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 (GARCH) and unconditional skewness effects (TARCH) in returns. Interestingly, we find that the conditional asymmetry in developing countries is *negatively* correlated 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 negative relationship 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 means and volatilities of returns are higher than in developed markets; the conditional mean and volatility of returns vary significantly over time; the 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 or kurtosis 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 simple

[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.

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 the relative difference between the 75th (and 25th) conditional quantile and the conditional median of $r_{n,t}$. The intuition is as follows. If at time t the interquartile range is not centered at the median, then the return distribution is asymmetric. The statistic is normalized to be between -1 and 1. Extreme outliers have no effect on it as they do not impact the median, as well as the 25th and 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 denote our measure as CA_t (for conditional asymmetry at time t) to emphasize the fact that we are not using the conditional third moment of returns.

We use the new approach to estimate the conditional asymmetry in 76 portfolio returns: 73 individual country returns, a developed markets (henceforth DM) portfolio comprised of 21 developed economies, an emerging markets (henceforth EM) portfolio comprised of 52 emerging economies, and a global world (henceforth W) portfolio. The data, obtained from Datastream, is daily from 1980 to June 30, 2010. We estimate the CA_t of annual returns since most of the macroeconomic variables, used later in the papers, are available at that frequency. This is also a horizon of interest to many investors.

Before examining conditional asymmetries we study the (original/historical) *unconditional* robust measure of asymmetry for all countries and portfolios and compare it to the traditional third moment-based skewness measure. We do so for returns as well as for GARCH- and TGARCH-filtered returns (subsequently sometimes called de-GARCHed or de-TARCHed returns). Our first finding is that GARCH and especially TARCH models are suitable for capturing the unconditional skewness of developed market returns. In contrast, the results for emerging markets are mixed. The de-TARCHed returns have in general smaller skewness, although in some cases significant (unconditional) skewness still remains.

[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.

Second, we estimate the *conditional* asymmetry measure CA_t for all portfolios and study their distributional properties. We find that the returns of the world portfolio and large developed markets are generally more negatively skewed than emerging market returns.[3] More interestingly, we find that the correlation between CA_t measures of DM and EM portfolio returns is either zero or slightly negative, depending on whether or not we de-TARCH the returns. This intriguing result is of interest for at least two reasons. First, it is in sharp contrast with the results 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 exhibit significant co-movements. These facts might be taken to imply that the benefits from international diversification are limited. However, the zero-to-negative co-movement 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. Second, Pukthuanthong and Roll (2010) find that extreme return movements–or jumps–in international markets are strongly correlated. Our asymmetry measure complements their findings, as it 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]

Third, to understand the dynamics and co-movement of the estimated CA_t measures, we run two sets of time-series regressions. First, motivated by the international factor models literature (e.g., Solnik (1974), Korajczyk and Viallet (1989), Korajczyk and Viallet (1986), Harvey (1991)), we investigate whether the time variation in asymmetries can be linked to the world portfolio return, which is significantly negatively skewed. 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 implies 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 our CA_t measures are negatively related to volatility fluctuations. This result is consistent with the "leverage effect" findings 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)).

[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 (2006) 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.

Fourth, we examine to what extent the negative relation between the conditional skewness of DM and EM portfolio returns can be explained by economic fundamentals. It has been noted that macroeconomic fundamentals cannot easily account for conditional volatility movements (see e.g. Schwert (1989), Engle, Ghysels, and Sohn (2008) and Engle and Rangel (2008) among others). In contrast to conditional volatility, we find strong relationships between conditional skewness and macroeconomic fundamentals. In particular, we consider a set of variables that measure liquidity and the degree of development of international stock markets that have been suggested in the literature, 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 help predict future conditional skewness, and most interestingly the negative relation between the conditional skewness of DM and EM portfolio returns can be explained by the *opposite* sign of exposure to macroeconomic fundamentals for DM and EM portfolio returns. For example, DM portfolio conditional skewness relates positively to turnover, while EM portfolio conditional skewness is the opposite. With turnover 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 toward countries that are less negatively skewed, which in our setting are the emerging economies. In particular, when the investor conditions his decisions upon the estimated asymmetry measures, the optimal allocation corresponds to placing approximate 17 percent of the weight in emerging economies relative to the value-weighted allocation of only 9 percent. Moreover, taking into account conditional asymmetry in the portfolio allocation, leads to sizeable increases of the certainty equivalent return and the

Sharpe ratio.

While the analysis in this paper is mostly empirical, it should be noted that our findings have broader implications for the formulation of empirical asset pricing models. A large class of risk models rely 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.[5] Asymmetries in the dynamics of σ_t may yield (un)conditional skewness and the distribution of ε_t may also feature unconditional skewness. Yet, under standard assumptions returns, standardized by conditional volatility, i.e. $\varepsilon_t \equiv (r_t - \mu_t)/\sigma_t$, are i.i.d. and therefore should not exhibit any predictable patterns, including conditional asymmetry. Technically speaking, however, this assumption can be relaxed. Namely, one can still estimate GARCH models without the aforementioned i.i.d. assumption for ε_t. As discussed later in the paper, one can assume that ε_t is a martingale difference sequence and therefore allow for conditional skewness. Hence, we can examine the skewness properties of both returns as well as returns standardized by conditional variance estimates obtained from some type of GARCH model. The fact that we can study the conditional asymmetry of standardized returns allows us to examine the role of skewness after controlling for volatility dynamics.

The paper is structured as follows. Section 2 describes the quantile-based method of conditional asymmetry, tackles estimation issues, and provides the first set of empirical results using the international portfolio returns data. Section 3 explores the dynamics and co-movement of the estimated asymmetry measures within the context of time-series regressions, motivated by previous work. In Section 4, we use pooled regressions to link the conditional asymmetry in international markets to macroeconomic fundamentals. Section 5 covers international portfolio allocation with conditional asymmetry. Conclusions appear in section 6.

2 A Robust Measure of Conditional Asymmetry

We are interested in quantifying the asymmetry in the (conditional) distributions of n-period returns. To fix notation, 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 $F_{n,t|t-1}\left(r\right) = P\left(r_{t,n} < r | I_{t-1}\right)$,

[5] 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.

are strictly increasing. The unconditional first and second moments of $r_{t,n}$ are denoted by μ_n = $E\left(r_{t,n}\right)$ and σ_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.

In this section, we present the measure of conditional asymmetry (section 2.1), discuss its specification and estimation (section 2.2), present the data used in the estimation (section 2.3), and finally present the main results (section 2.4).

2.1 Econometric Approach

By far, the most popular measure of asymmetry is the unconditional skewness, or 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 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) and Bowley (1920) to look for robust measures of asymmetry that are not based on sample estimates of the third moment.

Bowley's (1920) robust coefficient of skewness is defined as:

$$CA\left(r_{t,n}\right)=\frac{\left(q_{0.75}\left(r_{t,n}\right)-q_{0.50}\left(r_{t,n}\right)\right)-\left(q_{0.50}\left(r_{t,n}\right)-q_{0.25}\left(r_{t,n}\right)\right)}{q_{0.75}\left(r_{t,n}\right)-q_{0.25}\left(r_{t,n}\right)} \tag{1}$$

where $q_{0.25}\left(r_{t,n}\right)$, $q_{0.50}\left(r_{t,n}\right)$ and $q_{0.75}\left(r_{t,n}\right)$ are the 25th, 50th, and 75th unconditional quantiles of $r_{t,n}$, and quantile θ is defined as $q_\theta\left(r_{t,n}\right)$ = $F^{-1}\left(r_{t,n}\right)$, for $\theta\in(0,1]$.[6] It is immediately clear that this skewness measure captures asymmetries of the inter-quartile range with respect to the median. Unlike $S(r_{t,n})$, it is robust to outliers, since the quantiles in equation (1) are not affected by them. The normalization in the denominator insures that the measure is unit independent with values between -1 and 1. For $CA\left(r_{t,n}\right)$ = 0 we have a symmetric distribution, while values diverging to -1 (1) indicate skewness to the left (right). To our knowledge, $CA\left(r_{t,n}\right)$ or other robust statistics of asymmetry, have received very limited attention in the empirical finance literature, the only exception being Kim and White (2004). The reason for that is undoubtedly the fact that, in order to construct (1), we need to

[6]The inverse of $F\left(r_{t,n}\right)$ is unique, since we assumed that $F\left(r_{t,n}\right)$ is strictly increasing. If $F\left(r_{t,n}\right)$ is not strictly increasing, then we can define the quantile as $q_{\theta_k}^*\left(r_{t,n}\right)\equiv\inf\left\{r:F\left(r_{t,n}\right)=\theta_k\right\}$.

estimate quantiles, which is not as straightforward as estimating other statistics. Fortunately, quantile regression methods have greatly improved in the last twenty-five years and we draw on results from that literature.

To illustrate the sensitivity of the third centered moment to outliers, we provide a 250-day rolling estimates of the $S\left(r_t\right)$ (top panel) and $CA\left(r_t\right)$ (bottom panel) for the developed and emerging markets portfolios, available from the period January 1, 1980 to June 30, 2010.[7] In the top panel of Figure 1, we display the rolling estimates of $S\left(r_t\right)$, which involve the third power of returns, of both portfolios. The rolling statistics are estimated in exactly the same fashion as one estimates rolling sample volatility (see for example French, Schwert, and Stambaugh (1987)). While the estimates in Figure 1 represent a simple ex-post estimate of the conditional skewness, they illustrate two key points. First, if we look at the rolling estimates of $S\left(r_t\right)$, we notice discontinuities that occur at the time when large outliers enter the rolling sample - in the case the 87 crash. Even one daily observation has an immediate and drastic impact on the annual skewness estimates. This result is not peculiar to the rolling regression 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 a similar plots for individual countries and the discontinuities are even more striking. In contrast, the rolling estimates of the robust skewness measure $CA\left(r_t\right)$ in the bottom panel are much less sensitive to outliers. Moreover, we observe a considerable time variation in the $CA\left(r_t\right)$ and $S\left(r_t\right)$ estimates, if we neglect the discontinuities.

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. For example, one might consider replacing $S(r_t)$ with a trimmed mean version. This would eliminate outliers and hence the sensitivity of moment-based estimates of skewness. The same arguments apply to $CA\left(r_t\right)$ as we (arbitrarily) picked the the 25th, 50th, and 75th quantiles. Indeed, other quantiles such as the 5th (1st), 50th and 95th (99th) could have been considered as well. While generalizations of $CA\left(r_{t,n}\right)$ can be defined along these lines, they do not change the main message of the paper.[8]

At a technical level, the above quantile-based skewness measure does not require moments to exist. This is particularly important for emerging market data, which are known to have fat tails. The measure

[7]While the remaining of the paper focuses on annual returns, here we provide 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.

[8]Results are not reported but available upon request. 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.

(1) also satisfies all conditions that Groeneveld and Meeden (1984) postulate any reasonable skewness measure should satisfy.[9]

Perhaps the biggest limitation of $CA\left(r_{t,n}\right)$ is that it is based on unconditional quantiles of $r_{t,n}$. As such, it provides unconditional measures of skewness but is not useful to study the dynamics of the conditional asymmetry and its time series properties. We follow White, Kim, and Manganelli (2008) and extend the CA measure to capture asymmetries in the conditional distribution by replacing the unconditional quantiles in (1) by their conditional analogues. More specifically, the conditional quantile θ of return $r_{t,n}$ is

$$q_{\theta,t}\left(r_{t,n}\right)=F_{t,n|t-1}^{-1}\left(r\right) \tag{2}$$

and a conditional version of (1) given information I_{t-1} can be defined as

$$CA_t\left(r_{t,n}\right)=\frac{\left(q_{0.75,t}\left(r_{t,n}\right)-q_{0.50,t}\left(r_{t,n}\right)\right)-\left(q_{0.50,t}\left(r_{t,n}\right)-q_{0.25,t}\left(r_{t,n}\right)\right)}{q_{0.75,t}\left(r_{t,n}\right)-q_{0.25,t}\left(r_{t,n}\right)}. \tag{3}$$

From now on, we define conditional asymmetry in terms of CA_t: if returns yield variations in CA_t, then their conditional distribution exhibits asymmetry. To better understand this measure, we discuss its properties in the framework of a widely-used and well-understood model of stock returns. This discussion will not only help us clarify the implication of this measure for those models but also to understand more generally what is needed to generate time-variation in conditional skewness.

2.1.1 Conditional Asymmetry and Return Dynamics

It is well-known that returns of developed and emerging markets have time-varying conditional first and second moments. Hence, as noted in the Introduction, we can write their returns as:

$$r_{t,n}=\mu_{t,n}+\sigma_{t,n}\varepsilon_{t,n} \tag{4}$$

If the dynamics of the conditional distribution of $r_{t,n}$ are captured by the first two conditional moments, then the distribution of $\varepsilon_{t,n}$, $F(\varepsilon_{t,n})$, is time-invariant and so is its quantile, $q_\theta\left(\varepsilon_{t,n}\right) = F^{-1}(\theta)$. The conditional variance can include any dynamics including asymmetries, such as in TARCH/GJR models.

[9]Another widely-used skewness measure, the Pearson coefficient of skewness, defined as $\frac{\mu-q_{0.5}\left(r_{t,n}\right)}{\sigma_n}$, does not satisfy these properties.

For model (4), the conditional quantile θ of returns is

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

which makes a few things clear. First, the variation in the quantiles of returns comes 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 TARCH/GJR 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. Fourth, if the distribution of $\varepsilon_{t,n}$ is not symmetric, even after taking into account volatility asymmetries, then the unconditional skewness measure will be nonzero, but there will be no conditional variation in CA_t. In other words, this model cannot generate fluctuations in the conditional asymmetry of returns.[10]

If model (4) is well-specified (including the mean and volatility), then the conditional asymmetry of returns $r_{t,n}$ and the filtered returns $\varepsilon_{t,n}$ should be the same. To the extent that the properties of $CA\left(r_{t,n}\right)$ differ from those of $CA\left(\varepsilon_{t,n}\right)$, it must imply that either the volatility model is misspecified, or that we need a more general model that captures conditional skewness. Hence, from an empirical perspective it is useful to consider the skewness of both $r_{t,n}$ and $\varepsilon_{t,n}$, as we do in the empirical section.

It is standard in the literature on ARCH-type models, to assume that $\varepsilon_{t,n}$ is an i.i.d. process and has an invariant distribution used for the purpose of likelihood-based estimation. Yet, one can estimate ARCH-type models under less restrictive conditions that allow for the presence of conditional skewness. For example, Escanciano (2009) studies the estimation of so called semi-strong GARCH models with ε_t a martingale difference sequence, notably allowing for conditional skewness. One practical implication is that one cannot use the standard likelihood based estimation procedures. Instead, one should rely on moment-based estimators. To facilitate the estimation we did use standard estimation procedures - viewed as a particular moment-based procedure with the moments determined by the score function. Therefore, in our empirical work we will estimate GARCH and TARCH models and examine both returns and standardized returns for conditional skewness features. While in principle, we should make a distinction between $\varepsilon_{t,n}$, and what we actually use, namely estimated $\hat{\varepsilon}_{t,n}$, we will not take into account estimation error when we consider the conditional quantile estimates of standardized returns.

One way to capture dynamics of quantiles is to allow for state variables that possibly differ across

[10]See also Engle and Manganelli (2004) for observations along similar lines.

quantiles, namely:

$$q_{\theta,t}\left(r_{t,n}\right)=\alpha_\theta+\beta_\theta Z_{\theta,t-1} \tag{5}$$

where $Z_{\theta,t-1}$ is a vector of state variables that might be quantile-specific. Expression (5) is quite general. If α_θ= 0, β_θ = $[1\ q_\theta\left(\varepsilon_{t,n}\right)]$ and $Z_{\theta,t-1}$ = $[\mu_{t,n}\ \sigma_{t,n}]'$ for all θ, we have specification (4). If we let n = 1 for a single period horizon, $Z_{\theta,t}$ = $[q_{\theta,t-1}\left(r_{t-1}\right)\quad \|r_{t-1}\|]'$ for all θ, we obtain the CaViaR specification of Engle and Manganelli (2004). Asymmetry is achieved when α_θ and β_θ are left unrestricted, when the conditioning variables $Z_{\theta,t-1}$ are different across quantiles, or both.

The above discussion made clear that a key ingredient in the measurement of conditional asymmetry using CA_t in expression (3), is the specification and estimation of the conditional quantile functions. More precisely, the parametrization of the quantile functions in (5) and the type of conditioning information that is used in the estimation are of primary importance. The choice of the functional form and the conditioning variables in the estimation of the conditional quantile regression is similar to that of any regression, whether we are estimating a conditional mean, conditional variance, or a conditional quantile. For instance, White, Kim, and Manganelli (2008) use a similar approach in a multi-quantile generalization of Engle and Manganelli's (2004) CaViaR approach to model conditional quantiles. Since we are interested in estimating the conditional quantiles $q_{\theta,t}\left(r_{t,n}\right)$ of returns at various horizons using as much information as possible (i.e. daily data), a different specification seems more suitable. In the next section, we present the new quantile specifications and discuss their advantages and shortcomings.

2.2 Conditional Quantiles Specifications and Estimation

To construct (3), we need to model and estimate the conditional quantiles of $r_{t,n}$ (or $\varepsilon_{t,n}$, but for for expositional reason we focus here on returns). We make the notation more explicit by denoting the quantile as $q_{\theta,t}\left(r_{t,n};\delta_{\theta,n}\right)$ where the parameters are collected in the vector $\delta_{\theta,n}$. The notation reflects the fact that the function q will be estimated for each quantile θ and the parameters $\delta_{\theta,n}$ are allowed to differ across quantiles and horizons. Since we will be investigating the conditional quantiles of returns at various horizons, we specify a model that uses all the information in I_{t-1} = $\{x_{t-1},x_{t-2},...\}$, where x_t is a vector of daily conditioning variables. To do so, we use a MIDAS approach, meaning Mi(xed) Da(ta) S(ampling), applied to quantile regressions.[11] We characterize a MIDAS quantile regression -

[11]MIDAS regressions were suggested in recent work by Ghysels, Santa-Clara, and Valkanov (2004), Ghysels, Santa-Clara, and Valkanov (2006), Ghysels, Sinko, and Valkanov (2006), Chen and Ghysels (2010) and Andreou, Ghysels, and Kourtellos (2010). The original work on MIDAS focused on volatility predictions (using MIDAS regressions or filtering), see also Alper,

where the conditional quantile pertains to multiple horizon returns and the regressors are daily returns - as follows:

$$q_{\theta,t}\left(r_{t,n};\delta_{\theta,n}\right) = \alpha_{\theta,n} + \beta_{\theta,n} Z_t\left(\kappa_{\theta,n}\right) \tag{6}$$

$$Z_t\left(\kappa_{\theta,n}\right) = \sum_{d=0}^{D} w_d\left(\kappa_{\theta,n}\right) x_{t-d} \tag{7}$$

where $\delta_{\theta,n} = (\alpha_{\theta,n}, \beta_{\theta,n}, \kappa_{\theta,n})$ are unknown parameters to estimate. The function $w_d\left(\kappa_{\theta,n}\right)$ is - as typical in MIDAS regressions - a parsimoniously parameterized lag polynomial driven by a low-dimensional parameter vector $\kappa_{\theta,n}$, and $Z_t\left(\kappa_{i,\theta,n}\right)$ is filtered from the observable daily conditioning information x_{t-d}. The parameters to be estimated $\delta_{\theta,n}$ will differ with the quantile and horizon of interest. The parsimoniously specified parametric MIDAS weights $w_d\left(\kappa_{\theta,n}\right)$ greatly reduce the number of lag coefficients to estimate $(D+1)$, which can be very large, given the frequency of the data. In other words, the parameters $\kappa_{\theta,n}$ in the filtering of the daily observations (equation (7)) and the parameters $\alpha_{\theta,n}$ and $\beta_{\theta,n}$ of the quantile (equation (6)) are estimated simultaneously. In general, the MIDAS regression framework allows us to investigate whether the use of high-frequency data necessarily leads to better quantile forecasts at various horizons.[12]

There are several benefits from using the MIDAS quantile specification (6)-(9) rather than other conditional quantile models, such as Engle and Manganelli (2004) and White, Kim, and Manganelli (2008). First, (6)-(7) is not a recursive quantile model: the conditioning information x_{t-d} in (6) can be any variable that has the ability to capture time variation in the quantile of the return distribution. 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 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 $Z_t\left(\kappa_{\theta,n}\right)$ and the quantiles are different only through the $\alpha_{\theta,n}$ and $\beta_{\theta,n}$ parameters. One similarity that our specification shares with White, Kim, and Manganelli (2008) is that we do not impose non-crossing restrictions on the quantiles. It turns out that crossing of quantiles does not seem to be an issue in the applications at hand.

Fendoglu, and Saltoglu (2008), Chen and Ghysels (2010), Engle, Ghysels, and Sohn (2008), Forsberg and Ghysels (2006), Ghysels, Santa-Clara, and Valkanov (2005), León, Nave, and Rubio (2007), among others.

[12]In the context of quantile regressions or skewness forecasts, the use of high-frequency data has not yet been explored. Arguably, an exception is the literature on tests for jumps in continuous time SV jump diffusions (see e.g. Aït-Sahalia and Jacod (2007), Andersen, Bollerslev, and Diebold (2007), Barndorff-Nielsen and Shephard (2004), among others). These tests typically apply to a decomposition of realized volatility into a continuous-path and discrete jump component and are not not so much viewed as estimates of skewness.

To estimate the quantile function (6), we need to specify the conditioning variables x_{t-d} and $w_d(\kappa_n)$. We address these model specification issues in the empirical section, as they are fairly standard in the literature. We estimate the parameters $\delta_{\theta,n}$ in (6-9) with non-linear least squares. More specifically, for a given quantile θ and horizon n, we minimize

$$\min_{\delta_{\theta,n}} T^{-1} \sum_{t=1}^{T} \rho_{\theta,n} \left(\varepsilon_{\theta,n,t} \right) \tag{8}$$

where $\varepsilon_{\theta,n,t} = r_{t,n} - q_{\theta,t} \left(r_{t,n}; \delta_{\theta,n} \right)$, $\rho_{\theta,n} \left(\varepsilon_{\theta,n,t} \right) = \left(\theta - 1 \left\{ \varepsilon_{\theta,n,t} < 0 \right\} \right) \varepsilon_{\theta,n,t}$ 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 (8), is asymptotically normally distributed with mean zero and a variance that can be consistently estimated (see White (1996), Weiss (1991), and Engle and Manganelli (2004)). Once we have estimates of $q_{0.25,t} \left(r_{t,n}; \delta_{0.25,n} \right)$, $q_{0.50,t} \left(r_{t,n}; \delta_{0.50,n} \right)$ and $q_{0.75,t} \left(r_{t,n}; \delta_{0.75,n} \right)$, we substitute them into expression (3) and obtain an estimate of the conditional skewness measure $CA_t \left(r_{t,n} \right)$.

2.3 Data an Preliminaries

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 (including the US) as well as 52 emerging markets. For most developed and many emerging markets, the data spans the period of January 1st 1980 to June 30, 2010 (the 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 countries with shorter data spans are introduced as soon as their returns are available. Following Pukthuanthong and Roll (2009), we filter returns to purge holidays and non-trading days.[13] We use the MCSI World Index from Datastream as a proxy for the global World (W) portfolio. Using the country returns, we construct two value-weighted portfolios of developed markets (DM) and emerging markets (EM) daily returns using market capitalizations obtained from Global Financial Data, Datastream, and the World Federation of Exchanges.[14] To construct the daily DM and EM portfolios for a given year, we use all available countries within each group at the beginning of that year. The DM and EM portfolio returns are computed based on market capitalization weights from the previous year.

[13] For the exact filtering procedure, please see the Appendix or Pukthuanthong and Roll (2009).

[14] More details are provided in the Appendix.

Table 1 presents return summary statistics for the W, DM, and EM portfolios as well as for all 73 countries. We present daily and yearly log returns statistics, where yearly log returns $r_{t,n}$ are computed as the sum of 250 daily log returns. The need for yearly returns arises because most of the macroeconomic variables (see below) are only available at annual frequency. Given the short time interval, we construct returns in an overlapping fashion. The serial correlation in returns that is induced by the overlap will be corrected for when computing the standard errors of the statistics. The countries are sorted by their market capitalization at the end of 2009. The first two columns after the index name display the initial date of the returns series and the number of daily observations available. All series are available until June 30, 2010. The next two columns contain the annualized mean and standard deviation of the log daily returns. The fifth and sixth columns display the traditional unconditional skewness (normalized third moment) of daily ($S(r_t)$) and yearly ($S(r_{t,n})$) log returns, while the seventh column displays the unconditional robust measure of skewness of the yearly returns ($CA(r_{t,n})$), defined in (1). Before proceeding, we make a few observations about $S(r_t)$, $S(r_{t,n})$, and $CA(r_{t,n})$.

The estimates of $S(r_t)$ across countries are mostly negative, a well-known fact documented in the prior literature. However, we also notice that yearly returns are also skewed and sometimes even more so than are daily returns. This fact, also discussed by Engle and Mistry (2007) and Ghysels, Plazzi, and Valkanov (2010), is surprising because Central Limit Theorem intuition would imply that skewness ought to converge to zero as the horizon increases. Moreover, the robust measure of skewness reaffirms the negative skewness of annual returns.[15] Finally, it is interesting to notice that with the exception of three countries (Japan, Australia, and Austria) all developed countries exhibit negative unconditional skewness.

We also present statistics of the returns filtered for GARCH and TARCH volatilities. Based on extensive evidence that the conditional mean and volatility of developed and emerging markets returns are time varying, following the discussion in section 2.2, we express all 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 a TARCH(1,1,1).[16] The GARCH- and TARCH-filtered returns are denoted by ε_t^G and ε_t^T and the corresponding yearly returns $\tilde{r}_{t,n}$ by $\tilde{r}_{t,n}^G$ and $\tilde{r}_{t,n}^T$, respectively. The filtered returns ought to display less unconditional skewness, especially

[15] Kim and White (2004) note that if we use CA as a measure of skewness, daily returns are not nearly as skewed. This fact has also been reproduced here and in Ghysels, Plazzi, and Valkanov (2010). However, annual returns are skewed, which deepens the relation between skewness of returns at short and long horizons. For a more systematic analysis of this term-structure of skewness, see Ghysels, Plazzi, and Valkanov (2010).

[16] We use the TARCH(1,1,1) specification of Zakoian (1994) to capture the asymmetry. Another model, the asymmetric GARCH(1,1) of Glosten, Jagannathan, and Runkle (1993), produces almost identical results.

under the TARCH. In fact, the TARCH model has been used extensively in the volatility literature to capture the unconditional skewness of returns. If it is successful, then ε_t^T and $\tilde{r}_{t,n}^T$ must not exhibit unconditional skewness. However, this does not mean that there is no conditional skewness in that data, as discussed in section 2.2. Relevant empirical results would be presented for both simple and filtered returns in order to insure that our findings are not driven by simple GARCH/TARCH dynamics.

Columns 9 through 11 of Table 1 display the unconditional skewness of the GARCH-filtered daily returns ($S(\varepsilon_t^G)$), yearly returns ($S\left(\tilde{r}_{t,n}^G\right)$), and the robust measure of skewness of the yearly returns ($CA\left(\tilde{r}_{t,n}^G\right)$). The last three columns display the same statistics for the TARCH-filtered returns, $S(\varepsilon_t^T)$, ($S\left(\tilde{r}_{t,n}^T\right)$), and $CA\left(\tilde{r}_{t,n}^T\right)$. If we compare 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, $S(r_{t,n})$ is equal to -0.981, decreases to -0.147 for the GARCH-filtered returns, and to 0.048 for the TARCH-filtered returns. Hence, the TARCH model is successful at capturing the unconditional skewness of returns for that series. For other portfolios, such as the emerging markets portfolio, even the GARCH and TARCH-filtered returns exhibit some unconditional skewness, which was also noted by Bekaert and Harvey (1997). But in general, looking at the developed and emerging countries, a similar picture emerges: the GARCH- and especially TARCH-filtered returns exhibit less unconditional skewness.

Another interesting fact is that while the traditional measure of skewness S is impacted significantly by the GARCH and TARCH filters, the CA skewness changes little with the filtered returns. This result highlights the fact that S can be - and empirically appears to be - invariant ARCH/GARCH effects.

2.4 Results

For all 76 portfolios, we obtain the conditional skewness estimates $CA_t\left(r_{t,n}\right)$ of returns by first estimating the 25th, 50th, and 75th conditional quantiles in (6-7) as discussed in section (2.2) and then plugging them in (3).[17] We follow Ghysels, Santa-Clara, and Valkanov (2006) and specify $w_d(\kappa_n)$ in (7) as:

$$w_d(\kappa_{\theta,n}) = \frac{f(\frac{d}{D}, \kappa_{1,\theta,n}; \kappa_{2,\theta,n})}{\sum_{d=1}^{D} f(\frac{d}{D}, \kappa_{1,\theta,n}; \kappa_{2,\theta,n})} \tag{9}$$

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

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 $\beta(a,b)$ = $\Gamma(a)\Gamma(b)/\Gamma(a+b)$. Ghysels, Sinko, and Valkanov (2006) and Sinko, Sockin, and Ghysels (2010) discuss the properties of (9) and other lag specifications in detail. A main advantage of this "Beta" function is its well-known flexibility. The function can take many shapes, including flat weights, gradually declining weights as well as hump-shaped patterns. For instance, with $\kappa_1 = \kappa_2 = 1$ one obtains equal weights, whereas for $\kappa_1 = 1$ and $\kappa_2 > 1$ one obtains a slowly decaying pattern that is typical for many time-series filters. The weights in (9) are normalized to add up to one, which allows us to identify a scale parameter β_n.

We follow Engle and Manganelli (2004), who find that absolute returns successfully capture time variation in the conditional distribution of returns, and use absolute daily returns as the conditioning variable in (7). While we could have used any conditioning information, the $|r_{t-d}|$ specification provides the most robust results. Alternative specifications based on the level and the squares of returns provided similar, but slightly noisier estimates.[18] More specifically, we use the three regressors, $|r_t|$, $\left|\varepsilon_t^G\right|$ and $\left|\varepsilon_t^T\right|$ as conditioning variables, each used in separate regressions. More generally, the problem of selecting the right conditioning variables in the MIDAS conditional quantile regressions from a set of possible candidates is exactly the same as in any other regression. In our context, if model (3) is the true data generating process, then it must be the case that $P\left(\varepsilon_{\theta,n,t} < 0 | I_{t-1}\right) = \theta$. In other words, $1\left\{\varepsilon_{\theta,n,t} < 0\right\}$ must be uncorrelated with past information. For convenience, we define the variable $Hit_{\theta,n,t} \equiv \theta - 1\left\{\varepsilon_{\theta,n,t} < 0\right\}$ which takes on the value of $\theta - 1$, if $\varepsilon_{\theta,n,t} < 0$, and θ, if $\varepsilon_{\theta,n,t} > 0$. It has a zero unconditional and conditional expectations (given I_{t-1}).[19]

The estimated quantiles have 4 parameters each ($\alpha_{\theta,n}, \beta_{\theta,n}\kappa_{1,\theta,n}, \kappa_{2,\theta,n}$). Since it is impractical to show all 4 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 following expositional choices. We present the main results for the world (W), developed markets (DM), emerging markets (EM) as well as for the largest countries in these portfolios, namely, the United States (US) and China (CHA).

[18] In the Appendix, we also present results from regressions based on squared, cubed, and simple returns.

[19] Based on this observation, a natural test for the validity of model (3) is to test whether $E\left(Z_{t-1}Hit_{\theta,n,t}\right)$ is significantly different from zero, where Z_{t-1} is a q-dimensional vector of I_{t-1} measurable variables. Such a test was proposed by Engle and Manganelli (2004), who show that $\left(\theta\left(1-\theta\right)E\left(T^{-1}M_T M_T'\right)\right)^{-1/2} T^{-1/2} Z'\, Hit_{\theta,n} \xrightarrow{d} N\left(0,I\right)$, where Z is a $T \times q$ matrix with rows Z_{t-1} and $Hit_{\theta,n}$ is a vector with elements $Hit_{\theta,n,t}$, for $t = 1,\ldots,T$. Based on that result, they propose the following test for in-sample model selection

$$DQ = \frac{Hit_{\theta,n}' Z\left(M_T M_T'\right)^{-1} Z' Hit_{\theta,n}}{\theta\left(1-\theta\right)}$$

and show that DQ has a χ^2 distribution with q degrees of freedom. Unfortunately, we use overlapping data which precludes us from using this test.

Table 2 presents a set of the estimation results for the five portfolio returns. The first panel displays the estimates of $\alpha_{\theta,n}$ and $\beta_{\theta,n}$ from the unfiltered returns $|r_t|$, for $\theta = 0.25, 0.50$, and 0.75 and $n = 250$. P-values, based on robust standard errors, are displayed below the estimates. In addition, we display the average hit rate, which should be close to zero, since it was used in the optimization step. Panels B and C present the same results for $\left|\varepsilon_t^G\right|$ and $\left|\varepsilon_t^G\right|$ returns, respectively. Note that the $\beta_{\theta,n}$ estimates are mostly significant at conventional levels of significance. One exception is the 75th quantile for the US, with a p-value of 15.1 $\%$. For the GARCH and especially TARCH returns, the results are even more impressive. The magnitude of $\beta_{\theta,n}$ is larger, which is due to the normalization. But more importantly, all the estimates are statistically significance. In fact, the estimates of $\beta_{\theta,n}$ are even more significant with the volatility-filtered returns. Hence, the main finding is that quantiles can be predicted with past absolute returns.

In Figure 2 we report the estimated 25th, 50th, and 75th conditional quantiles using estimates specified in (6) involving 250-day lagged daily absolute returns, for three portfolios: World Index (top), Developed Markets Index (middle), and Emerging Markets Index (bottom). We observe relatively little time variation in the median and third quartile for the World and DM portfolios. In contrast, the EM portfolio has slightly more variation in the median and third quartile. The real variation appears to be in the lower quartile. For the World and DM 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. 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 current crisis. The pattern for the EM portfolio is remarkably different. The 25th quantile tends to move upwards during world financial crises, and in particular we observe an *upward* trend in the three depicted quartiles during the recent financial crisis. The results in Figure 2 give us a hint that the CA_t measures for the DM and EM portfolios might be negatively related, and indeed they are as shown in Figure 3 where we plot the estimated conditional robust measure of asymmetry appearing in equation (3), again for the three portfolios. The show the contrast between DM and EM, we have two plots, the first covers the world portfolio separately, whereas the second contains the DM and EM portfolios together. The top panel reveals the time series pattern, where most of the time CA_t features negative values - the well-know negative skewness of stock market returns - 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 severeness of the current crisis. The lower panel of Figure 3 is the most intriguing, and indeed displays the negative relation between conditional asymmetries in DM and EM portfolio returns. This finding is to the best of our knowledge not found in the existing literature, and has profound implications for many topics including portfolio allocation, international diversification, and most importantly begs the question: why do we observe this pattern?

To continue our analysis, we turn to Table 3 where we present summary statistics of the CA_t estimates for the simple returns (Panel A), as well as $\left|\varepsilon_t^G\right|$ (Panel B) and $\left|\varepsilon_t^G\right|$ (Panel C) returns. In addition to the world, DM, EM, US, and CHA portfolios, we also present averages of the statistics across countries (excluding the US and China), which are denoted by $\overline{DM_i}$ and $\overline{EM_i}$, respectively. In Panel A, we turn our attention to a few interesting findings. First, the average CA_t of THE world portfolio is lower than that of the DM portfolio which is in turn lower than that of the EM portfolio. This finding mirrors the summary statistics of the unconditional CA measures, where we also found that the asymmetry of the world portfolio returns is more negative than that of the developed markets returns which is in turn more negative than that of emerging markets. In fact, the average CA_t estimates are very similar to the unconditional CA estimates in Table 1. Differences in average asymmetries can also be observed between the US (-0.153) and CHA (0.041) portfolios. For the cross-country averages, we observe a similar patter, albeit the difference is not as noticeable. Therefore, it appears that large economies are generally more negatively skewed.

Second, and the most intriguing result noted in Figure 3, we note that the correlation between the CA_ts of the DM and EM portfolios is -0.316. In other words, the asymmetry observed in the two portfolios are negatively correlated. We note a similar negative correlation of -0.315 between the CA_ts of the US and CHA portfolios. However, the negative correlation is not entirely driven by the two largest economies: the average correlation between CA_ts of individual DM economies other than the US and the EM portfolio is -0.077. From an economic perspective, the negative correlation between the conditional asymmetries is interesting for two reasons. First, it implies that the international diversification benefits might be larger than suggested from a simple mean-variance framework. Second, a recent work by Pukthuanthong and Roll (2010) documents that extreme return movements across countries are positively correlated, which implies that their conditional skewnesses ought to also be positively correlated. However, the CA statistic measures asymmetries that are not due to tail behavior. In that sense, ours ia a new finding that complements the results of Pukthuanthong and Roll (2010).

Third, the average and all other summary statistics of CA_t are qualitatively similar for r_t, $\left|\varepsilon_t^G\right|$, and $\left|\varepsilon_t^G\right|$. This is expected, because as discussed above, the quantile-based measure of asymmetry is not sensitive to GARCH/TARCH effects. For the de-TARCHed returns in Panel C of Table Table 3, the average CA_t are similar but smaller in absolute value than the results in Panel A. Also, in Panel A, there seems to be a small, but statistically significant deterministic time trend in the CA_t series, but after accounting for volatility with a TARCH, it is no longer present.In Panel C, the correlation between DM and EM portfolios are positive but small. This result solidifies our finding that, no matter whether returns are simple or de-TARCHEd, the CA_t measures between DM and EM portfolios do not exhibit large and positive correlation. This finding implies that international diversification might be more desirable than suggested by a simple mean-variance analysis.

To conclude we turn our attention to Figure 4 where the MIDAS quantile regression weights of 250-day lagged absolute returns are displayed. The top panel covers the DM portfolio return and the bottom plot covers EM returns. A first striking observation is that the decay patterns for DM and EM portfolio quantile regressions 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 regression puts the weights on the recent daily observations. Hence, the recent past determines mostly the upper tail in the CA_t measure. The is not the case for the EM 75th percentile regression, where the weights center on daily absolute returns half a year ago. For the median quantile MIDAS regression the EM portfolio the recent past matters most, in contrast to the DM portfolio where the median regression has MIDAS weights peaking at roughly one month lag. Finally, the 25th quantile MIDAS weight are roughly flat for the DM portfolio and tilted towards the distance past for emerging markets. The plots show that the quantile regressions feature very different dynamics across quantiles as well as across markets.

3 Conditional Asymmetry and its Economic Fundamentals: Time-Series Regressions

We use time-series regressions to explore the dynamics and co-movement of the conditional asymmetry measures. In a first subsection we discuss the specifications that are motivated by economic theory and previous work. In a second subsection we revisit the leverage effect in a conditional setting, analyzing the relationship between conditional volatility and asymmetry.

3.1 Co-movement in Conditional Asymmetry

It is natural to ask whether to what degree the time-variation in country-specific CA_t measures is due to fluctuations in the world portfolio. In other words, can we trace the asymmetries 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), Korajczyk and Viallet (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 components due to systematic and idiosyncratic risk, 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:

$$\widehat{CA}_{i,t} = \alpha_i + \beta_i \widehat{CA}_{W,t} + u_{i,t} \tag{10}$$

where $\widehat{CA}_{i,t}$ and $\widehat{CA}_{W,t}$ are the estimated conditional asymmetry measures of country i and the world portfolio respectively, and β_i captures their co-movement.[21] In other words, we represent the $\widehat{CA}_{i,t}$ series as a linear function of one factor: $\widehat{CA}_{W,t}$. The residual $u_{i,t}$ captures movements in $\widehat{CA}_{i,t}$ that are orthogonal to $\widehat{CA}_{W,t}$. This approach is a simple way of linking co-movements between return asymmetries in the world portfolio with those of individual assets, 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 asymmetries in the distribution of country returns.[22]

In Table 4, we present the results from regressions (10), where the $\widehat{CA}_{i,t}$ are estimated using simple

[20] Our skewness 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. 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 which is what we try to avoid.

[21] Yet another approach is to decompose returns into systematic and idiosyncratic components and then to estimate the conditional skewness measure for each component, separately.

[22] 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.

returns (Panel A), as well as $\left|\varepsilon_t^G\right|$ (Panel B) and $\left|\varepsilon_t^G\right|$ (Panel C). 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. The correlations of the regression residuals $u_{i,t}$ are also displayed in the table.

In Panel A of Table 4, the estimate of β_i in the DM regression is 1.256, or as expected, the CA_ts of the DM and W portfolios are positively correlated. Moreover, the R^2 in these regressions are high, because developed markets represent a large component of the world portfolio. Similar results obtain if we look at the corresponding coefficients in Panels B and C. The β_i in the EM regression is -0.219. The negative sign is largely due to the volatility (or leverage) effect, discussed in the next subsection. Indeed, for the de-GARCHed returns in Panel B, the β_i is small (-0.015) and statistically insignificant. For the de-TARCHed returns, it is 0.092 and significant only at the 10 percent level. Moreover, the R^2s in the EM regressions are very low. While the positive co-movement in the DM case is expected, we find it intriguing that the asymmetry in emerging markets are uncorrelated with that of the world portfolio. This suggests that, in emerging markets, the asymmetries might be driven by other factors such political crises or financial market-liberalization trends.

Similar results are obtained for the US, CHA, and the other countries. More specifically, in column $\overline{DM_i}$ of Panel A, the average β_i of all DM countries other than the US is 0.213 and the average R^2 is 0.119. The average β_i of all EM countries other than CHA (column $\overline{EM_i}$) is -0.018 and statistically insignificant. These results are qualitatively similar when we look across all three panels. Overall, we find it surprising that fluctuations in $\widehat{CA}_{i,t}$, particularly in emerging markets, are not correlated with $\widehat{CA}_{W,t}$ as would be expected based on intuition from factor models.

3.2 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 this effect here for two reasons. First, replicating this stylized fact with the CA_t measure would lend further credence to the fact we are capturing conditional asymmetry of 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) and Bekaert and Harvey (1997)) who do not find support for leverage effects in emerging markets.

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

$$\widehat{CA}_{i,t} = \alpha_i + \beta_i \widehat{Vol}_{i,t} + e_{i,t} \tag{11}$$

where $\widehat{CA}_{i,t}$ is estimated as above and $\widehat{Vol}_{i,t}$ denotes an estimate of 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 use for normalizing the returns, that advantage of using MIDAS regressions for volatility is that $\widehat{CA}_{i,t}$ and $\widehat{Vol}_{i,t}$ use the same information set of daily returns.

In Table 5, we present regression (11) with asymmetry estimates based on simple, de-GARCHed and de-TARCHed returns and then regress $\widehat{CA}_{i,t}$ on $\widehat{Vol}_{i,t}$ which involves squared daily returns (since we are estimating volatility it does not make sense to de-GARCH or de-TARCH the returns). The estimates of α_i and β_i for the world, DM, EM, US, and CHA portfolios are displayed along with their p-values (based on Newey-West-robust standard errors with 60 lags) and the regressions R^2s. We also display the average regression estimates, average p-values, and average R^2s from the other country regressions.

We find that for the W and DM portfolios, the relation between the conditional measures of asymmetry and volatility is negative and statistically significant. This finding is consistent with the leverage effect results from the asymmetric GARCH literature. It is also in line the "volatility feedback" hypothesis of Campbell and Hentschel (1992).[23] It is interesting to note that volatility fluctuations explain from 9.7 percent (W portfolio) to as much as 58.7 percent (CHA portfolio) of the variation in CA_t.

For emerging markets, the estimate of β_i is positive. This has also been observed (in a different sample and with different methods) by Bekaert and Harvey (1995) and Bekaert and Harvey (1997). However, if we look at column $\overline{EM_i}$–which displays the average estimate of $beta_i$ across all EM markets–we observe a negative, large in absolute value, and statistically significant estimate of -3.955. This implies that the anomalous positive estimate in the EM portfolio is due to a few large countries. Further analysis (not reported here) confirms this. Moreover, not all large emerging markets exhibit a positive $\widehat{CA}_{i,t}$ - $\widehat{Vol}_{i,t}$ relation. For instance, the leverage effect is present in the CHA portfolio.

[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. Thus, the asymmetric effect.

4 Conditional Asymmetry and its Macroeconomic Determinants: Panel Regressions

Thus far, we have related a country's conditional asymmetry to the conditional asymmetry of the world portfolio and to fluctuations in volatility. While these results help us understand the time-series and co-movement properties of CA_t, they have very little to say about its economic determinants. More fundamentally, can we trace the cross-sectional and time-series differences in the asymmetry measures to economic fluctuations? In this section, we tackle this question by exploring whether CA_t can be explained by a set of predetermined state variables. In selecting these variables, we are again guided by both economic theory and evidence from previous studies which investigate the predictors of conditional mean (Fama and French (1989), Goyal and Welch (2007), among others), volatility (Bekaert and Harvey (1997), Engle, Ghysels, and Sohn (2008), 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 our conditioning variables are available only at annual frequency, our approach is to investigate whether variables observed at the end of year t forecast conditional skewness for year $t+1$.

We do so using panel regressions. More specifically, we run the following regression:

$$\widehat{CA}_{i,t+1} = \alpha_i + \beta_i X_{i,t} + e_{i,t} \tag{12}$$

where the vector $X_{i,t}$ contains the state variables (to be specified below), which are observable annually. We run the pooled regression for all countries and across time, using the annual estimates of our $CA_{i,t+1}$ measure, which is estimated using information available in year t. Additional details about the estimation are provided in the results section below.

4.1 Conditioning Variables: Description and Summary Statistics

The variables in $X_{i,t}$ can be divided into two subsets: financial quantities and macroeconomic indicators of a country's economy.

Financial variables: The first financial variable we consider is the conditional volatility of a country's stock market. As discussed in the previous section, volatility is necessary to capture the leverage effect. Moreover, Chen, Hong, and Stein (2001) document a positive, albeit not statistically significant, relationship between volatility and future skewness at the aggregate level. Similarly, Boyer, Mitton, and Vorkink (2010) find that idiosyncratic volatility is a strong predictor of skewness. For consistency with the previous section, our volatility measure (denoted VOL) is again the predicted annual volatility using a MIDAS model of 250-day lagged squared returns.

Next, we consider a set of variables that measure liquidity and the degree of development of the stock market. Among these, perhaps the most explored relationship has been that between skewness and turnover. Hong and Stein (2003) propose a model in which heterogeneity in investors' opinions generates conditional skewness in stock returns. The key ingredient in their model is the fact that bearish investors face short-sales constraints and are forced to step out of the market until they start trading with some bullish investors who revised their opinion. Thus, higher volatility occurs when negative news are released and thus induce negative skewness. Chen, Hong, and Stein (2001) use turnover as a proxy for the intensity of disagreement and find that periods of unusually high turnover are indeed generally associated with subsequent periods of lower (i.e. negative) return skewness. Our measure on turnover is the log of the ratio of the total value of shares traded during the period to the average market capitalization for the period (denoted by $TURN$). The source is the World Bank Database.

Two other variables, the 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, respectively, the relative and absolute size of the financial sector. The data are taken from the World Bank Database, Global Financial Data, and the World Federation of Exchanges. Just like the size of a stock, the size of the overall stock market can be related to the asymmetry in returns. For example, one can argue that small countries release less information and are harder to be under closer scrutiny of international investors. A similar argument is made by Chen, Hong, and Stein (2001) to justify the positive skewness found for smaller stocks.

Finally, we include a measure of market liquidity. The effect of liquidity on skewness is studied notably by Chordia, Roll, and Subrahmanyam (2000). Unfortunately, data on aggregate bid-ask spreads is available just for a very limited number of countries. Therefore, we rely on Roll's (1984) liquidity proxy, which we denote LIQ. For each year t, we calculate LIQ over daily returns during that year. 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.

Economic variables: Two interest-rate variables, a short-term interbank or government bond yield (denoted $TBILL$) and the spread between a long-term and the short-term rate (denoted $TSPR$), and the growth rate of real GDP (denoted $GDPg$) capture changes in the investment opportunity set and cross-sectional differences in macroeconomic conditions. We include the volatility of quarterly real GDP growth, $GDPVOL$, calculated over the current and past two years as a proxy for macro uncertainty. The source for these variables are Datastream, Global Financial Data, and the World Bank Database.

To the best of our knowledge, the link between stock returns skewness and the macro economy has been neither empirically explored nor cast in a theoretical model. Yet, some arguments can be made on why we might expect them to play a role in our analysis. One argument follows from the asymmetry in economic shocks which has been extensively documented and modeled in the macroeconomics literature (see e.g. Neftci (1984), Hamilton (1989), Sichel (1993) and Acemoglu and Scott (1997)). If some of these shocks propagate with lags and are amplified by leverage, we may expect these variables to have some potential in determining future asymmetry in returns. In addition, several studies have tried to relate the volatility of stock market returns to that of macro shocks (see Schwert (1989), Engle, Ghysels, and Sohn (2008) and Engle and Rangel (2008)). Finally, these variables may further act as fixed effects capturing cross-sectional differences in skewness which are either related to unobserved factors or to factors we cannot directly measure.

Table 6 reports univariate and joint summary statistics for the estimated robust conditional skewness and for the nine conditioning variables we consider. These 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 Table 6, we show the cross-sectional average (Avg) and standard deviation (Csd) of each variable's time series Mean and Standard Deviation. On the right hand side of Table 6, average time series correlations between the variables are displayed. 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 skewness predicted for year $t + 1$ (thus, the conditional skewness for 2009) estimated using the information of year t.

As we can see from the Table, the average conditional skewness is negative at -0.097 and is greater (less negative) for Emerging Markets at -0.089 than for Developed Markets (-0.118). For the financial and economic determinants, the differences between Developed and Emerging Markets are in line with common economic intuition and previous studies. The volatility of Emerging Market stock returns is larger and more cross-sectionally dispersed than Developed Markets. Emerging Markets exhibit on average a lower ratio of stock market capitalization to GDP, a much lower Turnover, fewer companies listed, and a smaller degree of Liquidity. They also exhibit short-term interest rates which are on average higher (about 16.5% compared to 6.5%), more cross-sectionally dispersed (about 17% compared to 2%), and more volatile (about 16% compared to 4%) than Developed Markets. GDP growth is somewhat higher on average for Emerging Markets during our sample period, but is much more volatile than for Developed Markets.

Turning our attention to correlations, a few results are noteworthy. First, there is a negative correlation between skewness and volatility. This effect is stronger 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 just some modest correlation, the largest being that between the number of listed companies and the relative size of the stock market (0.418 for DM and 0.351 for EM). Interestingly, the correlations for Emerging Markets are broadly consistent with those reported in Bekaert and Harvey (1997) despite the fact they are calculated on a different sample period. Third, stock returns volatility is positively correlated with economic uncertainty, in particular for Emerging countries.

4.2 Regression results

We present the results from running the pooled regressions (12) where $X_{i,t}$ contains the five financial variables, [$VOL, TURN, E/GDP, NCOMP, LIQ$], the four economic variables [$Tbill$,$TSPR$,$GDPg$, $VOLGDP$], and a linear time trend, $Trend$, which is meant to capture changes through time in unconditional volatility which are not captured by any of the other variables.[24] From a time-series perspective, the panel is unbalanced for two reasons. First, as already discussed, the starting date of each stock market index is different across countries and varies from the beginning of 1980 (for most of the Developed Markets) to the end of 2000 (for Bulgaria). In addition, not all the determinants may be available for the entire period of the stock market data. For example, international data on turnover begins in 1995 for most countries while the number of companies starts in 1988. Data on long-term government bond yields is sparse for Emerging Markets, and so is quarterly GDP. Our approach in this case is to include

[24] 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.

all country's data as long as their become available. The information on each country is then restricted to the smallest period for which observations on all conditioning variables are present.[25]

Table 7 reports the OLS estimates of the slope coefficients of our pooled regression. Below the estimates, round brackets denote t-statistics based on the standard OLS formula for spherical standard errors, while square brackets denote t-statistics obtained from clustered standard errors at both the country and year level.[26] As we did for Table 6, we separately look at the results for the World (i = 1 to 73), Developed Markets (i = 1 to 21), and Emerging Markets (i = 22 to 73).

Four regression specifications are reported for the world, DM and EM portfolios. The first involves conditional volatility, trend and a constant. The second regression adds all the financial variables, the third adds the macro variables. Finally, the fourth regression specification involves de-TARCHed returns and includes all the aforementioned regressors. For the world portfolio we find that VOL, $TURN$ appear to be the most significant, both having a negative impact on conditional skewness. Among the four economic variables $Tbill$ and $TSPR$ appear to be most significant and are positively related. Looking at the fourth specification we note that the conditional skewness of de-TARCHed returns yield similar results, including the fact that conditional volatility remains significant.

The next set of four columns covers developed market returns. We find results similar to those for the world portfolio with some notable exceptions. First, conditional volatility is no longer significant when we consider conditional skewness of de-TARCHed returns. This indicates that for developed markets de-TARCHed returns adequately remove conditional volatility. We also find more significant impact of the liquidity measured via LIQ on conditional skewness. For the macro economic variables we find that the volatility of GDP growth is now also more significant and its impact is negative. The most remarkable result in Table 7 emerges when we compare the findings for developed and emerging markets. The negative relation between the conditional skewness of DM and EM portfolio returns can be explained by the *opposite* sign of exposure to macroeconomic fundamentals. For example, DM portfolio conditional skewness relates positively to turnover, while EM portfolio conditional skewness is the opposite. Liquidity has a significant negative impact on conditional skewness for DM and the opposite sign for emerging markets. The response to short term interest rates is negative for DM portfolio returns conditional skewness, while EM conditional skewness reacts positively. The same is true for $TSPR$. In some cases we find the same sign. This includes GDP growth volatility and in the

[25]Given the fact we are using annual observations, restricting to 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.

[26]See Petersen (2009) for a detailed comparison of the relative performance of standard and clustered standard errors in financial panel data.

case of GDP growth - the impact is not statistically significant for DM, but has a negative impact on conditional skewness. Hence, more growth implies more downside risk for emerging markets. Finally, it is also noteworthy that conditional volatility remains significant even when the conditional skewness of EM of de-TARCHed returns.

5 Conditional Asymmetry and Portfolio Implications

Figure 5 displays the conditional annual volatility of DM and EM returns based on a MIDAS model on 250 lagged squared daily returns and the rolling correlation between the two returns series using a 250-day window of simple returns and filtered returns from a TARCH(1,1). The plots clearly show why it has often been argued that the benefits from international diversification are limited given the strong co-movements in volatility and high correlation in returns.

The asymmetry measure CA has revealed that international returns are not only skewed but also that the skewness varies significantly over time. In an international portfolio context, this finding implies that investors can improve upon the standard mean-variance allocation results by taking into account other features of the return distribution, such as its asymmetry, while making optimal portfolio decisions. A similar remark was made by Bekaert, Erb, Harvey, and Viskanta (1998). Moreover, the time variation in the skewness presents the intriguing possibility that investors may want to re-balance their positions based on the conditional asymmetry of a country relative to that of other countries. This is particularly true since, as we have observed, the conditional asymmetries of emerging and developed markets are either uncorrelated or negatively correlated. The straightforward approach of taking distributional asymmetries into account is to model the joint return distribution of 73 countries. Practically speaking, this is not possible, especially since we only have 29 years worth of data. Therefore, we use a 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 our case, the characteristic of interest is the asymmetry of a country return, CA. Since the approach is still novel and has to be modified for our application, we briefly describe it below.

5.1 Methodology

The goal is to investigate whether the estimated conditional return asymmetry $CA_{i,t}\left(r_{i,t}\right)$ will help improve investors' asset allocation. The subscript i denotes country i and there are N_t number of countries at each point in time, t. Here, we concentrate exclusively on yearly returns and drop the horizon subscript n. An investor chooses portfolio weights $w_{i,t}$ to maximize the conditional expected utility of the portfolio's return $r_{p,t+1}$,

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u\left(r_{p,t+1}\right)\right] \tag{13}$$

where $r_{p,t+1} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}$. Following Brandt, Santa-Clara, and Valkanov (2009), we specify the portfolio weights of each country as

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

where $w_{i,t}^{m}$ is the weight of country i in year t in the value-weighted market portfolio, χ is a parameter to be estimated, and $\widehat{CA}_{i,t}$ is the asymmetry measure of country i, standardized in each period t to have mean zero and unit standard deviation. The normalization $1/N_t$ allows the number of countries to vary across periods without affecting the allocation. The deviation $w_{i,t}^{ca}$ from the market weight, which can be interpreted as the "actively managed" weight, tilts the portfolio toward or away from $w_{i,t}^{m}$, depending on $CA_{i,t}$ relative to the cross-sectional mean. The portfolio return can similarly be decomposed into two parts

$$r_{p,t+1} = r_{t+1}^{m} + r_{t+1}^{ca}$$

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.

While the portfolio weights are optimized over the entire cross-section of countries, we also want to report the portfolio allocations and returns on developed and emerging countries. To investigate that, we report the sum of the weights placed on DM and EM returns, which are denoted as $w_{DM,t}$ = $\sum_i 1_{i,t}^{DM} w_{i,t}$ and $w_{EM,t}$ = $\sum_i 1_{i,t}^{EM} w_{i,t}$, where $1_{i,t}^{DM}$ ($1_{i,t}^{EM}$) is an index variable that equals to one if country i is developed (emerging) at time t and zero otherwise. To capture the part of those weights that are actively managed, we define $w_{DM,t}^{ca}$ = $\sum_i 1_{i,t}^{DM} w_{i,t}^{ca}$ and $w_{EM,t}^{ca} = \sum_i 1_{i,t}^{EM} w_{i,t}^{ca}$. Since $w_{DM,t}^{ca}$ + $w_{EM,t}^{ca}$ = 0, the actively managed part captures the net re-balancing between developed and emerging markets.

The total portfolio return can be decomposed as

$$r_{p,t+1} = r_{DM,t+1} + r_{EM,t+1} \tag{14}$$

where $r_{DM,t+1} = \sum_i 1_{i,t}^{DM} w_{i,t} r_{i,t+1}$ and $r_{EM,t+1} = \sum_i 1_{i,t}^{EM} w_{i,t} r_{i,t+1}$ are the returns attributable to developed and emerging markets, respectively. The DM portfolio return can further be decomposed into a market component and an actively managed component as

$$r_{DM,t+1} = r_{DM,t+1}^{m} + r_{DM,t+1}^{ca}$$

where $r_{DM,t+1}^{m} = \sum_{i=1}^{N_t} 1_{i,t}^{DM} w_{i,t}^{m} r_{i,t+1}$ and$r_{DM,t+1}^{ca} = \sum_{i=1}^{N_t} 1_{i,t}^{DM} w_{i,t}^{ca} r_{i,t+1}$. The emerging markets returns can be decomposed in a similar fashion. In sum, the portfolio return decomposition is $r_{p,t+1} = r_{DM,t+1}^{m} + r_{DM,t+1}^{a} + r_{EM,t+1}^{m} + r_{EM,t+1}^{a}$.

Based on these decompositions, we can compute two correlations

$$\begin{aligned} &\mathrm{Corr}\left(r_{DM,t+1}^{ca}, r_{EM,t+1}^{ca}\right) \\ &\mathrm{Corr}\left(r_{DM,t+1}, r_{EM,t+1}\right). \end{aligned}$$

The correlation of the actively managed part, $\mathrm{Corr}\left(r_{DM,t+1}^{ca}, r_{EM,t+1}^{ca}\right)$, is only due to fluctuations in CA. This is the correlation of interest to us. The total correlation between the DM and EM returns, $Corr\left(r_{DM,t+1}, r_{EM,t+1}\right)$, is affected not only by allocations due to CA but also by fluctuations in the market weights.

We can augment the setup to include other conditioning information, such as volatility or other macro variables by expanding the weight function as $w_{i,t} = w_{i,t}^{m} + \chi \frac{1}{N_t} \widehat{CA}_{i,t} + \eta' \frac{1}{N_t} \widehat{H}_{i,t} = w_{i,t}^{m} + w_{i,t}^{ca} + w_{i,t}^{h}$, where $\widehat{H}_{i,t}$ is a vector of other conditioning variables, η is a vector of coefficients to estimate. We are interested in $w_{i,t}^{ca}$ which is the part of the weights due solely to fluctuations in CA. This is very much like regression analysis, where we are looking for the marginal impact of a variable. All all decompositions carry through.

5.2 Results

We follow Brandt, Santa-Clara, and Valkanov (2009) and estimate the parametric portfolio functions by maximizing the sample analogue of the expected utility function with respect to the parameters of interest. The estimates obtain using the entire panel of 73 countries over 29 years of data.

In Table 8, we present the results for a power utility function with coefficient of relative risk aversion of 5. In the first column (VW), we present the results for the benchmark, value-weighted portfolio with no country-specific characteristics. In that portfolio, the average weight placed on EM countries is 9.329 percent (w_{EM}) and the return from those countries is 0.2 percent whereas the return from the DM countries is 8.5 percent. The correlation between those two returns is 0.623, which is not surprising since most countries have a positive beta with respect to the world portfolio. Column (1) contains the estimates of the parametric portfolio weights. The estimate χ of CA implies that investors prefer positively skewed returns. It is statistically significant at conventional levels. The inclusion of CA tilts the portfolio allocation toward EM countries, because their are less negatively skewed. The average $w^{ca}_{EM,t}$ is 7.781 percent (which implies that the average $w^{ca}_{DM,t}$ is -7.781 percent). Under the value weighted portfolio, the EM countries had an average weight of 9.329 percent which now increases to 17.109 percent (9.329+7.781). This is nothing but decomposition (14) for the EM countries. More interestingly, tilting the portfolio toward positively skewed stocks produces a return from this strategy of 2.8 percent for the EM countries and 1.0 percent for the DM countries. More importantly, the estimated $\text{Corr}\left(r^{ca}_{DM,t+1}, r^{ca}_{EM,t+1}\right)$ is -0.316. This is consistent with the previous (time-series) results that the skewness of EM and DM countries is negatively correlated. It is that negative correlation in the skews that also produces a negative correlation in the returns.

The total average returns $r_{EM,t+1}$ and $r_{DM,t+1}$ of the CA strategy are 3.1 percent and 9.5 percent, respectively. Some of that return is directly traceable to the CA part (previous panel), while the rest is due to the market weights. The correlation between these two returns is -0.001, which is quite different from that of the value-weighted case. This is due to the fact that the CA characteristic allows a certain amount of diversification, as show by the $\text{Corr}\left(r^{ca}_{DM,t+1}, r^{ca}_{EM,t+1}\right)$ of -0.316. The sum of the two parts equals to the total average return of the entire portfolio, which is 12.6 percent. Notice that adding the CA information increases the average return from 8.8 percent (value-weighted case) to 12.6 percent. The volatility of the portfolio return also increases but only slightly from 20.9 percent to 21.1 percent. The certainty equivalent increases significantly as well, from -21.8 percent to -0.7 percent. This is an increase of 21.1 percent. Of course, this is an in-sample exercise.

In panel (2), we include the estimated volatility as an additional country-specific characteristic. We do so, since we have already observed a negative correlation between the skewness and volatility. We control for volatility in the portfolio policy function to prevent the skewness effect to be due purely to its negative correlation with volatility. The inclusion of the volatility does not change the results significantly. The skewness is still significant, albeit the coefficient is slightly smaller in magnitude. The coefficient of the volatility is negative and also significant.

The inclusion of the volatility in the portfolio policy does not qualitatively change the allocations and portfolio returns. The average portfolio tilt that is due to EM is 5.73 percent, which implies that EM countries have an average weight of 15.059 percent (9.329+5.73). The correlation $\mathrm{Corr}\left(r^{ca}_{DM,t+1}, r^{ca}_{EM,t+1}\right)$ is unchanged at -0.316, because it only depends on the characteristic CA, but not on the coefficient estimate of χ. Interestingly, the average return of this strategy is only 7.6 percent, but its volatility is also very low at 13.3 percent, which produces a certainly equivalent return of 3.1 percent.

In panel (3), we include the log of market capitalization over GDP (ln(E/GDP)) and the growth rate of real GDP (GDP) of all countries. These two variables are significantly correlated with the CA measure, either in the entire cross section, or in the EM or DM sub-samples (see Table 7). The two variables are also available for all countries in the 1981 to 2009 period. Including other variables would significantly reduce the time series and cross-sectional dimension of our data. Including these two controls does not alter our results: the coefficient on the skewness measure remains significant and positive. The volatility coefficient, on the other hand, is now insignificant. The added measures are both significant and positive. In other words, the optimal portfolio is tilted toward countries with positive asymmetry, higher log market capitalization to GDP ratio, and higher GDP growth rates. None of the other allocation or returns results are altered by the introduction of the additional controls. The portfolio is still tilted toward EM countries who now get 17.772 percent of the allocation because of the CA characteristic. The correlation $\mathrm{Corr}\left(r_{DM,t+1}, r_{EM,t+1}\right)$ is -0.065. Moreover, the inclusion of the extra controls increases the returns of the overall portfolio, raises its volatility, and the certainty equivalent return reaches 30.5 percent.

6 Conclusions

We use a new approach to estimate the conditional asymmetry in portfolio returns and study a large cross-section developed and emerging markets. One of the most surprising results we find is that the correlation between asymmetries of DM and EM portfolio returns is either zero or slightly negative, depending on whether or not we de-TARCH the returns. This 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. This finding has profound implications for international diversification and prompts many questions about the sources of this negative relationship.

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 CA_t is negatively related to volatility fluctuations for DM as well as EM portfolio returns. This result is consistent with the leverage effect literature. Finally, we examine to what extent the negative 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 help predict future conditional skewness, and most interestingly the negative relation between the conditional skewness of DM and EM portfolio returns can be explained by the opposite sign of exposure to macroeconomic fundamentals for DM and EM portfolio returns.

To conclude, we investigate the economic relevance of return asymmetry in an international portfolio allocation setting. Using the parametric portfolio approach of Brandt, Santa-Clara, and Valkanov (2009) we find that the optimal portfolio is tilted toward countries that are less negatively skewed, which in our setting are the emerging economies.

The are still many issues that we did not cover and leave for future research, such as the term structure of conditional asymmetry (see e.g. Ghysels, Plazzi, and Valkanov (2010)) and many econometric issues in the estimation of conditional asymmetry.

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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 returns. S denotes the standard moment-based measure of skewness, while CA denotes the quantile-based robust measure of asymmetry from expression 1. ε^G and ε^T represent the residuals from fitting a GARCH(1,1) model or a TARCH (1,1,1) model, respectively, on the return series. Three, two, and one asterisks denote statistical significance of the asymmetry measures at the 1%, 5%, and 10%, respectively, obtained through Monte Carlo simulation of a standard normal r.v.

	Initial date	N	Mean	Std	$S(r_1)$	$S(r_{t,250})$	$CA(r_{t,250})$	$S(\varepsilon_t^G)$	$S(r_{t,250}^G)$	$CA(r_{t,250}^G)$	$S(\varepsilon_t^T)$	$S(r_{t,250}^T)$	$CA(r_{t,250}^T)$
W	02/01/80	7866	0.062	0.141	-0.531***	-0.981***	-0.264***	-0.368***	-0.149	-0.220***	-0.354***	0.044	-0.212***
DM	02/01/80	7956	0.096	0.139	-0.571***	-0.956***	-0.223***	-0.400***	-0.189	-0.167**	-0.371***	0.008	-0.146*
EM	02/01/80	7956	0.093	0.184	-0.546***	-0.413*	-0.031	-0.589***	-0.179	-0.052	-0.599***	-0.214	0.019
Developed Markets													
US	02/01/80	7940	0.103	0.176	-1.048***	-1.023***	-0.129*	-0.551***	-0.383*	-0.105	-0.503***	-0.283	-0.082
Japan	02/01/80	7904	0.062	0.216	-0.035*	0.250	-0.009	-0.063**	0.464**	0.013	-0.015	0.645**	0.100
U.K.	02/01/80	7956	0.106	0.193	-0.399***	-1.157***	-0.156**	-0.379***	-0.356*	-0.073	-0.336***	-0.255	-0.119*
Hong Kong	02/01/80	7744	0.084	0.294	-2.057***	-0.604**	-0.228***	-0.890***	-0.509**	-0.367***	-1.096***	-0.41*	-0.272***
France	02/01/80	7956	0.100	0.207	-0.252***	-0.377*	-0.228***	-0.360***	-0.104	-0.265***	-0.309***	0.136	-0.210***
Canada	02/01/80	7737	0.080	0.192	-1.134***	-0.927***	-0.176**	-0.922***	-0.361*	-0.242***	-0.554***	-0.401*	-0.184**
Spain	02/01/80	7753	0.073	0.212	-0.132***	0.281	-0.114	-0.455***	0.267	0.024	-0.395***	0.414*	0.066
Germany	02/01/80	7772	0.074	0.232	-0.214***	-0.316	-0.212***	-0.562***	-0.095	-0.276***	-0.497***	0.053	-0.271***
Australia	02/01/80	7956	0.101	0.224	-1.912***	-0.690***	0.013	-0.578***	-0.409*	-0.006	-0.486***	-0.263	0.035
Switzerland	02/01/80	7956	0.105	0.173	-0.337***	-0.011	-0.189**	-0.503***	0.024	-0.245***	-0.444***	0.192	-0.237***
Italy	02/01/80	7956	0.092	0.237	-0.187***	0.714***	-0.041	-0.273***	0.622**	0.007	-0.189***	0.757***	0.022
Sweden	02/01/80	7720	0.102	0.244	0.635***	-0.629**	-0.354***	0.648***	-0.214	-0.400***	1.465***	0.012	-0.385***
Netherlands	02/01/80	7956	0.111	0.196	-0.308***	-1.647***	-0.173**	-0.327***	-0.672**	-0.158**	-0.252***	-0.612**	-0.196**
Singapore	02/01/80	7956	0.109	0.222	-0.936***	-0.200	-0.055	-0.529***	-0.341	-0.050	-0.466***	-0.202	-0.085
Belgium	02/01/80	7956	0.100	0.185	-0.239***	-0.839***	-0.151**	-0.257***	-0.429*	-0.160**	-0.181***	-0.273	-0.132*
Norway	03/01/80	7955	0.099	0.263	-0.630***	-0.713***	-0.076	-0.400***	-0.293	-0.143*	-0.345***	-0.197	-0.079
Finland	03/01/91	4987	0.088	0.297	-0.192***	-0.811***	-0.206**	-0.300***	-0.561**	-0.126*	-0.263***	-0.522**	-0.169**
Denmark	02/01/80	7668	0.111	0.222	0.562***	-0.909***	-0.103	0.814***	-0.486**	-0.080	0.815***	-0.583**	-0.116*
Austria	02/01/80	7954	0.096	0.195	-0.249***	0.548**	0.255***	-0.429***	0.549**	0.222***	-0.306***	0.703***	0.263***
Ireland	02/01/80	7954	0.098	0.214	-0.754***	-0.966***	-0.212***	-0.481***	-0.121	-0.180**	-0.431***	-0.046	-0.171**
Iceland	05/01/93	4463	-0.022	0.347	-29.197***	-2.598***	-0.328***	-0.644***	-0.828***	-0.262***	-0.725***	-0.866***	-0.265***
Developing Markets													
China	04/04/91	4965	0.102	0.386	-0.383***	0.379*	0.373***	-0.656***	0.368*	0.195**	-0.374***	0.346	0.231***
Brazil	13/04/83	6939	0.109	0.628	0.567***	-0.638**	-0.276***	3.820***	-0.438*	-0.362***	0.369***	-0.463**	-0.293***
India	05/01/87	5964	0.088	0.288	-0.030	-0.412*	0.048	-0.236***	-0.128	0.083	0.063**	-0.169	0.123*
South Korea	02/01/80	7780	0.059	0.326	-0.391***	-0.735***	0.013	-0.358***	-0.217	-0.083	-0.410***	-0.185	-0.044
South Africa	02/01/80	7956	0.102	0.268	-0.530***	-0.244	0.041	-0.720***	-0.365*	-0.071	-0.654***	-0.292	-0.086
Taiwan	03/01/85	6514	0.083	0.311	-0.110***	0.057	0.041	-0.194***	0.272	-0.019	-0.078***	0.051	0.003
Russia	04/09/95	3468	0.120	0.444	-0.520***	-1.222***	-0.006	-0.385***	-0.682***	-0.164**	-0.239***	-0.652**	-0.172**
Mexico	05/01/88	5769	0.163	0.315	-0.413***	-0.932***	-0.227***	-0.380***	-0.370*	-0.132*	-0.689***	-1.102***	-0.232***

	Initial date	N	Mean	Std	$S(r_1)$	$S(r_{t,250})$	$CA(r_{t,250})$	$S(\varepsilon_t^G)$	$S(r_{t,250}^G)$	$CA(r_{t,250}^G)$	$S(\varepsilon_t^T)$	$S(r_{t,250}^T)$	$CA(r_{t,250}^T)$
Malaysia	03/01/80	7829	0.055	0.260	-1.384***	-0.803***	-0.071	-0.836***	-0.338	-0.118*	-1.144***	-0.293	-0.080
Turkey	05/01/88	5815	0.059	0.507	-0.195***	0.0790	-0.172**	-0.263***	-0.142	-0.124*	-0.226***	-0.058	-0.083
Chile	05/01/87	6008	0.130	0.190	-0.274***	-0.0170	-0.102	-0.283***	-0.176	-0.052	-0.269***	-0.128	-0.067
Indonesia	03/04/90	5282	0.008	0.436	-0.720***	-1.124***	-0.246***	-2.148***	-0.531**	-0.148**	-2.070***	-0.563**	-0.202**
Israel	24/04/87	6019	0.092	0.276	-0.344***	-0.587**	-0.306***	-0.375***	-0.477**	-0.287***	-0.352***	-0.509**	-0.326***
Thailand	05/01/87	6128	0.099	0.316	0.059**	-0.950***	-0.011	-0.306***	-0.557**	-0.022	-0.313***	-0.556**	-0.038
Poland	17/04/91	4897	0.109	0.350	-0.185***	1.157***	0.180**	-0.486***	0.377*	0.239***	-0.441***	0.695***	0.241***
Kuwait	29/12/94	4023	0.086	0.173	-0.003	-1.249***	-0.311***	6.993***	-0.692***	-0.206**	5.389***	-0.786***	-0.209***
Colombia	11/03/92	4774	0.109	0.216	-1.521***	0.122	-0.061	-1.780***	0.127	0.039	-2.051***	0.110	-0.029
Greece	03/10/88	5563	0.029	0.296	-0.030	0.070	-0.318***	0.078***	0.078	-0.297***	0.080***	0.169	-0.310***
Egypt	03/01/95	4001	0.068	0.245	-0.473***	-0.092	0.018	-0.092***	0.091	-0.085	-0.185***	0.112	-0.093
Philippines	03/01/86	6241	0.09	0.311	0.220***	0.060	-0.153**	0.469***	-0.228	-0.112	0.382***	-0.153	-0.083
Ukraine	02/02/98	3163	0.068	0.437	3.721***	-1.209***	-0.125*	4.445***	-1.323***	-0.153**	3.721***	-1.209***	-0.125*
Portugal	06/01/88	5740	0.028	0.189	-0.135***	-0.614**	-0.065	-0.374***	-0.102	-0.048	-0.373***	-0.025	-0.022
Peru	03/01/91	4989	0.218	0.272	-0.131***	-0.045	-0.058	-0.329***	-0.021	-0.009	-0.373***	-0.171	0.018
Nigeria	03/07/95	3760	0.114	0.197	-0.241***	-1.195***	-0.131*	-0.318***	-0.465**	-0.071	-0.400***	-0.494**	-0.099
Argentina	03/08/93	4323	0.002	0.373	-0.973***	-0.485**	-0.258***	-0.531***	-0.208	-0.361***	-0.574***	-0.239	-0.319***
Czech Republic	10/11/93	4337	0.129	0.275	0.698***	-0.443*	-0.294***	0.047**	-0.027	-0.102	0.387***	-0.076	-0.106
New Zealand	05/01/88	5867	0.076	0.205	-0.306***	-0.874***	-0.139*	-0.389***	-0.456**	-0.096	-0.401***	-0.478**	-0.088
Pakistan	02/01/89	5470	0.063	0.269	-0.267***	-0.492**	-0.161**	-0.234***	-0.151	-0.176**	-0.246***	-0.192	-0.208***
Jordan	22/11/88	5499	0.062	0.186	-0.221***	0.865***	0.172**	-0.235***	0.605**	0.087	-0.208***	0.738***	0.057
Saudi Arabia	05/01/98	2276	0.136	0.251	-1.236***	-0.456**	-0.24***	-0.175***	-0.105	-0.316***	-1.358***	-0.444*	-0.206**
Hungary	03/01/91	5000	0.077	0.320	-0.460***	-0.513**	-0.135*	-0.610***	-0.148	-0.180**	-0.509***	-0.052	-0.178**
Bangladesh	02/01/90	5056	0.063	0.302	-0.151***	-0.450*	-0.143*	1.571***	0.089	-0.091	-0.151***	-0.450*	-0.143*
Romania	22/09/97	3278	-0.010	0.340	-0.320***	-0.943***	-0.283***	-0.057**	-0.763***	-0.297***	0.059**	-0.650**	-0.213***
Croatia	03/01/97	3461	0.056	0.306	-0.015	-1.165***	-0.257***	-0.169***	-0.327	-0.191**	0.032	-0.335	-0.216***
Oman	23/10/96	3517	0.078	0.192	0.264***	-0.491**	-0.131*	-0.318***	-0.249	-0.226***	0.264***	-0.491**	-0.131*
Slovenia	03/01/94	4233	0.044	0.220	-0.361***	-0.714***	-0.134*	-0.417***	-0.030	-0.038	-0.503***	-0.360*	0.038
Trinidad and Tobago	03/01/96	3581	0.118	0.172	4.834***	0.282	0.086	5.083***	0.348*	0.161**	4.834***	0.282	0.086
Kenya	12/01/90	5188	0.013	0.270	0.284***	0.782***	0.118*	-14.836***	0.057	0.037	0.284***	0.782***	0.118*
Sri Lanka	03/01/85	6323	0.091	0.203	0.401***	0.055	-0.035	0.880***	-0.067	-0.093	0.928***	-0.079	-0.104
Tunisia	05/01/98	3230	0.098	0.106	0.058**	0.293	-0.060	0.373***	0.370*	0.080	0.396***	0.312	0.048
Venezuela	03/01/90	5346	0.056	0.446	-5.900***	0.038	-0.120*	-8.986***	-0.156	-0.076	-5.900***	0.038	-0.12*
Bulgaria	23/10/00	2488	0.165	0.313	-0.612***	-1.512***	-0.197**	0.312***	-1.019***	-0.018	0.288***	-0.954***	0.015
Morocco	05/01/88	5760	0.123	0.183	0.268***	-0.475**	-0.030	1.523***	-0.450*	0.071	1.345***	-0.468**	0.028
Slovakia	15/09/93	4292	0.033	0.268	1.247***	0.303	-0.185**	-0.612***	0.337	-0.065	-0.432***	0.213	-0.239***
Lithuania	03/01/00	2689	0.129	0.219	-0.333***	-1.008***	-0.218***	-0.475***	-0.228	-0.248***	-0.615***	-0.274	-0.260***
Ecuador	03/08/93	2985	-0.016	0.288	0.720***	-0.183	-0.16**	-2.672***	-0.014	-0.387***	-1.996***	0.448*	-0.052
Botswana	03/01/96	3692	0.153	0.226	6.622***	-0.313	-0.029	6.622***	-0.313	-0.029	6.622***	-0.313	-0.029
Malta	28/12/95	3703	0.072	0.158	0.640***	-0.031	0.210***	0.546***	-0.170	0.015	0.494***	-0.156	0.017
Latvia	04/01/00	2679	0.102	0.275	-0.606***	-1.748***	-0.279***	0.554***	-0.990***	-0.064	0.489***	-1.026***	-0.142*
Ghana	03/01/96	3460	-0.079	0.189	2.780***	0.005	-0.426***	2.922***	0.055	-0.418***	2.780***	0.005	-0.426***
Namibia	01/02/00	2659	0.048	0.207	0.187***	-0.535**	-0.295***	0.491***	-0.660**	-0.309***	0.358***	-0.561**	-0.277***
Estonia	04/06/96	3596	0.094	0.287	-0.888***	-0.537**	0.096	-0.167***	-0.057	0.126*	-0.099***	-0.015	0.138*

Table continued from previous page.

Table 2: Conditional Quantile Estimates of 5 Portfolio Returns

Estimated $\widehat{\alpha}$ and $\widehat{\beta}$, and corresponding p-values, of the MIDAS quantile regression of equation (6) for the 25th, 50th, and 75th quantiles of the World Index, Developed Markets Index, Emerging Markets Index, US, and China. The regressors are 250-day lagged absolute returns. The Table also shows the average Hit, defined as in $Hit_{\theta,n,t} \equiv \theta - 1\{\varepsilon_{\theta,n,t} < 0\}$. Panel A reports the results for the returns series r_t, Panel B for the GARCH(1,1)-filtered returns ε^G, and Panel C for the TARCH(1,1)-filtered returns ε^G.

	World			Developed			Emerging			U.S.			China		
Panel A : r															
	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}
$\widehat{\alpha}$	0.276	0.148	0.124	0.268	0.089	0.144	-0.299	0.039	0.228	0.238	0.191	0.250	-0.097	0.064	0.733
pval-$\widehat{\alpha}$	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.163	0.000	0.000	0.000	0.000	0.003	0.095	0.000
$\widehat{\beta}$	-54.404	-9.065	7.203	-48.636	7.415	9.039	25.626	9.620	11.280	-33.783	-8.319	-4.548	-7.056	-4.824	-24.424
pval-$\widehat{\beta}$	0.000	0.106	0.061	0.000	0.078	0.019	0.000	0.003	0.000	0.000	0.041	0.151	0.000	0.030	0.000
Avg Hit $\times 10^2$	-0.010	-0.007	-0.003	-0.010	0.006	0.010	0.003	-0.006	0.023	0.010	-0.020	-0.010	-0.011	0.000	0.011
Panel B : ε^G															
	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}
$\widehat{\alpha}$	0.998	0.370	0.409	1.015	0.376	0.406	0.067	0.446	0.704	0.335	0.297	0.285	-0.288	-0.375	0.471
pval-$\widehat{\alpha}$	0.000	0.012	0.001	0.000	0.011	0.001	0.518	0.005	0.000	0.004	0.025	0.003	0.000	0.024	0.000
$\widehat{\beta}$	-152.520	-44.787	-35.849	-154.800	-46.355	-34.340	-39.897	-57.334	-64.614	-60.938	-38.144	-22.640	12.713	44.520	-48.648
pval-$\widehat{\beta}$	0.000	0.020	0.031	0.000	0.017	0.028	0.004	0.007	0.009	0.000	0.034	0.082	0.217	0.067	0.014
Avg Hit $\times 10^2$	-0.051	-0.400	-0.424	0.613	-0.227	-0.198	-0.049	0.045	-0.418	0.140	-0.618	-0.036	0.034	-0.336	0.123
Panel C : ε^T															
	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}	Q_{25}	Q_{50}	Q_{75}
$\widehat{\alpha}$	0.947	0.423	0.402	0.863	0.447	0.447	-0.299	-0.057	0.099	0.243	0.449	0.458	-0.356	-0.285	0.297
pval-$\widehat{\alpha}$	0.000	0.002	0.001	0.000	0.001	0.000	0.000	0.098	0.001	0.013	0.000	0.000	0.000	0.005	0.000
$\widehat{\beta}$	-140.970	-49.919	-33.760	-129.890	-52.965	-37.993	33.814	13.469	8.626	-48.391	-58.755	-46.509	25.875	31.806	-22.664
pval-$\widehat{\beta}$	0.000	0.006	0.030	0.000	0.003	0.007	0.000	0.029	0.094	0.000	0.000	0.000	0.022	0.034	0.018
Avg Hit $\times 10^2$	0.085	-0.197	-0.193	0.276	0.006	-0.185	0.016	0.006	-0.003	0.036	0.046	-0.361	0.056	-0.022	-0.034

Table 3: Summary Statistics of Conditional Asymmetry Estimates (CA) of 5 Portfolio Returns

Summary statistics for the daily series of 250-day robust measure of conditional asymmetry (CA) for the World Index (W), Developed Markets Index (DM), Emerging Markets Index (EM), US, China (CHA), average across developed markets excluding the US ($\overline{DM_i}$) and average emerging market excluding China ($\overline{EM_i}$). The left hand side of the Table reports Mean; Standard deviation (Std); Minimum (Min); Maximum (Max); OLS coefficient on a time trend (Trend), with two and three asterisks denoting statistical significance at the 5% and 1% level, respectively, based on Newey-West standard errors with 60 lags. The right hand side of the Table shows the correlation matrix. Results are reported for the raw 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	$\overline{DM_i}$	$\overline{EM_i}$
Mean	-0.258	-0.230	-0.039	-0.153	0.041	-0.132	-0.102
Std	0.198	0.349	0.194	0.223	0.174	0.179	0.209
Min	-0.690	-0.880	-0.339	-0.771	-0.652	-0.683	-0.810
Max	0.606	0.898	0.988	0.941	0.514	0.659	0.698
Trend	-0.009	-0.035***	-0.036***	-0.017**	0.014**	-0.014	-0.019

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.714	1					
EM	-0.224	-0.316	1				
US	0.678	0.695	-0.312	1			
CHA	-0.350	-0.375	0.055	-0.315	1		
$\overline{DM_i}$	0.204	0.253	-0.077	0.158	-0.069	1	
$\overline{EM_i}$	-0.006	-0.028	0.085	-0.020	-0.006	0.003	1

Panel B: ε^G

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
Mean	-0.245	-0.188	-0.084	-0.149	-0.014	-0.098	-0.071
Std	0.209	0.190	0.112	0.097	0.161	0.162	0.218
Min	-0.630	-0.588	-0.435	-0.989	-0.751	-0.681	-0.694
Max	0.631	0.645	0.192	0.250	0.627	0.615	0.633
Trend	-0.010	-0.018**	0.000	-0.002	-0.001	-0.008	-0.009

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.949	1					
EM	-0.028	-0.040	1				
US	0.276	0.269	0.000	1			
CHA	-0.245	-0.318	0.015	0.054	1		
$\overline{DM_i}$	0.032	0.029	0.023	0.069	0.015	1	
$\overline{EM_i}$	0.002	-0.003	0.033	0.049	-0.005	0.015	1

Panel C: ε^T

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
Mean	-0.223	-0.201	0.053	-0.128	0.038	-0.094	-0.057
Std	0.137	0.156	0.153	0.075	0.095	0.149	0.226
Min	-0.526	-0.636	-0.587	-0.259	-0.485	-0.646	-0.710
Max	0.542	0.426	0.710	0.719	0.368	0.444	0.683
Trend	-0.005	-0.009*	0.002	-0.002	0.001	-0.007	-0.013

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
W	1						
DM	0.830	1					
EM	0.083	0.061	1				
US	-0.186	0.020	0.164	1			
CHA	-0.259	-0.217	0.075	0.265	1		
$\overline{DM_i}$	-0.006	-0.018	0.036	0.013	0.000	1	
$\overline{EM_i}$	0.006	-0.007	0.029	0.012	0.001	0.014	1

Table 4: Conditional Asymmetry of Systematic and Idiosyncratic Components - Summary Statistics

Summary statistics for the regression of each portfolios' CA on the asymmetry of the World Index. Results are shown for the Developed Markets Index (DM), Emerging Markets Index (EM), US, China (CHA), average across developed markets excluding the US ($\overline{DM_i}$), and average across emerging market excluding China ($\overline{EM_i}$). The left hand side of the Table reports the intercept (α) and slope (β) OLS estimates, their p-values based on Newey-West standard errors with 60 lags, and the corresponding R^2. The right hand side of the Table shows the correlation matrix of the estimated residuals. Results are reported for the raw 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	$\overline{DM_i}$	$\overline{EM_i}$
α	0.094	-0.096	0.044	0.163	-0.058	-0.119
pval-α	0.010	0.000	0.037	0.005	0.070	0.047
β	1.256	-0.219	0.763	-0.463	0.213	-0.018
pval-β	0.000	0.001	0.000	0.005	0.013	0.117
R^2	0.510	0.050	0.460	0.123	0.119	0.051

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
DM	1					
EM	-0.230	1				
US	0.411	-0.224	1			
CHA	-0.170	-0.089	-0.119	1		
$\overline{DM_i}$	0.169	-0.036	0.034	0.023	1	
$\overline{EM_i}$	-0.034	0.090	-0.023	-0.005	0.003	1

Panel B: ε^G

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
α	0.023	-0.088	-0.118	0.165	-0.074	-0.083
pval-α	0.010	0.000	0.000	0.000	0.030	0.035
β	0.861	-0.015	0.128	-0.229	0.069	-0.017
pval-β	0.000	0.314	0.000	0.011	0.097	0.097
R^2	0.900	0.001	0.076	0.060	0.065	0.046

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
DM	1					
EM	-0.048	1				
US	0.021	0.008	1			
CHA	-0.299	0.007	0.122	1		
$\overline{DM_i}$	-0.003	0.026	0.063	0.026	1	
$\overline{EM_i}$	-0.016	0.036	0.050	-0.007	0.015	1

Panel C: ε^T

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
α	0.010	0.073	-0.151	0.211	-0.078	-0.073
pval-α	0.202	0.000	0.000	0.000	0.020	0.037
β	0.947	0.092	-0.102	-0.394	0.025	-0.037
pval-β	0.000	0.079	0.000	0.015	0.058	0.100
R^2	0.690	0.007	0.035	0.067	0.114	0.073

	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
DM	1					
EM	-0.018	1				
US	0.318	0.185	1			
CHA	0.009	0.118	0.198	1		
$\overline{DM_i}$	-0.028	0.036	0.011	-0.001	1	
$\overline{EM_i}$	-0.019	0.029	0.011	0.003	0.016	1

Table 5: Relation between Conditional Asymmetry and Conditional Volatility

Summary statistics for each portfolios' CA on its conditional volatility using regression (11) with asymmetry estimates based on simple, de-GARCHed and de-TARCHed returns and then regress $\widehat{CA}_{i,t}$ on $\widehat{Vol}_{i,t}$ which involves squared daily returns (since we are estimating volatility it does not make sense to de-GARCH or de-TARCH the returns). Results are shown for the World Index (W), Developed Markets Index (DM), Emerging Markets Index (EM), US, China (CHA), average across developed markets excluding the US ($\overline{DM_i}$), and average across emerging market excluding China ($\overline{EM_i}$). The left hand side of the Table reports the intercept (α) and slope (β) OLS estimates, their p-values based on Newey-West standard errors with 60 lags, and the corresponding R^2. The right hand side of the Table shows the correlation matrix of the estimated residuals. Results are reported for the raw 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	$\overline{DM_i}$	$\overline{EM_i}$		W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
α	0.122	0.758	-0.417	0.414	0.999	0.159	0.245	W	1						
pval-α	0.191	0.002	0.000	0.005	0.000	0.066	0.036	DM	0.677	1					
								EM	-0.148	-0.326	1				
β	-2.918	-7.778	2.243	-3.560	-2.134	-1.208	-3.955	US	0.641	0.632	-0.301	1			
pval-β	0.003	0.000	0.000	0.000	0.000	0.027	0.041	CHA	-0.021	0.197	-0.126	-0.073	1		
								$\overline{DM_i}$	0.144	0.172	-0.029	0.081	0.021	1	
R^2	0.097	0.217	0.199	0.185	0.587	0.241	0.263	$\overline{EM_i}$	0.002	-0.006	0.060	-0.001	0.020	0.005	1

Panel B: ε^G

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$		W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
α	0.239	0.286	-0.025	0.009	0.672	0.050	-0.121	W	1						
pval-α	0.037	0.013	0.230	0.361	0.000	0.035	0.035	DM	0.942	1					
								EM	-0.096	-0.109	1				
β	-3.725	-3.737	-0.352	-0.996	-1.340	-0.653	-0.148	US	0.207	0.194	-0.037	1			
pval-β	0.000	0.000	0.035	0.000	0.000	0.056	0.039	CHA	-0.049	-0.074	0.223	0.083	1		
								$\overline{DM_i}$	0.026	0.019	0.010	0.040	0.007	1	
R^2	0.142	0.169	0.015	0.076	0.376	0.080	0.185	$\overline{EM_i}$	-0.002	-0.010	0.036	0.053	0.032	0.014	1

Panel C: ε^T

	W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$		W	DM	EM	US	CHA	$\overline{DM_i}$	$\overline{EM_i}$
α	0.077	0.076	0.265	-0.193	0.729	-0.032	-0.186	W	1						
pval-α	0.202	0.208	0.000	0.000	0.000	0.066	0.064	DM	0.815	1					
								EM	-0.034	-0.027	1				
β	-2.304	-2.186	-1.259	0.403	-1.289	-0.218	0.786	US	-0.160	0.055	0.201	1			
pval-β	0.000	0.001	0.000	0.004	0.000	0.040	0.046	CHA	0.093	0.086	0.177	0.018	1		
								$\overline{DM_i}$	-0.011	-0.023	0.024	0.012	-0.048	1	
R^2	0.127	0.085	0.100	0.021	0.308	0.113	0.236	$\overline{EM_i}$	0.023	0.003	0.039	-0.001	0.005	0.014	1

Table 6: 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 conditional volatility of a country's stock market, a measure of liquidity (LIQ), turnover (TURN), a country's stock market relative to its nominal GDP (E/GDP), the number of companies listed in the Exchange (NCOMP), a short-term interbank or government bond yield (T-bill) and the spread between a long-term and the short-term rate (TSPR), the growth rate of real GDP (GDPg) and the volatility of quarterly real GDP growth. 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 (Csd) 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	Csd	Mean	Csd	Vol	E/GDP	TURN	NCOMP	LIQ	Tbill	TSPR	GDPg	VOLGDP
CA	-0.097	0.157	0.213	0.106	-0.139	-0.041	-0.062	-0.031	-0.082	0.028	0.052	0.009	-0.064
VOL	0.244	0.076	0.042	0.026		-0.127	0.212	-0.016	0.414	0.102	-0.113	-0.146	0.205
E/GDP	-1.406	0.913	0.841	0.425			0.271	0.371	-0.142	-0.494	0.046	0.199	-0.269
TURN	3.343	1.175	0.731	0.415				0.181	0.140	-0.200	-0.058	0.071	-0.007
NCOMP	5.222	1.353	0.444	0.418					-0.037	-0.194	0.040	0.013	-0.184
LIQ	-0.009	0.004	0.006	0.003						0.187	-0.051	-0.089	0.229
Tbill	13.601	15.187	12.469	26.237							-0.523	-0.048	0.125
TSPR	0.352	2.136	2.703	3.483								-0.102	0.018
GDPg	0.033	0.019	0.038	0.021									-0.292
VOLGDP	0.051	0.024	0.021	0.022									1

Panel B: Developed Markets

	Mean		Standard Deviation		Correlations								
	Avg	Csd	Mean	Csd	Vol	E/GDP	TURN	NCOMP	LIQ	Tbill	TSPR	GDPg	σ(GDPg)
CA	-0.118	0.156	0.194	0.083	-0.319	-0.046	-0.223	-0.047	-0.284	0.019	0.118	0.047	-0.080
VOL	0.209	0.034	0.043	0.023		-0.034	0.352	0.077	0.478	-0.095	-0.023	-0.179	0.104
E/GDP	-0.729	0.717	0.737	0.211			0.269	0.418	-0.122	-0.631	0.056	0.182	-0.388
TURN	4.333	0.411	0.478	0.197				0.202	0.162	-0.338	-0.074	-0.097	-0.001
NCOMP	5.976	1.333	0.301	0.215					-0.088	-0.267	0.069	0.047	-0.178
LIQ	-0.007	0.001	0.004	0.002						0.100	-0.076	-0.078	0.180
Tbill	6.474	2.210	4.015	1.366							-0.612	0.167	0.301
TSPR	0.733	0.575	1.549	0.517								-0.229	-0.095
GDPg	0.027	0.013	0.024	0.009									-0.238
VOLGDP	0.048	0.018	0.014	0.005									1

Panel C: Emerging Markets

	Mean		Standard Deviation		Correlations								
	Avg	Csd	Mean	Csd	Vol	E/GDP	TURN	NCOMP	LIQ	Tbill	TSPR	GDPg	VOLGDP
CA	-0.089	0.158	0.221	0.114	-0.066	-0.039	0.004	-0.025	-0.001	0.031	0.013	-0.006	-0.055
VOL	0.258	0.083	0.041	0.027		-0.164	0.154	-0.054	0.388	0.182	-0.166	-0.132	0.264
E/GDP	-1.679	0.842	0.881	0.480			0.272	0.351	-0.149	-0.439	0.040	0.205	-0.200
TURN	2.936	1.145	0.832	0.437				0.172	0.132	-0.143	-0.048	0.140	-0.010
NCOMP	4.911	1.246	0.508	0.466					-0.015	-0.164	0.023	-0.001	-0.187
LIQ	-0.010	0.004	0.006	0.003						0.222	-0.037	-0.093	0.258
Tbill	16.479	17.157	15.884	30.493							-0.472	-0.135	0.023
TSPR	0.130	2.641	3.377	4.241								-0.029	0.112
GDPg	0.035	0.020	0.044	0.021									-0.324
VOLGDP	0.053	0.027	0.025	0.027									1

Table 7: Financial and Economic Determinants of Conditional Asymmetry

The table reports OLS estimates of the pooled regression of the conditional asymmetry of each country's stock market on a constant (Const), a time trend (Trend), the conditional volatility of the stock market VOL, the logarithm of the ratio between the stock market capitalization and the nominal GDP (E/GDP), the logarithm of the Turnover and of the number of companies listed in the Exchange (TURN and NCOMP), the relative bid-ask spread as defined in Roll (1984) (LIQ), the short-term nominal interest rate (Tbill), the Term Spread (TSPR), real GDP growth (GDP) and its volatility measured on the last three years of the quarterly series (Vol(GDP)). All variables are sampled at annual frequency from (at most) 1981 until 2009. Below the estimates, two t-statistics are reported based on standard errors calculated using the standard OLS (homoskedastic) formula (round brackets) or clustered by year and country (square brackets). In specifications (1) to (3), the dependent variable is the conditional asymmetry of the returns series, while in specification (4) it is the conditional asymmetry of the residuals from a TARCH(1,1) model. N denotes the total number of available observations for each specification.

	World				DM				EM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VOL	-0.526	-0.708	-0.983	-0.780	-1.415	-1.196	-0.845	-0.049	-0.519	-0.706	-1.306	-1.486
	(-6.858)***	(-6.479)***	(-4.721)***	(-3.984)***	(-7.700)***	(-4.140)***	(-2.828)***	(-0.197)	(-5.664)***	(-5.872)***	(-4.766)***	(-4.973)***
	[-3.361]***	[-4.008]***	[-3.639]***	[-2.190]**	[-3.567]***	[-2.730]***	[-1.826]*	[-0.095]	[-3.266]***	[-3.313]***	[-2.778]***	[-3.331]***
E/GDP		-0.034	-0.048	-0.032		-0.064	-0.103	-0.124		-0.018	-0.030	0.000
		(-3.659)***	(-3.293)***	(-2.356)**		(-2.913)***	(-4.009)***	(-5.818)***		(-1.701)	(-1.707)*	(0.008)
		[-2.006]**	[-1.941]*	[-1.264]		[-1.191]	[-1.824]*	[-2.453]***		[-0.869]	[-1.198]	[0.005]
TURN		-0.004	0.028	0.024		-0.059	-0.078	-0.042		0.000	0.061	0.044
		(-0.515)	(2.027)**	(1.819)*		(-2.054)**	(-2.506)***	(-1.624)***		(0.048)	(3.784)***	(2.517)***
		[-0.361]	[1.662]*	[1.412]		[-1.747]*	[-2.060]**	[-0.810]		[0.036]	[5.109]***	[4.523]***
NCOMP		0.020	0.007	0.011		0.000	-0.025	0.008		0.032	0.025	0.019
		(2.783)***	(0.712)	(1.164)		(-0.015)	(-1.653)*	(0.626)		(3.609)	(1.774)*	(1.218)
		[1.230]	[0.362]	[0.599]		[-0.007]	[-0.959]	[0.320]		[1.884]	[1.574]	[1.720]*
LIQ		-0.573	0.129	6.872		-9.411	-14.058	-3.648		-0.017	6.691	12.314
		(-0.393)	(0.047)	(2.650)***		(-2.200)**	(-2.877)***	(-0.895)		(-0.011)	(2.135)**	(3.603)***
		[-0.288]	[0.035]	[1.849]*		[-1.642]	[-2.065]**	[-0.515]		[-0.007]	[2.047]**	[3.462]***
Tbill			1.218	0.145			-3.070	-4.491			1.601	1.166
			(2.890)***	(0.366)			(-2.613)***	(-4.581)***			(3.310)***	(2.210)**
			[1.673]*	[0.179]			[-1.744]*	[-2.679]***			[2.495]**	[1.586]
TSPR			1.352	1.484			-2.538	-4.959			1.300	1.875
			(2.206)**	(2.573)***			(-1.158)	(-2.713)***			(2.152)**	(2.845)***
			[1.469]	[1.311]			[-1.059]	[-1.847]*			[1.420]	[1.707]*
GDPg			-0.719	-0.752			-0.319	0.580			-1.372	-1.271
			(-1.635)	(-1.819)*			(-0.354)	(0.772)			(-2.659)***	(-2.259)**
			[-1.276]	[-1.308]			[-0.416]	[0.489]			[-2.143]**	[-2.296]**
VOLGDP			-0.840	-1.254			-3.388	-2.481			-1.634	-1.651
			(-1.534)	(-2.433)**			(-3.184)***	(-2.795)***			(-2.600)***	(-2.41)**
			[-1.212]	[-1.721]*			[-2.254]**	[-1.639]			[-2.348]**	[-2.479]**
Trend	-0.002	-0.004	0.004	0.000	-0.001	0.002	-0.003	-0.010	-0.005	-0.004	0.015	0.011
	(-2.486)**	(-2.433)**	(1.252)	(0.134)	(-1.245)	(0.633)	(-0.667)	(-2.213)**	(-3.348)***	(-2.048)**	(3.326)***	(2.230)**
	[-1.904]*	[-2.221]**	[0.927]	[0.092]	[-1.206]	[0.470]	[-0.528]	[-1.467]	[-3.047]***	[-1.88]*	[3.292]***	[1.910]*
Const	0.070	0.037	-0.178	-0.085	0.204	0.373	0.987	0.590	0.145	-0.015	-0.564	-0.320
	(2.850)***	(0.608)	(-1.652)*	(-0.836)	(5.087)***	(2.951)***	(4.138)***	(2.967)***	(3.569)***	(-0.216)	(-3.916)***	(-2.039)**
	[1.350]	[0.299]	[-1.213]	[-0.640]	[2.196]**	[1.718]*	[3.261]***	[1.644]	[2.340]**	[-0.112]	[-3.616]***	[-2.242]**
R^2	0.037	0.068	0.095	0.103	0.104	0.175	0.246	0.190	0.043	0.068	0.181	0.191
N	1467	1066	538	538	581	302	281	281	886	764	257	257

Table 8: International Portfolio Allocation

This table shows estimates of the portfolio policy in equation (13) 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 aversions of 5 (columns 1-4), 3 (columns 5-8), and 7 (columns 9-12). Column (VW) displays the benchmark results of value-weighted weights without any conditioning information. Column (1) displays the results with the CA measure; in column (2), the estimated annual volatility (VOL) is added; in column (3), the log market capitalization of the country's stock market relative to its GDP (E/GDP) and the real growth rate of GDP (GDPg) are added. Column (4) displays the results for the de-tarched CA measure. We use annual data for all 73 countries during the 1981–2009 period. Standard errors are reported in parenthesis below the coefficients. LRT 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 $corr(r_{EM}^{CA}, r_{DM}^{CA})$ is the correlation between these returns. The next panel displays the same measures but for the entire strategy (market+CA). The last panel displays 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.

		$\gamma = 5$				$\gamma = 3$				$\gamma = 7$			
	(VW)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CA	—	2.932	2.159	3.182	1.300	3.473	3.249	4.922	1.161	2.774	1.683	2.481	1.351
Std.Err.	—	(0.980)	(1.072)	(1.288)	(0.532)	(1.488)	(1.623)	(2.095)	(0.860)	(0.739)	(0.811)	(0.931)	(0.383)
VOL	—		-1.575	-0.075			-0.619	1.974			-1.990	-0.875	
Std.Err.			(0.710)	(0.942)			(1.114)	(1.618)			(0.527)	(0.666)	
E/GDP				2.757				5.112				1.845	
Std.Err.				(1.325)				(2.203)				(0.965)	
GDPg				3.799				5.463				3.088	
Std.Err.				(1.109)				(1.712)				(0.815)	
LRT p-value		0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.489	0.000	0.000	0.000	0.000
$w_{EM}^{CA} \times 100$	—	7.781	5.730	8.444	2.121	9.216	8.622	13.062	1.894	7.360	4.467	6.583	2.203
r_{EM}^{CA}	—	0.028	0.021	0.031	-0.010	0.033	0.031	0.047	-0.009	0.027	0.016	0.024	-0.010
r_{DM}^{CA}	—	0.010	0.008	0.011	0.004	0.012	0.011	0.017	0.004	0.010	0.006	0.009	0.004
$corr(r_{EM}^{CA}, r_{DM}^{CA})$	—	-0.316	-0.316	-0.316	-0.092	-0.316	-0.316	-0.316	-0.092	-0.316	-0.316	-0.316	-0.092
$w_{EM} \times 100$	9.329	17.109	15.059	17.772	11.450	18.545	17.951	22.391	11.223	16.689	13.796	15.912	11.532
r_{EM}	0.002	0.031	0.001	0.188	-0.007	0.036	0.025	0.301	-0.006	0.029	-0.009	0.142	-0.008
r_{DM}	0.085	0.095	0.075	0.092	0.089	0.097	0.089	0.135	0.089	0.095	0.069	0.075	0.090
$corr(r_{EM}, r_{DM})$	0.623	-0.001	-0.247	-0.065	0.299	-0.077	-0.146	0.004	0.336	0.025	-0.338	-0.112	0.286
$\bar{r}$	0.088	0.126	0.076	0.280	0.082	0.133	0.114	0.436	0.083	0.124	0.059	0.217	0.082
$\sigma(r)$	0.209	0.211	0.133	0.305	0.207	0.219	0.188	0.489	0.206	0.208	0.114	0.233	0.208
CE(r)	-0.218	-0.007	0.031	0.136	-0.103	0.056	0.060	0.214	-0.010	-0.072	0.014	0.104	-0.194
β	—	0.814	0.430	0.622	0.929	0.780	0.624	1.019	0.937	0.824	0.347	0.472	0.927

Figure 1: Rolling Estimates of Skewness and Robust Asymmetry Measures

Skewness S (top plot) - using the sample average of the third power of returns - and robust asymmetry CA (bottom plot) using equation (1) - for the Developed Markets and Emerging Market indices based on a 250-day rolling window of daily returns.

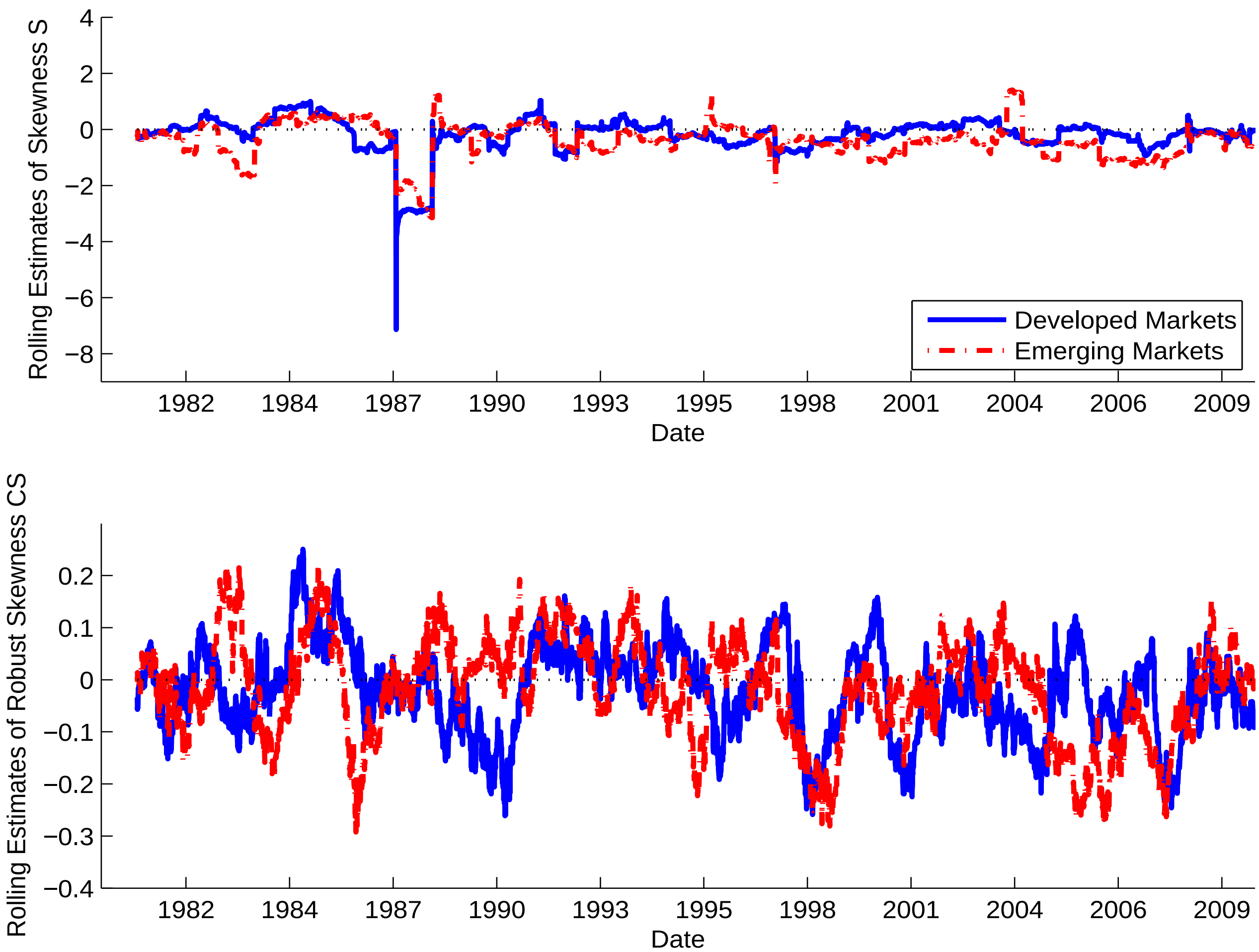


Figure 2: Conditional Quantile Estimates of Annual Returns: World, Developed Markets, and Emerging Markets

Estimated 25th, 50th, and 75th conditional quantiles using estimates specified in (6) involving 250-day lagged daily absolute returns, for the World Index (top), Developed Markets Index (middle), and Emerging Markets Index (bottom).

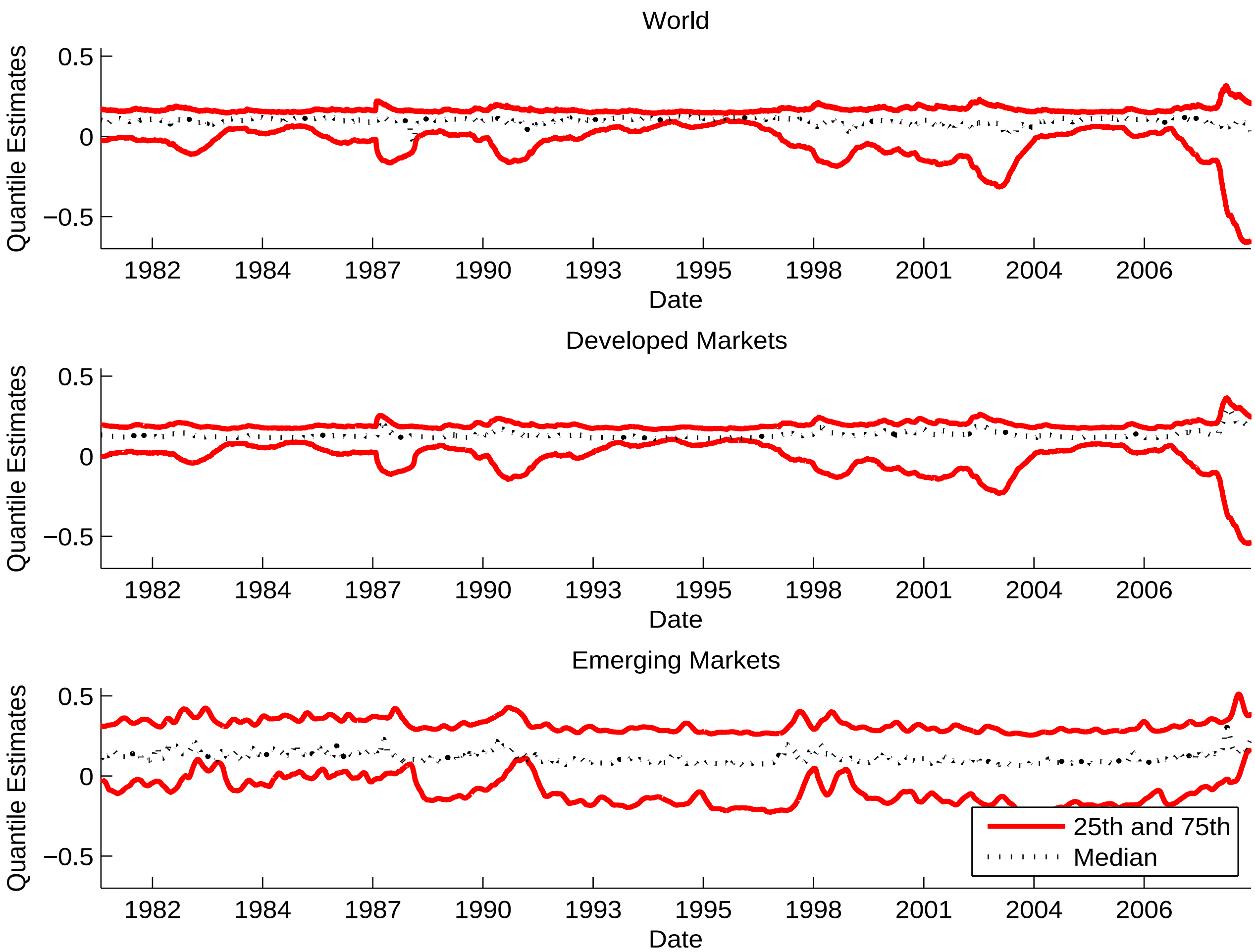
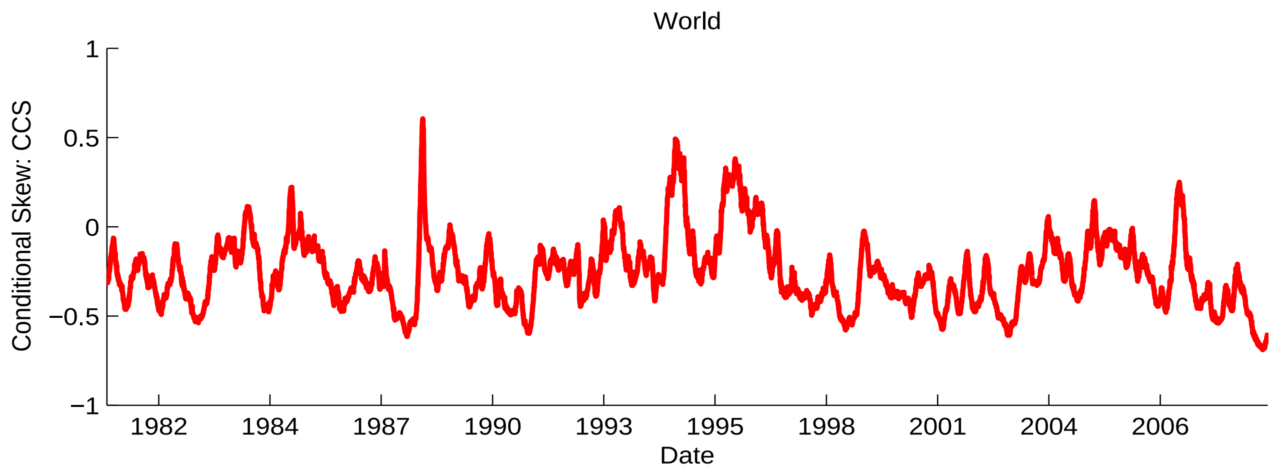


Figure 3: Conditional Asymmetry: World, Developed Markets, and Emerging Markets

Estimated conditional robust measure of asymmetry appearing in equation (3), for the World Index (top), Developed Markets and Emerging Markets (bottom) obtained from the conditional quantiles of Figure **??** using conditional quantile estimates specified in (6) involving 250-day lagged daily absolute returns.



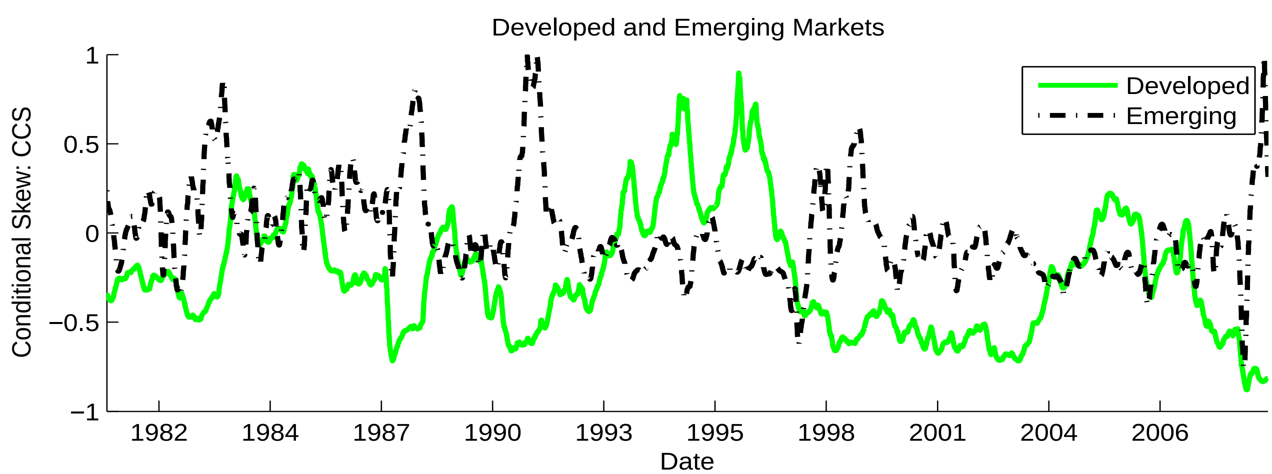


Figure 4: Weights on Filtered Daily Absolute Returns

MIDAS quantile regression weights of the 250-day lagged absolute returns for the Developed Markets (top plot) and Emerging Markets (bottom plot) for 25th, 50th, and 75th conditional quantiles.

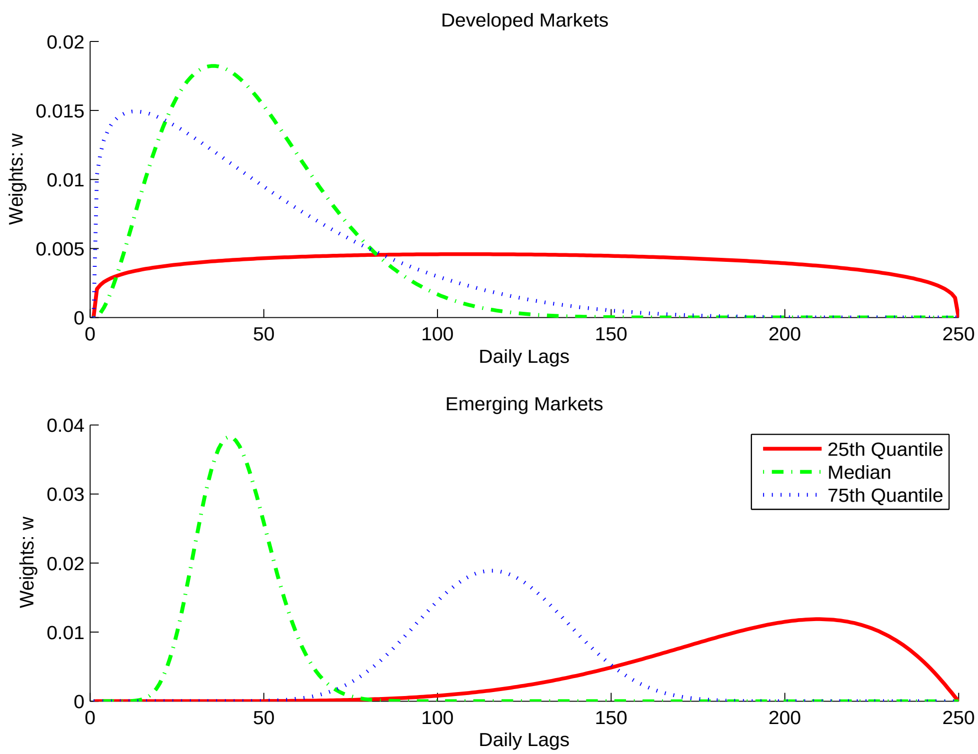


Figure 5: Conditional volatility and rolling correlation

The top figure shows the conditional annual volatility of Developed Markets and Emerging Markets returns based on a MIDAS model on 250 lagged squared daily returns. The bottom figure displays the rolling correlation between the two returns series using a 250-day window of simple returns (solid line) or filtered returns from a TARCH(1,1) (dotted line).