Conditional Skewness of Stock Market Returns in Developed and Emerging Markets and its Economic Fundamentals*

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Abstract

We use a quantile-based measure of conditional skewness or asymmetry of asset returns that is robust to outliers and therefore particularly suited for recalcitrant series such as emerging market returns. We study the following portfolio returns: developed markets, emerging markets, the world, and separately 73 countries. We find that the conditional asymmetry of returns varies significantly over time. This is true even after taking into account conditional volatility effects and unconditional skewness effects in returns. Interestingly, we find that the conditional asymmetry in developing countries features low correlation with that in emerging markets. This finding has implications for portfolio allocation, given the fact that the correlation of the returns themselves has been historically high and is increasing. In contrast to conditional volatility fluctuations, which are hard to explain with macroeconomic fundamentals, we find a strong relationship between the conditional skewness and macroeconomic variables. Moreover, the low correlation between conditional asymmetry across developed and emerging markets can be explained by macroeconomic fundamental factors in the cross-section, as both markets feature opposite responses to those fundamentals. The economic significance of the conditional asymmetry is also demonstrated in an international portfolio allocation setting.

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1 Introduction

A significant body of research has documented and compared several characteristics of emerging and developed stock market returns. For instance, it is well-established that, in emerging markets: the unconditional mean and volatility of returns is higher than in developed markets; the conditional mean and volatility vary significantly over time; the returns correlation and beta with the world portfolio has been lower, albeit increasing over time (see e.g. Bekaert and Harvey (1995), Harvey (1995), Bekaert and Harvey (1997), Fama and French (1998), Henry (2000), Engle and Rangel (2008), among many others).

Another important characteristic of emerging market returns is that they feature noticeable asymmetries, which implies that their first two moments are not sufficient to characterize the financial risk investors face in those markets. Moreover, it is a priori reasonable to assume that their conditional higher order moments might be time varying (much like their conditional first two moments), because emerging economies are, by their very nature, more likely to experience regulatory changes, financial market liberalization trends, political crises, and other shocks that may lead their market returns to deviate from normality. Unfortunately, very little work has been done on this topic. An exception is Bekaert, Erb, Harvey, and Viskanta (1998) who specifically note that: "It is not just that skewness and kurtosis are present in emerging markets–the skewness and kurtosis change through time."

The lack of empirical findings about the nature, dynamics and economic determinants of the conditional return asymmetries is partly due to the fact that higher order moments–being very sensitive to outliers–are more susceptible to estimation error than are the mean and the variance. Moreover, the approach of circumventing estimation difficulties by using implied (risk neutral) skewness is infeasible for most emerging countries, as their derivative markets are either small and illiquid or simply non-existent.[1] With emerging market data, which are particularly prone to outliers and other data imperfections, it seems that finding a robust way of quantifying the asymmetry in the distribution would be of particular interest to investors and academics alike.

In this paper, we offer a comprehensive empirical study of the conditional return asymmetry for a large cross-section of emerging and developed markets. Our first contribution is to provide a

[1] A recent flurry of papers have examined skewness extracted from options of a market index - like the S&P 500 - or from for a cross-section of individual stocks. See for example, Bali and Cakici (2009), Chang, Christoffersen, and Jacobs (2009), Conrad, Dittmar, and Ghysels (2009), Xing, Zhang, and Zhao (2010), among others. Such an approach would not be feasible for our international setting as many countries do not feature derivatives markets or have only primitive contracts with sparse liquidity.

simple measure of return asymmetry that has three distinguishing features, namely, robustness to outliers, the ability to capture time-variations in the conditional (rather than unconditional) distribution of returns and finally the measure can be defined for n-period, long-horizon returns, $r_{n,t}$, while using daily information. The asymmetry measure is based on whether the interval between conditional quantiles $1-\theta$ and θ is centered at the conditional median of $r_{n,t}$. For instance, let's consider the interquartile range, or $\theta = 0.75$, of the conditional distribution of $r_{n,t}$. If at time t the interquartile range is not centered at the median, then the return distribution is asymmetric. We denote our measure by $CA_{\theta,t}$ (for conditional asymmetry at time t) to emphasize the fact that we are not estimating the conditional third moment of returns. The interquartile range will be our leading case and the notation $CA_{0.75,t}$ will be simplified to CA_t. For other quantile pairs, we will use the appropriate subscript. The conditional returns distribution is symmetric when $CA_t = 0$ and the statistic is normalized to lie between -1 and 1.

Extreme outliers have no effect on CA_t as they do not impact the 25th, 50th, nor the 75th quantiles. The measure is a conditional version of an approach that can be traced back to Pearson (1895), Bowley (1920), and more recently, Kim and White (2004), who consider robust statistics that are not based on estimates of higher-order moments. We specify the conditional quantiles on which this statistic is based in a novel parametric way that exploits all the information in daily return data, yet preserves parsimony and robustness. Technically speaking we use the term "conditional asymmetry" rather than "conditional skewness," because the latter notion is traditionally associated with the third conditional moment of returns.[2]

We use the new approach to estimate the conditional asymmetry in 76 portfolio returns: 73 individual country returns, a developed markets portfolio (henceforth DM) comprised of 21 developed economies, an emerging markets portfolio (henceforth EM) comprised of 52 emerging economies, and a global world portfolio (henceforth W). The data, obtained from Datastream, is daily from January 1, 1980 to December 31, 2010. We estimate the CA_t of returns as well as for GARCH- and asymmetric GJR GARCH-filtered returns (subsequently sometimes called respectively deGARCHed and deTARCHed returns) where GJR GARCH refers to the model of Glosten, Jagannathan, and Runkle (1993). Our focus is primarily on annual returns, because this is the horizon of interest to many investors and also because most of the macroeconomic variables, used later in the paper, are available at that frequency.

[2]So far we used the term conditional skewness a few times -including in the title of the paper - as it is a more common in the literature. We will continue to occasionally do so in the remainder of the paper.

We estimate the CA_t measure for all aforementioned portfolios and document the following novel findings. First, there is a significant time variation in the conditional asymmetry of most annual portfolio returns. This is true for simple as well as deGARCHed and deTARCHed returns. Second, the returns of the world portfolio and large developed markets are, on average, more negatively skewed and exhibit larger fluctuations than emerging market returns.[3] Third, we find that the correlation between the CA_t measures of DM and EM portfolio returns is surprisingly low, in the range of 0.3 to 0.35, depending on the model. This intriguing result, which we find to be robust to quantile pairs other than the interquartile range, is of interest for at least two reasons. It is in sharp contrast with the fact that the correlation of the returns themselves is large, positive, and is increasing over our sample period. Moreover, the volatilities between developed and emerging markets also exhibit strong co-movements. These facts might be taken to imply that the benefits from international diversification are limited. However, the low correlation in conditional asymmetry implies that there might be benefits of international diversification and risk-sharing that are both significant and are not captured by standard mean-variance analysis. This finding also complements Pukthuanthong and Roll (2010) who find that extreme return movements–or jumps–in international markets are correlated. Our asymmetry measure is robust to outliers and hence not affected by outcomes in the tails of the distribution. Asymmetries in the distribution of returns that arise around the median are no less important than outliers, as a large mass of the return density is concentrated in that region.[4]

To understand the dynamics and co-movement of the CA_t measure, we run two sets of time-series regressions. First, we investigate whether the time variation in return asymmetries of a given portfolio are linked to the negative skewness of the world portfolio return. These regressions, loosely motivated by the international factor models literature (e.g., Solnik (1974), Korajczyk and Viallet (1989), Harvey (1991)), are designed to capture empirical commonalities in asymmetries across countries.[5] We find that while the asymmetry in developed markets can be explained by asymmetries in the world factor, this is not the case for emerging economies. This result suggests that, in emerging markets, the time-variation in the CA_t measure is most likely driven by country-specific shocks. In a second set of regressions, we show that the CA_t of simple returns

[3] Interestingly, this result parallels the finding in US data that large-cap stock returns are more negatively skewed than small-cap stock returns (e.g., Chen, Hong, and Stein (2001)).

[4] Along similar lines, Christoffersen, Errunza, Jacobs, and Jin (2011) also document upward trending correlations between DM and EM returns and emphasize diversification benefits due to higher moment dependence. They emphasize tail dependence, while we focus on conditional skewness without emphasizing tail behavior.

[5] An exact decomposition of the conditional asymmetry of returns using a factor model is unfortunately not possible, as we explain below.

are negatively related to volatility fluctuations. This result is a conditional version of the "leverage effect" in the asymmetric GARCH literature. The novelty is that while the leverage effect has been well-documented for the US and developed economies (Glosten, Jagannathan, and Runkle (1993), Zakoian (1994), Bekaert and Wu (2000), among others), the evidence for it in emerging markets has been less clear-cut (Bekaert and Harvey (1997)). More surprisingly, the CA_t of deTARCHed returns is also negatively correlated with the volatility of simple returns, which suggests that asymmetry in the volatility cannot fully account for the leverage effect.

We then examine whether economic fundamentals can explain the documented variation and low co-movement in skewness of DM and EM portfolio returns. It is a stylized fact that macroeconomic fundamentals cannot easily account for conditional volatility movements (see e.g. Schwert (1989), Engle, Ghysels, and Sohn (2010) and Engle and Rangel (2008) among others). In contrast to conditional volatility, we find a relationship between conditional skewness and macroeconomic fundamentals. In particular, we examine an extensive set of variables that measure liquidity and the degree of development of international stock markets that have been suggested in the literature, including: turnover, the capitalization of a country's stock market relative to its nominal GDP, the number of companies listed on the exchange, a measure of market liquidity, a short-term interbank or government bond yield, the growth rate of real GDP, and the volatility of quarterly real GDP growth. We find that many of these economic fundamentals help predict future conditional skewness, and most interestingly the low correlation between the conditional skewness of DM and EM portfolio returns can be explained by the often *opposite* sign of exposure to macroeconomic fundamentals for DM and EM portfolio returns. For example, the DM portfolio conditional skewness relates positively to turnover, while the EM portfolio conditional skewness is the opposite. With turnover is linked to heterogeneity of beliefs (Hong and Stein (2003), Chen, Hong, and Stein (2001)), we find that more disagreement has a negative impact on EM conditional skewness, but DM markets conditional skewness responds positively. The response to short-term interest rates is negative for DM portfolio returns conditional skewness - as the economy overheats there is an increase in downward risk for developed markets, while EM conditional skewness reacts positively.

Finally, we investigate the economic relevance of return asymmetry in an international portfolio allocation setting. We use a recent parametric portfolio approach of Brandt, Santa-Clara, and Valkanov (2009) which is particularly suitable for our application, since (1) it allows for country-specific conditional information (through the portfolio weights), (2) is able to accommodate a large number of assets, and (3) is not limited to mean-variance investors. We maximize the utility function of a constant relative risk aversion investor with a $\gamma = 5$, whose portfolio weights are a function of the conditional asymmetry measure CA_t and other country-specific variables. We find that the optimal portfolio is tilted away from the value-weighted portfolio and toward countries that are less negatively skewed, which also happen to be mostly emerging economies. In particular, when the investor conditions his decisions upon the estimated asymmetry measures, the optimal allocation corresponds to placing approximately 17 percent of the weight in emerging economies relative to the value-weighted allocation of only 9 percent. These results obtain even after controlling for other macroeconomic state variables. Taking into account conditional asymmetry in the portfolio allocation also leads to sizeable increases of the certainty equivalent return and the Sharpe ratio.

While the analysis in this paper is mostly empirical, our findings have broader implications for the formulation of asset pricing models. A large class of risk models relies on the fact that returns can be expressed as $r_t = \mu_t + \sigma_t \varepsilon_t$, where expected returns are characterized by μ_t and conditional volatility is described by σ_t.[6] The presence of conditional asymmetry in deTARCHed returns argues for the necessity of models that feature skewness not only in the volatility dynamics but also in the distribution of the economic shocks such as in Bekaert and Engstrom (2011).[7] More broadly, the prevalence of conditional skewness in returns suggests that this feature of the data ought to be incorporated in asset pricing models. While there are a few such attempts (Hong and Stein (2003), Brunnermeier, Gollier, and Parker (2007) and Brunnermeier and Pedersen (2009)), more work is needed in that direction if we are to explain the documented dynamics of the conditional skewness and its different characteristics across developed and emerging markets.

The paper is structured as follows. Section 2 describes the quantile-based method of conditional asymmetry and tackles estimation and testing issues. Section 3 provides a description of the data and a first set of empirical results using the international portfolio returns data. Section 4 presents the first set of key empirical results, documenting the time-variation and co-movement of CA_t. In Section 5, we use pooled regressions to link the conditional asymmetry in international markets to macroeconomic fundamentals. Section 6 covers international portfolio allocation with conditional asymmetry. Conclusions appear in section 7.

[6]This is called a location-scale transformation. For the purpose of simplicity, we focus here on a discrete single-period return, although our empirical analysis will involve multiple horizon returns.

[7]A number of ARCH-type models that accommodate skewness have been proposed in the literature, including Rockinger and Jondeau (2002), Jondeau and Rockinger (2003), Bauwens and Laurent (2005), among others. We do not pursue such an approach here, as our quantile-based methods will allow for return predictions at various frequencies - while keeping daily returns information - something that would not be easy to achieve with the existing models.

2 A Robust Measure of Conditional Asymmetry

We are interested in quantifying the asymmetry in the (conditional) distribution of n-period returns. The log continuously compounded n-period return of an asset is defined as $r_{t,n} = \sum_{j=0}^{n-1} r_{t+j}$ for $n \geq 2$, where r_t is the one-period (daily) log return. For simplicity, we assume that the unconditional cumulative distribution function (CDF) of $r_{t,n}$, denoted by $F_n(r) = P\left(r_{t,n} < r\right)$, and its conditional CDF given an information set I_{t-1}, denoted by $F_{n,t|t-1}\left(r\right) = P\left(r_{t,n} < r|I_{t-1}\right)$, are strictly increasing. The unconditional first and second moments of $r_{t,n}$ are denoted by $\mu_n = E\left(r_{t,n}\right)$ and $\sigma_n^2 = E\left(\left(r_{t,n} - \mu_n\right)^2\right)$ and their conditional analogues by $\mu_{n,t} = E\left(r_{t,n}|I_{t-1}\right)$ and $\sigma_{n,t}^2 = E\left(\left(r_{t,n} - \mu_{n,t}\right)^2|I_{t-1}\right)$, respectively. For the one-period returns, we simplify the notation by dropping the n subscript.

2.1 Preliminaries: Unconditional Robust Measures of Asymmetry

By far, the most popular measure of asymmetry is the unconditional skewness, or the third normalized moment of returns: $S\left(r_{t,n}\right) = E\left(r_{t,n} - \mu_n\right)^3/\sigma_n^3$. Conditional models of skewness based on autoregressive conditional third moments have been proposed by Harvey and Siddique (1999) and León, Rubio, and Serna (2005). A natural estimate of skewness is obtained by replacing expectations with sample averages. However, it is well-known that skewness estimates based on sample averages are sensitive to outliers, even more so than are estimates of the first two moments, because all observations are raised to the third power. This fact has prompted researchers since Pearson (1895), Bowley (1920), and more recently Hinkley (1975) to look for robust measures of asymmetry that are not based on sample estimates of the third moment.

Hinkley's (1975) robust coefficient of asymmetry (skewness) is defined as:

$$RA_\theta\left(r_{t,n}\right) = \frac{\left(q_\theta\left(r_{t,n}\right) - q_{0.50}\left(r_{t,n}\right)\right) - \left(q_{0.50}\left(r_{t,n}\right) - q_{1-\theta}\left(r_{t,n}\right)\right)}{q_\theta\left(r_{t,n}\right) - q_{1-\theta}\left(r_{t,n}\right)} \tag{1}$$

where $q_{1-\theta}\left(r_{t,n}\right)$, $q_{0.50}\left(r_{t,n}\right)$ and $q_\theta\left(r_{t,n}\right)$ are the $1-\theta$, 0.5, and θ unconditional quantiles of $r_{t,n}$, and quantile θ is defined as $q_\theta\left(r_{t,n}\right) = F_n^{-1}\left(r_{t,n}\right)$, for $\theta \in (0,1]$.[8] This skewness measure captures

[8]The inverse of $F_n\left(r_{t,n}\right)$ is unique, since we assumed that $F_n\left(r_{t,n}\right)$ is strictly increasing. If $F\left(r_{t,n}\right)$ is not strictly increasing, then we can define the quantile as $q_{\theta_k}^*\left(r_{t,n}\right) \equiv \inf\left\{r : F_n\left(r_{t,n}\right) = \theta_k\right\}$. The measure in equation (1) also satisfies all conditions that Groeneveld and Meeden (1984) postulate any reasonable skewness measure should satisfy. Another widely-used skewness measure, the Pearson coefficient of skewness, defined as $(\mu - q_{0.5}\left(r_{t,n}\right))/\sigma_n$, does not satisfy these properties.

asymmetry of quantiles $q_{1-\theta}(r_{t,n})$ and $q_\theta(r_{t,n})$ with respect to the median (i.e. $q_{0.50}(r_{t,n})$). In the specific case of $\theta = 0.75$, we are considering the inter-quartile range and (1) is known as Bowley's (1920) statistic. We will denote this latter measure simply as $RA(r_{t,n})$. The normalization in the denominator insures that the measure is unit independent with values between -1 and 1. When $RA_\theta(r_{t,n})$ = 0 the distribution is symmetric, while values diverging to -1 (1) indicate skewness to the left (right).

The asymmetry measure $RA_\theta(r_{t,n})$ is, unlike the moment-based skewness $S(r_{t,n})$, robust to outliers as they do not affect the quantiles. To illustrate this fact, we display in Figure 1 250-day rolling estimates of $S(r_t)$ (left panel) and $RA_\theta(r_t)$ for values of $\theta = .95$ (middle panel) and $\theta = .75$ (left panel) for two Developed Markets (DM) and Emerging Markets (EM) portfolios, available for the 1980–2010 period (details regarding the data will be provided later). We estimate $S(r_t)$ and $RA_\theta(r_t)$ using a rolling sample in exactly the same fashion as one estimates rolling sample volatility (see for example French, Schwert, and Stambaugh (1987)). Figure 1 shows results from simple daily log returns r_t (top panels) as well as from de-TARCHed returns ε_t^T (bottom panels).[9]

While the estimates in Figure 1 represent two ex-post measures of the conditional skewness (rather than ex-ante forecasts), they illustrate two key points. First, the rolling estimates of $S(r_t)$ exhibit significant discontinuities that occur at the time when large outliers enter the rolling sample – in this case the 87 crash. Even one daily observation has an immediate and drastic impact on the skewness estimates. In the bottom panels, similar results appear with de-TARCHed returns, which suggests that adjusting returns for asymmetric volatility effects does not fully account for the outliers. The discontinuities in the estimated $S(r_t)$ make it hard to analyze its time variation and to reconcile it with underlying economic variables, whose time series properties are much less erratic. This result is not peculiar to the rolling estimates, as noted by White, Kim, and Manganelli (2008), but rather is due to the use of a sample analogue of the third moment. Bekaert, Erb, Harvey, and Viskanta (1998) provide similar plots for individual countries and the discontinuities are even more striking. By contrast, the rolling estimates of the robust skewness measure $RA_\theta(r_t)$ in the top right panel of Figure 1 are much less sensitive to outliers.

A second important observation emerging from Figure 1 pertains to the correlation between the asymmetry estimates of the DM and EM series. In the top left panel, the correlation between

[9]While the remaining of the paper focuses on annual returns, we provide here conditional skewness estimates of daily returns. We do so for the sake of comparison with the previous literature which has mostly focused on the skewness of short-horizon returns.

the time-varying skewness estimates is 0.60. The high correlation is however largely influenced by a few large shocks. Deleting the three largest positive and negative daily returns of each portfolio, representing the top and bottom 0.04% of their distribution, lowers this correlation to 0.31. A similar point can be made by considering the rolling robust asymmetry measures $RA_{0.95}\left(r_t\right)$ (upper middle plot) and $RA_{0.75}\left(r_t\right)$ (upper right plot), which yield correlations of 0.35 and 0.20, respectively. The differences are remarkable and have significant economic implications for international portfolio allocation, as discussed below.

At a technical level, the quantile-based skewness measure $RA_\theta\left(r_{t,n}\right)$ does not presume the existence of moments. This is particularly important for emerging market data, which are known to have fat tails. To our knowledge, $RA_\theta\left(r_{t,n}\right)$ and its generalizations (see below), have received very limited attention in the empirical finance literature, the few exceptions include Kim and White (2004) and White, Kim, and Manganelli (2008) in a time series context and Zhang (2006) and Green and Hwang (2009) in a cross-sectional setting. The reason is undoubtedly the fact that we need to estimate quantiles, which is not as straightforward as estimating third moments. Fortunately, quantile regression methods have greatly improved in the last thirty years following the path breaking work of Koenker and Bassett (1978) and we draw on results from that literature.

Perhaps the biggest limitation of $RA_\theta\left(r_{t,n}\right)$ is that it is based on unconditional quantiles of returns. As such, it provides unconditional measures of skewness but is not useful to study the dynamics of conditional asymmetry and its predictive properties. We now extend the RA measure to capture asymmetries in the conditional distribution by replacing the unconditional quantiles in (1) by their conditional analogues and provide new models for the latter.

2.2 Conditional Robust Measure of Asymmetry

If $q_{\theta,t}\left(r_{t,n}\right)=F_{t,n|t-1}^{-1}\left(r\right)$ is the conditional quantile θ of return $r_{t,n}$, then we define the conditional asymmetry statistic, $CA_{\theta,t}$, given information I_{t-1} as:

$$CA_{\theta,t}\left(r_{t,n}\right)=\frac{\left(q_{\theta,t}\left(r_{t,n}\right)-q_{0.50,t}\left(r_{t,n}\right)\right)-\left(q_{0.50,t}\left(r_{t,n}\right)-q_{1-\theta,t}\left(r_{t,n}\right)\right)}{q_{\theta,t}\left(r_{t,n}\right)-q_{1-\theta,t}\left(r_{t,n}\right)}. \tag{2}$$

The expression in equation (2) is a conditional version of the robust asymmetry measure $RA_\theta\left(r_{t,n}\right)$ appearing in equation (1) involving conditional quantiles. When modeling such quantiles we want to be more explicit in our notation and denote them by $q_{\theta,t}\left(r_{t,n};\delta_{\theta,n}\right)$ where the unknown model parameters are collected in vector $\delta_{\theta,n}$. The notation reflects the fact that the function q will be estimated for each quantile θ and the parameters $\delta_{\theta,n}$ may differ across quantiles and horizons.[10] For instance, we can model $q_{\theta,t}(r_{t,n};\delta_{\theta,n})$ as an affine function of state variables, collected in a vector $Z_{\theta,t-1}$:

$$q_{\theta,t}(r_{t,n};\delta_{\theta,n}) = \alpha_{\theta,n} + \beta_{\theta,n} Z_{\theta,t-1} \tag{3}$$

where $\delta_{\theta,n} = (\alpha_{\theta,n}, \beta_{\theta,n})$ are unknown parameters to be estimated. In the above specification, we allow the conditioning variables $Z_{\theta,t-1}$ to also differ across quantiles. The choice of the functional form and conditioning variables in the estimation of conditional quantile regressions is similar to that of any regression, whether we are estimating a conditional mean, conditional variance, or a conditional quantile. Therefore, the parametrization of $q_{\theta,t}(r_{t,n};\delta_{\theta,n})$ and the type of conditioning information that is used are of primary importance.

To capture fluctuations in the quantiles of n-period returns, we use *daily* conditioning variables. We do so because, given that quantiles are hard to estimate precisely, we want to use all the richness of the high-frequency data. The alternative which is to aggregate the conditioning variables so that they match the frequency of the n-period returns would result in information loss and less precise quantile estimates. The horizon mismatch between the n-period returns and the daily observations compels us to use a mixed data sampling, or MIDAS, approach. While MIDAS models are not entirely new in finance, they are relatively recent and have never been used in the context of quantile regressions.[11]

We characterize a MIDAS quantile regression - where the conditional quantile pertains to multiple horizon returns and the regressors are daily returns - as follows:

$$\begin{aligned} q_{\theta,t}(r_{t,n};\delta_{\theta,n}) &= \alpha_{\theta,n} + \beta_{\theta,n} Z_{t-1}(\kappa_{\theta,n}) && (4) \\ Z_{t-1}(\kappa_{\theta,n}) &= \sum_{d=0}^{D} w_d(\kappa_{\theta,n})\, x_{t-1-d} && (5) \end{aligned}$$

where $\delta_{\theta,n} = (\alpha_{\theta,n}, \beta_{\theta,n}, \kappa_{\theta,n})$ are unknown parameters to estimate. The quantiles are an affine function of $Z_{t-1}(\kappa_{i,\theta,n})$ which consists of linearly filtered x_{t-1-d} representing daily conditioning

[10] We continue to use the notation CA instead of $\widehat{CA}$ whenever we use estimated asymmetry measures. The distinction between the population process and sample estimates will be clear from the context.

[11] The original work on MIDAS focused on volatility predictions, see Ghysels, Santa-Clara, and Valkanov (2005) and Ghysels, Santa-Clara, and Valkanov (2006). For other contributions, see recent survey on MIDAS by Andreou, Ghysels, and Kourtellos (2011) and Armesto, Engenmann, and Owyang (2010) as well as the survey specifically on MIDAS and volatility prediction by Ghysels and Valkanov (2011).

information with lag of d days. The weights $w_d(\kappa_{\theta,n})$ are parameterized as a lag polynomial function whose shape is captured by a low-dimensional parameter vector $\kappa_{\theta,n}$. Asymmetry is achieved when $\alpha_{\theta,n}$ and $\beta_{\theta,n}$ differ across quantiles, when the conditioning variables $Z_{t-1}(\kappa_{\theta,n})$ are different across quantiles, or both. Moreover, the $Z_{t-1}(\kappa_{\theta,n})$ can differ across θ's even when the daily data in x_{t-1-d} is the same, because the estimated filtering weights $w_d(\kappa_{\theta,n})$ are not necessarily the same across quantiles.

The parsimonious specification of the MIDAS weights $w_d(\kappa_{\theta,n})$ greatly reduces the number of lag coefficients to estimate from $D+1$ (which can be very large, given the frequency of the data), to only a few parameters. The parameters $\kappa_{\theta,n}$ governing the filtering of the daily observations appearing in equation (5) and the parameters $\alpha_{\theta,n}$ and $\beta_{\theta,n}$ in the quantile regression equation (4) are estimated jointly as further discussed below. The MIDAS regression framework allows us to use high-frequency data in the estimation of quantile forecasts at various horizons. The benefits and trade-offs of using high-frequency data in the context of quantile regression estimation or skewness forecasts is a topic that has not received much attention. While it is not the primary focus of this paper, we offer some first insights in that direction.[12]

There are several benefits from using the MIDAS quantile specification (4) - (5) rather than other conditional quantile models. First, (4) - (5) is not a recursive quantile model: the conditioning information x_{t-d-1} can be any variable that has the ability to capture time variation in the quantile of the return distribution. This allows us to handle the mismatch of sampling frequencies, unlike autoregressive specifications, such as Engle and Manganelli's (2004) CaViaR which obtains for n = 1 (a single period horizon) when $Z_{\theta,t-1}$ = $[q_{\theta,t-1}(r_{t-1}) \quad \|r_{t-1}\|]'$ for all θ. Second, the MIDAS weights filter the potentially noisy daily data. This is particularly important while working with returns of emerging markets. Third, we can forecast skewness at various horizons (in this case, annual) while keeping the information set fixed (i.e., daily frequency). Fourth, if the $\kappa_{\theta,n}$ are the same across quantiles, then so is the filtered conditioning variable $Z_{t-1}(\kappa_{\theta,n})$ and the quantiles differ only through the $\alpha_{\theta,n}$ and $\beta_{\theta,n}$ parameters. However, differences in the $\kappa_{\theta,n}$ imply that the filtered predictors are also different across quantiles.[13]

[12] Arguably, an exception is the literature on tests for jumps in continuous time stochastic volatility jump diffusions. These tests typically apply to a decomposition of realized volatility into a continuous-path and discrete jump component. Such analysis requires intra-daily returns data which is not available for emerging markets.

[13] We do not explicitly consider the issue of quantile crossings, see e.g. Dette and Volgushev (2008) and Chernozhukov, Fernández-Val, and Galichon (2010) for the recent literature. It turns out, however, that crossing of quantiles does not seem to be an issue in the applications at hand. Moreover, the topic of suitable regularity conditions for the proper dynamics of the MIDAS quantile functions is beyond the scope of the current paper, see however Ghysels, Ru, Valkanov, and White (2011).

To estimate the quantile function (4), we need to specify the functional form of $w_d(\kappa_{\theta,n})$ and the conditioning variables x_{t-1-d} in the definition of $Z_{t-1}(\kappa_{\theta,n})$. We address these model specifications briefly, as they are fairly standard in the literature. We follow Ghysels, Santa-Clara, and Valkanov (2006) and specify $w_d(\kappa_{\theta,n})$ as a so called "Beta" polynomial.[14] A main advantage of this "Beta" function is its well-known flexibility using only two parameters κ_1 and κ_2. It can take many shapes, including flat weights, gradually declining weights as well as hump-shaped patterns. In Appendix A we provide the technical details regarding estimation of MIDAS quantile regressions.

We also need to clarify the choice of conditioning variables x_{t-1-d}. We follow Engle and Manganelli (2004), who find that absolute returns successfully capture time variation in the conditional distribution of returns, and use $|r_{t-1-d}|$ as the conditioning variable in (5). While we could have used any conditioning information, the $|r_{t-1-d}|$ specification provides the most robust results. Alternative specifications based on transformations of daily returns yield similar, but slightly noisier estimates.[15] More generally, the problem of selecting the conditioning variables in the MIDAS quantile regression is exactly the same as in any other regression. In our context, if model (2) is the true data generating process, then it must be the case that $Pr\left(e_{\theta,n,t} < 0 | I_{t-1}\right) = \theta$, where $e_{\theta,n,t} \equiv r_{t,n} - q_{\theta,t}\left(r_{t,n}; \delta_{\theta,n}\right),$. In other words, the variable $Hit_{\theta,n,t} \equiv \theta - 1\left\{e_{\theta,n,t} < 0\right\}$ which takes on the value of $\theta - 1$ if $e_{\theta,n,t} < 0$, and θ if $e_{\theta,n,t} > 0$, must have a zero unconditional and conditional expectations (given I_{t-1}). In Appendix A, we also use this observation to formulate a test for the validity of model (2).

2.3 Understanding the CA_t Measure

It is well-known that developed and emerging markets returns have time-varying conditional first and second moments (Bekaert and Harvey (1997)). Hence, we can write their returns as:

$$r_{t,n} = \mu_{t,n} + \sigma_{t,n}\varepsilon_{t,n} \tag{6}$$

If the dynamics of the conditional distribution of $r_{t,n}$ are captured entirely by the first two conditional moments, then the distribution of $\varepsilon_{t,n}$, $F(\varepsilon_{t,n})$, is time-invariant and so are its quantiles,

[14] Ghysels, Sinko, and Valkanov (2006) and Sinko, Sockin, and Ghysels (2010) discuss the properties of such polynomial lag and other specifications in detail. The expression for the polynomial appears in equation (15) of Appendix A.

[15] Results from regressions based on simple, squared, and cubed returns are available upon request.

$q_\theta\left(\varepsilon_{t,n}\right) = F^{-1}(\theta)$. Under that assumption, the conditional quantile θ of returns in (6) is:

$$q_{\theta,t}\left(r_{t,n}\right) = \mu_{t,n} + \sigma_{t,n} q_\theta\left(\varepsilon_{t,n}\right) \tag{7}$$

The conditional variance $\sigma_{t,n}$ can include asymmetries, such as in the GJR GARCH model. Note that the quantile function (7) can be expressed as (3), if $\alpha_\theta = 0$, $\beta_\theta = [1\ q_\theta\left(\varepsilon_{t,n}\right)]$ and $Z_{t-1} = [\mu_{t,n}\ \sigma_{t,n}]'$ for all θ.

Specification (7) helps us clarify a few important points. First, variations in the quantiles of returns may come from variations in the conditional mean and conditional variance. Second, the mean has the same impact on all quantiles and hence cannot impact the skewness (conditional or unconditional) of returns. Third, if all the asymmetry is successfully captured by the volatility dynamics (such as in asymmetric GJR GARCH models) and the distribution of $\varepsilon_{t,n}$ is symmetric, then the conditional skewness of returns will be zero, even though the unconditional distribution might not be. In other words, time variation in the first and second moments may not be enough to generate fluctuations in the conditional asymmetry of returns.

Finally, if the distribution of $\varepsilon_{t,n}$ is time-invariant, as the location-scale model assumes, then we do not expect time-series variation in $CA_{\theta,t}$. Hence, it is important to consider the skewness of both $r_{t,n}$ and $\varepsilon_{t,n}$, as we do in the empirical section. The evidence in the bottom panels of Figure 1 already revealed that there is considerable time variation in the asymmetry measure of $\varepsilon_{t,n}$ for both DM and EM.

A profound question that has been extensively debated in the literature and that one cannot easily answer is whether extreme events should be completely eliminated in the estimation of statistics. From an economic perspective, since events in the tails of $F_{n,t|t-1}\left(r\right)$ enter into investors' assessment of risk, they should not be neglected. There is a voluminous literature that aims at estimating extreme events through the modeling of jumps, extreme value theory or other approaches (for references see inter alia Pukthuanthong and Roll (2010)). In the international context, the paper by Pukthuanthong and Roll (2010) looks at several such measures to identify jumps and understand their temporal correlation. All of the papers in the jump literature have the common feature that they are focusing on extreme quantiles of the conditional distribution.

The proposed $CA_{\theta,t}$ measure provides a complementary view to this literature in that it captures asymmetries between quantiles $1-\theta$ and θ of the distribution. If significant economic events fall outside of that interval but are important from an investor's perspective, then θ should be adjusted to reflect that fact. In practice, the selection of the quantile θ will be dictated by the application at hand. From an econometric perspective, extreme quantiles are harder to estimate. In keeping with the robustness spirit of the paper, we focus primarily on the 75th-25th quantiles, since they can be accurately estimated. Also, there is a tradition in finance to look at the interquartile range, as the 25th and the 75th quantiles are the half-way point between the median and the extreme tails of the distribution.

There are several ways of constructing statistics that are robust to outliers. While there is no best way of accomplishing this, it is helpful to consider the alternatives. In our context, one alternative is to modify the traditional skewness $S(r_t)$ such that extreme events are trimmed from the sample. This would eliminate outliers and hence the sensitivity of moment-based estimators of skewness. This approach would ultimately involve deciding what trimming threshold to use. A similar issue arises with the robust statistics discussed in Sections 2.1 and 2.2 and the choice of θ. For instance, while the $RA\left(r_t\right)$ statistic has historically been defined for $\theta = 0.75$ (Bowley (1920)), there is no good reason to rule out other points of the distribution $F_{n,t|t-1}\left(r\right)$. In this regards, it is worth turning our attention again to Figure 1 where the middle plots display the rolling sample asymmetry measures for returns as well as $\varepsilon_{t,n}$ for both DM and EM using θ = .95. We observe that the patterns are similar to those in the right hand side panels involving the interquartile range-based asymmetry measure with θ = .75. The time series patterns are similar and the correlations between the measures for DM and EM are just slightly higher with θ = .95.

The discussion makes it clear that, in the absence of a priori reason to choose a given θ, the main $CA_{\theta,t}$ results should be presented over a grid of values. We take this approach to also verify that the main results are not predicated on one particular choice of θ. As a preview, we show later - and as Figure 1 already suggested - that results of $CA_{\theta,t}$ for various θ's do not alter the main message of the paper.[16]

3 Data and Initial Observations

We have daily US dollar-denominated log returns, r_t, for a total of 76 indices, which include 73 country and 3 global portfolio indices. The country portfolios, obtained from Datastream, are divided into 21 developed markets and 52 emerging markets. For most developed and a few

[16]In contrast, we find that trimmed mean estimates of third power of returns critically depend on the amount of trimming. Results are also not reported here, but available upon request from the authors.

emerging markets, the data spans the full period from January 1, 1980 to December 31, 2010 (emerging markets data prior to 1980 is almost non-existent). In the interest of completeness, our goal is to include as many countries as possible, and economies with shorter data spans are introduced as soon as their returns become available. Following Pukthuanthong and Roll (2009), we filter returns to purge holidays and non-trading days. We use the MCSI World Index from Datastream as a proxy for the global World (W) portfolio. Countries are classified as emerging or developed following recent papers by Bekaert and Harvey (1997) and Bekaert, Harvey, Lundblad, and Siegel (2011). We construct two value-weighted portfolios of developed (DM) and emerging (EM) markets daily returns using country returns and market capitalizations, recorder at the end of the previous year, from Global Financial Data, Datastream, or the World Federation of Exchanges. For a given year, we construct the DM and EM portfolios with all available countries within each group at the beginning of that year.

Table 1 presents return summary statistics for the W, DM, and EM portfolios as well as for all 73 individual countries, which are sorted by their market capitalization at the end of 2010. We report daily and yearly log returns statistics, where yearly log returns $r_{t,250}$ are computed as the sum of 250 daily log returns. Given the sample size, we construct returns in an overlapping fashion and properly account for the induced autocorrelation in our statistics. The first two columns after the index or country name display the initial date of the returns series and the number of daily available observations. With the exception of Finland and Iceland, all DM series start on January 2, 1980. Among the emerging markets, there is considerable variation in the initial date, ranging from January 2, 1980 (for Malaysia, South Africa, and South Korea) to October 23, 2000 (for Bulgaria).

EM exhibits larger volatility than DM and comparable skewness at daily frequency. At one-year horizon (column $S(r_{t,250})$), the DM portfolio is very negatively skewed (-0.958) whereas the skewness of the EM portfolio is approximate half as large (-0.462). Country annual returns are also skewed (column $S(r_{t,250})$) and sometimes even more so than are daily returns.[17] The robust measure of skewness (column $RA(r_{t,250})$) reaffirms the negative skewness of annual returns. With the exception of three countries (Japan, Australia, and Austria) all developed countries exhibit negative unconditional skewness. Among the emerging economies, 14 have positive RA estimates and China has the largest one.

[17]This fact, also discussed by Engle and Mistry (2007) and Ghysels, Plazzi, and Valkanov (2010), is surprising because intuition based on Central Limit Theorem arguments would imply that skewness ought to converge to zero as the horizon increases.

We also report summary statistics of deGARCHed and deTARCHed returns. Following the discussion in Section 2.3, we express daily log returns as $r_t = \mu_t + \sigma_t \varepsilon_t$. Estimates of ε_t are obtained by subtracting an AR(1) model for the conditional mean and dividing by one of two widely-used volatility models, either a GARCH(1,1) or the asymmetric GJR GARCH(1,1) of Glosten, Jagannathan, and Runkle (1993). We denote the deGARCHed returns with ε_t^G and the deTARCHed returns with ε_t^T, and the corresponding yearly returns by $\varepsilon_{t,250}^G$ and $\varepsilon_{t,250}^T$, respectively.[18] The filtered returns ought to display less unconditional skewness, especially under the asymmetric GJR GARCH. In fact, the asymmetric GJR GARCH model has been used extensively in the volatility literature to capture unconditional skewness of returns. However, failure to detect unconditional skewness in the data does not imply that there is no time-variation in the conditional skewness, as discussed in Section 2.3.

Columns 9 through 11 of Table 1 display the unconditional skewness of the GARCH-filtered daily returns ($S(\varepsilon_t^G)$), yearly returns ($S\left(\varepsilon_{t,250}^G\right)$), and the robust measure of skewness of the yearly returns ($RA\left(\varepsilon_{t,250}^G\right)$). The last three columns display the same statistics for the TARCH-filtered returns, $S(\varepsilon_t^T),$ ($S\left(\varepsilon_{t,250}^T\right)$), and $RA\left(\varepsilon_{t,250}^T\right)$. Comparing the unfiltered return statistics (columns 6-8) to those of the filtered returns (columns 9-14), we see that the latter are less skewed. As expected, the TARCH-filtered returns exhibit the least amount of unconditional skewness. For instance, for the world portfolio return, $S(r_{t,250})$ is equal to -0.980 and decreases to -0.018 (0.150) for the deGARCHed (deTARCHed) returns. In some case, such as the EM portfolio, deGARCHed and deTARCHed returns continue to exhibit unconditional skewness. In general, however, the GARCH- and especially TARCH-filtered returns exhibit less unconditional skewness across developed and emerging countries. Also, the robust asymmetry measures are less affected by observations in the far tails of the distribution. This is particularly evident in the case of Iceland and for several emerging economies such as Russia and Indonesia.

Overall, the S and RA measures are positively related. Their cross-sectional correlation is about 0.55 for returns, 0.42 for GARCH-filtered returns, and just 0.38 for TARCH-filtered daily returns. The relationship tends to be stronger among developed markets, as they are generally characterized by lower volatility and fewer outliers. Another interesting finding is that the traditional

[18] More specifically, we first fit an AR(1) to the daily returns and fit a GARCH or GJR GARCH model. We aggregate the daily residual on an annual basis. Hence, all that filtering is done at daily frequency and then we aggregate. There are some non-trivial temporal aggregation issues here, notably due to the fact that GARCH models don't easily aggregate. The advantage of our approach is that if daily deGARCHed or deTARCHed returns are truly i.i.d. then we expect that adding up such residuals on a yearly basis will still result in constant quantiles. Any dynamic predictable pattern - which is key to our analysis - will be translated into a yearly horizon pattern via the aggregation scheme we use. A less appealing alternative would have been to fit GARCH models to annual returns.

measure of skewness S is impacted significantly by the GARCH and TARCH filters, whereas the RA measure is not. This result, which highlights the fact that RA is invariant to ARCH/GARCH effects, can also be gleaned from the rolling estimates of RA in Figure 1. In the bottom plot of the figure, we display 250-day rolling window RA estimates for the DM and EM portfolios based on TARCH-filtered returns. We observe that filtering the returns does not alter the time-series dynamics of RA which varies in the same range as the RA calculated with simple returns (top plot).

In sum, the RA measure captures features of the marginal distribution of returns which are not revealed by the moment-based skewness. We now apply our MIDAS approach to estimate CA_t, which is a conditional version of RA, and study its evolution over time and its time-series and cross-sectional determinants.

4 Results

For all 76 portfolios, we obtain the conditional skewness estimates $CA_t\left(r_{t,n}\right)$ of annual ($n = 250$) returns by first estimating the 25th, 50th, and 75th conditional quantiles in expressions (4) and (5) as discussed in Appendix A and then substituting them into expression (2). The $CA_t\left(r_{t,n}\right)$ is our leading case, but we also present results for a grid of θs below. The estimated quantiles have three parameters each ($\alpha_{\theta,n}, \beta_{\theta,n}, \kappa_{2,\theta,n}$), because we impose κ_1 = 1 as explained in Appendix A. Since it is impractical to show 3 estimates for 76 portfolios, 3 quantiles, and 3 conditioning variables ($|r_t|$, $\left|\varepsilon_t^G\right|$ and $\left|\varepsilon_t^T\right|$), we make the expositional choice of presenting the main results for annual returns of the world, developed markets, and emerging markets as well as for the largest countries in the portfolios, namely, the United States and China. The remainder of the section is organized as follows: in a first subsection we discuss the estimates of CA_t, in a second we study co-movements in conditional asymmetry and volatility feedback and a final subsection reports on robustness checks.

4.1 Estimates of CA_t

Table 2 presents the results for the five portfolio returns: W, DM, EM, US, and CHA. Panel A displays the estimates of $\alpha_{\theta,250}$ and $\beta_{\theta,250}$ from the unfiltered returns $r_{t,250}$, for θ = $0.25, 0.50$, and 0.75. The hypothesis $\beta_{\theta,250}$=0 is the most important from an economic perspective, because if true, then the quantile does not exhibit time-variation. Henceforth, most of the discussion will focus on estimation and testing of $\beta_{\theta,250}$. As discussed in Appendix B, we use the Davies (1987) max-t procedure to test for $\beta_{\theta,250} = 0$ because the $\kappa_{\theta,250}$s are unidentified under the null. We display p-values (rather than the more customary t-statistics) because the distribution of the max-t statistic is non-standard and has to be simulated.[19]

In Panel A, the estimate of $\beta_{0.25,250}$ is negative and statistically significant at either the 1% or the 5% level for four of the five portfolios. The exception is EM for which $\beta_{0.75,250}$ is statistically different from zero with a p-value of 1.6%. Hence, for all portfolios at least one of the quantiles is time-varying. This implies that $CA_t\left(r_{t,n}\right)$ is time varying for all five portfolios. These results are not only novel but also extremely encouraging, given the conservative nature of the Davies test and the fact that we use the actual finite-sample distribution rather than the asymptotic approximation in computing the p-values. Moreover, the magnitude of $\beta_{0.25,250}$ is larger in absolute value than $\beta_{0.75,250}$ for W, DM, and US, which implies asymmetry and a large downside risk. For EM and CHA, the asymmetry is not pronounced as the estimates of $\beta_{0.25,250}$ and $\beta_{0.75,250}$ are very similar. Finally, in four of the five portfolios, $\beta_{0.25,250} < 0$ and $\beta_{0.75,250} > 0$ as expected because the state variables mimic volatility which changes the scale of the distribution as it fluctuates. Hence, at least part of the observed time variation in $q_{\theta,t}\left(r_{t,n}\right)$ is due to time-varying volatility.

Next, we turn to the GARCH- and GJR-filtered returns, which by construction should not exhibit volatility effects. Panels B and C display the same results for $\varepsilon^G_{t,250}$ and $\varepsilon^T_{t,250}$. Because we divided the returns by their volatility, the scales are different and the magnitude of the estimates is not directly comparable with Panel A. A few observations are in order. First, in both panels $\beta_{0.25,250}$ and $\beta_{0.75,250}$ are statistically different from zero which implies that there is time variation in the quantiles even after the volatility has been filtered out. In other words, the time variation in the quantiles is not entirely due to a volatility (scale) effect. Rather there are dynamics in the conditional distribution of $\varepsilon^G_{t,250}$ and $\varepsilon^T_{t,250}$ that need further exploration. Second, $\beta_{0.25,250}$ and $\beta_{0.75,250}$ are both negative, which verifies that the volatility effect is no longer present. Third, $\beta_{0.25,250}$ is larger in absolute value than $\beta_{0.75,250}$, which implies that there is some asymmetry in the conditional distribution. While it is more pronounced in the GARCH-filtered returns (Panel B), it is still very much present even for the GJR-filtered returns (Panel C). These results confirm that

[19] The Davies (1987) procedure ultimately provides a conservative test of the null relative to the usual statistics. In empirical finance, it has been used by Bos and Newbold (1984), Bonomo and Garcia (1996), Guidolin and Timmermann (2008), among others. We also report the value of $\kappa_{2,\theta,250}$ that correspond to the obtained max-t statistic. Since the value is not estimated, we cannot compute standard errors. In the robustness section, we provide results which neglect the Davies (1987) problem and optimize over $\kappa_{2,\theta,250}$ and the results are very similar to what we discuss below.

the first novel finding of the paper – the time variation of return quantiles and CA_t – holds true for simple and volatility-filtered returns.

Finally, we provide p-values for two sets of specification tests, found in the bottom part of all panels in Table 2. The first test reports p-values ($pval$) of the null that the unconditional coverage of the estimated quantile, reported in row "Coverage", is equal to the nominal level θ ($\times 100$). Given that the estimation in (16) is non-linear, it is useful to report the accuracy of estimation of the quantiles. The null cannot be reject for all country-quantiles combinations, which implies that the quantile regressions are estimated accurately. A second set of conditional tests checks whether information contained in average past returns ($pval(t')$), squared returns ($pval(t'')$), or both ($pval(t''')$) could provide information in constructing quantiles beyond that contained in past absolute returns. This specification test of the conditional model aims to validate the choice of our conditioning variable. The null hypothesis is rejected in a few instances in Panel A and mostly for the EM portfolio. This is expected because squared returns capture the time-varying volatility of simple returns. In the deGARCHed and deTARCHed returns (Panels B and C), we observe that the null cannot be rejected for the W, DM, EM, and US portfolios and for all quantiles. Only for CHA do we observe a couple of rejections for the 25th quantile at the 5 percent level. Overall, these numbers are reassuring that our simple model captures adequately the behavior of the series and does not systematically neglect valuable conditioning information.

To visualize the documented time variation in quantiles, we plot in Figure 2 the estimated 25th, 50th, and 75th conditional quantiles for the DM (top) and EM (bottom) portfolios based on estimates in Table 2 for returns (solid lines) and TARCH-filtered returns (dashed lines). The plots display relatively little time variation in the median and upper quartile of both the DM and EM portfolios. In contrast, the real variation appears to be in the lower quartile. For the DM series, we clearly identify the episodes of financial stress, such as the '87 crash, the burst of the Internet Bubble and, at the end of the sample, the recent financial crisis of 2007-2008. Each are marked by a downward movement in the 25th quantile. The sharpest drop occurs at the end of the sample, marking the severity of the crisis. The pattern for the EM portfolio is remarkably different. The 25th quantile tends to move at a lower overall level with smaller variation. Another important observation from Figure 2 is that the upper quartile is flat for TARCH-filtered returns, whereas the lower quartile is not. This means that TARCH-filtered returns are obviously not i.i.d., but most importantly that taking out the volatility effect does not effectively capture the downside risk dynamics. This finding is of independent interest – beyond the scope of our paper and is explored further in current research.

In Figure 3, we plot the estimated $CA_t\,(r_{t,n})$ in equation (2) for the DM and EM portfolios (simple and TARCH-filtered returns). The top panel reveals the time series pattern of $CA_t\,(r_{t,n})$ for DM features strong time variation with the well-known negative skewness of stock market crashes - but occasionally also appears to be positive, notably right after the '87 stock market crash. We also note the negative trend at the end of the sample, again illustrating the severity of the recent crisis. The $CA_t\,(r_{t,n})$ for EM exhibits less time variation and is markedly different: it is mostly negative at the beginning of the sample, turns positive in the 1990s, then decreases to zero and into negative territory during the 2007-2008 crisis. In the lower panel of Figure 3, the $CA_t\,(r_{t,n})$ for TARCH-filtered returns display similar patterns. Given the distinct time series of DM and EM asymmetry measures, it is not surprising to note that their correlation is 0.32 for the simple returns and 0.35 for the TARCH-filtered returns.

Table 3 presents the summary statistics of the estimated $CA_t\,(r_{t,n})$ time series. The average $CA_t\,(r_{t,n})$ in four of the portfolios is very similar to the unconditional estimate $RA_t\,(r_{t,n})$ in Table 1 which is an indication that the model correctly captures the conditional asymmetry. For example, the robust asymmetry 250-day returns to EM is -0.057 (Table 1), compared to an average CA_t of -0.054. The only exception is China when looking at unfiltered returns. Moreover, the standard deviation in conditional asymmetry is always almost as large as the mean for all countries. Thus, even if developed economies are on average highly negatively skewed, their skewness varies substantially over time and can turn positive. The statistics are largely unchanged for r_t, $\varepsilon^G_{t,250}$ and $\varepsilon^T_{t,250}$, which is consistent with our discussion above of the quantile-based measure of asymmetry not being sensitive to (GJR) GARCH effects. If anything, removing asymmetry in volatility has the effect of reducing trends in the CA_t series.

On the right-hand side panels of Table 3, we report the correlation matrix between $CA_t\,(r_{t,n})$s of all portfolios. As already reported in Figure 3, the correlation between the DM and EM portfolios is positive but small: it is 0.32 for the simple returns and comparable at 0.35 for deGARCHed and deTARCHed returns. In other words, no matter whether we account or not for volatility dynamics, the $CA_t\,(r_{t,n})$ measure between DM and EM exhibits limited correlation. Moreover, if we look at the average pairwise correlation between an emerging and a developed country excluding US and CHA, we observe that it is a tiny 0.012 (Panel A). In fact, the correlation of CHA and the world portfolio is negative at -0.342 while the average correlation of all other emerging economies is just slightly positive at 0.072. Very similar results obtain for de-GARCHed and de-TARCHed returns. Taken together, these correlation findings imply that international diversification might be more desirable than suggested by a simple mean-variance analysis – a topic we further explore in Section 6.

To conclude, we turn our attention to Figure 4 where the MIDAS quantile weights of 250-day lagged absolute returns are displayed for the DM (top) and EM (bottom) portfolio returns. A first interesting observation is that the decay patterns for DM and EM weights are very different. A second notable observation is that the decay patterns are also very different for the 25th, 50th and 75th percentile. For the DM portfolio, the 75th percentile and median regression puts the weights on the recent daily observations. Hence, the recent past determines mostly the upper tail in the $CA_t\left(r_{t,n}\right)$ measure. This is not so much the case for the EM 75th percentile regression. In fact, for the EM portfolio most of the dependence on the recent past appears to be for the lower quartile. With some exceptions, we find that returns and TARCH-filtered returns display similar overall decay patterns.

4.2 Co-Movements in Conditional Asymmetry and Volatility Feedback

In this subsection, we use time series regressions based on the estimated $CA_t\left(r_{t,n}\right)$ in order to explore its dynamics and relationship with other variables. First we discuss the co-movement between country asymmetries and the world portfolio. Then, we revisit the leverage effect in a conditional setting, analyzing the relationship between conditional volatility and asymmetry. We abbreviate the notation from $CA_t\left(r_{t,n}\right)$ to CA_t as it is understood that all returns are at annual frequency.

4.2.1 Co-movements in Conditional Asymmetry

It is natural to ask to what degree the time-variation in country CA_t can be traced to a world factor. This question is particularly relevant because, as we saw in Table 3, the world portfolio returns exhibit significant conditional asymmetry. In the framework of an international factor model (e.g., Solnik (1974), Korajczyk and Viallet (1989), Cho, Eun, and Senbet (1986), Harvey (1991)), asymmetries in the distribution of returns may arise either because of shocks to systematic risk factors that affect the cross section of returns or because of country-specific shocks. While it might be tempting to decompose the conditional asymmetry of a portfolio return into systematic and idiosyncratic risk components, the mechanics of such a decomposition are not straightforward and would likely involve distributional assumptions, which is what we have so far been trying to avoid.[20]

Rather, we propose an alternative approach. For each portfolio, we run the time-series regressions:

$$CA_{i,t} = \delta_{0,i} + \delta_{1,i} CA_{W,t} + u_{i,t} \tag{8}$$

where $CA_{i,t}$ and $CA_{W,t}$ are the estimated conditional asymmetry measures of country i and the world portfolio, respectively. The approach of representing the $CA_{i,t}$ series as a linear function of one factor, $CA_{W,t}$, is a simple way of linking co-movements between return asymmetries in the world portfolio with those of individual countries without resorting to distributional assumptions about the factors and idiosyncratic components of returns. It also captures the basic intuition from a factor model, namely, that the systematic world factor might be the source of asymmetry in the distribution of country returns.[21] Based on that intuition, we expect the estimates of $\delta_{1,i}$ to be positive for all portfolios. We also look at correlations among the residuals $u_{i,t}$ which capture movements in $CA_{i,t}$ that are orthogonal to $CA_{W,t}$.

Table 4 presents the results from regressions (8), where the $CA_{i,t}$ are estimated using simple (Panel A), deGARCHed (Panel B), and deTARCHed (Panel C) returns. In keeping with the format of previous tables, we display results for the world, DM, EM, US, and CHA portfolios, as well as averages of the estimates across developed and emerging countries (excluding the US and China), which are reported in columns $\overline{DM_i}$ and $\overline{EM_i}$, respectively. P-values, reported in parentheses, are based on Newey-West standard errors with 250 daily lags.

Focusing on Panel A, the estimated slope coefficient $\delta_{1,i}$ in the DM regression is 0.834, or as expected, the CA_ts of the DM and W portfolios are positively correlated. The corresponding p-values indicate that the estimates are statistically significant at conventional levels. Similar results obtain for the US. The $\delta_{1,i}$ in the EM regression is also positive and statistically significant, but it is

[20] Our asymmetry measure is a function of quantiles of returns $q_\theta\left(r_{i,t,n}\right)$ (conditional or unconditional). A general decomposition of the return quantiles into the quantiles of the systematic and idiosyncratic fluctuations is not possible without further assumptions about the joint distribution of the factors and the idiosyncratic shocks. Namely, modeling the systematic and idiosyncratic parts of return separately involves the marginal distributions. If we want to transition from the marginals to the joint distribution of returns, we have to take a stand on the dependence between these two marginal distributions. One way of doing this would be through some parametric assumptions, such as a copula function. However, this would involve making distributional assumptions, and would critically depend on the choice of copula.

[21] Also related is Engle and Mistry (2007), who under certain identifying assumptions, working with the third moment of returns rather than with quantile-based measures of asymmetry, derive a linear relation between the skewness of the asset return and the skewness of the systematic factor.

much smaller in magnitude (0.119). For CHA, fluctuations in conditional asymmetry are actually *negatively* correlated with that of the world portfolio. Unfortunately, it is misleading to simply look at the $\delta_{1,i}$ estimates in order to compare economic significance across regressions, because the left-hand side variables have different variability. The R^2s are a better measure for that purpose. The R^2 in the DM and US regressions is high, as these markets represent a significant component of the world portfolio. The R^2 in the EM and CHA regressions is significantly lower. We find it intriguing that such a small fraction of the asymmetric shocks in emerging market returns are explainable by the asymmetry in world portfolio returns. This same finding can be glimpsed from the $\overline{DM_i}$ and $\overline{EM_i}$ columns: the average R^2 across developed countries (0.292) is about three times that of the averaged R^2 in emerging markets (0.111). These findings suggests that, in emerging markets, factors such as political crises, financial market-liberalization trends, or other country-specific shocks might be predominantly important in explaining the time variation in CA_t. The volatility-filtered estimates in Panels B and C remain statistically significant, albeit with somewhat lower estimates, which indicates that volatility co-movements do not account for the significant $\delta_{1,i}$ estimates in Table 4.

The correlations of the residuals in regression (8) are displayed to the right in Table 4. Interestingly, in Panel A the correlation between the estimated $u_{DM,t}$ and $u_{EM,t}$ is negative (-0.286) and so is that between the US and CHA residuals (-0.210). Also, the correlation between the average $\overline{DM_i}$ and $\overline{EM_i}$ is nearly zero (0.016). Similar numbers are observed in the other two panels. The finding that variations in $CA_{i,t}$ that are orthogonal to $CA_{W,t}$ are either mutually uncorrelated or negatively correlated is another indication that some of the differences in $CA_{i,t}$ between developed and emerging economies might be due to geo-political or idiosyncratic reasons.

4.2.2 Conditional Asymmetry and Volatility

A large body of literature has established a relation between higher volatility and negative returns. This finding, known as the "leverage effect" has been documented in many ways. We revisit it here for two reasons. First, replicating this stylized fact with the CA_t measure would lend further credence to the argument that we are capturing conditional asymmetry in returns. Second, while the leverage effect has been well-documented for the US and developed markets, its presence in emerging markets has not been examined as closely. The only exceptions are Bekaert and Harvey (1995, 1997) who do not find support for the leverage effect in emerging markets.

For each portfolio in our sample, we estimate the following time-series regressions:

$$CA_{i,t} = \gamma_{0,i} + \gamma_{1,i} VOL_{i,t} + \varphi_{i,t} \tag{9}$$

where $CA_{i,t}$ is estimated as above and $VOL_{i,t}$ denotes portfolio i's volatility, which is estimated from a MIDAS regression as in Ghysels, Santa-Clara, and Valkanov (2006). While there are many volatility models - including the ARCH-type models we employ for normalizing the returns - the advantage of using a MIDAS volatility model is that $CA_{i,t}$ and $VOL_{i,t}$ use the same information set of daily returns.

In Table 5, we present results for regression (9) where $CA_{i,t}$ is based on simple, deGARCHed, and deTARCHed returns and $VOL_{i,t}$ involves squared daily returns.[22] The p-values are again based on Newey-West standard errors with 250 daily lags. In Panel A, $\gamma_{1,i}$ is negative and statistically significant for the W, DM, EM, US, and CHA portfolios. This finding is consistent with the leverage effect results from the asymmetric GARCH literature and is also in line with the "volatility feedback" hypothesis of Campbell and Hentschel (1992).[23] Volatility fluctuations explain from 28 percent (W portfolio) to as much as 85 percent (CHA portfolio) of the variation in $CA_{i,t}$. The negative $CA_{i,t}$ - $VOL_{i,t}$ relation is not due to a few countries as the average of the estimates without the U.S. and China ($\overline{DM_i}$ and $\overline{EM_i}$) yield consistently similar results.

More surprising is the finding that a negative relation between the conditional asymmetry and volatility exists even for deGARCHed and deTARCHed returns (panels B and C). The point estimates, while smaller in magnitude, are clearly statistically significant at conventional levels. In panel C in particular, we expect to see no correlation between the $CA_{i,t}$ of deTARCHed returns and conditional volatility, if the TARCH volatility filtering adequately captures the asymmetry. This is clearly not the case. Our finding is intriguing because it has three important implications. First, the deTARCHed returns are not i.i.d. since they exhibit conditional asymmetry. This point has already been made above using slightly different methods. Second, emerging economies also exhibit a negative relation between conditional skewness and volatility. Finally, our results suggest that the traditional notion of leverage effect (i.e., asymmetry in the conditional volatility) ought to be extended to a conditional version, one which accommodates a negative relation between conditional skewness and conditional volatility.

[22] Since we are estimating volatility it does not make sense to deGARCH or deTARCH the returns.

[23] Asymmetries arises in their model because large good news increase volatility and thus risk premia, partly offsetting the positive effect on today's return. On the contrary, when large bad news come they raise both volatility and risk premia, whose effect is to depress even more contemporaneous returns.

4.3 Robustness Checks

We perform a series of robustness checks to verify that our results are not driven by a fortuitous choice of the quantiles used to construct $CA_{\theta,t}$, by the estimation strategy, or by the sampling frequency.

Different quantiles. The results thus far were presented for CA_t which involve estimating the 25th and 75th quantiles. However, the general formulation of $CA_{\theta,t}$ in expression (2) makes it clear that any quantile pairs ($1-\theta$-θ) might be used in the analysis. We verified that our main results hold true for a range of θ values. Specifically, we estimated $CA_{\theta,t}$ for a grid of θs ranging from 0.55 to 0.95 across the three returns specifications.[24] Then, we checked that for DM deTARCHed returns the correlation between the benchmark CA_t and the other $CA_{\theta,t}$s is no lower than 0.91 ($CA_{0.55,t}$) and is in the range of 0.95-0.99 for the other θs. For the EM deTARCHed returns, the same correlation is no lower than 0.96 ($CA_{0.55,t}$) and is in the range of 0.97-0.99 for the other θs. In other words, all these asymmetry measures are highly correlated.

We also verify that the low correlation in the conditional asymmetry between the DM and EM portfolios is not driven by our choice of θ in $CA_{\theta,t}$. The rolling sample quantiles reported in Figure 1 already hint at the fact that changing the quantiles measure from $RA_{0.75}$ to $RA_{0.95}$ produce comparable results. To show this with the conditional quantile specification we turn our attention to Figure 5 which displays the correlation between $CA_{\theta,t}$s of DM and EM portfolios for a grid of θs ranging from 0.55 to 0.95 across the three returns specifications. The correlations appear rather stable across quantiles, with a decrease as we get closer to the median. Importantly, they never exceed 0.40 even for the most extreme quantiles. Hence, we conclude that the CA_t measure is representative of the asymmetry across a wide spectrum of quantiles. This evidence is consistent with the observation in section 2.1 that the DM and EM portfolios feature low correlation once the effect of observations in the extreme tails of the distribution are excluded.

Unconstrained estimation. As discussed above and detailed in Appendix A, we estimate the quantiles by imposing a downward sloping weighting scheme for the MIDAS polynomials and a positive intercept for the quantile regressions. These constraints, imposed to improve the optimization, have the effect of shrinking the estimates. However, they are not necessary to obtain the main findings. Indeed, we re-estimate the quantile regressions in (4)-(5) without imposing any

[24] We do not go beyond $\theta = 0.95$, because practically speaking such extreme conditional quantiles are poorly estimated.

constraints on the coefficients $(\alpha, \beta, \kappa_1, \kappa_2)$ and find that the main results of the paper still hold. Some EM countries feature somewhat anomalous lower quantiles, most likely associated with local minima in the estimation. The correlation between the CA_t of the DM and EM portfolios is now closer to zero or sometimes even negative.

Role of exchange rates. Following common practice (e.g., Bekaert and Harvey (1997), Guidolin and Timmermann (2008)), we consider US dollar-denominated returns. This is the perspective of an unhedged US investor whose investments, denominated in the same currency, represent feasible trading strategies. Yet, one may wonder whether and how much of the above-documented asymmetry is due to exchange rates fluctuations. It has been argued that expected returns on currency portfolios represent a premium for skewness (Bates (1996)). Unfortunately, we cannot decompose the CA_t of the dollar-denominated returns into that of local-currency and exchange rate returns without making further distributional assumptions. We leave this topic for further research.

Non–overlapping monthly returns. As an additional robustness check, we estimate the CA_t measure on 22-day non-overlapping returns to evaluate the impact of overlap and sampling frequency on our results. The resultant series, not shown for conciseness, exhibit similar patterns to the ones in Figure 3. The correlation between the DM and EM portfolios is again low, ranging from 0.37 for returns to 0.08 for deTARCHed returns. However, non-overlapping monthly returns produce noticeably noisier estimates of CA_t. They are also less suitable for studying the impact of lower-frequency macroeconomic variables, which is the next topic of our investigation.

5 Conditional Asymmetry and its Macroeconomic Determinants

While our previous results delve into the time-series and co-movement properties of CA_t, they have little to say about its economic determinants. In this section, we ask the economically more interesting question of whether fluctuations and cross-sectional differences in the asymmetry measures can be linked to economic fundamentals. We tackle this question by regressing CA_t on a set of predetermined state variables. In selecting these variables, we are guided by economic theory and evidence from previous predictability studies of conditional mean (Fama and French (1989), Goyal and Welch (2007), among others), volatility (Bekaert and Harvey (1997), Engle, Ghysels, and Sohn (2010), Engle and Rangel (2008), Schwert (1989), among others) and skewness (Chen, Hong, and Stein (2001), Boyer, Mitton, and Vorkink (2010), among others). Since most of the conditioning variables are available at annual frequency, our approach is to explore whether variables observed at the end of year t forecast CA_{t+1}.

More specifically, we investigate the relationship between $CA_{i,t+1}$ and several economic determinants by running the following pooled regression for all countries and across time:

$$CA_{i,t+1} = \zeta_0 + \zeta_1' X_{i,t} + v_{i,t} \tag{10}$$

where the vector $X_{i,t}$ contains as many as nine predetermined country-specific variables in addition to a linear time trend.[25] $CA_{i,t+1}$ is estimated from simple, deGARCHed, or deTARCHed returns, as above. We first describe the conditioning variables and then discuss the regression results.

5.1 Conditioning Variables

The conditioning variables, available for each country, can be divided into two subsets: financial quantities and macroeconomic indicators. The data sources are Datastream, Global Financial Data, the World Federation of Exchanges, and the World Bank Database. Summary statistics are discussed in Appendix C with reference to Table C.1.

Financial variables: The first financial variable is the conditional volatility of a country's stock market, VOL, calculated as in section 4.2. Volatility is a traditional measure of economic uncertainty and, as discussed above, it is also necessary to capture the leverage effect. In different contexts, Chen, Hong, and Stein (2001) document a negative, albeit not statistically significant, relationship between volatility and future skewness at the aggregate level, while Boyer, Mitton, and Vorkink (2010) find that idiosyncratic volatility is a strong predictor of skewness.

Next, we consider three measures of the degree of stock market development. The first one is turnover ($TURN$), calculated as the log of the ratio of the total value of shares traded to the average market capitalization for the period. Chen, Hong, and Stein (2001) use turnover as a proxy for the intensity of disagreement among investors and find that periods of unusually high turnover are associated with subsequently lower (i.e., negative) skewness of returns. Two other variables, the

[25]The linear trend is meant to capture changes through time in unconditional asymmetry which are not captured by any of the other variables. An alternative approach is to include year fixed effects. We verified that our results are robust to year fixed effects but the t-statistics deteriorate as more regressors are included. This is to be expected given the loss of degrees of freedom arising from the addition of the 28 time dummies.

market capitalization of a country's stock market relative to its nominal GDP (denoted E/GDP) and the number of companies listed in the Exchange (denoted $NCOMP$), both measured in logs, capture the relative and absolute size of the financial sector, respectively (Bekaert and Harvey (1997), Engle and Rangel (2008)). Chen, Hong, and Stein (2001) show that in the US, the size of a company is inversely related to the skewness of its returns.

Finally, we include a measure of market liquidity. The effect of liquidity on skewness is studied notably by Chordia, Roll, and Subrahmanyam (2000). Since data on aggregate bid-ask spreads is available only for a very limited number of countries, we rely on Roll's (1984) liquidity proxy calculated as $LIQ_t = -\sqrt{|\mathrm{Cov}_t(r_\tau, r_{\tau-1})|}$, where $\mathrm{Cov}_t(r_\tau, r_{\tau-1})$ denotes the one-day auto-covariance of daily returns within year t. Therefore, LIQ_t is the effective liquidity of daily returns during that year.[26]

Economic variables: Two interest-rate variables–a short-term interbank or government bond yield ($TBILL$) and the spread between a long-term and the short-term rate ($TSPR$)–and the growth rate of real GDP ($GDPg$) capture changes in the investment opportunity set and cross-sectional differences in macroeconomic conditions. We include the volatility of quarterly real GDP growth ($GDP\sigma$) over the current and past two years as a proxy for macroeconomic uncertainty. These variables have also been used in recent papers by Engle and Rangel (2008) and Bekaert, Harvey, Lundblad, and Siegel (2011). The first study relates them to low-frequency volatility in developed and emerging markets whereas the second one uses them to investigate the economic reasons behind equity markets segmentation.

To the best of our knowledge, the link between stock returns skewness and the macroeconomy has not been empirically explored nor cast in a theoretical model. Yet, it is reasonable to suspect that macroeconomic fundamentals play a role in our analysis. For instance, asymmetries in economic shocks, which have been extensively documented and modeled in the literature (see e.g. Neftci (1984), Hamilton (1989), Sichel (1993)) might be a contributing factor. In addition, several studies have related with some success the volatility of stock market returns to that of macro shocks (see Schwert (1989), Engle and Rangel (2008), and Engle, Ghysels, and Sohn (2010)). At the very least, the proposed variables will play the role of fixed effects, capturing cross-sectional

[26] Admittedly, it is possible that this quantity is capturing effects other than bid-ask spreads. For example, positive correlation in returns may be due to asynchronous trading, which is more severe in countries where stocks trade infrequently. Alternatively, one can think of the covariance (correlation) in stock returns as related to the profitability of momentum strategies, arguably a measure of market inefficiency. Yet, all these interpretations share the property that higher (less negative) values of LIQ are associated with more liquid markets.

differences in CA_t that are either related to unobservable or hard-to-measure factors.

5.2 Regression Results

In Table 6 we report coefficient estimates from three pooled versions of regression (10). In the first one (World), we include all countries in our database (i = 1 to 73). Results from pooling only across developed countries (i = 1 to 21) and emerging economies (i = 22 to 73) are also displayed. We ran all regressions with $CA_{i,t+1}$ estimated from simple, deGARCHed, or deTARCHed returns. Since the results are very similar, for conciseness, the table presents only the deTARCHed results, which are perhaps the most economically interesting ones. For each group of countries, we report three regression specifications. The first one involves conditional volatility, a time trend, and a constant. The second one adds the four financial variables, and the third one includes the four macroeconomic quantities. For each regression, we report two types of p-values, one from OLS standard errors (round brackets) and a second one using clustered standard errors at the year level (square brackets).[27] We will mainly discuss the clustered results.

For the world regressions, the coefficient of VOL is negative and statistically significant despite the fact that $CA_{i,t+1}$ was estimated with deTARCHed returns. This pooled estimate is in agreement with the time-series evidence from the previous table and indicates that the link between conditional asymmetry and volatility is non-linear. In specification (3), the coefficient of E/GDP is negative and that of turnover is positive, both statistically significant at conventional levels. Among the four economic variables, the coefficients of $TSPR$, $GDPg$ and $GDP\sigma$ are significant. For developed markets, the results are similar with a few notable exceptions. The conditional volatility is no longer significant in the presence of macroeconomic variables. This indicates either that, for developed markets, a TARCH model accurately captures the asymmetric conditional volatility or that the volatility of GDP growth, which now has a larger coefficient, captures the underlying macroeconomic uncertainty. We also report a larger impact of E/GDP. The coefficient of turnover is also significant and has a negative sign, which is consistent with the Chen, Hong, and Stein (2001) findings and hypothesis that it proxies for intensity of disagreement

[27] The resultant panel is unbalanced due to the fact that the starting date of each stock market index is potentially different (see Table 1) and that not all the determinants may be available for the entire period of the stock market data. For example, international data on the number of listed companies and on turnover starts in the late ’80s for most countries. Data on long-term government bond yields is sparse for emerging markets and so is quarterly GDP. Using only the countries having at least a certain number of time series observations would severely reduce our sample size and bias our analysis toward developed markets.

among investors. All four macroeconomic variables are now significant at conventional levels. In the emerging markets regressions, the effect of conditional volatility is negative and significant. Two of the macroeconomic variables also have significant impact. The coefficient of turnover is positive and significant which is more in line with the interpretation that, in emerging markets, it proxies for the level of financial development (rather than for disgreement among investors). In all markets, the volatility of GDP growth is significant and negatively related to $CA_{i,t+1}$ above and beyond the impact of VOL. This finding is reminiscent of the David and Veronesi (2009) model in which investors' learning about fundamentals leads to a non-linear relation between uncertainty about macroeconomic quantities and stock returns.

Table 6 contains two important results. First, several of the economic variables enter with opposite signs in the developed and emerging markets regressions. For example, turnover relates negatively to $CA_{i,t+1}$ for developed markets but enters with a positive sign for emerging economies. The coefficient on the short-term interest rate is negative for developed and positive for emerging countries. The same is true for $TSPR$. The relative size of the stock market (E/GDP) and liquidity also enter with opposite signs, although the coefficients are not always statistically significant. The opposite signs finding is of particular interest because it suggests that the low correlations is CA_t between DM and EM economies documented in Figures (1), (3), and Table (3) can be traced to the opposite response of those markets to economic fundamentals.

Second, the conditioning variables in Table 6 explain a non-trivial fraction of the variation in $CA_{i,t+1}$. The R^2 for developed (emerging) markets is 22% (17%) in the most comprehensive regression. For the whole panel of countries, the R^2 is lower (9%) because of the opposite effect of some variables in the developed versus emerging countries regressions. We should reiterate that the above results obtain for deTARCHed returns. This finding is noteworthy, especially if we consider that researchers have found it challenging to establish a link between macroecnomic fundamentals and return volatility (e.g., Schwert (1989), Engle and Rangel (2008), and Engle, Ghysels, and Sohn (2010)). The reported R^2s are difficult to compare with those in volatility regressions because of different methodologies, datasets, and sampling frequencies. However, the overall picture that emerges is that at least part of the conditional asymmetry variation is associated with economic fundamentals.

6 Conditional Asymmetry and Portfolio Implications

The benefits of international diversification and the related topic of global market integration have been extensively explored, mainly by modeling the time-varying means and co-movement of stock returns.[28] To capture the gist of that literature–and at the risk of over-simplifying a complex subject–in Figure 6 we display the rolling correlation of deTARCHed returns between the DM and EM portfolios (first graph) and the TARCH(1,1,1) volatility estimates of these portfolios (second graph). These plots illustrate why it is often argued that the benefits from international diversification are limited: the correlation of returns increases over our sample to as high as 0.80 and the volatilities exhibit similar variations across time.

The behavior of the first two moments is in sharp contrast with that of the skewness. The rolling RA measure, displayed for convenience in the bottom plot of Figure 6, and its conditional version CA_t reveal that return asymmetries of emerging and developed markets do not exhibit significant co-movement. In an international portfolio context, this finding suggests that investors can improve upon the standard mean-variance allocation by taking into account other features of the return distribution, such as asymmetries, while making optimal portfolio decisions (Harvey (1994), Bekaert, Erb, Harvey, and Viskanta (1998), and Jondeau and Rockinger (2006)). However, if we want to explore the cross-sectional richness of the data, the straightforward approach of modeling the joint conditional return distribution of 73 countries is practically speaking not possible, especially since we only have at most 30 years of data. Therefore, we adopt the parametric portfolio approach of Brandt, Santa-Clara, and Valkanov (2009), which consists of directly specifying the portfolio weights as a function of country-specific characteristics. In that context, the characteristic of interest is the conditional asymmetry of a country return, $CA_{i,t}$. Our ultimate goal is to quantify the impact of this characteristic on the optimal asset allocation across countries. Since the approach is fairly novel and has to be modified for our application, we briefly describe it below.[29]

[28] Among the many papers on the topic, see Solnik (1974), Stulz (1981, 1987), Korajczyk and Viallet (1989), King, Sentana, and Wadhwani (1994), Bekaert and Harvey (1995), Harvey (1995), Bekaert and Harvey (1997), Pukthuanthong and Roll (2009), Engle and Rangel (2008)

[29] For an alternative, albeit computationally more involved, approach see Jondeau and Rockinger (2006). See also Christoffersen, Errunza, Jacobs, and Jin (2011) for a discussion of international portfolio diversification and higher moments of asset returns. They emphasize kurtosis in their analysis instead of skewness which is the topic of the present paper.

6.1 Methodology

We investigate whether and to what extent the estimated conditional return asymmetry $CA_{i,t}$ would alter a representative investor's optimal asset allocation across the 73 country returns relative to the natural benchmark–the world value-weighted portfolio return. As in the previous section, the subscript denotes country i and let N_t be the number of countries in the sample at time t. An investor chooses portfolio weights $w_{i,t}$ to maximize the conditional expected utility of her portfolio return $r_{p,t+1}$,

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u\left(r_{p,t+1}\right)\right] \tag{11}$$

where $r_{p,t+1} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}$. We focus on yearly returns and drop the horizon subscript n to simplify the notation. Following Brandt, Santa-Clara, and Valkanov (2009), we specify the portfolio weights of each country as:

$$\begin{aligned} w_{i,t} &= w_{i,t}^m + \chi \frac{1}{N_t} \widetilde{CA}_{i,t} \\ &= w_{i,t}^m + w_{i,t}^{CA} \end{aligned} \tag{12}$$

where $w_{i,t}^m$ is the year-t weight of country i in the value-weighted (market) portfolio and $\widetilde{CA}_{i,t}$ is the asymmetry measure of country i, standardized to have mean zero and unit standard deviation each period. The normalization $1/N_t$ allows the number of countries to vary across periods.

The weights in expression (12) are estimated by maximizing objective function (11) with respect to the parameter χ. The estimated $w_{i,t}^{CA}$ can be interpreted as the "actively managed" allocation. It tilts the portfolio toward or away from $w_{i,t}^m$ depending on country i's $\widetilde{CA}_{i,t}$ relative to the cross-sectional mean. Based on (12), the total portfolio return can be decomposed into two parts:

$$r_{p,t+1} = r_{t+1}^m + r_{t+1}^{CA} \tag{13}$$

where $r_{t+1}^m = \sum_{i=1}^{N_t} w_{i,t}^m r_{i,t+1}$ is the value-weighted market return and $r_{t+1}^{CA} = \sum_{i=1}^{N_t} w_{i,t}^{CA} r_{i,t+1}$ is the return from the actively managed portfolio.

We also decompose the portfolio return into investments traced to developed versus emerging countries by writing $w_{i,t} = w_{DM,t} + w_{EM,t}$, where $w_{DM,t} = \sum_i 1_i^{DM} w_{i,t}$, $w_{EM,t} = \sum_i 1_i^{EM} w_{i,t}$ and 1_i^{DM} (1_i^{EM}) is a dummy variable that equals one if country i is developed (emerging), and zero otherwise. Then, similarly to equation (12), we express $w_{DM,t}$ as $w_{DM,t} = w_{DM,t}^m + w_{DM,t}^{CA}$, where

$w_{DM,t}^{m} = \sum_i 1_{i,t}^{DM} w_{i,t}^{m}$ is the value-weighted component and $w_{DM,t}^{CA} = \sum_i 1_{i,t}^{DM} w_{i,t}^{CA}$ is the actively managed weight. The decomposition for emerging economies is analogous. Hence, the portfolio weight can be expanded as $w_{i,t} = w_{DM,t}^{m} + w_{EM,t}^{m} + w_{DM,t}^{CA} + w_{EM,t}^{CA}$ and the portfolio return is:

$$\begin{aligned} r_{p,t+1} &= r_{DM,t+1} + r_{EM,t+1} \\ &= (r_{DM,t+1}^{m} + r_{EM,t+1}^{m}) + (r_{DM,t+1}^{CA} + r_{EM,t+1}^{CA}) \end{aligned} \tag{14}$$

where the total return attributable to developed markets, $r_{DM,t+1} = \sum_i 1_i^{DM} w_{i,t} r_{i,t+1}$, is expressed as the sum of a market component, $r_{DM,t+1}^{m} = \sum_{i=1}^{N_t} 1_i^{DM} w_{i,t}^{m} r_{i,t+1}$, and an actively managed component, $r_{DM,t+1}^{CA} = \sum_{i=1}^{N_t} 1_i^{DM} w_{i,t}^{CA} r_{i,t+1}$, and similarly for EM. Note that $r_{DM,t+1}$ and $r_{EM,t+1}$ are not proper portfolio returns as their weights do not sum up to one. Rather, they are components of $r_{p,t+1}$ that are attributable to developed versus emerging countries.

The impact of $CA_{i,t}$ on the portfolio allocation is captured by the actively-managed weights $w_{DM,t}^{CA}$ and $w_{EM,t}^{CA}$. They reflect the net re-balancing between developed and emerging markets, or $w_{DM,t}^{CA} + w_{EM,t}^{CA} = 0$ (because $\widetilde{CA}_{i,t}$ is standardized cross-sectionally). We will report these weights, the returns associated with the re-balancing, $r_{DM,t+1}^{CA}$ and $r_{EM,t+1}^{CA}$, and also their correlation $\rho\left(r_{DM,t+1}^{CA}, r_{EM,t+1}^{CA}\right)$. The total correlation between the DM and EM returns, $\rho\left(r_{DM,t+1}, r_{EM,t+1}\right)$, which is affected by fluctuations in market weights, will also be reported.

We generalize the parametric weight function in (12) to include other conditioning information as $w_{i,t} = w_{i,t}^{m} + \chi \frac{1}{N_t} \widetilde{CA}_{i,t} + \eta' \frac{1}{N_t} H_{i,t} = w_{i,t}^{m} + w_{i,t}^{CA} + w_{i,t}^{h}$, where $H_{i,t}$ is a vector of other country-specific characteristics, and η is a vector of coefficients to be estimated. We are interested in $w_{i,t}^{CA}$ which is the part of the weights due solely to fluctuations in $CA_{i,t}$.

6.2 Results

We estimate the parametric portfolio weights (12) by maximizing the sample analogue of the expected utility (11) with respect to the parameters of interest. In Table 7 we present the findings for a power utility investor with a coefficient of relative risk aversion γ who allocates his wealth over the entire panel of 73 countries and 30 years of data. The range of γs that we consider, between 3 and 7, is standard in the literature.[30]

We start off by discussing the $\gamma = 5$ results. The first column (VW) displays statistics for

[30] See Brandt, Santa-Clara, and Valkanov (2009) and references therein.

the benchmark, value-weighted portfolio with no country-specific characteristics. In that portfolio, the average investment in all EM countries (w_{EM}) is 9.162% and the balance 90.838% is invested in the DM economies. The return from emerging markets (r_{EM}) is small at 0.7% compared with that of 8% from developed countries (r_{DM}). The correlation between the two returns is about 0.6, which is not surprising since most countries have a positive beta with respect to the world portfolio. The total return of the portfolio in our sample is 8.7% ($\bar{r}$) with a standard deviation of 20% per annum.[31]

Column (1) contains the optimal portfolio results of an investor who conditions her allocation on country $\widetilde{CA}_{i,t}$ (equation (12)). The positive coefficient on $\widetilde{CA}_{i,t}$ (4.677) reflects the fact that investors prefer positively skewed returns. Its p-value indicates statistical significance at conventional levels. To gauge the economic significance of $\widetilde{CA}_{i,t}$, we turn to its impact on the portfolio composition and performance. Its introduction tilts the portfolio allocation toward EM countries, as they are less negatively skewed. Indeed, the average $w^{CA}_{EM,t}$ is 6.505% which implies that, on average, 6.505% of the portfolio is allocated from DM to EM countries. Therefore, the overall weight on emerging markets in the optimal portfolio increases to 15.691% (9.162%+6.505%). Also, tilting the portfolio toward positively skewed stocks produces a return from this strategy of 6% for the EM countries and 11.1% for the DM countries. Some of that return is directly traceable to the $\widetilde{CA}_{i,t}$ part (previous panel), while the rest is due to market fluctuations. Interestingly, the estimated $\rho\left(r^{CA}_{DM}, r^{CA}_{EM}\right)$ is -0.469. This is consistent with the time-series results in the previous section that the asymmetry of EM and DM portfolios are weakly correlated and thus the $\widetilde{CA}_{i,t}$ characteristic allows a certain degree of diversification. The 16.9% average return of the optimal portfolio is almost twice as large as the value-weighted benchmark and its volatility increases only 2% per annum (from 20% to 22%). Overall, these numbers imply a large 23.3% increase in the certainty equivalent, from -15.7% to 7.6%. Such an effect seems implausibly high. It is partly due to in-sample over-fitting and partly to the 2007-2008 crisis, which benefits our portfolio greatly. The exclusion of year-2008 observations (second panel in Table 7) produces a more reasonable increase in the certainty equivalent return from 4.4% to 9.2%.

Next, we include conditional volatility as an additional country-specific characteristic in the portfolio policy function. This allows us to check whether skewness is merely proxying for volatility through the leverage effect. The results in column (2) reassure us that this is not the case.

[31] The certainty equivalent return of -15.7% is mainly due to the severe 2007-2008 crisis which exhibited unusually high volatility and low returns. The exclusion of year 2008 observations produces a dramatic increase of the certainty equivalent return to 4.4%, as discussed below and shown in the Table.

Conditioning on volatility does not alter the optimal strategy in a significant fashion. The coefficient on $\widetilde{CA}_{i,t}$ (4.261) is still significant and comparable in magnitude to that in column (1). The coefficient on volatility is, as expected, negative and significant (-1.134). It is however significantly smaller in magnitude than that of $\widetilde{CA}_{i,t}$. The average share of emerging markets in the optimal portfolio is similar at 15% to that in column (1), and so are the statistics of the optimal portfolio returns.

Can macroeconomic variables provide valuable information beyond that already contained in the $\widetilde{CA}_{i,t}$ measure? Motivated by the encouraging results in Table 6, we address this question by conditioning our strategy on the orthogonal components of (log of) market capitalization over GDP and the growth rate of real GDP with respect to $\widetilde{CA}_{i,t}$. These are denoted by E/GDP$^{\perp}$ and GDPg$^{\perp}$ in Table 7 and the results are reported in column (3). We use the orthogonal components because of significant multicollinearity with $\widetilde{CA}_{i,t}$. The inclusion of these two controls has little effect on our results: the coefficient on the skewness measure remains significant and actually increases to 6.449. The volatility coefficient, on the other hand, is now insignificant. The coefficient on E/GDP$^{\perp}$ equals -6.617 while that of GDP growth is 9.110. Since emerging economies are characterized by lower values of relative market capitalization and higher GDP growth (see Table C.1), the effect of these additional controls is to increase the optimal allocation into emerging economies to about 18%. The correlation $\rho\left(r_{DM}^{CA}, r_{EM}^{CA}\right)$ is now even more negative at -0.64. The corresponding optimal portfolio displays both a sharp increase in average return and volatility. The net effect is an even larger certainty equivalent of 17%.

As a robustness check, we extend the portfolio results along two dimensions. First, to prevent the recent financial crisis from driving the results, we re-estimate the model while excluding year-2008 data. The statistical and economic significance of $\widetilde{CA}_{i,t}$ is preserved, although the coefficient is now smaller in magnitude. The certainty equivalent return is higher across all specifications and, as mentioned above, the inclusion of the asymmetry measure into the portfolio weight function yields a more economically plausible increase of about 5% (from 4.4% to 9.2%). The average portfolio weight into emerging markets increases from 8.825% (column VW) to 15.571% (column 3). Second, we re-estimate the portfolio policy for different degrees of risk-aversion and display the results for $\gamma = 3$ and $\gamma = 7$. The findings, reported in the table, are consistent with economic intuition: a more risk-averse investor trades less aggressively based on the conditioning information and the certainty equivalent returns are a few percents lower for each specification. The investment into emerging markets, albeit smaller, is still in the range of 14% to 16%.

Overall, the Table 7 numbers convey a remarkably uniform message: conditioning on the $CA_{i,t}$ measure has a substantial effect on asset allocation which falls in line with economic intuition.

7 Conclusions

We use a new approach to estimate the conditional asymmetry in portfolio returns, CA_t, and study a large cross-section of developed and emerging markets. Estimates of CA_t reveal several new results the most notable of which is that the correlation between asymmetries of developed and emerging portfolio returns is only weakly correlated. This finding is in sharp contrast with the results that the correlation of the returns themselves is large, positive, and the volatilities between developed and emerging markets exhibit significant co-movements. It has profound implications for international diversification and risk sharing, some of which are explored in this paper. Namely, employing the parametric portfolio approach of Brandt, Santa-Clara, and Valkanov (2009) to study the international asset allocation across 73 country portfolio returns, we find that the optimal portfolio is tilted toward countries that are less negatively skewed, which in our sample are the emerging economies. In other words, the introduction of conditional asymmetry results in the optimal portfolio placing a larger weight on emerging economies than does the value-weighted portfolio.

The weak correlation of the CA_ts between developed and emerging economies prompts many interesting questions about its economic provenance and significance. We find that while the asymmetry in developed markets can be explained by asymmetries in the world portfolio return, this is not the case for emerging economies. This implies that, in emerging markets, the time-variation in the CA_t measure is most likely driven by country-specific shocks. We also show that the CA_t is negatively related to volatility fluctuations for DM as well as EM portfolio returns. This result is consistent with the leverage literature. Finally, we examine to what extent the weak relation between the conditional skewness of DM and EM portfolio returns can be explained by economic fundamentals, including: (1) turnover, (2) the capitalization of a country's stock market relative to its nominal GDP, (3) the number of companies listed on the exchange, (4) a measure of market liquidity, (5) a short-term interbank or government bond yield, (6) the growth rate of real GDP and (7) the volatility of quarterly real GDP growth. We find that most of these economic fundamentals account for a sizeable part of fluctuations in conditional asymmetry. In addition, the exposures of the CA_t measure to macroeconomic fundamentals have the opposite sign for the DM and EM portfolios, which explains the above mentioned negative correlation.

Our novel empirical results suggest a rich agenda for future research. For instance, while our portfolio results do not directly link expected returns and conditional asymmetry, an explicit investigation of this relation would be of great importance for asset pricing. Moreover, our investigation was primarily on one-year returns, but it also suggests that the term structure of conditional asymmetry may provide a new perspective on the understanding of risk premia at different horizons. We know remarkably little about this topic, but the current mixed-data approach provides a tractable framework for further explorations.

Appendix

A Specification, Estimation and Testing of Quantiles

We follow Ghysels, Santa-Clara, and Valkanov (2006) and specify the weighting scheme $w_d(\kappa_{\theta,n})$ in the quantile regression (5) as:

$$w_d(\kappa_{\theta,n}) = \frac{f(\frac{d}{D}, \kappa_{1,\theta,n}; \kappa_{2,\theta,n})}{\sum_{d=1}^{D} f(\frac{d}{D}, \kappa_{1,\theta,n}; \kappa_{2,\theta,n})} \tag{15}$$

where: $f(z, a, b)$ = $z^{a-1}(1-z)^{b-1}/\beta(a, b)$ and $\beta(a, b)$ is based on the Gamma function, or $\beta(a, b)$ = $\Gamma(a)\Gamma(b)/\Gamma(a + b)$. [32] A main advantage of this "Beta" function is its well-known flexibility. It can take many shapes, including flat weights, gradually declining weights as well as hump-shaped patterns. For instance, equal weights obtain when κ_1 = κ_2 = 1, whereas for $\kappa_1 = 1$ and $\kappa_2 > 1$ the $w_d(\kappa_{\theta,n})$ exhibit a slowly decaying pattern that is typical for many time series filters. The weights are normalized to add up to one which allows us to identify a scale parameter $\beta_{\theta,n}$.

We estimate the parameters $\delta_{\theta,n}$ in (4) and (5) with non-linear least squares. In some cases the estimation of the MIDAS polynomial parameters was very imprecise. Moreover, for the purpose of hypothesis testing - discussed in the next section - we opted to fix $\kappa_{1,\theta,n}$ = 1 and profiled the second parameter $\kappa_{2,\theta,n}$. For this reason we do report standard errors for the MIDAS polynomial parameters. With $\kappa_{\theta,n}$ fixed at $\underline{\kappa}_{\theta,n}$, we denote the remaining parameters as the vector $\underline{\delta}_{\theta,n}$ = $\left(\alpha_{\theta,n}, \beta_{\theta,n}, \underline{\kappa}_{\theta,n}\right)$.

More specifically, for a given quantile θ and horizon n, we minimize

$$\min_{\underline{\delta}_{\theta,n}} T^{-1} \sum_{t=1}^{T} \rho_{\theta,n}\left(e_{\theta,n,t}\right) \tag{16}$$

where $e_{\theta,n,t}$ = $r_{t,n} - q_{\theta,t}\left(r_{t,n}; \delta_{\theta,n}\right)$, $\rho_{\theta,n}\left(e_{\theta,n,t}\right)$ = $\left(\theta - 1\left\{e_{\theta,n,t} < 0\right\}\right) e_{\theta,n,t}$ is the usual "check" function used in quantile regressions. The novelty here is the MIDAS structure in the non-linear quantile estimation. Under suitable regularity conditions, the estimator $\hat{\delta}_{\theta,n}$, of the p-dimensional parameter vector that minimizes (16) is asymptotically normally distributed with mean zero and

[32] Ghysels, Sinko, and Valkanov (2006) and Sinko, Sockin, and Ghysels (2010) discuss the properties of (15) and other lag specifications in detail.

a variance that can be consistently estimated.[33] Once we have estimates of $q_{1-\theta,t}(r_{t,n};\delta_{1-\theta,n})$, $q_{0.50,t}(r_{t,n};\delta_{0.50,n})$ and $q_{\theta,t}(r_{t,n};\delta_{\theta,n})$, we substitute them into expression (2) and obtain an estimate of the conditional skewness measure $CA_{\theta,t}(r_{t,n})$.[34]

The unrestricted estimation of quantiles for the EM portfolio turned out to be quite challenging in part because our sample starts out with a small set of countries and gradually becomes more diversified as data from more countries becomes available. Therefore, we impose two types of relatively mild restrictions to obtain more precise conditional quantile estimates: (1) we imposed a downward sloping weighting scheme for the MIDAS polynomial and (2) we imposed a positive intercept for the quantile regression. The former was achieved by using a Beta polynomial with the first parameter fixed at one, resulting in MIDAS polynomial estimated with only one parameter.

In order to verify our model accuracy, we conduct three specification tests on the parameters of the MIDAS quantile regressions. Clearly, if the quantile model is well specified, then so would be $CA_{\theta,t}$. First, we test whether the main parameters of the model, $\alpha_{\theta,n}$ and $\beta_{\theta,n}$ are significantly different from zero. In fact, the economically most interesting hypothesis is whether $\beta_{\theta,n} = 0$ for all quantiles and a given horizon n. Under that null hypothesis, there is no time variation in the quantiles and the $CA_{\theta,t}$ measure should be constant. However, under this null hypothesis, the parameters $\kappa_{\theta,n}$ are unidentified and the standard t-statistic for $\beta_{\theta,n} = 0$ does not yield the correct inference. This is a well-known problem in econometrics and, as shown by Davies (1987), a modification of the t-statistic can be used to evaluate statistical significance if the impact of nuisance parameters is properly accounted for. This is done by maximizing the objective function in (16) for $\alpha_{\theta,n}$, $\beta_{\theta,n}$ and a series of $\kappa_{\theta,n}$ chosen on a grid and then taking the maximum over all the $\kappa_{\theta,n}$. This procedure produces a maximal t-statistic across the grid of $\kappa_{\theta,n}$. The distribution of this "max-t" statistic can be simulated based on artificial (simulated) data for which we know the null hypothesis holds true. Details of the simulation are discussed in section B of the Appendix.

Second, we check the accuracy of the estimation by reporting the average coverage of the conditional quantile $q_{\theta,t}(r_{t,n})$ and verify that it is equal to θ. This simple test is a validation of the accuracy of the unconditional probability $Pr(e_{\theta,n,t} < 0) = \theta$.

Third, we want to check whether the quantile model successfully captures all conditioning information in I_{t-1}. In other words, we want to test whether $E(\Psi_{t-1}Hit_{\theta,n,t})$ is significantly different from

[33] See Koenker and Bassett (1978), White (1996), Weiss (1991), Engle and Manganelli (2004), Koenker and Xiao (2006), among others.

[34] We estimate the quantiles separately. A joint estimating, while theoretically more efficient, has proven difficult to implement in practice.

zero, where Ψ_{t-1} is a q-dimensional vector of I_{t-1} measurable variables. The simplest approach of doing this is to test whether $Hit_{\theta,n,t}$ is uncorrelated with past $Hit_{\theta,n,t}$. Unfortunately, since we use overlapping data to estimate the quantiles, $Hit_{\theta,n,t}$ will be serially correlated by construction. An alternative approach is to test whether $Hit_{\theta,n,t}$ is correlated with any other variables in I_{t-1}, such as daily simple (rather than absolute) returns, or squared returns. For instance, to investigate whether lagged simple returns should have been included in the estimation of the quantiles, we can simply regress $Hit_{\theta,n,t}$ on lagged returns and test for their joint significance. We formulate variants of that approach by testing whether $Hit_{\theta,n,t}$ is correlated with the yearly average of past daily returns, the year average of past squared returns, and a joint hypothesis using both averages. Because of the overlap, these statistical tests are carried out using Newey-West standard errors with 250 lags.

B Davies test

For a given quantile θ and horizon n, under the null hypothesis of $\beta_{\theta,n} = 0$ the parameters $\kappa_{\theta,n}$ are unidentified and standard testing procedures for $\beta_{\theta,n}$ do not provide the correct inference. However, as shown by Davies (1987), the t-statistic can still be used to evaluate statistical significance if the impact of nuisance parameters is properly accounted for. This is done by looking at the maximum t-statistics across estimations based on artificial data for which we know the null hypothesis holds true.

In our setting, the empirical distribution of the Davies (1987) test for each $\theta = [0.25, 0.50, 0.75]$ and return specification $(r, \epsilon^G, \epsilon^T)$ for all portfolio returns is obtained as follows:

(i) aggregate the daily returns to annual frequency ($n = 250$);

(ii) subtract the unconditional θ-quantile;

(iii) generate an i.i.d. sample of T standard normal random variables, where T is the sample size of the actual daily returns, and use the absolute values of this series as x_{t-1-d} in (5) to create the conditioning variable $Z_{t-1}(\kappa_{\theta,n})$;

(iv) for every $\kappa_{2,\theta,n}$ in the $[1, 10]$ range and $\kappa_{1,\theta,n}$=1, find the point estimates of ($\alpha_{\theta,n}, \beta_{\theta,n}$) that minimize the objective function (16) and obtain their corresponding t-statistics;

(v) store the max of the t-statistics for $\beta_{\theta,n}$ across the $\kappa_{2,\theta,n}$ range;

(vi) repeat steps (iii) to (v) 1,000 times.

The p-values for the sample estimates of $\beta_{\theta,n}$ in Table 2 are obtained by comparing the actual t-statistic with the simulated distribution.

C Summary statistics of conditioning variables

Table C.1 reports univariate and joint summary statistics for the CA and the nine conditioning variables described in Section 5. These statistics are calculated for the whole set of countries in Panel A, and then separately for developed (Panel B) and emerging (Panel C) markets. On the left-hand side of Table C.1, we display the cross-sectional average (Avg) and standard deviation (Std) of each variable's time series mean and standard deviation. On the right-hand side, average time series correlations between the variables are shown.[35] We observe that the average CA_t is negative (-0.082) and is greater (less negative) for emerging markets (-0.072) than for developed markets (-0.108). For the financial and economic determinants, the differences between developed and emerging markets are in line with common economic intuition and previous studies. Compared to developed countries, emerging economies feature higher and more dispersed stock volatility, a lower ratio of stock market capitalization to GDP, a much lower turnover, fewer listed companies, a smaller degree of liquidity, higher and more volatile interest rates, and somewhat higher but more volatile GDP growth.

We next turn our attention to the correlation matrices. The negative correlation between CA and volatility is more pronounced for developed markets (correlation of -0.319) than for emerging markets (-0.066), and is consistent with the effect described in Campbell and Hentschel (1992). Second, the four measures of stock market development and liquidity display only modest correlation, the largest being between the relative size of the stock market and turnover (0.508 for DM) and the number of listed companies (0.418 for DM and 0.351 for EM). Interestingly, the correlations for the EM portfolio are broadly consistent with those reported in Bekaert and Harvey (1997) despite the fact they are calculated for a different sample period. Third, as expected, stock return volatility is positively correlated with economic uncertainty ($GDP\sigma$) and the correlation is highest for emerging economies.

[35] For consistency with our estimation approach, the correlations are calculated between conditioning variables observed at the end of year t (say, 31 December 2008) and the conditional asymmetry predicted for year $t + 1$ (the conditional asymmetry for 2009) estimated using the information of year t (using absolute returns from 1 January 2008 to 31 December 2008).

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Table 1: Summary Statistics

Initial date, total number of usable observations (N), annualized mean (Mean), annualized standard deviation (Std), and measures of asymmetry at the 1-day (subscript t) and 250-day (subscript $t, 250$) horizon of country portfolios and individual country log returns. S denotes the standard moment-based measure of skewness, while RA denotes the quantile-based robust measure of asymmetry from expression (1). ε^G and ε^T are the residuals from fitting a GARCH(1,1) model or a TARCH (1,1,1) model, respectively, on the return series. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% confidence level, respectively, obtained through Monte Carlo simulation of a standard normal r.v.

	Initial date	N	Mean	Std	$S(r_t)$	$S(r_{t,250})$	$RA(r_{t,250})$	$S(\varepsilon_t^G)$	$S(\varepsilon_{t,250}^G)$	$RA(\varepsilon_{t,250}^G)$	$S(\varepsilon_t^T)$	$S(\varepsilon_{t,250}^T)$	$RA(\varepsilon_{t,250}^T)$
W	01/02/80	7998	0.068	0.141	-0.520^a	-0.980^a	-0.238^a	-0.325^a	-0.018	-0.211^a	-0.272^a	0.150	-0.184^b
DM	01/02/80	8088	0.101	0.139	-0.561^a	-0.958^a	-0.204^b	-0.355^a	-0.033	-0.156^b	-0.278^a	0.117	-0.145^c
EM	01/02/80	8088	0.099	0.184	-0.557^a	-0.462^b	-0.057	-0.575^a	-0.207	-0.130^c	-0.570^a	-0.157	-0.085
Developed Markets													
U.S.	01/02/80	8072	0.108	0.175	-1.038^a	-1.033^a	-0.113	-0.546^a	-0.287	-0.111	-0.469^a	-0.237	-0.055
Japan	01/02/80	8038	0.066	0.215	-0.038^c	0.260	0.008	-0.053^b	0.506^b	0.060	-0.005	0.634^b	0.103
U.K.	01/02/80	8088	0.112	0.193	-0.389^a	-1.162^a	-0.135^c	-0.355^a	-0.258	-0.028	-0.309^a	-0.143	-0.053
Hong Kong	01/02/80	7877	0.086	0.292	-2.062^a	-0.600^b	-0.189^b	-0.887^a	-0.453^c	-0.299^a	-0.663^a	-0.407^c	-0.250^a
France	01/02/80	8088	0.105	0.208	-0.244^a	-0.356^c	-0.210^a	-0.332^a	0.040	-0.181^b	-0.274^a	0.271	-0.152^b
Canada	01/02/80	7871	0.087	0.191	-1.126^a	-0.945^a	-0.185^b	-0.900^a	-0.316	-0.208^a	-1.040^a	-0.280	-0.213^a
Spain	01/02/80	7889	0.076	0.214	-0.122^a	0.300	-0.126^c	-0.428^a	0.393^c	0.051	-0.371^a	0.600^b	0.063
Germany	01/02/80	7904	0.080	0.232	-0.210^a	-0.307	-0.182^b	-0.553^a	-0.014	-0.216^a	-0.456^a	0.188	-0.214^a
Australia	01/02/80	8088	0.109	0.224	-1.883^a	-0.698^a	0.010	-0.559^a	-0.349^c	0.033	-0.379^a	-0.231	0.051
Switzerland	01/02/80	8088	0.110	0.173	-0.334^a	-0.006	-0.166^b	-0.488^a	0.104	-0.214^a	-0.428^a	0.254	-0.195^b
Italy	01/02/80	8088	0.096	0.237	-0.184^a	0.740^a	-0.030	-0.246^a	0.758^a	0.016	-0.209^a	0.869^a	0.023
Sweden	01/02/80	7852	0.111	0.244	0.627^a	-0.641^b	-0.351^a	0.651^a	-0.132	-0.366^a	0.775^a	-0.039	-0.375^a
Netherlands	01/02/80	8088	0.116	0.196	-0.298^a	-1.633^a	-0.174^b	-0.319^a	-0.596^b	-0.094	-0.277^a	-0.507^b	-0.116^c
Singapore	01/02/80	8088	0.114	0.221	-0.941^a	-0.222	-0.098	-0.502^a	-0.283	-0.108	-0.371^a	-0.180	-0.083
Belgium	01/02/80	8088	0.103	0.185	-0.230^a	-0.837^a	-0.134^c	-0.235^a	-0.326	-0.079	-0.188^a	-0.190	-0.061
Norway	01/03/80	8087	0.108	0.263	-0.616^a	-0.711^a	-0.038	-0.381^a	-0.262	-0.063	-0.299^a	-0.196	-0.045
Finland	01/03/91	5119	0.100	0.295	-0.193^a	-0.807^a	-0.147^b	-0.278^a	-0.553^b	-0.049	-0.272^a	-0.511^b	-0.055
Denmark	01/02/80	7806	0.116	0.222	0.558^a	-0.922^a	-0.105	0.807^a	-0.461^b	-0.076	0.925^a	-0.422^c	-0.087
Austria	01/02/80	8088	0.105	0.196	-0.243^a	0.567^b	0.259^a	-0.406^a	0.719^a	0.278^a	-0.379^a	0.821^a	0.285^a
Ireland	01/02/80	8086	0.099	0.214	-0.742^a	-0.929^a	-0.190^b	-0.471^a	0.001	-0.192^b	-0.417^a	0.086	-0.199^b
Iceland	01/05/93	4597	-0.014	0.343	-29.333^a	-2.655^a	-0.368^a	-0.610^a	-0.865^a	-0.231^a	-0.555^a	-0.835^a	-0.214^a
Emerging Markets													
China	04/04/91	5110	0.115	0.382	-0.391^a	0.385^c	0.338^a	-0.630^a	0.420^c	0.165^b	-0.573^a	0.454^c	0.184^b
Brazil	04/13/83	7073	0.114	0.622	0.569^a	-0.643^b	-0.247^a	3.977^a	-0.419^c	-0.329^a	3.871^a	-0.323	-0.332^a
India	01/05/87	6140	0.095	0.287	-0.045^c	-0.492^b	0.019	-0.231^a	-0.194	0.013	-0.170^a	-0.160	0.040
South Korea	01/02/80	7964	0.061	0.324	-0.414^a	-0.731^a	0.006	-0.356^a	-0.215	-0.072	-0.372^a	-0.164	-0.066
South Africa	01/02/80	8088	0.110	0.267	-0.528^a	-0.264	0.016	-0.727^a	-0.337	-0.039	-0.703^a	-0.291	-0.040
Taiwan	01/03/85	6696	0.092	0.308	-0.116^a	0.029	-0.030	-0.177^a	0.346	0.002	-0.149^a	0.480^b	0.009
Russia	09/04/95	3596	0.134	0.437	-0.530^a	-1.248^a	0.050	-0.377^a	-0.639^b	-0.098	-0.296^a	-0.540^b	-0.090
Mexico	01/05/88	5901	0.170	0.313	-0.419^a	-0.944^a	-0.189^b	-0.378^a	-0.368^c	-0.135^c	-0.322^a	-0.247	-0.148^b

Table 1 (Cont'd): Summary Statistics

	Initial date	N	Mean	Std	$S(r_t)$	$S(r_{t,250})$	$RA(r_{t,250})$	$S(\varepsilon_t^G)$	$S(\varepsilon_{t,250}^G)$	$RA(\varepsilon_{t,250}^G)$	$S(\varepsilon_t^T)$	$S(\varepsilon_{t,250}^T)$	$RA(\varepsilon_{t,250}^T)$
Saudi Arabia	01/02/98	2367	0.137	0.247	-1.245^a	-0.405^c	-0.273^a	-0.139^a	0.149	-0.179^b	-0.067^a	0.175	-0.125^c
Malaysia	01/03/80	7981	0.061	0.258	-1.387^a	-0.828^a	-0.100	-0.721^a	-0.290	-0.095	-0.809^a	-0.252	-0.085
Turkey	01/05/88	5957	0.061	0.503	-0.201^a	0.077	-0.182^b	-0.253^a	-0.121	-0.132^c	-0.236^a	-0.059	-0.137^c
Chile	01/05/87	6148	0.145	0.189	-0.267^a	-0.012	-0.114^c	-0.254^a	-0.260	-0.174^b	-0.268^a	-0.239	-0.165^b
Indonesia	04/03/90	5414	0.018	0.431	-0.729^a	-1.160^a	-0.224^a	-2.156^a	-0.556^b	-0.120^c	-1.943^a	-0.523^b	-0.158^b
Israel	04/24/87	6151	0.103	0.274	-0.350^a	-0.608^b	-0.311^a	-0.371^a	-0.482^b	-0.286^a	-0.373^a	-0.424^c	-0.264^a
Thailand	01/05/87	6260	0.111	0.314	0.053^b	-0.979^a	-0.004	-0.279^a	-0.515^b	0.033	-0.172^a	-0.479^b	0.039
Kuwait	12/29/94	4155	0.095	0.637	-0.007	-1.208^a	-0.324^a	41.319^a	0.277	-0.301^a	42.848^a	0.765^a	-0.282^a
Poland	04/17/91	5029	0.122	0.348	-0.189^a	1.181^a	0.170^b	-0.456^a	0.530^b	0.227^a	-0.413^a	0.630^b	0.234^a
Colombia	03/11/92	4908	0.122	0.216	-1.493^a	0.061	-0.030	-1.626^a	0.040	0.156^b	-1.649^a	0.074	0.163^b
Greece	10/03/88	5695	0.032	0.297	-0.026	0.098	-0.317^a	0.090^a	0.184	-0.272^a	0.120^a	0.258	-0.279^a
Ukraine	02/02/98	3312	0.077	0.429	3.763^a	-1.264^a	-0.131^c	4.519^a	-1.363^a	-0.145^c	4.861^a	-1.270^a	-0.104
Egypt	01/03/95	4145	0.076	0.242	-0.478^a	-0.065	0.111	-0.055^b	0.125	-0.077	-0.050^b	0.140	-0.070
Philippines	01/03/86	6404	0.100	0.312	0.286^a	0.008	-0.145^c	0.725^a	-0.224	-0.064	0.606^a	-0.158	-0.033
Portugal	01/06/88	5872	0.034	0.190	-0.133^a	-0.569^b	-0.046	-0.296^a	-0.069	0.009	-0.293^a	-0.027	0.014
Peru	01/03/91	5125	0.239	0.270	-0.141^a	-0.021	-0.049	-0.302^a	0.008	-0.149^b	-0.240^a	0.024	-0.144^c
Nigeria	07/03/95	3960	0.112	0.195	-0.217^a	-1.245^a	-0.100	-0.335^a	-0.686^a	-0.164^b	-0.335^a	-0.686^a	-0.164^b
Argentina	08/03/93	4461	0.021	0.371	-1.030^a	-0.680^a	-0.306^a	-0.513^a	-0.266	-0.358^a	-0.492^a	-0.276	-0.348^a
Czech Republic	11/10/93	4473	0.130	0.273	0.689^a	-0.396^c	-0.216^a	0.155^a	0.041	-0.139^c	0.221^a	0.072	-0.139^c
New Zealand	01/05/88	5999	0.083	0.204	-0.309^a	-0.873^a	-0.111	-0.380^a	-0.428^c	-0.094	-0.367^a	-0.408^c	-0.083
Pakistan	01/02/89	5678	0.066	0.267	-0.303^a	-0.549^b	-0.194^b	-0.327^a	-0.176	-0.209^a	-0.285^a	-0.154	-0.202^b
Jordan	11/22/88	5647	0.062	0.184	-0.224^a	0.862^a	0.197^b	-0.214^a	0.702^a	0.149^b	-0.214^a	0.702^a	0.149^b
Hungary	01/03/91	5134	0.082	0.320	-0.454^a	-0.495^b	-0.083	-0.573^a	-0.152	-0.118^c	-0.508^a	-0.113	-0.122^c
Bangladesh	09/22/97	3417	0.011	0.337	-0.317^a	-0.951^a	-0.219^a	-0.041^c	-0.802^a	-0.191^b	0.015	-0.709^a	-0.141^c
Romania	01/02/90	5435	0.057	0.324	-3.649^a	-0.235	0.004	-1.854^a	0.174	-0.013	-1.774^a	0.192	-0.006
Croatia	01/03/97	3593	0.068	0.303	0.004	-1.097^a	-0.290^a	-0.112^a	-0.256	-0.228^a	-0.110^a	-0.171	-0.214^a
Oman	10/23/96	3655	0.082	0.189	0.264^a	-0.491^b	-0.061	-0.217^a	-0.234	-0.158^b	-0.223^a	-0.204	-0.137^c
Trinidad and Tobago	01/03/96	3834	0.114	0.167	4.926^a	0.357^c	0.165^b	5.224^a	0.393^c	0.168^b	5.458^a	0.358^c	0.226^a
Slovenia	01/01/99	3131	0.060	0.190	-0.430^a	-0.745^a	-0.098	-0.041^c	-0.113	-0.058	-0.045^b	-0.101	-0.041
Kenya	01/12/90	5350	0.016	0.267	0.289^a	0.704^a	0.129^c	-14.943^a	0.004	0.062	-14.718^a	-0.225	0.002
Sri Lanka	01/03/85	6625	0.096	0.202	0.299^a	0.063	-0.060	0.812^a	-0.087	-0.093	0.812^a	-0.087	-0.093
Tunisia	01/05/98	3364	0.102	0.108	0.085^a	0.254	-0.088	0.334^a	0.389^c	0.123^c	0.335^a	0.391^c	0.119^c
Venezuela	01/03/90	5478	0.047	0.441	-5.970^a	0.105	-0.145^c	-9.415^a	-0.074	-0.045	-9.414^a	-0.074	-0.045
Bulgaria	10/23/00	2620	0.162	0.308	-0.608^a	-1.385^a	-0.299^a	0.311^a	-0.769^a	0.057	0.312^a	-0.769^a	0.057
Morocco	01/05/88	5892	0.127	0.182	0.268^a	-0.453^c	0.016	1.524^a	-0.476^b	-0.119^c	1.528^a	-0.477^b	-0.119^c
Slovakia	09/15/93	4424	0.041	0.266	1.235^a	0.349^c	-0.125^c	-0.598^a	0.400^c	-0.027	-0.597^a	0.400^c	-0.027
Lithuania	01/03/00	2824	0.141	0.222	-0.249^a	-0.989^a	-0.234^a	-0.009	-0.185	-0.286^a	-0.009	-0.185	-0.286^a
Ecuador	08/03/93	3086	-0.004	0.286	0.715^a	-0.223	-0.183^b	-2.626^a	-0.096	-0.397^a	-2.617^a	-0.086	-0.387^a
Botswana	01/03/96	3836	0.147	0.223	6.651^a	-0.299	0.004	6.650^a	-0.299	0.005	6.699^a	-0.278	-0.003
Malta	12/28/95	3837	0.080	0.158	0.626^a	0.028	0.231^a	0.554^a	0.030	0.080	0.554^a	0.030	0.080
Latvia	01/04/00	2811	0.115	0.274	-0.569^a	-1.796^a	-0.226^a	0.521^a	-1.052^a	-0.106	0.521^a	-1.052^a	-0.105
Ghana	01/03/96	3830	-0.041	0.189	2.771^a	-0.139	-0.390^a	2.940^a	-0.117	-0.393^a	2.940^a	-0.117	-0.393^a
Namibia	02/01/00	2791	0.067	0.204	0.175^a	-0.573^b	-0.238^a	0.519^a	-0.731^a	-0.233^a	0.633^a	-0.687^a	-0.275^a
Estonia	06/04/96	3728	0.115	0.285	-0.880^a	-0.612^b	-0.054	-0.185^a	-0.060	-0.026	-0.077^a	-0.003	-0.017

Table continued from previous page.

Table 2: Conditional Quantile Estimates of 5 Portfolio Returns

Estimated parameters of the MIDAS quantile regression of equation (4) for the 25th, 50th, and 75th quantiles of the world, developed markets, emerging markets, US, and China portfolio returns. p-values of the corresponding t-tests are reported below the estimates. The p-value for β is obtained using the Davies (1987) procedure as described in Appendix B. The Table also shows the unconditional coverage (Coverage), defined as $E[1\{\varepsilon_{\theta,n,t} < 0\}]$, and the p-value of the hypothesis that it equals the corresponding quantile. Finally, the last three rows of each panel report the p-values of the t-test for the slope coefficient in the regression of Hit_t on the equally-weighted average of past 250-day returns (t'), squared returns (t''), and the p-value of the joint F-test, all of which are based on Newey-West standard errors with 250 lags. Panel A reports the results for the return series $r_{t,250}$, Panel B for the GARCH(1,1)-filtered returns $\varepsilon^G_{t,250}$, and Panel C for the TARCH(1,1)-filtered returns $\varepsilon^T_{t,250}$.

	World			Developed			Emerging			U.S.			China		
Panel A: $q_{\theta,t}(r_{t,250})$															
θ	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75
$\alpha_{\theta,250}$	0.124	0.007	0.055	0.097	0.000	0.043	0.000	0.000	0.046	0.069	0.008	0.092	0.000	0.000	0.248
$pval$	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)	(0.000)	(1.000)	(1.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)	(1.000)	(0.000)
$\beta_{\theta,250}$	-34.124	3.506	5.704	-30.725	4.180	7.096	-19.604	3.954	17.316	-27.572	2.337	1.742	-22.212	-6.766	-24.332
$pval$	(0.011)	(0.288)	(0.083)	(0.008)	(0.232)	(0.032)	(0.163)	(0.465)	(0.016)	(0.040)	(0.538)	(0.722)	(0.001)	(0.135)	(0.001)
$\kappa_{2,\theta,250}$	2.000	6.000	6.000	2.000	7.000	5.000	6.000	1.300	2.000	2.000	7.000	75.000	1.100	1.200	1.500
Coverage (%)	25.003	50.020	75.010	24.997	50.336	75.016	27.461	51.996	75.016	25.010	49.993	75.003	26.183	52.695	76.347
$pval$	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(0.668)	(0.668)	(0.668)	(0.999)	(0.999)	(0.999)	(0.661)	(0.661)	(0.661)
$pval(t')$	0.780	0.742	0.492	0.951	0.630	0.452	0.232	0.089	0.022	0.846	0.578	0.267	0.934	0.942	0.560
$pval(t'')$	0.100	0.959	0.961	0.111	0.966	0.894	0.011	0.219	0.738	0.356	0.984	0.878	0.168	0.938	0.852
$pval(t''')$	0.083	0.919	0.676	0.132	0.830	0.533	0.025	0.121	0.072	0.427	0.786	0.435	0.385	0.994	0.843
Panel B: $q_{\theta,t}(\varepsilon^G_{t,250})$															
θ	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75
$\alpha_{\theta,250}$	0.933	0.168	0.191	0.771	0.162	0.165	0.291	0.077	0.284	0.373	0.116	0.203	0.000	0.000	0.207
$pval$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)	(1.000)	(0.000)
$\beta_{\theta,250}$	-142.555	-20.836	-10.557	-121.555	-20.658	-6.760	-64.942	-6.084	-11.061	-67.241	-14.086	-12.463	-31.666	-8.936	-13.772
$pval$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.022)	(0.000)	(0.032)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
$\kappa_{2,\theta,250}$	1.300	1.020	1.010	1.300	1.110	1.010	1.400	1.000	6.000	1.130	1.020	1.010	1.030	1.000	1.400
Coverage (%)	24.430	49.700	74.703	25.537	49.783	75.043	24.918	50.007	74.713	25.102	49.822	74.884	25.352	50.665	75.873
$pval$	(0.919	(0.919)	(0.919)	(0.923)	(0.923)	(0.923)	(0.988)	(0.988)	(0.988)	(0.987)	(0.987)	(0.987)	(0.927)	(0.927)	(0.927)
$pval(t')$	0.433	0.809	0.990	0.604	0.956	0.847	0.724	0.751	0.167	0.495	0.712	0.370	0.811	0.852	0.952
$pval(t'')$	0.385	0.632	0.574	0.522	0.698	0.419	0.378	0.528	0.253	0.596	0.740	0.470	0.019	0.085	0.701
$pval(t''')$	0.635	0.891	0.827	0.798	0.873	0.480	0.648	0.799	0.217	0.775	0.740	0.275	0.042	0.189	0.920

Table 2 (Cont'd): Conditional Quantile Estimates of 5 Portfolio Returns

	World			Developed			Emerging			U.S.			China		
	Panel C: $q_{\theta,t}(\varepsilon^{T}_{t,250})$														
θ	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75	0.25	0.50	0.75
$\alpha_{\theta,250}$	0.719	0.160	0.189	0.644	0.162	0.161	0.204	0.000	0.337	0.206	0.146	0.249	0.000	0.000	0.184
$pval$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)	(1.000)	(0.000)
$\beta_{\theta,250}$	-112.591	-19.461	-10.869	-103.709	-20.158	-6.494	-51.485	4.224	-17.530	-43.924	-18.720	-18.592	-31.569	-8.564	-10.182
$pval$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)	(0.000)	(0.127)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.042)
$\kappa_{2,\theta,250}$	1.070	1.020	1.010	1.020	1.110	1.010	1.180	10.000	1.190	1.000	1.110	1.060	1.000	1.000	1.010
Coverage (%)	24.683	49.633	74.797	24.312	49.914	74.832	24.918	50.217	74.674	24.878	49.914	74.568	25.392	50.929	75.992
$pval$	(0.958)	(0.958)	(0.958)	(0.906)	(0.906)	(0.906)	(0.988)	(0.988)	(0.988)	(0.984)	(0.984)	(0.984)	(0.918)	(0.918)	(0.918)
$pval(t')$	0.134	0.601	0.783	0.158	0.811	0.957	0.804	0.696	0.177	0.257	0.942	0.579	0.720	0.849	0.947
$pval(t'')$	0.534	0.594	0.795	0.565	0.529	0.670	0.371	0.713	0.518	0.875	0.708	0.344	0.019	0.090	0.692
$pval(t''')$	0.335	0.792	0.920	0.376	0.819	0.913	0.611	0.858	0.287	0.518	0.918	0.516	0.044	0.215	0.917

Table continued from previous page.

Table 3: Summary Statistics of Conditional Asymmetry Estimates (CA_t)

Summary statistics of the daily series of 250-day robust measure of conditional asymmetry (CA_t) for the world (W), developed markets (DM), emerging markets (EM), the US, and China (CHA). We also report averages across developed markets excluding the US ($\overline{DM_i}$) and across emerging markets excluding China ($\overline{EM_i}$). The left-hand side of the table reports means, standard deviations (Std), minima (Min), maxima (Max), OLS coefficient on a time trend (Trend). Superscripts a, b, and c indicate statistical significance at the 10%, 5% and 1% level, respectively, based on Newey-West standard errors with 250 lags. The right-hand side of the table shows the correlation matrix of the CA_t series. Results are reported for simple returns r in Panel A, for GARCH(1,1)-filtered returns ε^G in Panel B, and for TARCH(1,1)-filtered returns ε^T in Panel C.

Panel A: r

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
Mean	-0.246	-0.265	-0.054	-0.160	-0.040	-0.124	-0.074
Std	0.278	0.236	0.088	0.273	0.057	0.117	0.138
Min	-0.755	-0.714	-0.302	-0.864	-0.225	-0.429	-0.521
Max	0.861	0.503	0.183	0.455	0.182	0.305	0.276
Trend	-0.026^a	-0.032^a	0.013^a	-0.027^a	0.001	-0.011^c	-0.022

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.980	1					
EM	0.379	0.320	1				
US	0.820	0.820	0.289	1			
CHA	-0.342	-0.358	0.060	-0.394	1		
$\overline{DM_i}$	0.021	0.041	-0.010	-0.001	-0.024	1	
$\overline{EM_i}$	0.072	0.075	0.163	0.061	0.044	0.012	1

Panel B: ε^G

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
Mean	-0.171	-0.141	-0.136	-0.132	0.028	-0.086	-0.045
Std	0.233	0.157	0.063	0.117	0.026	0.091	0.105
Min	-0.483	-0.394	-0.316	-0.342	-0.048	-0.323	-0.321
Max	1.000	0.536	0.062	0.256	0.127	0.311	0.317
Trend	-0.015^a	-0.018^a	0.003	-0.070^c	0.000	-0.006^c	-0.016

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.953	1					
EM	0.407	0.346	1				
US	0.632	0.682	0.266	1			
CHA	-0.264	-0.316	0.186	-0.317	1		
$\overline{DM_i}$	0.230	0.231	0.155	0.138	-0.022	1	
$\overline{EM_i}$	0.119	0.116	0.139	0.071	0.086	0.045	1

Panel C: ε^T

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
Mean	-0.188	-0.163	-0.086	-0.097	0.048	-0.075	-0.047
Std	0.214	0.152	0.081	0.070	0.026	0.092	0.104
Min	-0.421	-0.357	-0.305	-0.239	-0.028	-0.301	-0.313
Max	0.997	0.572	0.168	0.094	0.141	0.323	0.304
Trend	-0.007	-0.010^a	0.005^b	0.000	0.001	-0.08^c	-0.019

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.963	1					
EM	0.407	0.345	1				
US	0.620	0.662	0.180	1			
CHA	-0.324	-0.372	0.229	-0.429	1		
$\overline{DM_i}$	0.203	0.206	0.087	0.102	-0.066	1	
$\overline{EM_i}$	0.171	0.164	0.149	0.097	0.056	0.053	1

Table 4: Relation between Country Conditional Asymmetry and World Conditional Asymmetry

Estimates of regression (8) for each portfolio's $CA_{i,t}$ on the asymmetry of the world portfolio, $CA_{W,t}$. Results are shown for developed markets (DM), emerging markets (EM), the US, and China (CHA). Average statistics across developed markets excluding the US ($\overline{DM_i}$) and across emerging markets excluding China ($\overline{EM_i}$) are also reported. The left-hand side tableau of the Table reports the OLS intercept (δ_0) and slope (δ_1), the p-value of their t-tests based on Newey-West standard errors with 250 lags, and the R^2 statistic. The right-hand side tableau shows the correlation matrix of the estimated residuals. Results are reported for the returns series r in Panel A, for GARCH(1,1)-filtered returns ε^G in Panel B, and for TARCH(1,1)-filtered returns ε^T in Panel C.

Panel A: r

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
δ_0	-0.059	-0.024	0.039	0.073	-0.108	-0.072
$pval$	0.000	0.106	0.407	0.459	0.062	0.086
δ_1	0.833	0.119	0.805	-0.382	0.007	0.039
$pval$	0.000	0.002	0.000	0.073	0.043	0.228
R^2	0.960	0.144	0.673	0.117	0.294	0.112

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
DM	1					
EM	-0.287	1				
US	0.142	-0.046	1			
CHA	-0.139	0.295	-0.210	1		
$\overline{DM_i}$	0.137	-0.023	-0.036	-0.011	1	
$\overline{EM_i}$	0.029	0.146	0.003	0.048	0.016	1

Panel B: ε^G

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
δ_0	-0.032	-0.117	-0.077	0.052	-0.042	-0.028
$pval$	0.030	0.000	0.006	0.000	0.088	0.091
δ_1	0.640	0.110	0.319	-0.050	0.143	0.102
$pval$	0.000	0.000	0.002	0.123	0.041	0.161
R^2	0.909	0.166	0.399	0.069	0.236	0.107

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
DM	1					
EM	-0.162	1				
US	0.350	0.010	1			
CHA	-0.248	0.361	-0.202	1		
$\overline{DM_i}$	0.032	0.074	-0.008	0.064	1	
$\overline{EM_i}$	0.000	0.112	-0.024	0.117	0.019	1

Panel C: ε^T

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
δ_0	-0.035	-0.057	-0.059	0.041	-0.032	-0.025
$pval$	0.020	0.000	0.002	0.000	0.056	0.094
δ_1	0.683	0.154	0.202	-0.062	0.126	0.125
$pval$	0.000	0.000	0.004	0.026	0.080	0.159
R^2	0.927	0.166	0.384	0.105	0.206	0.104

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
DM	1					
EM	-0.201	1				
US	0.319	-0.103	1			
CHA	-0.248	0.424	-0.309	1		
$\overline{DM_i}$	0.034	0.019	-0.032	0.036	1	
$\overline{EM_i}$	-0.017	0.114	-0.029	0.119	0.020	1

Table 5: Relation between Conditional Asymmetry and Conditional Volatility

Summary statistics of regression (9) for each portfolio's $CA_{i,t}$ on its 250-day conditional volatility. Results are shown for developed markets (DM), emerging markets (EM), the US, and China (CHA). Average statistics across developed markets excluding the US ($\overline{DM_i}$) and across emerging markets excluding China ($\overline{EM_i}$) are also reported. The left-hand side tableau of the Table reports the OLS intercept (δ_0) and slope (δ_1), the p-value of their t-tests based on Newey-West standard errors with 250 lags, and the R^2 statistic. The right-hand side tableau shows the correlation matrix of the estimated residuals. Results are reported for the returns series r in Panel A, for GARCH(1,1)-filtered returns ε^G in Panel B, and for TARCH(1,1)-filtered returns ε^T in Panel C.

Panel A: r

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
γ_0	0.634	0.538	0.256	0.815	1.283	-0.060	0.121
$pval$	(0.027)	(0.030)	(0.000)	(0.001)	(0.000)	(0.065)	(0.095)
γ_1	-6.825	-6.386	-1.826	-6.102	-3.332	-0.145	-1.022
$pval$	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.028)	(0.101)
R^2	0.282	0.329	0.609	0.357	0.851	0.327	0.265

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.976	1					
EM	0.244	0.219	1				
US	0.768	0.759	0.077	1			
CHA	0.019	0.011	-0.052	0.076	1		
$\overline{DM_i}$	-0.001	0.017	0.024	-0.034	-0.077	1	
$\overline{EM_i}$	0.008	0.005	0.068	0.000	-0.013	0.012	1

Panel B: ε^G

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
γ_0	0.408	0.307	0.007	0.214	0.175	0.137	0.134
$pval$	(0.064)	(0.045)	(0.803)	(0.037)	(0.000)	(0.094)	(0.075)
γ_1	-4.487	-3.567	-0.846	-2.168	-0.343	-0.899	-1.027
$pval$	(0.006)	(0.002)	(0.000)	(0.000)	(0.000)	(0.014)	(0.075)
R^2	0.173	0.233	0.250	0.243	0.422	0.206	0.229

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.947	1					
EM	0.309	0.272	1				
US	0.563	0.612	0.141	1			
CHA	-0.079	-0.091	-0.318	-0.036	1		
$\overline{DM_i}$	0.194	0.190	0.167	0.078	-0.114	1	
$\overline{EM_i}$	0.062	0.053	0.080	0.027	-0.005	0.027	1

Panel C: ε^T

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
γ_0	0.242	0.162	0.096	0.072	0.159	0.124	0.119
$pval$	(0.207)	(0.231)	(0.030)	(0.216)	(0.000)	(0.079)	(0.067)
γ_1	-3.329	-2.589	-1.074	-1.062	-0.321	-0.769	-0.941
$pval$	(0.016)	(0.010)	(0.000)	(0.002)	(0.000)	(0.053)	(0.057)
R^2	0.113	0.130	0.245	0.165	0.434	0.167	0.220

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.960	1					
EM	0.320	0.275	1				
US	0.577	0.622	0.057	1			
CHA	-0.085	-0.084	-0.161	-0.028	1		
$\overline{DM_i}$	0.191	0.189	0.102	0.069	-0.048	1	
$\overline{EM_i}$	0.111	0.105	0.094	0.047	0.017	0.030	1

Table 6: Financial and Economic Determinants of Conditional Asymmetry

OLS estimates for pooled regression (10). The conditional asymmetry of deTARCHed returns is regressed on the conditional volatility of the stock market VOL, the log of the ratio between the stock market capitalization and the nominal GDP (E/GDP), the log of turnover (TURN) and of the number of companies listed (NCOMP), the relative bid-ask spread as defined in Roll (1984) (LIQ), the short-term interest rate (Tbill), the Term Spread (TSPR), real GDP growth (GDP) and its volatility measured on the last three years of the quarterly series (GDPσ). The regressions include a constant and a time trend. All variables are sampled at annual frequency. Below the estimates, two p-values are reported based on standard errors calculated using the standard OLS formula (round brackets) or clustered by year (square brackets). N denotes the total number of available observations for each specification.

	World			Developed Markets			Emerging Markets		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
VOL	-0.358	-0.374	-0.394	-0.478	-0.432	-0.250	-0.384	-0.379	-0.561
	(0.000)	(0.000)	(0.003)	(0.001)	(0.025)	(0.194)	(0.000)	(0.000)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.023]	[0.342]	[0.000]	[0.000]	[0.001]
E/GDP		-0.008	-0.043		-0.078	-0.126		0.019	0.011
		(0.189)	(0.000)		(0.000)	(0.000)		(0.004)	(0.347)
		[0.175]	[0.000]		[0.000]	[0.000]		[0.001]	[0.283]
TURN		0.007	0.017		-0.011	-0.048		0.014	0.050
		(0.203)	(0.047)		(0.515)	(0.009)		(0.019)	(0.000)
		[0.239]	[0.001]		[0.477]	[0.000]		[0.028]	[0.000]
NCOMP		-0.003	-0.003		0.018	0.015		-0.007	-0.024
		(0.543)	(0.577)		(0.015)	(0.094)		(0.193)	(0.010)
		[0.494]	[0.336]		[0.000]	[0.005]		[0.221]	[0.000]
LIQ		1.108	-0.937		1.479	2.844		1.313	-1.080
		(0.227)	(0.583)		(0.545)	(0.297)		(0.178)	(0.604)
		[0.291]	[0.667]		[0.533]	[0.255]		[0.270]	[0.628]
TBILL			0.212			-1.846			0.438
			(0.419)			(0.001)			(0.180)
			[0.344]			[0.000]			[0.212]
TSPR			1.023			-1.492			1.054
			(0.008)			(0.117)			(0.012)
			[0.001]			[0.026]			[0.005]
GDPg			0.701			1.677			0.214
			(0.001)			(0.000)			(0.425)
			[0.000]			[0.000]			[0.311]
GDPσ			-0.268			-0.665			-0.224
			(0.098)			(0.007)			(0.297)
			[0.036]			[0.000]			[0.070]
R^2	0.032	0.039	0.092	0.036	0.124	0.224	0.044	0.072	0.170
N	1535	1273	685	602	423	389	933	850	296

Table 7: International Portfolio Allocation

Estimates of the portfolio policy in equation (11) with the conditional asymmetry measure and other annual country-specific characteristics. The portfolio policy is estimated by maximizing the sample analogue of the expected power utility with relative risk aversion $\gamma = 5$ (columns 1-4), $\gamma = 3$ (columns 9-12), and $\gamma = 7$ (columns 13-16). Columns 5-8 report the estimate with $\gamma = 5$ when excluding 2008 return data. Columns labeled (VW) display the benchmark results of value-weighted weights without any conditioning information. Specification (1) reports the results with the CA measure; in specification (2), the estimated annual volatility (VOL) is added; in specification (3), the orthogonal components of E/GDP and GDPg with respect to CA, denoted with E/GDP$^{\perp}$ and GDPg$^{\perp}$, are added. We use annual data for all available countries during the 1981–2010 period. p-values are reported in parenthesis below the coefficients. LR denotes the p-value of the likelihood ratio test under the null that all coefficients are equal to zero. Row w_{EM}^{CA} displays the average weight placed on the EM countries in the active strategy away from the value-weighted portfolio, r_{EM}^{CA} and r_{DM}^{CA} are the returns attributable to the CA variable, and $\rho(r_{EM}^{CA}, r_{DM}^{CA})$ is the correlation between these returns. The following four rows display the same measures but for the entire strategy. The last four rows report the average of the total portfolio return, its standard deviation, the certainty equivalent of the strategy, and the beta of the strategy with respect to the value-weighted portfolio.

	Full sample, $\gamma = 5$				Sample ex-2008, $\gamma = 5$				Full sample, $\gamma = 3$				Full sample, $\gamma = 7$			
	(VW)	(1)	(2)	(3)	(VW)	(1)	(2)	(3)	(VW)	(1)	(2)	(3)	(VW)	(1)	(2)	(3)
CA		4.677	4.261	6.449		3.687	3.589	5.877		5.717	5.525	9.265		4.373	3.799	5.322
$pval$		(0.000)	(0.000)	(0.001)		(0.005)	(0.006)	(0.004)		(0.001)	(0.003)	(0.004)		(0.000)	(0.000)	(0.000)
VOL			-1.134	-0.343			-0.937	-0.380			-1.104	0.002			-1.177	-0.492
$pval$			(0.019)	(0.568)			(0.052)	(0.510)			(0.149)	(0.998)			(0.002)	(0.274)
E/GDP$^{\perp}$				-6.617				-5.945				-10.332				-5.104
$pval$				(0.048)				(0.074)				(0.054)				(0.040)
GDPg$^{\perp}$				9.110				8.271				14.687				6.830
$pval$				(0.002)				(0.004)				(0.002)				(0.001)
LR		0.000	0.000	0.000		0.010	0.000	0.000		0.000	0.000	0.000		0.000	0.000	0.000
w_{EM}^{CA} (%)		6.505	5.926	8.796		4.334	4.218	6.746		7.951	7.683	12.636		6.082	5.283	7.259
r_{EM}^{CA}		0.053	0.048	0.075		0.048	0.047	0.079		0.064	0.062	0.108		0.049	0.043	0.062
r_{DM}^{CA}		0.029	0.027	0.042		0.006	0.006	0.011		0.036	0.034	0.060		0.027	0.024	0.034
$\rho(r_{EM}^{CA}, r_{DM}^{CA})$		-0.469	-0.469	-0.486		-0.372	-0.372	-0.390		-0.469	-0.469	-0.486		-0.469	-0.469	-0.486
w_{EM} (%)	9.162	15.691	15.112	17.958	8.825	13.184	13.068	15.571	9.162	17.137	16.869	21.798	9.162	15.268	14.469	16.421
r_{EM}	0.007	0.060	0.036	0.099	0.013	0.061	0.036	0.115	0.007	0.071	0.051	0.155	0.007	0.056	0.030	0.076
r_{DM}	0.080	0.110	0.132	0.186	0.097	0.104	0.127	0.153	0.080	0.116	0.139	0.231	0.080	0.108	0.130	0.167
$\rho(r_{EM}, r_{DM})$	0.596	-0.355	-0.577	-0.643	0.364	-0.308	-0.588	-0.532	0.596	-0.418	-0.561	-0.667	0.596	-0.330	-0.586	-0.622
$\bar{r}$	0.087	0.169	0.168	0.284	0.110	0.165	0.163	0.268	0.087	0.188	0.190	0.386	0.087	0.164	0.160	0.243
$\sigma(r)$	0.200	0.219	0.195	0.272	0.157	0.192	0.176	0.257	0.200	0.243	0.229	0.400	0.200	0.213	0.185	0.226
CE(r)	-0.157	0.076	0.103	0.167	0.044	0.092	0.110	0.163	-0.018	0.116	0.131	0.227	-0.290	0.045	0.084	0.137
β	-	0.656	0.380	0.379	-	0.859	0.567	0.688	-	0.579	0.295	0.226	-	0.678	0.402	0.437

Table C.1: Financial and Economic Determinants – Summary Statistics

The entries are summary statistics of economic and financial series used to relate to conditional asymmetry. The financial variables are the 250-day conditional volatility of a country's stock market (VOL), a measure of liquidity (LIQ), log turnover (TURN), the log of a country's stock market relative to its nominal GDP (E/GDP), the log of the number of companies listed in the Exchange (NCOMP), a short-term interbank or government bond yield (TBILL) and the spread between a long-term and the short-term rate (TSPR), the growth rate of real GDP (GDPg) and the annualized volatility of quarterly real GDP growth (GDPσ). The summary statistics are calculated for the whole universe of countries in Panel A, and then separately for Developed Markets (Panel B) and Emerging Markets (Panel C). On the left hand side of the Table, we show the cross-sectional average (Avg) and standard deviation (Std) of each variable's time series Mean and Standard Deviation. On the right hand side of the Table, average time series correlations between the variables are displayed.

Panel A: World

	Mean		Standard Deviation		Correlations									
	Avg	Std	Mean	Std	CA	VOL	E/GDP	TURN	NCOMP	LIQ	Tbill	TSPR	GDPg	GDPσ
CA	-0.082	0.150	0.140	0.090	1	-0.152	-0.074	-0.099	-0.037	0.115	-0.049	0.142	-0.013	-0.097
VOL	0.244	0.075	0.040	0.024		1	-0.105	0.187	0.011	-0.421	0.090	-0.102	-0.096	0.163
E/GDP	-1.406	0.913	0.841	0.424			1	0.308	0.371	0.140	-0.495	0.046	0.199	-0.269
TURN	3.323	1.051	0.689	0.335				1	0.186	-0.124	-0.224	0.081	0.142	-0.102
NCOMP	5.222	1.353	0.444	0.418					1	0.037	-0.194	0.040	0.013	-0.184
LIQ	-0.009	0.004	0.006	0.003						1	-0.187	0.051	0.089	-0.229
TBILL	0.136	0.152	0.125	0.262							1	-0.523	-0.048	0.125
TSPR	0.004	0.021	0.027	0.035								1	-0.102	0.018
GDPg	0.033	0.019	0.038	0.021									1	-0.292
GDPσ	0.103	0.048	0.042	0.044										1

Panel B: Developed Markets

	Mean		Standard Deviation		Correlations									
	Avg	Std	Mean	Std	CA	VOL	E/GDP	TURN	NCOMP	LIQ	Tbill	TSPR	GDPg	GDPσ
CA	-0.108	0.153	0.134	0.077	1	-0.020	-0.151	-0.061	-0.107	0.038	0.026	0.111	-0.027	-0.044
VOL	0.208	0.033	0.039	0.013		1	-0.041	0.310	0.081	-0.487	-0.106	-0.002	-0.174	0.069
E/GDP	-0.729	0.717	0.737	0.211			1	0.508	0.418	0.122	-0.631	0.056	0.182	-0.388
TURN	4.146	0.380	0.543	0.189				1	0.320	-0.141	-0.519	0.149	0.010	-0.240
NCOMP	5.976	1.333	0.301	0.215					1	0.088	-0.267	0.069	0.047	-0.178
LIQ	-0.007	0.001	0.004	0.002						1	-0.100	0.076	0.078	-0.180
TBILL	0.065	0.022	0.040	0.014							1	-0.612	0.167	0.301
TSPR	0.007	0.006	0.016	0.005								1	-0.229	-0.095
GDPg	0.027	0.013	0.024	0.009									1	-0.238
GDPσ	0.096	0.037	0.027	0.010										1

Panel C: Emerging Markets

	Mean		Standard Deviation		Correlations									
	Avg	Std	Mean	Std	CA	VOL	E/GDP	TURN	NCOMP	LIQ	Tbill	TSPR	GDPg	GDPσ
CA	-0.072	0.149	0.142	0.095	1	-0.206	-0.042	-0.115	-0.008	0.146	-0.080	0.160	-0.008	-0.128
VOL	0.258	0.082	0.040	0.027		1	-0.130	0.136	-0.018	-0.395	0.170	-0.161	-0.064	0.218
E/GDP	-1.680	0.843	0.883	0.480			1	0.225	0.351	0.147	-0.441	0.041	0.206	-0.200
TURN	2.985	1.053	0.749	0.364				1	0.131	-0.118	-0.103	0.041	0.197	-0.019
NCOMP	4.911	1.246	0.503	0.466					1	0.015	-0.164	0.023	-0.001	-0.187
LIQ	-0.010	0.004	0.006	0.003						1	-0.222	0.037	0.093	-0.258
TBILL	0.165	0.172	0.159	0.305							1	-0.472	-0.135	0.023
TSPR	0.001	0.026	0.034	0.042								1	-0.029	0.112
GDPg	0.035	0.020	0.044	0.021									1	-0.324
GDPσ	0.107	0.054	0.051	0.054										1

Figure 1: Rolling Estimates of Skewness and Robust Asymmetry

Rolling moment-based skewness $S(r_t) = E(r_t - \mu)^3 / \sigma^3$ and rolling robust asymmetry $RA_\theta(r_t)$ measure:

$$RA_\theta(r_t) = \frac{(q_\theta(r_t) - q_{0.50}(r_t)) - (q_{0.50}(r_t) - q_{1-\theta}(r_t))}{q_\theta(r_t) - q_{1-\theta}(r_t)}$$

using rolling sample quantiles for the developed markets (DM) and emerging markets (EM) portfolios based on a 250-day rolling window. Estimates of $S(r_t)$, $RA_{0.95}(r_t)$ ($\theta = 0.95$), and $RA_{0.75}(r_t)$ ($\theta = 0.75$) are displayed in the left-hand-side, middle, and right-hand-side plots, respectively. Simple and TARCH-filtered returns are used in the estimation of the top and bottom plots, respectively.

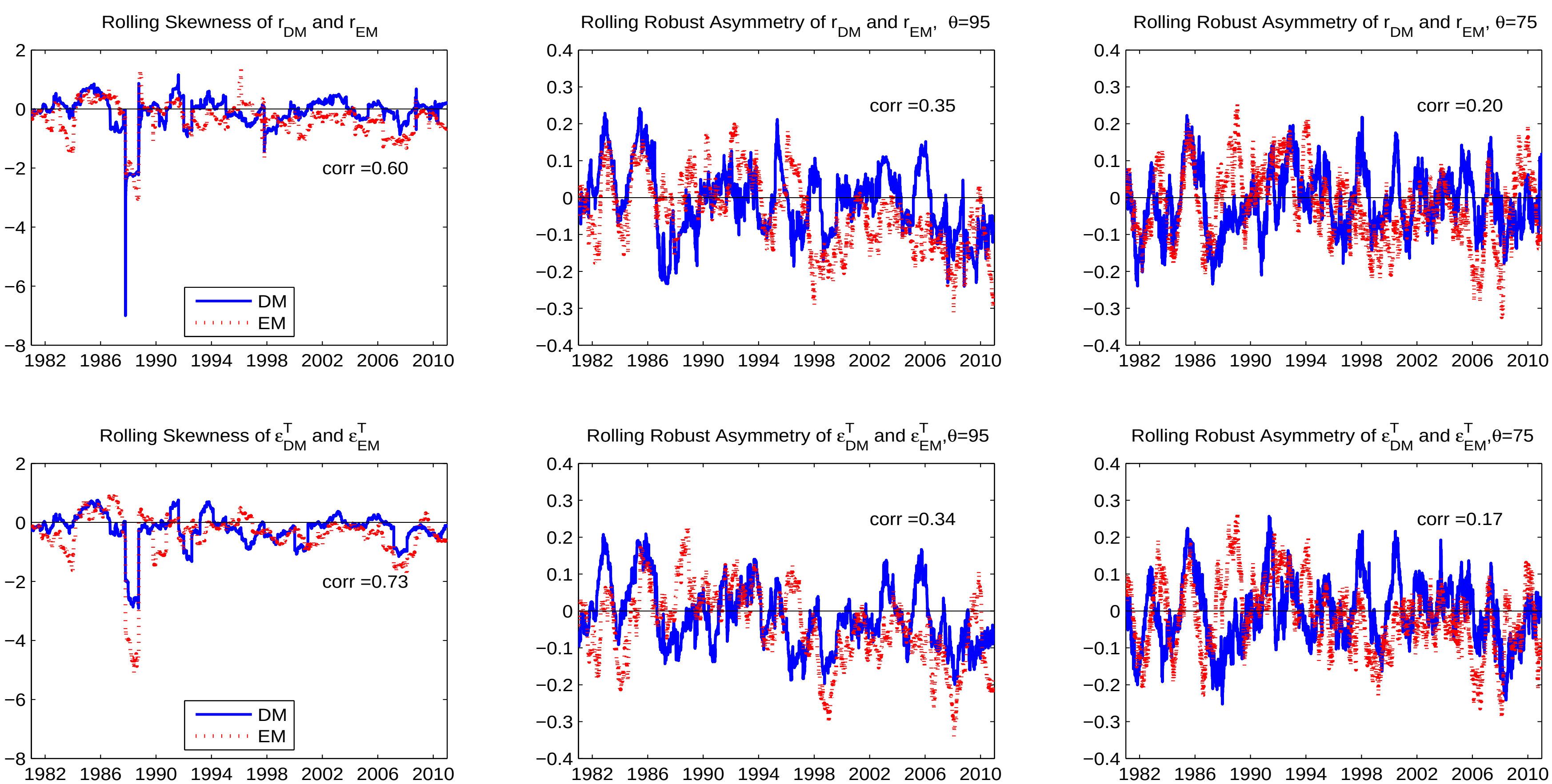

Figure 2: Conditional Quantile Estimates of Annual Returns: Developed Markets and Emerging Markets

Estimated 25th, 50th, and 75th conditional quantiles using the estimates in Table 2 for developed markets (top panel) and emerging markets (bottom) annual portfolio returns. Each plot displays the quantiles of simple and TARCH-filtered returns.

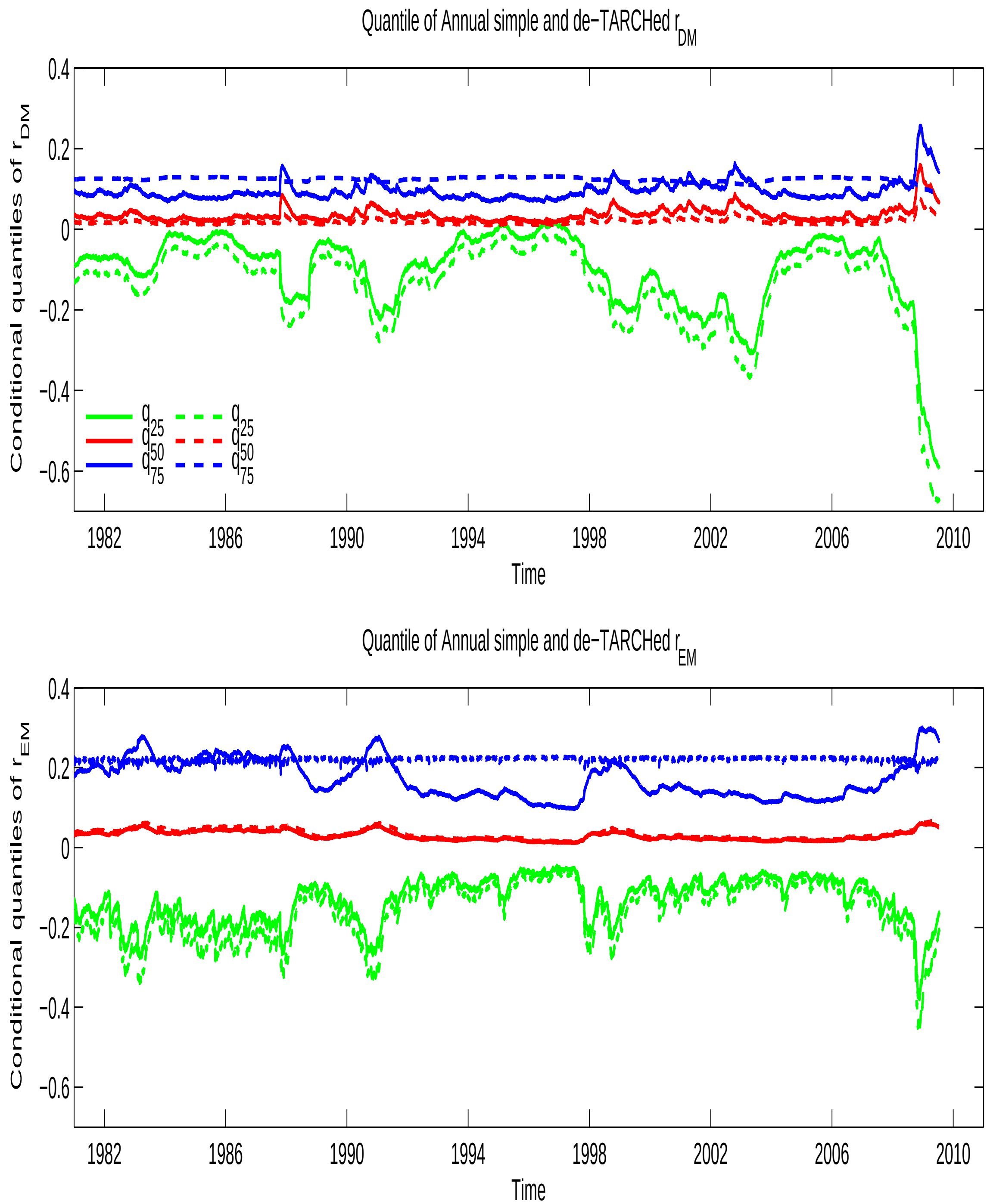

Figure 3: Conditional Asymmetry CA_t: Developed Markets and Emerging Markets

Estimated conditional robust measure of asymmetry as defined in equation (2) for the developed markets and emerging markets portfolios implied by the conditional quantiles of Figure 2 for simple (top plot) and TARCH-filtered (bottom plot) annual returns.

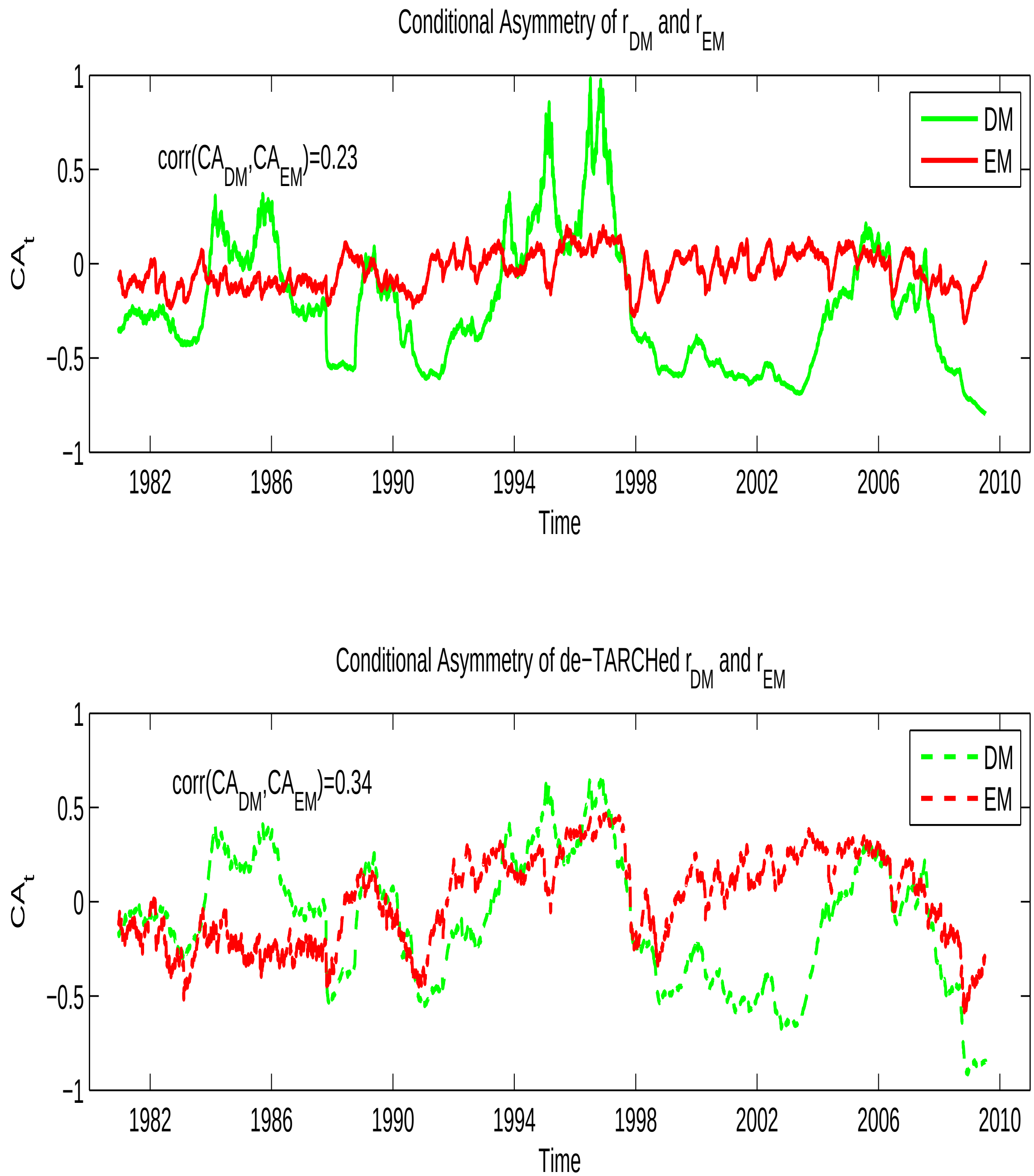

Figure 4: Weights on Daily Absolute Returns in Quantile MIDAS Regressions

MIDAS 25th, 50th, and 75th quantile regression weights of the 250-day lagged absolute returns for the developed markets (top plot) and emerging markets (bottom plot). Solid lines display the weights for simple returns, while dotted lines refer to TARCH-filtered returns.

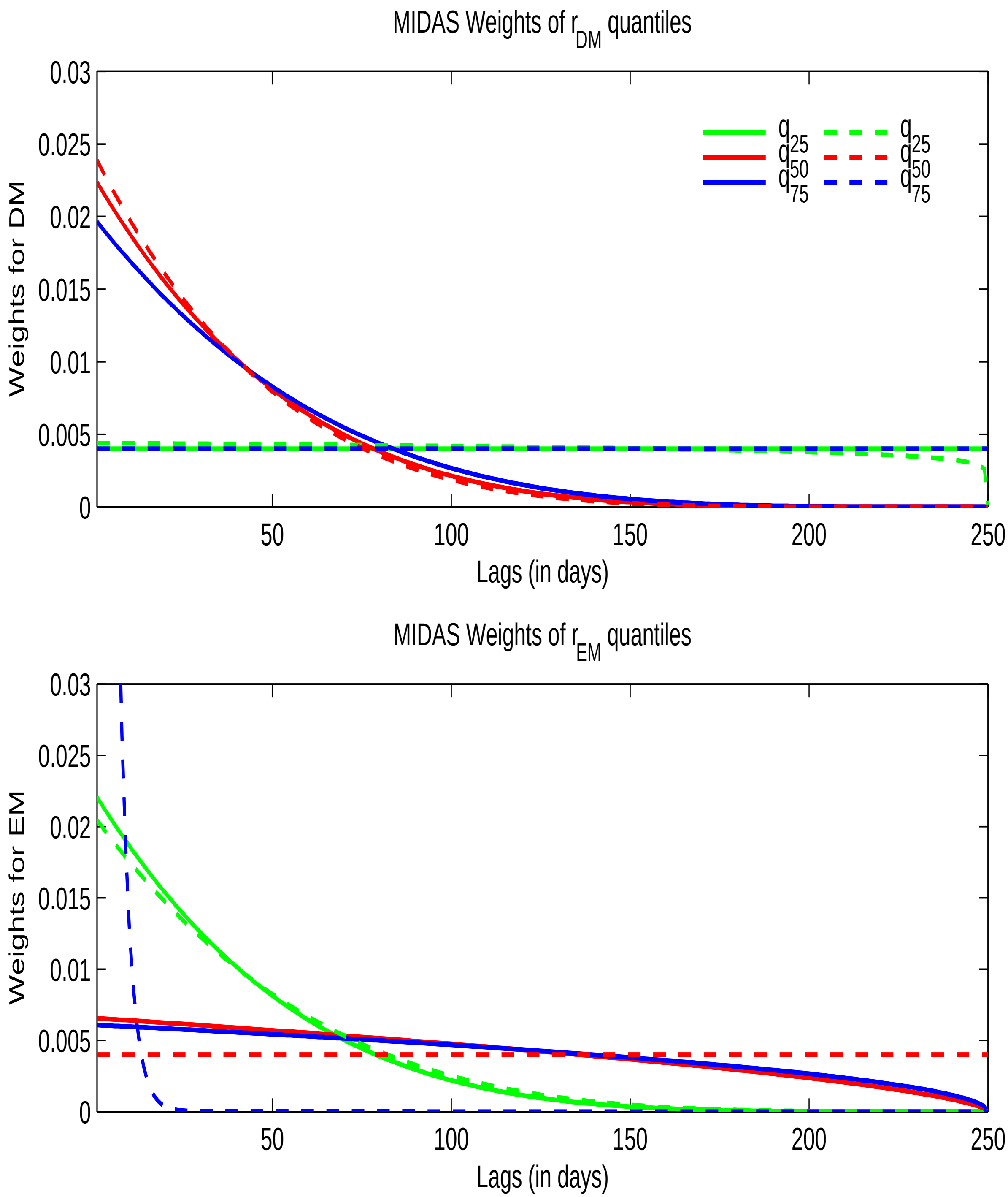

Figure 5: Correlations between $CA_{\theta,t}$s for DM and EM Portfolios for Different θs

The plot displays the correlation between the $CA_{\theta,t}$s of the DM and EM portfolios for a grid of θ values ranging from 0.55 to 0.95, where for each portfolio return:

$$CA_{\theta,t}\left(r_{t,n}\right) = \frac{\left(q_{\theta,t}\left(r_{t,n}\right) - q_{0.50,t}\left(r_{t,n}\right)\right) - \left(q_{0.50,t}\left(r_{t,n}\right) - q_{1-\theta,t}\left(r_{t,n}\right)\right)}{q_{\theta,t}\left(r_{t,n}\right) - q_{1-\theta,t}\left(r_{t,n}\right)}.$$

The three plots display results for annual simple, deGARCHed and deTARCHed returns, respectively.

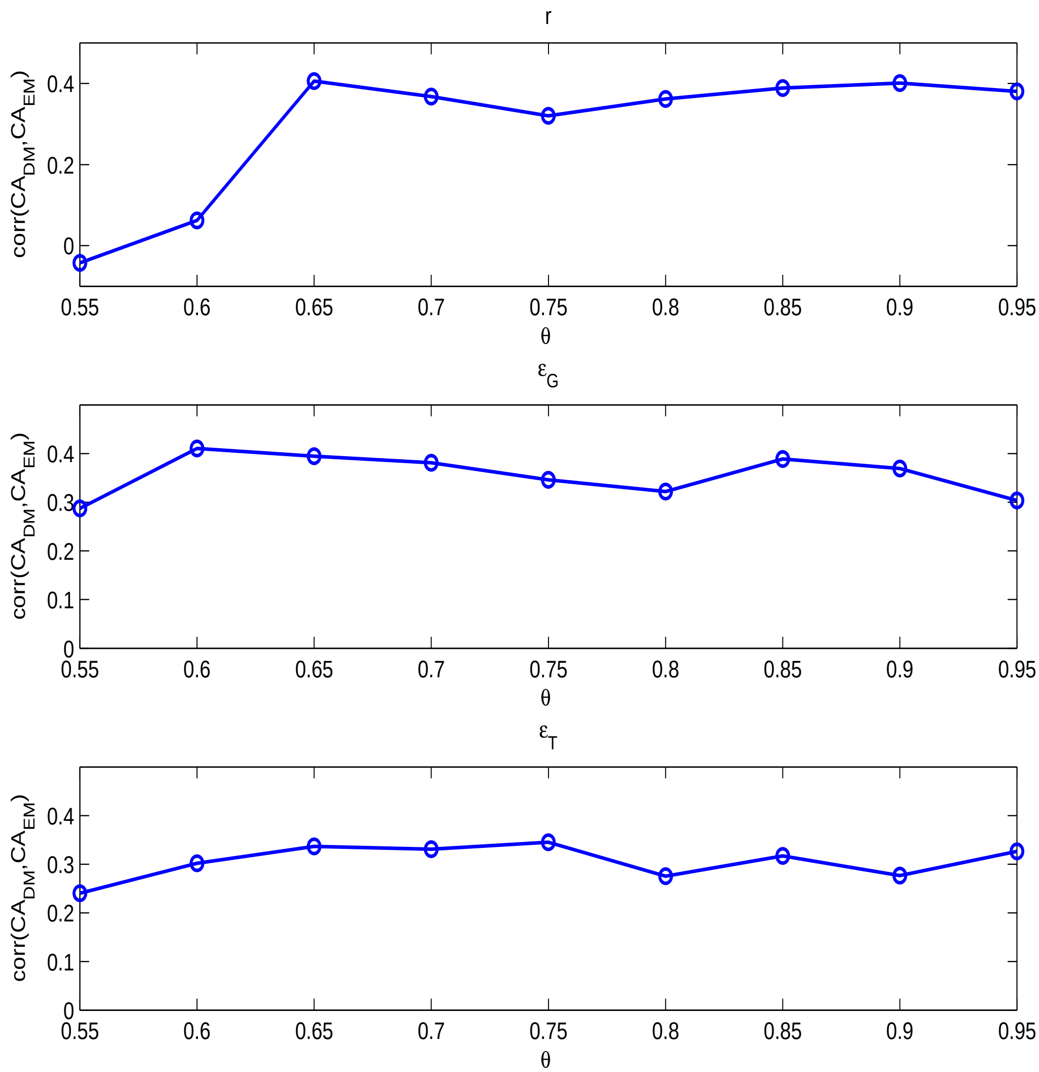

Figure 6: Rolling Estimates of Correlations, Volatility and Robust Asymmetry Measures

Rolling correlation (top plot) and robust asymmetry (bottom plot) of TARCH-filtered daily returns to Developed Markets and Emerging Markets, based on a 250-day rolling window. The middle plot displays the corresponding daily TARCH volatilities.