	***	0.177	0.043	***
t=1993	0.125	0.030	***	0.294	0.037	***	0.184	0.042	***
t=1994	0.062	0.030	**	0.232	0.038	***	0.120	0.042	***
t=1995	0.159	0.030	***	0.321	0.037	***	0.210	0.042	***
t=1996	0.177	0.030	***	0.340	0.037	***	0.227	0.042	***
t=1997	0.177	0.030	***	0.326	0.036	***	0.216	0.041	***
t=1998	0.197	0.030	***	0.339	0.036	***	0.231	0.040	***
t=1999	0.240	0.031	***	0.402	0.038	***	0.289	0.042	***
t=2000	0.243	0.031	***	0.405	0.038	***	0.291	0.043	***
t=2001	0.346	0.031	***	0.495	0.037	***	0.384	0.041	***
t=2002	0.430	0.030	***	0.569	0.035	***	0.457	0.040	***
t=2003	0.206	0.030	***	0.377	0.038	***	0.252	0.044	***
t=2004	0.089	0.031	***	0.268	0.039	***	0.141	0.045	***
t=2005	0.183	0.031	***	0.348	0.038	***	0.225	0.044	***
MC/GDP	0.048	0.012	***	0.053	0.011	***	**	0.012	***
Return				-0.154	0.023	***	-0.098	0.024	***
GDP/cap.							4.17E-06	7.75E-07	***

	Model 6			Model 7			Model 8		
	Coef.	Stdv.		Coef.	Stdv.		Coef.	Stdv.	
t=1991	0.091	0.030	0.002	0.257	0.040	***	0.164	0.043	***
t=1992	0.094	0.030	0.002	0.255	0.040	***	0.163	0.043	***
t=1993	0.110	0.030	< 0.001	0.262	0.039	***	0.174	0.042	***
t=1994	0.049	0.030	0.106	0.206	0.039	***	0.116	0.042	***
t=1995	0.139	0.030	< 0.001	0.290	0.039	***	0.203	0.041	***
t=1996	0.160	0.030	< 0.001	0.313	0.039	***	0.224	0.042	***
t=1997	0.164	0.030	< 0.001	0.306	0.038	***	0.217	0.041	***
t=1998	0.183	0.030	< 0.001	0.319	0.037	***	0.232	0.040	***
t=1999	0.233	0.030	< 0.001	0.387	0.040	***	0.294	0.043	***
t=2000	0.241	0.030	< 0.001	0.396	0.039	***	0.299	0.043	***
t=2001	0.334	0.031	< 0.001	0.478	0.039	***	0.388	0.041	***
t=2002	0.410	0.031	< 0.001	0.545	0.038	***	0.457	0.040	***
t=2003	0.185	0.031	< 0.001	0.348	0.041	***	0.249	0.044	***
t=2004	0.075	0.031	0.015	0.245	0.042	***	0.142	0.045	***
t=2005	0.173	0.031	< 0.001	0.331	0.040	***	0.230	0.044	***
Short	0.079	0.016	< 0.001	0.064	0.015	***	0.017	0.017	
Return				-0.134	0.023	***	-0.089	0.024	***
GDP/cap.							4.41E-06	8.55E-07	***

* Coefficient significant at the 10% level
** Coefficient significant at the 5% level
*** Coefficient significant at the 1% level

References

Andersen, T., Bollerslev, T., Diebold, F. and Ebens, H. (2001), 'The distribution of realized stock return volatility', *Journal of Financial Economics* **61**(1), 43–76.

Andersen, T. G., Bollerslev, T. and Diebold, F. X. (2003), 'Some Like it Smooth, and Some Like it Rough: Untangling Continuous and Jump Components in Measuring, Modeling, and Forecasting Asset Return Volatility', *SSRN eLibrary* .

Aydemir, A., Gallmeyer, M. and Hollfield, B. (2005), 'Financial Leverage Does Not Cause the Leverage Effect', *Working paper* . Carnegie Mellon University.

Barndorff-Nielsen, O. and Shephard, N. (2006), 'Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation', *Journal of Financial Econometrics* **4**(1), 1–30.

Bauwens, L., Laurent, S. and Rombouts, J. (2006), 'Multivariate GARCH models: a survey', *Journal of Applied Econometrics* **21**(1), 79.

Bekaert, G. and Harvey, C. (1997), 'Emerging equity market volatility', *Journal of Financial Economics* **43**(1), 29–77.

Bekaert, G. and Wu, G. (2000), 'Asymmetric volatility and risk in equity markets', *Review of Financial Studies* **13**(1), 1–42.

Black, F. (1976), 'Studies of stock price volatility changes', *Proceedings of the 1976 Meetings of the Business and Economic Statistics Section, American Statistical Association* **177**, 81.

Bollerslev, T., Chou, R. and Kroner, K. (1992), 'ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence', *Journal of Econometrics* **52**(1-2), 5–59.

Bris, A., Geotzmann, W. and Zhu, N. (2003), 'Short-Sales in Global Perspective', *Working Paper* .

Bris, A., Goetzmann, W. and Zhu, N. (2007), 'Efficiency and the Bear: Short Sales and Markets Around the World', *The Journal of Finance* **62**(3), 1029–1079.

Brooks, R. (2007), 'Power arch modelling of the volatility of emerging equity markets', *Emerging Markets Review* **8**(2), 124–133.

Brooks, R., Faff, R., McKenzie, M. and Mitchell, H. (2000), 'A multi-country study of power ARCH models and national stock market returns', *Journal of International Money and Finance* **19**(3), 377–397.

Bushman, R. and Smith, A. (2003), 'Transparency, Financial Accounting Information, and Corporate Governance', *Economic Policy Review* **9**(1).

Campbell, J. and Hentschel, L. (1992), 'No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns', *Journal of Financial Economics* **31**, 281–318.

Chang, J., Khanna, T. and Palepu, K. (2000), 'Analyst Activity Around the World', *Working paper, The Wharton School of the University of Pennsylvania* .

Charoenrook, A. and Daouk, H. (2005), 'Market-wide short-selling restrictions', *Working paper, Vanderbilt University and Cornell University* .

Christie, A. (1982), 'The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects', *Journal of Financial Economics* **10**(4), 407–432.

Chui, A. C. W., Titman, S. and Wei, K.-C. (2008), 'Individualism and Momentum Around the World', *SSRN eLibrary* .

Ding, Z., Granger, C. W. J. and Engle, R. F. (1993), 'A long memory property of stock market returns and a new model', *Journal of Empirical Finance* **1**(1), 83–106.

Djankov, S., La Porta, R., Lopez-de Silanes, F. and Shleifer, A. (2008), 'The law and economics of self-dealing', *Journal of Financial Economics* .

Engle, R., Lilien, D. and Robins, R. (1987), 'Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model', *Econometrica* **55**(2), 391–407.

Fan, J. and Wang, Y. (2007), 'Multi-Scale Jump and Volatility Analysis for High-Frequency Financial Data', *Journal of the American Statistical Association* **102**(480), 1349–1362.

Figlewski, S. and Wang, X. (2001), 'Is the "Leverage Effect" a Leverage Effect?', *Unpublished working paper, New York University* .

Fraser, P. and Power, D. (1997), 'Stock return volatility and information: an empirical analysis of Pacific Rim, UK and US equity markets', *Applied Financial Economics* **7**(3), 241–253.

Giot, P. and Laurent, S. (2004), 'Modelling daily Value-at-Risk using realized volatility and ARCH type models', *Journal of Empirical Finance* **11**(3), 379–398.

Glosten, L., Jagannathan, R. and Runkle, D. (1993), *On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks*, Federal Reserve Bank of Minneapolis, Research Dept.

Griffin, J. M., Kelly, P. J. and Nardari, F. (2007), 'Measuring Short-Term International Stock Market Efficiency', *SSRN eLibrary* .

Hansen, P. and Lunde, A. (2005), 'A forecast comparison of volatility models: Does anything beat a GARCH (1, 1)?', *Journal of Applied Econometrics* **20**(7), 873–889.

Hens, T. and Steude, S. (2009), 'The Leverage Effect without Leverage: An Experimental Study', *Finance Research Letters* .

Hentschel, L. (1995), 'All in the family Nesting symmetric and asymmetric GARCH models', *Journal of Financial Economics* **39**(1), 71–104.

Hofstede, G. (2001), *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations*, Sage Publications.

Hong, H., Lim, T. and Stein, J. (2000), 'Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies', *The Journal of Finance* **55**(1), 265–295.

Jayasuriya, S., Shambora, W. and Rossiter, R. (2005), 'Asymmetric Volatility in Mature and Emerging Markets', *Working Paper, Ohio University* .

La Porta, R., Lopez-de Silanes, F. and Shleifer, A. (2006), 'What Works in Securities Laws?', *Journal of Finance* **61**(1), 1–32.

La Porta, R., Lopez-de Silanes, F., Shleifer, A. and Vishny, R. (1998), 'Law and Finance', *Journal of Political Economy* **106**(6).

Lambert, P. and Laurent, S. (2000), 'Modelling Skewness Dynamics in Series of Financial Data', *Discussion paper, Institut de Statistique* .

Lambert, P. and Laurent, S. (2001), 'Modelling financial time series using GARCH-type models and a skewed Student density', *Universite de Liege* .

Lee, S. and Mykland, P. (2006), 'Jumps in Real-Time Financial Markets: A New Nonparametric Test and Jump Dynamics', *Review of Financial Studies* .

Li, Q., Yang, J., Hsiao, C. and Chang, Y. (2005), 'The relationship between stock returns and volatility in international stock markets', *Journal of Empirical Finance* **12**(5), 650–665.

Marshall, B. R., Cahan, R. H. and Cahan, J. (2008), 'Technical Analysis Around the World: Does it Ever Add Value?', *SSRN eLibrary* .

McQueen, G. and Vorkink, K. (2004), 'Whence GARCH? A Preference-Based Explanation for Conditional Volatility', *Review of Financial Studies* **17**(4), 915–949.

Miller, M. and Modigliani, F. (1958), ‘The Cost of Capital, Corporation Finance and the Theory of Investment’, *American Economic Review* **48**(3), 261–297.

Mittnik, S. and Paolella, M. (2000), ‘Conditional Density and Value-at-Risk Prediction of Asian Currency Exchange Rates’, *Journal of Forecasting* **19**(4), 313–333.

Nelson, D. B. (1991), ‘Conditional heteroskedasticity in asset returns: A new approach’, *Econometrica* **59**(2), 347–70.

Pindyck, R. S. (1984), ‘Risk, inflation, and the stock market’, *American Economic Review* **74**(3), 335–51.

Poon, S. and Granger, C. (2003), ‘Forecasting Volatility in Financial Markets: A Review’, *Journal of Economic Literature* **41**(2), 478–539.

Schwert, G. (1989), ‘Why Does Stock Market Volatility Change Over Time?’, *The Journal of Finance* **44**(5), 1115–1153.

Selçuk, F. (2005), ‘Asymmetric stochastic volatility in emerging stock markets’, *Applied Financial Economics* **15**(12), 867–874.

Sentana, E. and Wadhwani, S. (1992), ‘Feedback Traders and Stock Return Autocorrelations: Evidence from a Century of Daily Data’, *The Economic Journal* **102**(411), 415–425.

Shefrin, H. (2005), *A behavioral approach to asset pricing*, Elsevier.

Tauchen, G., Zhang, H. and Liu, M. (1996), ‘Volume, volatility, and leverage: A dynamic analysis’, *Journal of Econometrics* **74**(1), 177–208.

Tetlock, P. (2007), ‘Giving Content to Investor Sentiment: The Role of Media in the Stock Market’, *The Journal of Finance* **62**(3), 1139–1168.

Wang, Y. (2006), 'Selected review on wavelets', *Frontier Statistics, Festschrift for Peter Bickel (H. Koul and J. Fan, eds.)* pp. 163–179.