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# Pricing of Skewness in Emerging Markets

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**Abstract**

We empirically test the prediction of Barberis and Huang (2008) model which predicts that if traders in the stock markets have cumulative prospect theory preferences then the positively skewed stocks should on average have lower returns. We use the data from 20 developing and emerging economies to test this prediction. Two measures of anticipated stock skewness are used: one based on past self-skewness and another based on group skewness as introduced by Zhang (2005). Our results are as follows. First, while the evidence is somewhat mixed, in general the data rejects the Barberis and Huang's prediction. Second, in our data from these 20 countries, the past self-skewness is better skewness predictor than the group variables which is in contrast with Zhang's result.

## 1. Introduction

The observation that third moment of the asset returns distribution can be priced has been noticed by researchers since as early as seventies (Kraus and Litzenberger, 1976). In a standard single-factor CAPM model only the first two moments of portfolio returns matter. However, an immediate extension of the standard CAPM that allows the stochastic discount factor to be quadratic in the market return (and not linear as in the CAPM) leads to the prediction that asset coskewness with the market should be priced. This prediction has been confirmed by many empirical studies, (e.g. Harvey and Siddique, 2000).

Models based on expected-utility preferences predict that while the asset's coskewness with the market should be priced, its idiosyncratic skewness should not.[3] If we assume that agents

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[3]This is always the case for expected utility preferences with concave, skewness-loving utility functions. The case of convex, skewness-loving utility functions has not been fully analyzed yet. See BH (2008) for discussion.

have cumulative prospect theory (CPT) preferences, as suggested by Tversky and Kahneman (1992), then idiosyncratic skewness should be priced as well (Barberis and Huang (2008); BH (2008) hereafter). The intuition is as following: Investors with CPT preferences like portfolios with positively skewed returns. Such portfolio offers a small probability of a very large payoff and since CPT investors overweigh small probabilities they find that such portfolios are attractive. As the result, these investors like to have large undiversified position in a positively skewed security and are willing to pay a higher price for it. Zhang (2005) finds supportive empirical evidence of BH (2008)'s theory in the US market.

A major challenge in testing BH (2008)'s model is to construct a good "ex-ante" skewness measure which is what CPT investors care about. The most natural candidate — past skewness — is potentially problematic. In order to capture small probability events one need to use a long history of returns which raises the concern of survivorship bias as well as overlooks the possibility that the stock's skewness can dramatically change over its life cycle. Zhang (2005) tries to avoid these problems by using the group approach to measure expected skewness. He groups similar stocks, i.e. stocks with similar characteristics such as industry, size, or book to market ratio, and calculates the intra-group cross-sectional skewness using only recent returns. He demonstrates that group skewness predicts future self-skewness better than past self-skewness. Furthermore, the group skewness estimates are more advantageous comparing to simple self-skewness measures. First, it uses only recent returns aiming to avoid long history dependence. Second, since there are more stocks than time periods using cross-sectional returns is more likely to capture small event probabilities.

We use Zhang's measures to test BH (2008) model prediction with data from 20 developing and emerging economies. We analyze both the pooled data and the data on the country level and test whether the BH (2008)'s prediction holds and how different measures for estimating expected skewness compares with past self-skewness approach.

The contribution of our analysis is as follows. First, testing the BH (2008) model using the data from 20 countries greatly enhances our understanding of how robust is the effect of idiosyncratic skewness on asset pricing. Second, the setup considered by BH is based on the standard framework with frictionless markets and rational investors except that investors have CPT and not EU preferences. The actual stock markets are naturally quite different from this idealistic framework and, due to historical and institutional differences, more so for developing countries. Therefore, by studying stock markets with many idiosyncrasies that are ignored by the classical setup we can see the applicability of the BH argument and to what extent it depends on particularities of the stock markets in different countries. Third, Zhang's group methodology while advantageous both by the construction itself and by its performance in the U.S. data has not been theoretically justified yet nor has it been confirmed with more empirical studies. If we show that group skewness approach's performance is consistently better than that of past self-skewness approach, then we can provide a strong empirical evidence in favor of the group methodology. This in turn could justify theoretical research of the issue as well as its use in further empirical studies.

The analysis in our paper consists of two parts. In the first part we use the pooled data from all 20 economies and in the second part we analyze the data from each individual country separately. For both pooled and country-level analysis we start by constructing variables that could proxy stocks' ex-ante skewness. In total, we used 8 different measures: a past self-skewness measure which were calculated as skewness of past 36 month returns; five group measures where groups were defined based on stock's nationality, its size or book-to-market ratio; two distributional measures which capture asymmetry in cross-sectional return distribution by looking at the relative positions of the left and the right tails with respect to the median. The latter method specifically focuses on the tails of the distribution thereby reflecting the intuition that the CPT investors tend to overweight the probability of tails and therefore the importance of the outliers. Having constructed the proxies for skewness we first estimate how well each proxy predicts the future realized skewness and then whether and how they affect the stock returns.

Our results are as follows. First, the BH (2008)'s prediction that positively skewed stocks have lower returns is in general not supported by our data. We find that it is much more common that stock with higher idiosyncratic skewness is correlated to higher returns which is the opposite of the BH prediction. There are only few instances where the data support the BH model. The positive effect remains after controlling for market capitalization, book-to-market ratio, lagged returns, asset coskewness with the market and idiosyncratic volatility of returns. This suggests that the BH's effect is not robust when looking at the data from emerging and developing countries.

Second, in contrast with Zhang's result, we show that the self-skewness predicts future skewness better than other variables. While on the country level there are few instances when a particular group skewness variable would perform better than self-skewness variables for the most of the cases the self-skewness tend to be a more robust predictor of the future skewness. Our result suggests that the Zhang's group skewness approach does not immediately extend to other countries. In particular, despite its potential advantages over self-skewness approach the latter consistently outperforms it in our data.

The rest of the paper is organized as follows. Section 2 provides review of relevant literature. Section 3 describes the data and methodology. We show the results of our analysis in Section 4. We conclude in Section 5.

## 2. Literature Review

Higher moments of stock returns are important subjects in finance literatures. Beedles and Simkowitz (1980) find that positive skewness persists over time in cross-sectional stock returns. While Singleton and Wingender (1986) find that skewness is not persistent in the time series of stock returns. DeFusco, et. al (1996) using bootstrap method find that skewness is persistent even in time series of stock returns. They find that "individual stock returns rarely tend to show a statistically significant decrease in skewness".

Kraus and Litzenberger (1976) find that investors have an aversion to variance as well as a preference for positive skewness. They use their model to demonstrate that coskewness should be priced. Further, they suggest that investors prefer odd systematic moments of returns while averse of even systematic moments of returns. They document that coskewness can be used as a supplement to the covariance measure to explain the individual returns of NYSE stocks. In their latter work, Kraus and Litzenberger (1983) use consumption-oriented CAPM model with higher order moments to show that investors prefer expected return and positive skewness while they are averse of variance of return. Friend and Westerfield (1980) find that coskewness is only priced in the time period of year 1972 to 1976 but not any other periods. Fang and Lai (1997) use four-moment CAPM model and find that systematic variance, skewness and kurtosis are all correlated to stock returns. Systematic variance and kurtosis are positively correlated to returns while systematic skewness is negatively correlated to stock returns. The results are robust across different time periods.

While most researches are focus on systematic skewness i.e. coskewness of stock returns, BH (2008) suggest that idiosyncratic skewness of individual stock returns is also an important pricing factor. BH (2008) propose a model in which investors have Cumulative Prospect Theory (CPT) preferences. In contrast to prediction of a standard expected utility case, stocks' self-skewness can be priced in their model. They predict that "a positively skewed security can be "overpriced" and can earn a negative average excess return." Zhang (2005) finds supportive evidence of BH (2008) prediction. He also constructs other skewness

measures and show that the prediction is robust with all different measures of skewness.
Scholars also find that skewness of returns is related to other factors and try to explain the connections. Campbell and Siddique (2000) find that conditional skewness is priced. Furthermore, skewness is negatively correlated with momentum expected returns. The lower the momentum expected returns, the higher the skewness of the stocks. Adrian and Rosenberg (2008) find that short run volatility is correlated to aggregate level of skewness. They argue that short run volatility is correlated with market-wise skewness while long run volatility is correlated to business cycles. Smith (2007) finds that when the conditional market skewness is positive, then investors are willing to pay 7.78% annually per unit of gamma, while they only need a premium of 1.80% when the market is negatively skewed. Hutson et. al. (2008) document that volume and skewness are related in a complicated way. Using daily and monthly data from 11 countries, they find supportive evidence which supports the investor heterogeneity theory to explain return asymmetries.
The fact that stock returns in emerging market are more positively skewed is well documented in literatures. Bae, et. al. (2006) document that stock returns in emerging market are more positively skewed than those in developed economies. Further, they argue that stock skewness is negative correlated to corporate governance quality. Using data from 38 countries, they find that positively skewed stocks are mostly from markets with poor corporate governance.

## 3. Data and Methodology

Our original sample included data from 20 emerging countries as defined by Morgan Stanley Emerging Market Index. The data is obtained from Thomson DataStream. The sample starts on July 1991 and ends on March 2008. A summary of the data is given in Table 1.

[Insert Table 1 here]

The primary goal of this paper is to test the BH (2008)'s prediction that idiosyncratic skewness should be priced and that stocks with higher skewness should have lower returns. Zhang (2005) tests the prediction using the U.S. data and confirms it. In our paper, we test the BH model using data from emerging markets.
The reason we focus on developing markets is that there are several important aspects in which they differ from more established markets such as the U.S. market. First, stock markets in developing economies and stocks traded there are relatively young. The former means that there was less time to perfect the rules and organizational structure of the market and the latter means that traders would often have less information about stocks, for example, because of a shorter data horizon. Second, there are many institutional restrictions and regulations that do not exist in the developed economies. For example, government regulations in China make Chinese stock market quite different from the frictionless and perfect markets usually assumed in theoretical models. Such differences make the theoretical setting used in BH — investors that are rational in all aspects except for having CPT (and not EU) preferences and who operate in a frictionless market — too simplified to capture all the specifics of stock markets in developing countries. Therefore, using developing countries to test the BH prediction can provide a very important insight on the applicability and robustness of the BH (2008)'s story and the underlying Cumulative Prospect Theory assumption.
The main challenge in testing the BH (2008) model is to construct a good predictor of the ex-ante skewness. In the model itself, the main driving factor behind investors' actions is the *ex-ante* skewness. In other words, investors' beliefs that the future payoff of a particular stock has a lottery-like distribution with a small chance to win a large payoff. Using the most immediate candidate for ex-ante skewness proxy — the past skewness of stock returns — can

be potentially problematic. The reason being that on one hand we cannot use a short time interval when constructing the past skewness variable since we are specifically interested in small probability events. At the same time, using long intervals of time can be plainly infeasible because many developing markets have rather short history. Furthermore, it is prone to survivorship bias and overlooks the possibility that stock skewness can dramatically change over time.

Zhang (2005) suggests an alternative approach to avoid these problems. The idea is to group stocks with similar characteristics (e.g. country, industry, size or book-to-market ratio) and then calculate the cross-sectional skewness of *recent* returns within this group. The immediate advantage of this approach is that it does not require long history of returns yet it is capable of capturing small probability events because of the large size of the cross-section. This is particularly useful in the context of emerging markets where the majority of stocks has a very short history. Zhang (2005) showed that in the US data group skewness predicts future skewness better than the past self-skewness and that both measures predict future returns consistently with the BH model. Except for Zhang (2005) there is little theoretical or empirical guidance with regards to which approach — group skewness or self-skewness — should work better. That being the case, we use both approaches in this paper. Doing so provides us with a good robustness check of the results. Furthermore, given the advantages of Zhang's methodology it is an interesting and important question on its own to test how well the group skewness approach performs when we use a different and larger data set.

We start with constructing the eight variables that will serve as proxies for expected skewness. The first variable, $SelfSkew36$, is defined as the past self-skewness of stock log returns during 36 months. The log returns are used because as noticed in Chen et al. (2001) using arithmetic returns will lead to a strong correlation between the second and the third moments of a return distribution.

When calculating group skewness we use three grouping criteria: country, size within a country and book-to-market ratio ($BTM$) within a country. When grouping by country we calculate group skewness as follows. First, we calculate the skewness of returns of all stocks given a particular country in a particular month, $SkewC_t^*$. Then similar to Zhang (2005) we calculate a weighted average of monthly country skewness using $SkewC^*$ from the last three months:

$$SkewC_t = (3 \cdot SkewC_{t-1}^* + 2 \cdot SkewC_{t-2}^* + SkewC_{t-3}^*)/6. \quad (1)$$

Using the weighted average, on one hand, reduces the noise and, on the other hand, this particular weighting scheme reflects the belief that the more recent group skewness should have a stronger effect.

Grouping by size and $BTM$ is performed in the following fashion. Stocks are grouped to 5 or 10 piles by either the size or the book-to-market ratio within each country. The skewness is then computed as the skewness within each group. Then we apply the technology from equation (1) to get the expected skewness. In total, this defines four group variables denoted as $BM10$, $BM20$, $ME10$ and $ME20$. The letters specify whether we use book-to-market ratio ($BM$) or size ($ME$) ranking. Numbers specify whether the group consists of 10% (10 piles) or 20% (5 piles) of the country stocks.

The following example clarifies the construction. Take stock $s$ in period $t$ that is traded in country $c$. We sort all stocks in country $c$ in period $t$ by their size (or by their BTM). Say the size of stock $s$ is at $34^{th}$-percentile of the size distribution. Then the variable $ME10_t^*$ will be defined as the skewness of all stocks from the $30^{th}$ to the $40^{th}$ percentile of the size distribution. Variable $ME20_t^*$ will be defined as the skewness of all stocks from the $20^{th}$ to $40^{th}$-percentile of the distribution. Then similarly to the definition of $SkewC$ we construct the weighted average so that

$$ME10_t = (3 \cdot ME10^*_{t-1} + 2 \cdot ME10^*_{t-2} + ME10^*_{t-3}) / 6.$$

Variables $ME20$, $BM10$ and $BM20$ are defined similarly except that for the last two we would use ranking based on the book-to-market ratio.

Finally, we follow Zhang (2005) and construct two more variables that capture the relative position of the 5% and 1% tails thereby focusing on outliers lying in the tails of the distribution. They are defined as follows:

$$C95 = \frac{(P_{95} - P_{50}) - (P_{50} - P_5)}{(P_{95} - P_5)},$$

and

$$C99 = \frac{(P_{99} - P_{50}) - (P_{50} - P_1)}{(P_{99} - P_1)},$$

where $P_i$ is the $i^{th}$ percentile of the empirical return distribution within the country of the stock. These variables are used to take into account the possibility that investors who care about skewness pay more attention to the tails of the distribution.

Thus overall we have one variable that is constructed based on the past self-skewness using the previous 36 months; five group skewness variables where the groups are defined based on the country of the stock, the size of the stock or its BTM ratio. Finally we have two group variables, $C99$ and $C95$, that are defined based on the tails of the empirical distribution of returns within a given country. In our analysis we will use all eight variables as proxies for ex-ante self-skewness. This is done to see the robustness of the effect as well as to test which of the proxies perform well and do predict the stock skewness.

We conclude this section by describing the other variables that we use in the study. All of them are standard determinants of the stock returns. To control for the size and book-to-market factors we included the standard $SMB$ an $HML$ factors. The average of stock lagged log returns from month $t-j$ to month $t-i$ are denoted as $Rt_{-i:-j}$. The index return in a given country is denoted as $Rindex$ and lags are indexed similarly to the stock lags. To control for the stock co-skewness with the market we use two variables $coskew_{36}$ and $coskew_{60}$. The variables are defined as in Harvey and Siddique (2000). Numbers 36 and 60 specify whether we use 36 or 60 monthly returns to construct the co-skewness. The results are similar for both $coskew_{36}$ and $coskew_{60}$ variables so we only report the former. Finally to control for idiosyncratic volatility of returns we use variable $idio$ similar to the definition in Ang et al. (2004). We take standard deviation of past 36 month residuals of the market model regression:

$$r^c_{i,t} = \alpha_i + \beta_i R^c_t + \varepsilon_{i,t}.$$

Here $r^c_{i,t}$ is the return of stock $i$ in market $c$ at time $t$, $R^c_t$ is the market return of the country at time $t$, $\alpha_i$ is the intercept and $\varepsilon_{i,t}$ is the residual term which is used to calculate idiosyncratic risk. All variables including the skewness variables are calculated using the country currency and are not adjusted to inflation.

## 4. Results

The analysis in the paper consist of two parts. In the first part, we use our entire sample comprised of the data from all 20 countries. In the second part, we perform our analysis for each country individually. In both parts we are interested in two questions. First, we study the performance of the eight skewness proxies and compare the group skewness approach with the past self-skewness approach. Second, we test whether the idiosyncratic skewness is priced as predicted by the BH model.

*1. Pooled Data Analysis*

We begin our analysis by studying how well the skewness proxies predict future self-skewness. To do this, we divide the entire sample into non-overlapping three-year periods. Given that for all countries the last month is the same — March 2008 — whereas the first months differ the division is done from the end of the sample. We define the first period as the one that begins in April 2005 and ends in March 2008, the second period begins in April 2002 and ends in March 2005 and so on. For each period we calculate the realized monthly self-skewness over the next 36 months as well as the eight expected skewness proxies given the data from the *prior* period. The self-skewness proxy is calculated given all 36 months of the prior period and group skewness proxies are calculated given most recent 3 months of the prior period. Then we combine the data from each period (one cross-section per a three-year period) and test whether skewness proxies predict realized skewness.

The following example clarifies the timing. Take a particular stock in period between April 2005 and March 2008. The realized skewness is calculated using the returns between April 2005 and March 2008. The timing of skewness proxies is then calculated as follows. Variable $SelfSkew36$ is the skewness of returns of that stock from April 2002 to March 2005; the group skewness variables are defined using the skewness in three months: January, February and March of 2005. Then for each stock and each period, we regress the realized skewness on each of the skewness proxies. Results of our estimations are presented in Table 2.

[Insert Table 2 here]

For each skewness variable we estimate three specifications. The first one is the short specification with the only independent variable being the skewness variable itself. In Table 2 it is the first line for each skewness variable. In the second specification we also add controls for book-to-market and size by using variables $lnME$ and $lnBM$. Finally, in the third specification we add lagged stock returns. As can be immediately seen from Table 2 not all of the eight skewness variables predict future skewness. While every variable is significant in at least one of the specifications, only variables $SelfSkew36$ and $ME10$ are significant in all three of them. Furthermore, only $SelfSkew36$ is significant at 1% level in all three specifications. Variable $ME10$ is significant at 5% level in two specifications and all other variables reach 5% significance in one specification at most.

Overall, we conclude that our findings differ from those of Zhang (2005). Using the U.S. data he showed that group variables predict future skewness better than past self-skewness. In contrast, our results show that for the pooled-data past self-skewness is superior predictor of the skewness. There are two potential explanations for the difference in results. First, we use data from different economies which can be responsible for the difference. Second, the main grouping variable used by Zhang (2005) is the industry to which the stock belonged whereas we used different grouping variables. The former factor seems to be more responsible for the difference in results than the latter. The reason is that while the main grouping variable in Zhang (2005) *is* the stock industry he also considered several other grouping criteria which are similar to those in our study. For example, Zhang (2005) also uses size and book-to-market ratio as grouping variables and the corresponding group skewness variables performs well in his data. In contrast in our paper group variables based on $BTM$ and size did not outperform the past self-skewness.

**Result 1:** *Only two skewness variables robustly predict future skewness:* $SelfSkew36$*, and* $ME10$*. The past self-skewness has the best performance and is significant at a higher level* *than* $ME10$. *Our findings are in contrast with Zhang (2005).*

Next, we test predictions of the BH (2008) model and study whether stocks with higher expected skewness have lower returns or not. For the sake of uniformity with the following within-country analysis we will continue to use all eight proxies for anticipated skewness. As before, for each of the eight skewness variables we estimated several specifications to check for the robustness of the effect. In addition to skewness variables all specifications included $HML$ and $SMB$ factors to control for value and size as well as the market return. In Table 3 we report two specifications: the short one and the long one. The short one used the four variables mentioned above, and the long one also included lags of market and stock returns as well as idiosyncratic volatility, $idio$, and coskewness with the market, $coskew_{36}$.

[Insert Table 3 here]

It follows from Table 3 that variables $SelfSkew36$, $C99$ and $C95$ are robustly significant at 1% level, and variables $ME10$, $BM10$ and $BM20$ are significant at 10% level in both specifications. The sign of $SelfSkew36$ is negative, however, it does not mean that stocks with higher skewness pay lower returns. We showed earlier (see Table 2) that past values of $SelfSkew36$ are *negatively* correlated with future values of $SelfSkew36$. Thus our pooled-data result does not support the BH hypothesis and shows that stocks with higher levels of expected skewness pay a higher expected return. The further support of our result comes from variable $ME10$ which was another robust predictor of future skewness. $ME10$ is positively correlated with future skewness, and as follows from Table 3 stocks with higher $ME10$ have higher returns. Thus again, it shows that stocks with higher skewness pay higher returns which is in contrast with the BH hypothesis. The last piece of evidence comes from variables $BM10$ and $BM20$. Both variables are positively correlated with future skewness as was shown in Table 2 though not always significant. Table 3 shows that stocks with higher $BM10$ and $BM20$ pay significantly higher returns which contradicts the BH hypothesis.

The only piece of evidence in favor of the BH hypothesis comes from variable $C95$. Table 3 shows that stocks with higher $C95$ pay higher returns and in Table 2 we see that there is one specification where $C95$ is negatively correlated with future skewness and the effect is significant at 10% level. However, this is very weak as only one out of three specifications generates significant predictive power of $C95$ and the significance level is only at 10%.

**Result 2:** *Results reported in Tables 2 and 3 do not confirm the BH (2008)'s prediction. We shows that stocks with higher anticipated skewness pay higher returns which is the opposite of the BH's prediction.*

## *2. Within country analysis*

Above we used the data pooled from all the 20 economies together. In this section we study each country individually. Our goal is the same: we want to analyze the effect of skewness on stock returns and, in particular whether results reported in the previous section hold on the country level. Our methodology is also same as before. First, we test which of the eight proxy variables successfully predicts future skewness and then we will test the BH's prediction.

To test whether the eight proxies predict future skewness we conduct fixed-effect panel data estimation. We consider several alternative specifications and in this paper we report two of them: a short regression where the dependent variable is the skewness proxy and the independent variable is the future skewness for the next 36 month; and a long regression where in addition we control for $lnME$ and $lnBM$. The statistical significance and signs of skewness measures remained the same in all specifications except for variable $SkewC3$ in

Russia where it changed the sign. The timing of the regression analysis is the same as in pooled-data estimation. For each country the data are taken from non-overlapping 36 month periods with the last period ending on March 2008.

[Insert Table 4 here]

Table 4 shows the results of the fixed-effect panel data estimation. The first row for each country shows the short regression and the second row shows the long regression. We report results of both specifications since it helps to evaluate the robustness of proxies performance. As in pooled data analysis in Table 2, the past self-skewness performs the best in predicting the future skewness. It is significant at 1% level for all countries except for Columbia where it is significant at 5% level and Hungary where it is significant at 10% level. Performance of other skewness predictors is somewhat weaker, as for many countries they are insignificant. However, it is still the case that variables $C99$, $C95$, $SkewC3$ and $ME20$ are significant for more than 50% of cases. Variable $ME10$ which was a good predictor for the pooled-data seems to perform worse than variable $ME20$ when looking at country-level data. Thus, similar to what we already have established using the pooled-level data, the past skewness predicts future skewness better than group variables which is in contrast with Zhang (2005) results.

**Result 3:** *In contrast to Zhang (2005), we show that past self-skewness is a better and more robust predictor of future skewness as compared to group skewness variables.*

Next we test the BH's prediction for each country individually. Several models were estimated and here we report the results of the two of them. In the short model the only explanatory variables were the corresponding skewness measure, market return and $SMB$ with $HML$. In the long model we also added co-skewness, idiosyncratic volatility of returns and lags of market and stock returns. The results are presented in Table 5.

[Insert Table 5 here]

First, we look at variable $SelfSkew36$ which was the most robust predictor of future skewness. Combining estimation results in Tables 4 and 5 we can conclude that only for one country, Argentina, the results are consistent with the BH prediction. In Argentina, historical values of $SelfSkew36$ are negatively correlated with future values and stocks with higher historical $SelfSkew36$ pay higher returns. Combining altogether it means that in Argentina stocks with higher anticipated skewness pay lower returns as suggested by BH (2008). Five counties — Columbia, Chile, Mexico, Pakistan and Russia — do not generate any statistically significant effect. For all remaining countries the BH prediction is rejected and stocks with higher anticipated skewness pay higher premium.

Among other skewness variables that were most successful in predicting the future skewness results are more mixed. Variable $ME20$ is similar to $SelfSkew36$ in that it largely refutes the BH prediction. Only one country, Israel, is consistent with the BH's prediction and for other countries there is either no statistically significant result (11 countries) or the effect of skewness is positive (8 countries). Other three skewness variables that predicted future skewness reasonably well are slightly more favorable: $SkewC3$ is consistent with the BH prediction for 6 countries and rejects it for 7 countries; $C99$ is consistent with the BH prediction for 7 countries and rejects it for 8 countries; finally, $C95$ is consistent with the BH prediction for 9 countries and rejects it for 6 countries. Overall, while the results *are* somewhat mixed we conclude that the data do not provide support sufficiently strong to the BH theory and are more likely to contradict it.

Next, we look at each country individually to see how many countries support the prediction. Ignoring the skewness variable that are insignificant we want to see how many skewness variables generate statistically lower returns (as predicted by the BH) and how many generate higher returns. It turns out that for every country there is at least one skewness variable that predicts higher returns. Furthermore, for five countries — Brazil, Chile, Hungary, Poland and South Africa — all skewness variables that generate significant effect predict higher returns for stocks with higher skewness. For most of the remaining countries the skewness variables are also more likely to generate positive effect. For example, if we look at India we see that only variable $SkewC3$ generates significantly negative effect on returns, at the same time variables $SelfSkew36$, $BM20$, $C99$ and $C95$ generate positive effect. There are only two countries that provide some support to the BH prediction, which are China and Peru. For China there are four skewness variables that generate negative effect: $SkewC3$, $BM20$, $C99$ and $C95$. For Peru only $SelfSkew36$ generates positive effect, three other variables $BM20$, $C99$ and $C95$ generate negative effect and the remaining variables do not generate statistically significant effect.

Again the overall conclusion is that apart from few exceptions the data do not support the BH prediction and stocks with higher positive skewness are more likely to have higher rate of return rather than lower as suggested by the BH. We summarize our findings as follows:

**Result 4:** *For the majority of cases, our data reject the Barberis and Huang (2008) conjecture that stocks with higher skewness should have lower returns. In particular, the variable which is the most robust predictor of future skewness,* $SelfSkew36$ *consistently generated positive effect on returns and not negative as predicted by BH.*

## 5. Conclusion

In this paper we analyze whether stock idiosyncratic skewness is priced as suggested by Cumulative Prospect Theory. We use two ways to measure ex-ante idiosyncratic skewness which are past self-skewness and the group skewness. As the group variables we use the skewness of all stocks within the country in a given time period and all the stocks with similar $ME$ or $BM$ ratios within one country in a given time period.

We show that past self-skewness is the best proxy for the future skewness among the eight proxies we used and this holds both for the pooled data and for the country-level data. This is in contrast with the Zhang (2005)'s findings in which he shows that in the US data the group skewness variables perform quite well and actually tend to predict the future skewness better.

Our second main result is that emerging markets data do not support the Barberis and Huang (2008)'s model. For majority of instances, both for pooled and country-level data, we have that stocks with higher skewness pay higher rates of return and not lower as predicted by the BH (2008). This is also in contrast with the Zhang (2005)'s paper in which he shows that for the U.S. data the BH (2008) prediction holds.

## 6. Tables

**Table 1: Summary of Data by Country or Region Predict Future Skewness.**

| Country | DataStream Code | N | End of Sample Period | Begin of Sample Period |
|---|---|---|---|---|
| Argentina | AG | 12316 | 8-Mar | Nov-93 |
| Brazil | BR | 34317 | 8-Mar | Jul-91 |
| Colombia | CB | 2549 | 8-Mar | 1-Nov |
| Chile | CL | 33442 | 8-Mar | Jul-91 |
| China | CN | 151730 | 8-Mar | May-92 |
| Hungary | HN | 5476 | 8-Mar | Jul-91 |
| Indonesia | ID | 21484 | 8-Mar | 2-Aug |
| India | IN | 115828 | 8-Mar | Jul-91 |
| Israel | IS | 16109 | 8-Mar | Jul-91 |
| South Korean | KO | 75714 | 8-Mar | 1-May |
| Malaysia | L: | 135006 | 8-Mar | Jul-91 |
| Mexico | MX | 20278 | 8-Mar | Jul-91 |
| Peru | PE | 4340 | 8-Mar | 3-May |
| Philippines | PH | 34139 | 8-Mar | Jul-91 |
| Pakistan | PK | 18912 | 8-Mar | Dec-92 |
| Poland | PO | 20270 | 8-Mar | Sep-91 |
| Thailand | Q: | 44102 | 8-Mar | Jan-96 |
| South Africa | R: | 55353 | 8-Mar | Nov-95 |
| Russia | RS | 8370 | 8-Mar | Jan-96 |
| Taiwan | TW | 134635 | 8-Mar | Jul-91 |

**Table 1. The data comes from Thomson DataStream.**

**Table 2: Testing Whether Past and Group Skewness Variables Predict Future Skewness.**

| SelfSkew36 | SkewC3 | BM10 | BM20 | ME10 | ME20 | C99 | C95 |
|---|---|---|---|---|---|---|---|
| -0.333*** | 0.042** | 0.093*** | 0.085** | 0.100*** | 0.094*** | 0.188* | -0.069 |
| -0.345*** | 0.026 | 0.056* | 0.047 | 0.073** | 0.063* | 0.025 | -0.201 |
| -0.339*** | 0.017 | 0.043 | 0.035 | 0.059* | 0.052 | -0.054 | -0.300* |

**Table 2. The estimated coefficients of skewness variables and their significance. The estimation technique is fixed-effect panel-data regression. Three stars mean significance at 1% level, two stars at 5% level and one star at 10% level. The first line reports the results of the short specification that includes only the skewness variable. In the second specification we added controls for market size and book-to-market ratio; finally, in the third specification we also control for lagged stock returns.**

**Table 3: Effect of Stock Skewness on Return**

| Country | Skewness | SMB | HML | Rindex | $Rindex_{-1}$ | $Rindex_{-2}$ | $Rt_{-1}$ | $Rt_{-2:-7}$ | $Rt_{-8:-13}$ |
|---|---|---|---|---|---|---|---|---|---|
| **SelfSkew36** | -0.003*** | 1.185*** | 0.148 | 0.620*** | | | | | |
| **SelfSkew36** | -0.002*** | 1.195*** | 0.220 | 0.620*** | 0.122*** | 0.041* | -0.081*** | -0.049*** | -0.002 |
| **SkewC3** | -0.000 | 1.183*** | 0.110 | 0.611*** | | | | | |
| **SkewC3** | -0.001 | 1.200*** | 0.205 | 0.603*** | 0.122*** | 0.044** | -0.080*** | -0.050*** | -0.002 |
| **BM10** | 0.001* | 1.212*** | 0.103 | 0.601*** | | | | | |
| **BM10** | 0.001* | 1.207*** | 0.206 | 0.600*** | 0.118*** | 0.038* | -0.081*** | -0.058*** | -0.007 |
| **BM20** | 0.001* | 1.173*** | 0.111 | 0.610*** | | | | | |
| **BM20** | 0.001* | 1.191*** | 0.206 | 0.603*** | 0.120*** | 0.040* | -0.081*** | -0.053*** | -0.004 |
| **ME10** | 0.002** | 1.219*** | 0.107 | 0.600*** | | | | | |
| **ME10** | 0.002* | 1.212*** | 0.209 | 0.600*** | 0.116*** | 0.037* | -0.081*** | -0.058*** | -0.008 |
| **ME20** | 0.002** | 1.164*** | 0.115 | 0.609*** | | | | | |
| **ME20** | 0.001 | 1.184*** | 0.210 | 0.603*** | 0.120*** | 0.040* | -0.081*** | -0.054*** | -0.005 |
| **C99** | 0.110*** | 0.536 | 0.241* | 0.497*** | | | | | |
| **C99** | 0.109*** | 0.580 | 0.325** | 0.490*** | 0.085*** | 0.028 | -0.083*** | -0.056** | 0.002 |
| **C95** | 0.116*** | 0.885*** | 0.162 | 0.471*** | | | | | |
| **C95** | 0.117*** | 0.912** | 0.249* | 0.450*** | 0.096*** | 0.035* | -0.080*** | -0.051** | 0.011 |

**Table 3. Results of fixed-effect panel-data estimation. Three stars mean significance at 1% level, two stars at 5% level and one star at 10% level. For each skewness variable we report estimates for two specifications. The first one is the short model that includes the skewness variable, *SMB*, *HML* and the index return. The long specification also includes lags of index return, lags of stock return as well as the stock co-skewness with the market and idiosyncratic volatility of returns (the last two are not reported in the table).**

**Table 4: Predicting Future Skewness by Country**

| Country | SelfSkew36 | SkewC3 | BM10 | BM20 | ME10 | ME20 | C99 | C95 |
|---|---|---|---|---|---|---|---|---|
| AG | -0.386*** | 0.172*** | 0.258 | 0.219** | -0.017 | 0.733*** | -0.746* | -2.931*** |
| AG | -0.422*** | 0.158*** | 0.249 | 0.266** | 0.017 | 0.711*** | -0.860* | -2.963*** |
| BR | -0.269*** | 0.058*** | 0.240*** | 0.187*** | 0.159*** | 0.225*** | 0.771*** | 1.334*** |
| BR | -0.284*** | 0.027** | 0.160*** | 0.123*** | 0.071** | 0.146*** | 0.507** | 1.670*** |
| CB | -0.325* | -0.161* | 0.010 | 0.137 | 0.180 | 0.182 | 0.196 | 0.076 |
| CB | -0.345* | -0.095 | -0.219 | -0.115 | 0.131 | 0.089 | -0.205 | -0.238 |
| CL | -0.259*** | 0.060*** | 0.279*** | 0.197*** | 0.203** | 0.097* | 0.930*** | 0.499** |
| CL | -0.318*** | 0.040*** | 0.212*** | 0.121** | 0.116 | 0.061 | 0.601** | 0.506** |
| CN | -0.373*** | -0.047*** | 0.037** | 0.009 | -0.008 | -0.009 | -0.536*** | -0.258** |
| CN | -0.364*** | -0.114*** | 0.005 | -0.038** | -0.054*** | -0.056*** | -0.736*** | -0.578*** |
| HN | -0.180* | -0.223* | 0.121 | -0.094 | -0.082 | 0.251* | 0.810** | 0.209 |
| HN | -0.193** | -0.253* | 0.114 | -0.094 | -0.074 | 0.259* | 0.948** | 0.254 |
| ID | -0.282*** | -0.342*** | 0.032 | -0.008 | -0.012 | -0.019 | 2.059*** | 0.608* |
| ID | -0.366*** | -0.377*** | 0.018 | -0.032 | -0.043 | -0.037 | 1.823*** | 0.257 |
| IN | -0.396*** | -0.067*** | -0.011 | 0.006 | -0.007 | -0.009 | 0.136 | 0.305*** |
| IN | -0.379*** | -0.054** | 0.015 | 0.033*** | 0.025 | 0.019 | 0.592*** | 0.605*** |
| IS | -0.212*** | 0.200** | 0.070 | -0.100 | -0.185* | -0.313** | 0.713* | -0.297 |
| IS | -0.205*** | 0.173** | 0.117 | -0.060 | -0.186* | -0.282** | 0.641 | -0.181 |
| KO | -0.661*** | 0.025 | 0.022 | 0.041** | 0.068*** | 0.064*** | -0.621*** | -0.563*** |
| KO | -0.667*** | -0.028 | 0.018 | 0.027 | 0.034 | 0.035* | -0.166 | -0.211* |
| L: | -0.286*** | -0.011 | 0.044** | 0.049** | 0.051** | 0.028 | 0.071 | 0.128 |
| L: | -0.300*** | -0.097*** | 0.003 | -0.004 | 0.016 | -0.006 | -0.169*** | -0.397*** |
| MX | -0.239*** | 0.148*** | 0.124 | 0.075 | 0.052 | 0.080 | -0.209 | 0.010 |
| MX | -0.302*** | 0.049 | 0.094 | -0.021 | 0.016 | -0.004 | 0.371 | 0.272 |
| PE | -0.802*** | 0.050 | -0.259 | -0.103 | -0.187 | -0.280** | -1.789* | -0.675** |
| PE | -0.763*** | 0.050 | -0.260 | -0.325* | -0.184 | -0.320** | -0.934 | -0.265 |
| PH | -0.390*** | 0.082*** | 0.050 | 0.076 | 0.157** | 0.145*** | -0.059 | -0.423** |
| PH | -0.413*** | 0.034 | 0.000 | 0.029 | 0.178*** | 0.133** | 0.051 | -0.060 |
| PK | -0.308*** | 0.061 | 0.194** | 0.185** | -0.066 | 0.148* | 0.734*** | 0.455*** |
| PK | -0.331*** | -0.148* | 0.061 | 0.016 | -0.317*** | -0.120 | 0.513** | 0.451*** |
| PO | -0.217*** | 0.002 | -0.093 | -0.003 | 0.014 | -0.032 | -0.026 | -0.580 |
| PO | -0.188*** | 0.059 | -0.191 | -0.136 | -0.084 | -0.094 | 0.297 | -0.057 |
| Q: | -0.267*** | -0.146*** | 0.053 | 0.090*** | 0.102*** | 0.105*** | -1.697*** | -0.990*** |
| Q: | -0.332*** | -0.092** | 0.049 | 0.074** | 0.099*** | 0.085*** | -0.565* | -0.373** |
| R: | -0.396*** | 0.054** | 0.023 | 0.031 | 0.063 | 0.051* | 0.161 | 0.140 |
| R: | -0.440*** | 0.082*** | -0.002 | 0.012 | 0.057 | 0.052* | -0.038 | 0.153 |
| RS | -0.477*** | 0.106** | 0.450** | 0.508*** | 0.089 | 0.380 | 1.646*** | 1.142** |
| RS | -0.589*** | -0.181* | 0.191 | 0.014 | -0.421* | 0.098 | 1.198* | 1.117** |
| TW | -0.321*** | 0.004 | 0.006 | 0.008 | 0.053*** | 0.055*** | -0.460*** | -0.626*** |
| TW | -0.296*** | -0.005 | -0.013 | -0.011 | 0.046*** | 0.048*** | -0.510*** | -0.634*** |

**Table 4. The first row for each country is a short regression with only the corresponding skewness variable. The second row is the long regression that included also $lnME$ and $lnBM$ .**

**Table 5: Effect of Stock Skewness on Returns by Country.**

| Country | SelfSkew36 | SkewC3 | BM10 | BM20 | ME10 | ME20 | C99 | C95 |
|---|---|---|---|---|---|---|---|---|
| AG | 0.001 | -0.001 | -0.000 | 0.000 | 0.002 | 0.001 | 0.065*** | 0.074*** |
| AG | 0.002** | 0.004*** | 0.003* | 0.006*** | 0.008*** | 0.008*** | 0.063*** | 0.057*** |
| BR | -0.002*** | 0.001*** | 0.003*** | 0.002*** | 0.001** | 0.002*** | 0.066*** | 0.057*** |
| BR | -0.003*** | 0.001*** | 0.004*** | 0.004*** | 0.002*** | 0.003*** | 0.070*** | 0.054*** |
| CB | -0.000 | 0.004*** | 0.002 | -0.004 | 0.000 | 0.005 | 0.077*** | 0.067*** |
| CB | -0.000 | 0.003*** | 0.003 | -0.002 | 0.001 | 0.004 | 0.077*** | 0.067*** |
| CL | -0.000 | 0.001*** | 0.002 | 0.003*** | 0.002* | 0.003*** | 0.053*** | 0.060*** |
| CL | -0.000 | 0.001*** | 0.002* | 0.003*** | 0.003** | 0.002*** | 0.052*** | 0.063*** |
| CN | -0.003*** | 0.004*** | 0.002*** | 0.002*** | -0.002*** | 0.000 | 0.095*** | 0.060*** |
| CN | -0.004*** | 0.007*** | 0.003*** | 0.004*** | -0.000 | 0.002*** | 0.106*** | 0.071*** |
| HN | -0.006** | 0.003* | 0.006* | 0.005 | 0.003 | 0.002 | 0.061*** | 0.100*** |
| HN | -0.003 | -0.001 | -0.001 | -0.002 | -0.001 | -0.005 | 0.081*** | 0.110*** |
| ID | -0.003** | -0.003*** | 0.007*** | 0.006*** | 0.007*** | 0.006*** | 0.177*** | 0.171*** |
| ID | -0.004*** | 0.005*** | 0.011*** | 0.011*** | 0.010*** | 0.010*** | 0.198*** | 0.173*** |
| IN | -0.000 | 0.003*** | 0.002*** | 0.002*** | 0.001*** | 0.001*** | 0.188*** | 0.268*** |
| IN | -0.003*** | 0.002*** | 0.000 | 0.001*** | 0.000 | 0.000 | 0.173*** | 0.256*** |
| IS | -0.004 | -0.001* | 0.004** | 0.005*** | 0.001 | 0.007*** | 0.053*** | 0.104*** |
| IS | -0.004** | -0.001** | 0.004* | 0.003** | 0.000 | 0.005** | 0.039** | 0.113*** |
| KO | -0.004** | -0.001*** | 0.004*** | 0.003*** | 0.010*** | 0.008*** | 0.248*** | 0.451*** |
| KO | -0.008*** | -0.001*** | 0.002*** | 0.001** | 0.007*** | 0.006*** | 0.222*** | 0.400*** |
| L: | -0.001* | -0.002*** | -0.000 | -0.001** | 0.002*** | 0.001*** | 0.147*** | 0.173*** |
| L: | -0.005*** | -0.003*** | -0.000 | -0.001*** | 0.002*** | 0.001*** | 0.142*** | 0.173*** |
| MX | -0.001 | -0.001 | -0.006*** | -0.007*** | -0.001 | -0.003*** | 0.032*** | 0.040*** |
| MX | -0.000 | 0.004*** | -0.002* | -0.002* | 0.003*** | 0.001 | 0.018*** | 0.010* |
| PE | -0.005** | -0.000 | 0.005** | 0.004* | 0.002 | -0.001 | 0.038*** | 0.074*** |
| PE | -0.006** | -0.000 | 0.005** | 0.005** | 0.003 | 0.001 | 0.048*** | 0.084*** |
| PH | -0.002** | -0.000 | 0.004*** | 0.006*** | 0.007*** | 0.006*** | 0.138*** | 0.141*** |
| PH | -0.003*** | 0.000 | 0.002 | 0.004*** | 0.005*** | 0.004*** | 0.135*** | 0.145*** |
| PK | -0.004 | -0.000 | 0.002 | 0.002 | -0.000 | 0.001 | 0.090*** | 0.214*** |
| PK | -0.003 | 0.002*** | 0.004** | 0.003 | 0.002 | 0.003 | 0.094*** | 0.207*** |
| PO | -0.006*** | 0.002*** | -0.005** | -0.005*** | -0.006*** | -0.007*** | 0.088*** | 0.187*** |
| PO | -0.006*** | 0.002** | -0.002 | -0.001 | -0.002 | -0.003** | 0.092*** | 0.181*** |
| Q: | -0.001** | -0.000 | 0.001*** | 0.002*** | 0.002*** | 0.001*** | 0.121*** | 0.084*** |
| Q: | -0.002*** | 0.000 | 0.002*** | 0.002*** | 0.003*** | 0.002*** | 0.120*** | 0.088*** |
| R: | -0.003* | 0.001 | 0.005*** | 0.006*** | 0.008*** | 0.005*** | 0.120*** | 0.191*** |
| R: | -0.006*** | -0.000 | 0.004*** | 0.004*** | 0.006*** | 0.005*** | 0.122*** | 0.182*** |
| RS | -0.003 | 0.002 | 0.003 | 0.004 | 0.003 | 0.006* | 0.017 | 0.054*** |
| RS | -0.004 | 0.006*** | 0.011** | 0.013*** | 0.007** | 0.012*** | 0.025** | 0.027*** |
| TW | 0.000 | 0.000 | 0.006*** | 0.006*** | 0.009*** | 0.008*** | 0.217*** | 0.323*** |
| TW | -0.003*** | -0.003*** | 0.003*** | 0.002*** | 0.005*** | 0.004*** | 0.202*** | 0.313*** |

**Table 5. The first row is the short specification that includes the corresponding skewness variable, and the three Fama-French factors: market return, $SMB$ and $HML$. The second row shows the estimation results of the long model where we also included lags of market and stock returns as well as co-skewness and idiosyncratic volatility of returns.**

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