Market Crash Risk and Slow Moving Capital

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Abstract

Index option skew is a variable commonly looked at by investors to assess market conditions - commonly referred to as a risk reversal or crash risk. In the cross-section, value stocks and junk bonds do poorly when the price of risk reversals increases. However, investors are slow to fully incorporate this information into prices leading to significant predictability in value vs. growth stocks as well as junk vs. investment grade bonds. Using data on mutual fund flows, we find that investors rotate out of value stocks slowly following increases in the price of risk reversals confirming the underreaction observed in returns. The predictability of value vs. growth and junk vs. investment grade is economically significant and poses a challenge to strictly rational models of information processing by investors.

1 Introduction

Professional investors commonly look to the options market to assess market conditions through the premium the market places on portfolio protection. Specifically, they look at the difference in implied volatility between the put and call options on the S&P 500 index. As investors become more cautious about future market outcomes, they purchase more puts - often financing the investment by selling calls - which increases the difference in the implied volatility between puts and calls; this trade is known as a risk reversal. Our work attempts to understand if the cross-section of securities efficiently incorporates information regarding changes in the price of risk reversals. We use the cross-section of equity securities as our primary test assets and verify our conclusions in the corporate bond market as well.

Our findings are two-fold: the value-minus-growth (HML)[1] trade performs poorly when the price of risk reversals increases. HML incorporates information into its price slowly and thus continues to do poorly the following month as well. These conclusions also hold in the corporate bond market: the junk-minus-investment grade trade performs poorly when the price of risk reversals increases but also continues to perform poorly the following month. Using mutual fund flow data, we find that following increases in the price of risk reversals - which can happen because investors become more risk averse or because the distributional characteristics of the underlying market change - investors rotate out of value funds and into growth funds. However, this rotation happens slowly contributing to the predictability we find in HML.

Our work contributes to understanding how information diffuses from the options market to the equity market. Several papers have explored how individual option skew relates to future returns Conrad et al. (2013) find that risk neutral skewness of individual options forecasts higher future returns while Xing et al. (2010) find that a larger differential between out of the money put options and call options forecasts a lower future return attributing the result to slow information diffusion (and forces out risk neutral skewness in a multivariate setting). Ang et al. (2012) show that individual stock options contain information regarding future returns of individual stocks. Brunnermeier et al. (2008) examines the difference between put and call volatility in currency pairs showing that currencies involved in carry trades exhibit significant crash risk as measured by the

[1]We refer to a trade that goes long value and short growth as well as the formal value factor constructed by Fama and French (1992) as HML.

respective options. Pan (2002) shows that the difference between out of the money put volatility and out of the money call volatility is largely driven by a downward jump risk premium. Bollen and Whaley (2004) finds that S&P skew is largely driven by buying pressure from investors for puts but remains agnostic to the reasons. Unlike the aforementioned papers, we examine how investor risk neutral estimates of market crash risk derived from S&P 500 options affects the cross-section of stock and credit returns.

Our findings that the value minus growth (HML) factor is highly correlated with innovations in skew changes ties with another literature on understanding the value premium. In a series of papers Fama and French (1992, 1993, 1996, 1998) show that high book-to-market securities earn high returns relative to low book-to-market stocks. The rational asset pricing literature has advocated for an ICAPM style model where growth and value stocks have covariance with state variables. Campbell and Vuolteenaho (2004) examine the covariance of securities with discount rates and cash flows. Using an ICAPM they show that the price of risk associated with discount rate covariance is lower; value stock betas are mostly composed of cash flow betas while growth stock betas are discount rate betas. Therefore value stocks should command a higher return per unit of market beta. Petkova and Zhang (2005) show that market β of value stocks is higher in bad states of the world. Our work poses a challenge for a strictly rational interpretation of HML since the factor that is supposed to explain returns is itself predictable. This is also important for empirical papers that document anomalies in the stock market: if certain factors are predictable then examining exposure to static factors is no longer a high enough threshold. We need to think about how dynamic portfolios of factors affect the strength of other anomalies.

2 Risk Reversals

Intuitively, risk reversals correspond to a self financing position that an individual uses to express concern about negative market outcomes. It has also been used extensively, for example Brunnermeier et al. (2008), as a measure of crash risk. Specifically, if the implied volatility of puts is higher than calls, this implies that traders believe the risk neutral distribution of returns is negatively skewed. The theoretical motivation for using the option skew to forecast returns comes from Pan (2002) who constructs a model to attempt to reconcile the dynamics of spot prices of the S&P 500 with option prices on the same. Pan finds that a model that only includes a volatility risk premium is inadequate to fit the option series and a model that includes jumps with state dependent intensity is necessary. Specifically, she uses a model that incorporates a time varying jump intensity that rises with volatility: when market volatility increases, so does the probability of a large downward jump. Unlike a model that only includes a risk premium for volatility, this model isn't rejected by the data and is able to price the full term structure of options well. The model estimates a risk premium of 5.5% for diffusive risk and 3.5% for jump risk on the S&P 500. Jump risk is specifically reflected in out of the money puts: for at the money options, approximately 55% of the overall risk premia is due to jump risk. For a 5% out of the money put, 80% of the risk premia is due to jumps while for a 5% out of the money call, only 30% is due to jumps. This differential ability by out of the money puts and calls to capture the magnitude of the jump risk premium is reflected in our construction of $SKEW$. Specifically define

$$SKEW_t \equiv \frac{1}{N}\sum_{j=1}^{N} IV(P)_{j,t} - \frac{1}{N}\sum_{j=1}^{N} IV(C)_{j,t} \tag{2.1}$$

where $IV(P)$ ($IV(C)$) is the volatility of 1 year S&P 500 out of the money (OTM) put (call) options at equally spaced delta grid points. Thus this is simply the average volatility on out of the money (OTM) S&P 500 put options minus the average volatility on OTM S&P 500 call options. We use the interpolated volatility surface from OptionMetrics to compute $SKEW$ monthly from 1996-2012 based on data availability. The surface provides a set of volatilities for put and call options in increments of five delta units and thus is symmetric around the at the money (ATM) point. Since our work will focus on monthly data and option markets close 15 minutes after equity markets, we use the second to last day of the month to compute our implied volatility related metrics to prevent any look ahead bias.

To get a better sense of how $SKEW$ relates, empirically, to the moments of the risk neutral distribution we follow the methodology of Bakshi et al. (2003) and extract the model free moments from the cross section of S&P 500 option prices. We proxy for market volatility using the VIX index and extract the risk neutral skewness, $RNSKEW$. As noted earlier, a high positive $SKEW$ represents risky states of the world from the perspective of the investor. Analogously a highly positive VIX represents high (risk neutral) forecasted levels of volatility; a highly *negative* $RNSKEW$

represents a *negatively* skewed distribution. The point to keep in mind is that a *negative* innovation in $RNSKEW$ is an *increase* in risk from the perspective of an investor. The opposite is true for VIX and $SKEW$: a *positive* innovation to these variables corresponds to a riskier distribution. We extract innovations at the monthly frequency using univariate ARMA models chosen by BIC for each quantity ($SKEW$, VIX and $RNSKEW$). All of the quantities are can be described by a low order ARMA model.

Our goal is to understand how $SKEW$ innovations, ε_{skew}, relate to innovations in risk neutral moments. We do this parametrically using linear regression and non-parametrically using local polynomial regressions. Namely, we run two forms of regressions:

$$\varepsilon_{skew,t} = f(\varepsilon_{rnskew,t}, \varepsilon_{vix,t}) \tag{2.2}$$

$$\varepsilon_{skew,t} = a + \beta_v \varepsilon_{vix,t} + \beta_{rns} \varepsilon_{rnskew,t} + \beta_i (\varepsilon_{vix,t} \varepsilon_{rnskew,t}) + \eta_t \tag{2.3}$$

where $f(\cdot)$ is a second order local polynomial. Figure 1 presents a surface representing the results of fitting (2.2). Variables are standardized prior to running these regressions so that magnitudes can be more easily interpreted. The arrows point in the positive direction for each variable.

The figure plots the fitted values of $\varepsilon_{skew,t}$ from regression (2.2) against $\varepsilon_{vix,t}$ and $\varepsilon_{rnskew,t}$. It shows ε_{skew} is high when there is an increase in volatility *and* the distribution of returns becomes more negatively skewed. Thus $SKEW$ is a measure of the joint behavior of volatility and skewness. This empirical result is consistent with the theoretical model of Pan (2002) who specifies risk neutral jump intensity as a function of volatility. Specifically, in her model the jump intensity increases with market volatility and this is our finding as well. This can be examined in a linear regression context also: the table below the figure presents results of regression (2.3). The results are the same as those explained by the plot: $SKEW$ increases when the distribution becomes more negatively skewed ($\varepsilon_{rnskew} < 0$) and volatility increases ($\varepsilon_{vix} > 0$). Additionally, there is a significant interaction effect that was highlighted by the plots: $SKEW$ increases particularly strongly when there is an increase in volatility and the distribution of returns becomes more negatively skewed.

It is helpful to understand how $SKEW$ varies through time in relation to the VIX and the business cycle since investors are generally familiar with the time-series pattern of these quantities. Figure 2 presents a plot of $SKEW$ for our sample along with the VIX and $SKEW$ orthogonalized to the VIX (using linear regression) labeled $OrthSKEW$; recessions are highlighted using gray bars. The variables have been standardized. One obvious pattern is the correlation that $SKEW$ exhibits with the VIX: roughly 60%. However, there are subtle differences in the pattern: $SKEW$ was higher relative to its normal levels than the VIX (relative to its normal levels) prior to the dot-com bubble bursting. It also spiked up prior to the 2008 financial crisis and has remained elevated after the crisis. We will see further in the article that these features are important in predicting HML returns.

3 Security Underreaction

3.1 Equities

Pan (2002) provides the motivation for examining $SKEW$ as a measure of aversion by investors to jumps in the S&P 500: she finds that the overwhelming majority of the difference in OTM put and call volatilities corresponds to the jump premium (as opposed to actual jump realizations). We document that $SKEW$ does, in fact, have significant forecasting power for the overall market return consistent with it being a measure of risk premium. If investors who trade S&P 500 options (and the underlying index since options investors often delta hedge their positions) are more sophisticated than the average investor in the cross-section of equities, then information from $SKEW$ will diffuse through the cross-section slowly.

The finance literature has already identified several variables that forecast future market returns. We are careful to control for these other variables to understand the multivariate implications of $SKEW_t$ on market returns. The variables that we consider are the dividend yield on the S&P 500, the smoothed earnings yield defined as the 10 year trailing moving average of aggregate earnings on the S&P 500 divided by the index price level, the term premium defined as the difference between the 10 year and 3 month treasury bond yield and the default premium defined as the difference in yield on Moody's AAA index and Moody's BAA index. To understand the relationship between $SKEW_t$ and expected market returns, we run the following regression:

$$R^e_{m,t} = a + \rho_m R^e_{m,t-1} + \beta_s SKEW_{t-1} + \beta_{dp} dp_{t-1} + \beta_{dy} dy_{t-1} + \beta_{sey} sey_{t-1} + \beta_{tp} tp_{t-1} + \varepsilon_{m,t} \quad (3.1)$$

using monthly data from 1996 - 2012. Our sample is constrained by the availability of options data. Additionally, much of the expected return literature - see Cochrane (2011) for a recent summary - has reported stronger effects at longer horizons. Therefore, we also run a regression of 6 month market excess returns on predictor variables:

$$R^e_{m,t\to t+5} = a + \rho_m R^e_{m,t-1} + \beta_s SKEW_{t-1} + \beta_{dp} dp_{t-1} + \beta_{dy} dy_{t-1} + \beta_{sey} sey_{t-1} + \beta_{tp} tp_{t-1} + \varepsilon_{m,t} \quad (3.2)$$

Table 1 reports the results. As noted earlier, since options markets close later than equity markets, we skip an extra day between information on $SKEW_t$ and any equity return to prevent look-ahead bias. Thus in monthly data, $SKEW_t$ represents observations on the second to last day of the month. $SKEW$ has significant forecasting power for market returns even in the presence of other state variables. A one volatility point higher $SKEW$ corresponds to roughly 30 - 60 basis points of expected market returns the following month. Similarly the second half of the table shows that a one volatility point increase in $SKEW$ is related to 1.8% higher expected return over the following 6 months.

We next turn to the cross-section of equities: to determine if innovations in $SKEW$ are differentially important in the cross-section (this is not a pre-determined conclusion) we use the Fama-French 25 portfolios as our basis assets (since individual equity security returns are noisy) and regress excess returns of each portfolio, $R^e_{i,t}$, on ε_{skew} controlling for market returns and volatility innovations proxied by innovations in the VIX index:

$$R^e_{i,t} = a + \beta_m R^e_{m,t} + \beta_v \varepsilon_{vix,t} + \beta_{\varepsilon_{skew}} \varepsilon_{skew,t} + \nu_t \quad (3.3)$$

We are careful to control for volatility innovations because Pan's model (and our earlier empirical results) specifies jump intensity to be a function of volatility so we want to be sure we aren't picking up changes in the volatility risk premium. Table 2 presents the multiple β of each portfolio with respect to ε_{skew}. The results here are clear: growth stocks have a positive exposure to increases in the jump risk premium while value stocks have a negative exposure. That is, when the risk neutral distribution becomes riskier, value stocks do poorly while growth stocks do well. The results are especially strong in small and medium stocks.

Since HML is the factor that has exposure to ε_{skew} (while the small-minus-big factor does not), we use the HML portfolio directly rather than each individual Fama-French portfolio in subsequent results. As mentioned in the introduction, we are interested in understanding how efficient securities in the cross-section are at incorporating information regarding changes in jump risk premium into their prices; we find a significant lag in the price adjustment process. In addition to doing poorly at time t when there is a positive innovation to $SKEW_t$, $R_{hml,t+1}$ is also highly negative; value stocks continue to underperform the following month. Figure 3 plots the cumulative response to $\varepsilon_{skew,t}$ from the regression of

$$R_{hml,t} = a + \beta_m R^e_{m,t} + \beta_{\varepsilon,j}\varepsilon_{skew,t-j} + \epsilon_t \tag{3.4}$$

for $j = 0...12$. The Newey-West error bounds are presented in the plot in dashes; j is measured on the x-axis. For each j, the figure plots $\sum_{k=0}^{j} \beta_{\varepsilon,k}$ and assumes that estimates of $\beta_{\varepsilon,j}$ are independent. This regression can be interpreted as asking: if there is a one volatility point increase in $SKEW$ at time t and a one volatility point increase in $SKEW$ at $t-1$, ..., $t-j$ then what is the cumulative effect on HML at time t?

We see a striking pattern: while $R_{hml,t}$ is indeed highly negatively correlated with $\varepsilon_{skew,t}$, there is a significant delay in the price adjustment process. The plot shows that the $j = 0$ and $j = 1$ coefficients for $R_{hml,t}$ are highly negative and significant (with associated t-statistics of -2.94 and -3.84, respectively). Following an increase in $SKEW$, HML continues to underperform the following month. In fact, we see that the price adjustment process actually takes up to 4 months to fully realize. This is a startling finding: to confirm these results we extend the sample internationally to Europe and Japan[2]. Note that our analysis is done from the perspective of a US investor (thus, for example, market returns refer to the CRSP value weighted market return). We also attempt to control for the effect of time-varying HML market β. As noted earlier, Petkova and Zhang (2005) found that the market β of HML varies through time; it is possible that a high level

[2] While this gives us comfort against data snooping concerns, we note that there is a 40% correlation between US HML returns and JPY HML returns; a 60% correlation between US and Europe HML returns.

of $SKEW_{t-1}$ forecasts a higher market β at time t. To be precise, imagine that

$$R_{hml,t} = \beta_{m,t} R^e_{m,t} + \eta_t \tag{3.5}$$

$$\beta_{m,t} = \beta_0 + \beta_1 SKEW_{t-1} \tag{3.6}$$

then the appropriate attribution regression to run for HML is

$$R_{hml,t} = \beta_0 R^e_{m,t} + \beta_1 (SKEW_{t-1} \cdot R^e_{m,t}) + \eta_t \tag{3.7}$$

We would like to eliminate the possibility that a time varying market β is driving our results so we include the interaction of $SKEW_{t-1}$ and $R^e_{m,t}$ into the regression. Therefore, for each region we run a forecasting regression of the form:

$$R_{hml,t} = a + \beta_m R^e_{m,t} + \beta_s \left(\sum_{j=1}^{4} \varepsilon_{skew,t-j} \right) + \beta_i (R^e_{m,t} \cdot SKEW_{t-1}) + \nu_t \tag{3.8}$$

where we use the sum of the last four innovations in $SKEW$ based on the results of Figure 3. Table 3 presents the summary statistics of HML returns in each region (Panel A) and reports the results from this regression (Panel B).

Panel A shows that HML in all three regions has a high return and a high CAPM alpha during our sample period. The units are left in their natural monthly frequency (the Sharpe ratio is annualized). Thus HML, in the US, has a CAPM alpha of .347% per month. The sample statistics in all three regions are similar with Europe having the highest Sharpe ratio. Panel B reports that a one volatility point unexpected increase in $SKEW$ over the last four months leads to a .6% lower HML return the following month in the US, .25% lower HML return in Japan and .37% lower HML return in Europe. The adjusted R^2 statistics are also quite large: a simple univariate forecasting regression in the US can explain 10% of the variation in HML returns in monthly data. The t-statistics are also very large: in the US the t-statistic associated with $\sum_{j=1}^{4} \varepsilon_{skew,t-j}$ is -6; this is directly linked to the Sharpe ratio of a strategy that one can construct (ie Sharpe (1994)).

To construct a realistic trading strategy from these regressions, we would like to avoid estimating an ARMA model for innovation extraction and also avoid estimating the distributed lag model for forecasting R_{hml}. While this is certainly the optimal method, our sample is relatively small and we want to avoid all possibility of look-ahead bias in parameters. To get around this constraint, we will simply use the level of $SKEW$: since several lags of innovations seem important (as noted earlier) and $SKEW$ is not terribly persistent, we hope that older innovations that are irrelevant will have decayed sufficiently and thus not erode our forecasting performance. To do this we simply run regression (3.8) but replace the term $\sum_{j=1}^{4} \varepsilon_{skew,t-j}$ with $SKEW_{t-1}$:

$$R_{hml,t} = a + \beta_m R^e_{m,t} + \beta_s SKEW_{t-1} + \beta_i (R^e_{m,t} \cdot SKEW_{t-1}) + \nu_t \tag{3.9}$$

Table 4 reports these results. Comparing the two tables we can immediately see that our forecasting performance is worse using the level of $SKEW$ as to be expected: the t-statistic is cut in half in the US and so is the R^2. Thus, backtest results that we report using $SKEW$ as a forecasting variable is a lower bound on the true performance that an investor can achieve.

These results imply a strategy, which we refer to as active HML, that would selectively rotate into and out of HML being long value (growth) and short growth (value) stocks at different points in time. We are careful to prevent any look-ahead bias in the parameters and ensure this strategy is realistic. We begin by computing a forecast for returns on HML using

$$R_{hml,t-1} = a + \beta_s SKEW_{t-2} + \epsilon_{t-1} \tag{3.10}$$

allowing 36 months burn in period for estimation of β_s. Based on this model we compute the forecast for the following month's HML return, $\hat{R}_{hml,t}$. Assuming an endowment of $\mathcal{W}_{t-1}$, we build a portfolio by putting $w_{hml,t-1}$ of $\mathcal{W}_{t-1}$ into HML. Assuming that margin accounts pay no interest rate and require 50% of the absolute value of the position (so that if one wants to go long HML by purchasing "H" and selling "L" then one has to put up margin equivalent to half of the position), the remainder of the endowment, $(1 - |w_{hml,t-1}|)\mathcal{W}_{t-1}$, is invested into the risk free rate[3]. The weight is defined as $w_{hml,t-1} = \tanh\left(\frac{\hat{R}_{hml,t}}{\sqrt{\frac{1}{t}\sum_{j=1}^{t}(\hat{R}_{hml,j} - \bar{\hat{R}}_{hml,t})^2}}\right)$. This is the hyperbolic tangent of the forecasted HML return scaled by the standard deviation of previous HML forecasts. The hyperbolic tangent is applied so that $w_{hml,t-1} \in [-1, 1]$. The gross return to this portfolio

[3] We assume that $\mathcal{W}_{t-1} > 0$; if at any point this condition is violated the strategy stops.

$\frac{\mathcal{W}_t}{\mathcal{W}_{t-1}} = 1 + w_{hml,t-1}R_{hml,t} + (1 - |w_{hml,t-1}|)R_{free,t}$ where $R_{free,t}$ is the risk free rate realized at time t. Each successive month, the window over which the model is estimated expands but always only includes historical data. Rebalancing is done monthly for both active and passive HML. The monthly rebalancing for passive HML assures that the investor puts half of his wealth in being long "H" and half into being short "L". The cumulative return to passive and active HML is presented in Figure 4. The shaded regions represent times when the strategy is short HML while the white areas represent times when the strategy is long HML.

As is evident from the plot, the position direction is quite persistent; since HML is such a large aggregate, transaction costs here are also minimal. However, the performance of active HML is significantly better than passive HML. An investment of \$1.00 in HML in 1999 becomes roughly \$1.50 by the end of 2012. This same dollar invested in active HML becomes roughly \$2.50 by the end of 2012. The annualized information ratio, $IR \equiv \frac{E(R^{active}_{hml,t} - R^{passive}_{hml,t})}{\sigma(R^{active}_{hml,t})}$, for this strategy is .36. The times when this strategy is short HML correspond to significantly anomalous market conditions. For example we see that this strategy is short HML during the run-up in tech stocks of the late 90's. It is also short HML during/post the 2008 financial crisis. These two periods account for a substantial portion of the profit generated by this strategy. This is to be expected: we are attempting to pick up states of the world when the price investors are willing to pay for portfolio insurance spikes and these states should not be a frequent occurrence.

While we have been fortunate that our time sample includes diversity in business cycle conditions, we are still constrained by the availability of options data from OptionMetrics. To verify that our results work in other time samples - a truly out of sample test - we attempt to impute the value of $SKEW$ based on quantities that $SKEW$ should be picking up. To extend the sample in a principled way, we use the LASSO variable selection method of Tibshirani (1996). This methodology is an ℓ^1 penalized regression that selects variables among a candidate set that best capture the true relationship and kicks out all irrelevant ones. The set of possible variables that we include is $I_t \equiv \{\overline{\kappa}_3, R_{hml,t}, R^e_{m,t}, dy_t, tp_t, dp_t\}$ and I_{t-1}. $\overline{\kappa}_3$ is the physical third cumulant of market returns computed over the past 3 months of daily data, $R_{hml,t}$ is the US HML return, $R^e_{m,t}$ is the market return, dy_t is the dividend yield, tp_t is the term premium, dp_t is the default premium. The logic for including these variables is simple: $\overline{\kappa}_3$ could capture the portion of $SKEW$ corresponding to the physical distribution (though based on Pan (2002) we know that it will be a very small effect), and dy_t, tp_t, and dp_t could capture portions of the jump risk premium.

To operationalize this technology, we use five-fold cross validation using the 1996-2012 sample, to fit the LASSO model to the $SKEW$ using I_t and I_{t-1}. The cross validation is needed to select the shrinkage parameter that LASSO uses to determine how aggressive it should be in shrinking regression coefficients. For a particular shrinkage parameter, we divide the sample (1996-2012) into 5 sections, pick a section to leave out, fit LASSO over the remaining four sections and compute the root-mean-square error of the model in forecasting the level of $SKEW$ in the left out section; we then leave a different section out and repeat the process. The average root-mean-square error for this particular value of the shrinkage parameter is recorded. A shrinkage parameter is selected that creates the lowest forecasting error. This shrinkage parameter corresponds to a particular set of variables out of the available set. A simple OLS model is then fit from 1996-2012 using the selected set of variables and is used to compute a fitted value of $SKEW$, termed $\widehat{SKEW}$, going back to 1963.

We validate that our results hold over this significantly longer non-overlapping sample period: we show that $\widehat{SKEW}$ has forecasting power for R^e_m and R_{hml} is slow to respond to innovations in $\widehat{SKEW}$, termed $\hat{\varepsilon}_{skew}$. Using the sample from 1963 - 1996, the first part of the Table 5 shows that R_{hml} responds slowly to innovations in $\hat{\varepsilon}_{skew}$: a one volatility point increase in $\widehat{SKEW}$ corresponds to 40 - 50 basis points poorer performance in HML the following month. The second part of the table shows that $\widehat{SKEW}$ is capable of forecasting the market return the following month as we saw in the 1996 - 2012 sample using $SKEW$. The R^2 in these regressions is significantly lower as one would expect: we are attempting to capture characteristics of a variable that is best reflected through option prices and thus our ability to do this is limited. However, it is reassuring that we can capture a relevant portion of it to validate our results.

3.2 Corporate Bonds

We have shown that HML responds to innovations in $SKEW$ slowly in three regions and over a lengthy time sample; these results led us directly to an implementable trading strategy. Do these results hold in other asset classes? We examine corporate bonds to try and answer this question. At the same time, it provides another out of sample test of our results regarding slow investor reaction to changes in crash risk. Corporate bonds are a natural asset class to examine because they contain a large cross-section (like equities) and have assets that are considered risky in absolute terms (junk bonds) by investors and those that are considered safe (investment grade bonds). Bank of America/ML provides total return indices by rating category (AAA through CCC) which we use as basis assets.

We first examine if these assets have differential exposure to innovations in $SKEW$ in Table 6. We see clearly that AAA bonds enjoy a positive return while CCC bonds have a negative return when $SKEW$ increases contemporaneously. Thus the long CCC, short AAA trade performs poorly when crash risk increases; this is the same type of result that we saw with value and growth stocks.

We next ask the question: do these securities incorporate changes in risk premia into their prices efficiently? We saw that the cross-section of equities does not and thus HML incorporates changes in $SKEW$ with a delay. To answer this question we run the analysis in equation (3.4) replacing $R_{hml,t}$ on the left hand side of the regression with $R_{CCC-AAA,t}$: the return of CCC bonds minus the return on AAA bonds. Figure 5 presents the results of this analysis. At lag zero we see the contemporaneous results presented in Table 6: the long junk short investment grade (CCC-AAA) trade performs poorly when there is a positive innovation in $SKEW$. However, we also see that it proceeds to perform poorly the following month as well (until reversing in month two). That is, these securities are also slow to fully incorporate all available information into their prices though they are more expedient than the cross-section of equities (which took 4 months). One can speculate regarding the reason for this: one story might be that corporate bonds have a more sophisticated investor base since fewer retail investors participate actively in the bond market. Another reason might be that jump risk is highly relevant for credit investors since they are concerned about bankruptcy. A significantly negative jump in the market (and thus in equity valuations) could drastically alter the probability of bankruptcy. Therefore, credit investors may be more sensitive to this particular information than equity investors.

These results can be presented in a regression framework using equation (3.8) replacing R_{hml} on the left hand side with returns on each bond rating category and using one lag of $SKEW$ innovations as opposed to four based on Figure 5. Table 7 presents the results of these regressions. We see that a one point increase in $SKEW$ predicts a -77 basis point return to $R_{CCC-AAA}$ the following month. These results confirm that underreaction to changes in crash risk is prevalent in the financial markets.

4 Investor Trading Behavior

We have shown that prices are slow to fully incorporate information from $SKEW$ into HML. A large behavioral/frictional literature has documented significant delays in price reactions, discussed nicely by Hong and Stein (1999); Duffie (2010). Ang et al. (2012) show that options on individual securities have relevant information for future returns of those securities not captured by the standard risk factors. They propose that sophisticated investors express their views in the options market and this information is reflected in individual stock returns slowly.

Our work finds results that are similar: innovations in $SKEW$ contain information about future HML returns. While there is a clear contemporaneous reaction as shown in Figure 3, there is also a significant delay. We confirm that investors are in fact slow to react to this information by examining mutual fund flows. Just like HML returns, we find that flows into value and growth mutual funds are predictable using past innovations in $SKEW$. A positive innovation in $SKEW$ causes investors to withdraw money from value funds while not withdrawing money from growth funds.

We first classify funds by value style using their four factor exposure

$$R_{f,t} = a + \beta_{m,t} R_{m,t} + \beta_{smb,t} R_{smb,t} + \beta_{hml,t} R_{hml,t} + \beta_{umd,t} R_{umd,t} + \epsilon_{f,t} \tag{4.1}$$

using 36 months rolling regression as in Chan et al. (2002) among others. Funds are arranged into quintiles each month based on last month's HML exposure: $\beta_{hml,t-1}$. We further define

$$FLOW_{f,t} \equiv \frac{TNA_{f,t} - TNA_{f,t-1}(1 + R_{f,t})}{TNA_{f,t-1}} \tag{4.2}$$

for each fund f and month t where TNA is the total net assets and $R_{f,t}$ is the return of fund f. This is the percentage increase/decrease in the assets of the fund due to contributions/withdrawals by investors. Additionally as Chevalier and Ellison (1997) show, flows into mutual funds are highly dependent on the funds' past performance; we are sure to condition on this in our analysis so that any effect in investor behavior we find is due to information in $SKEW$ as opposed to past fund returns. Therefore, we also compute the 1 year rolling cumulative return of each fund: $R_{f,t-12 \to t-1}$. Then, for each value style bucket (1 - 5) a TNA_{t-1} weighted average of $FLOW_{f,t}$ (termed $FLOW_{b,t}$

for $b \in \{1, 2, .., 5\}$) and $R_{f,t-12\to t-1}$ (termed $R_{b,t-12\to t-1}$) is taken. We regress:

$$FLOW_{b,t} = a + \beta_{b,skew}\varepsilon_{skew,t-1} + \beta_{b,ret}R_{b,t-12\to t-1} + \nu_t \tag{4.3}$$

Results in Table 8 show that $\beta_{b,skew}$ is highly significant and negative for value stocks but roughly zero or positive for growth stocks. Investors pull money out of value funds in response to an increase in market crash risk with a lag. The magnitudes are significant: one volatility point increase in $SKEW$ causes a .2% outflow from value funds relative to growth funds the following month. This underreaction by investors to the information expressed by option market participants drives the predictability of HML returns.

One may be concerned that mutual funds pre-position their portfolios in anticipation of flows and thus dampen the effect of lagged information on stocks. Consider a savvy value mutual fund manager who received an inflow of money this month: he may decide that there is a good chance that he will also receive an inflow of money the next month since flows are persistent. Knowing this fact, he uses his cash position (or takes a loan from a bank) to purchase value stocks this month anticipating to return his cash position (or pay the loan) to equilibrium the next month. This would serve to dampen the predictability of value stocks due to investor underreaction. To account for this fact we extract innovations from flows into each quintile, $\varepsilon^{flow}_{b,t}$, and treat these as unexpected flows to the fund manager. We then regress these unexpected flows on $\varepsilon_{skew,t-1}$ and past fund returns, $R_{b,t-12\to t-1}$:

$$\varepsilon^{flow}_{b,t} = a + \beta_{b,skew}\varepsilon_{skew,t-1} + \beta_{b,ret}R_{b,t-12\to t-1} + \nu_t \tag{4.4}$$

The results of this regression are presented in Table 9. This, however, does not alter our conclusions: innovations in $SKEW$ predict unexpected flows into growth and value stocks. Investors withdraw .1% from value funds relative to growth funds in response to one volatility point increase in $SKEW$ the previous month.

5 Discussion and Conclusion

We have shown that returns to HML (as well as corporate bonds) have a significant amount of predictability. Utilizing this predictability, we perform an "out-of-sample" test of performance: active HML significantly improves the returns to an investor relative to an investment in passive HML. A dollar invested in passive HML in 1999 grows to approximately $1.50 by the end of 2012. On the other hand, that same investment grows to roughly $2.50 in active HML. Furthermore, this predictability is easy to extract: it does not require complex computation just the implied volatility skew on the S&P 500. Using mutual fund flow data, we show that this predictability is due to delayed reaction by investors.

Our results have deep implications for theories attempting to explain high returns on HML: theories must now consider explaining returns to active HML (a much more difficult thing to do given the favorable return profile). More generally, our results relate to a large literature on slow moving capital and segmented markets. We show how a large, heavily examined factor can have a significant amount of return predictability due to the slow rotation into and out of value/growth stocks by investors. One may regard slight economic frictions that prevent small stocks from re-pricing perfectly as unimportant. However, the return predictability that we identify here is on an aggregate, economically meaningful level. A significant portion of this predictability comes from periods when the market experiences stress: during the tech bubble and during the financial crisis of 2008. We highlight that these periods can generate significant mispricing for large aggregates.

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Table 1: $SKEW$ Forecasts of Future Market Excess Returns

We report the forecasting power of $SKEW$ for future market returns across the 1 month and 6 month horizon. We are careful to control for other variables that have been found to predict market returns in the literature.

Dependent Variable	$SKEW_{t-1}$	$R^e_{m,t-1}$	dp_{t-1}	dy_{t-1}	sey_{t-1}	tp_{t-1}	(Intercept)	R^2	N
$R^e_{m,t}$	0.260						-0.734	0.35%	201
	[1.221]						[-0.724]		
$R^e_{m,t}$	**0.377**	**0.162**					-1.357	2.31%	201
	[2.221]	**[1.978]**					[-1.429]		
$R^e_{m,t}$	**0.591**	0.171	**-3.659**	1.741	0.741	-0.315	**-4.078**	5.45%	201
	[2.176]	[1.934]	**[-2.051]**	[0.986]	[1.178]	[-1.031]	**[-2.291]**		
$R^e_{m,t\to t+5}$	**1.674**						-4.803	4.32%	196
	[2.025]						[-0.907]		
$R^e_{m,t\to t+5}$	**1.873**	0.272					-5.847	4.78%	196
	[2.346]	[1.233]					[-1.140]		
$R^e_{m,t\to t+5}$	2.142	0.300	-12.345	10.952	2.754	-1.208	-22.535	16.75%	196
	[1.516]	[1.305]	[-1.089]	[0.672]	[0.469]	[-0.466]	[-1.795]		

Table 2: Cross Sectional Sort by β to ε_{skew}

Multiple β of Fama-French 25 portfolio returns to innovations in $SKEW$; equation (3.3). Newey-West t-statistics are in brackets.

	Book-to-Market					
Size	Growth	2	3	4	Value	Value - Growth
Small	0.59	0.22	0.05	-0.13	-0.41	**-1.00**
	[1.07]	[0.47]	[0.15]	[-0.37]	[-0.99]	**[-2.89]**
2	0.67	0.17	-0.24	-0.26	-0.23	**-0.90**
	[1.41]	[0.51]	[-0.94]	[-0.84]	[-0.74]	**[-2.18]**
3	0.53	0.05	**-0.33**	-0.29	**-0.56**	**-1.09**
	[1.66]	[0.30]	**[-2.03]**	[-1.59]	**[-2.45]**	**[-2.67]**
4	0.47	-0.20	-0.32	-0.21	-0.24	-0.71
	[1.85]	[-1.10]	[-1.66]	[-1.03]	[-0.98]	[-1.87]
Large	0.02	-0.17	-0.34	**-0.52**	-0.27	-0.29
	[0.15]	[-1.11]	[-1.84]	**[-2.41]**	[-1.20]	[-1.14]
Large - Small	-0.57	-0.39	-0.39	-0.39	0.14	
	[-0.91]	[-0.70]	[-0.90]	[-0.92]	[0.27]	

Table 3: Forecast of $R_{hml,t}$ Using $\sum_{j=1}^{4} \varepsilon_{skew,t-j}$ 1996-2012

Panel A shows summary statistics for HML in US, Japan (JPY) and Europe (EUR): all of these regions have a significant value effect. The results are from the perspective of a US investor (CAPM α is with respect to the US market). Panel B shows that lagged innovations in $SKEW$ have significant forecasting power for HML in all of these regions.

(a) HML Summary Statistics By Region

Region	$\overline{R_t}$	$\min R_t$	$\max R_t$	$\sigma(R_t)$	Sharpe	CAPM α	N
US	0.267	-12.600	13.840	3.495	0.265	0.347	201
JPY	0.457	-13.820	10.080	3.092	0.512	0.545	201
EUR	0.487	-9.570	10.960	2.653	0.636	0.481	201

(b) R_{hml} Forecasts

Region	$\sum_{j=1}^{j=4} \varepsilon_{skew,t-j}$	$R_{m,t}$	$SKEW_{t-1} \cdot R_{m,t}$	(Intercept)	R^2	N
US	**-0.600**			**0.403**	10.87%	197
	[-6.010]			**[1.689]**		
US	**-0.576**	-0.154		**0.468**	15.07%	197
	[-5.159]	[-1.406]		**[1.773]**		
US	**-0.564**	-0.419	0.053	**0.428**	17.00%	197
	[-6.190]	[-1.692]	[1.403]	**[1.785]**		
JPY	**-0.255**			**0.505**	2.09%	197
	[-2.312]			**[1.939]**		
JPY	**-0.227**	**-0.183**		**0.582**	9.89%	197
	[-2.648]	**[-3.560]**		**[2.380]**		
JPY	**-0.223**	**-0.268**	0.017	**0.569**	9.74%	197
	[-2.412]	**[-3.108]**	[1.048]	**[2.399]**		
EUR	**-0.376**			**0.554**	7.15%	197
	[-4.621]			**[2.052]**		
EUR	**-0.379**	0.023		**0.545**	6.84%	197
	[-4.849]	[0.302]		**[1.837]**		
EUR	**-0.371**	-0.147	0.034	**0.520**	8.02%	197
	[-4.169]	[-0.822]	[1.261]	**[1.876]**		

Table 4: Forecast of $R_{hml,t}$ Using $SKEW_{t-1}$ 1996-2012

Reports the results of equation (3.9): forecasts of HML returns using the $SKEW$ level which is useful in turning our results into a trading strategy that avoids any look-ahead in parameters.

Region	$SKEW_{t-1}$	$R_{m,t}$	$SKEW_{t-1} \cdot R_{m,t}$	(Intercept)	R^2	N
US	**-0.524**			**2.695**	6.26%	201
	[-3.778]			**[4.217]**		
US	**-0.484**	-0.154		**2.581**	10.41%	201
	[-3.506]	[-1.559]		**[4.298]**		
US	**-0.507**	-0.480	0.065	**2.650**	13.54%	201
	[-4.396]	[-1.885]	[1.568]	**[4.671]**		
JPY	**-0.285**			**1.778**	2.05%	201
	[-2.203]			**[3.067]**		
JPY	**-0.238**	**-0.180**		**1.646**	9.58%	201
	[-2.014]	**[-3.573]**		**[3.152]**		
JPY	**-0.246**	**-0.286**	0.021	**1.668**	9.61%	201
	[-2.002]	**[-3.131]**	[1.253]	**[3.084]**		
EUR	**-0.380**			**2.245**	5.65%	201
	[-3.651]			**[4.756]**		
EUR	**-0.386**	0.025		**2.263**	5.39%	201
	[-3.602]	[0.346]		**[4.221]**		
EUR	**-0.401**	-0.181	0.041	**2.307**	7.41%	201
	[-3.203]	[-0.956]	[1.397]	**[3.818]**		

Table 5: Extending the Sample: 1963 - 1996

We extend the sample to 1963 by replicating $SKEW$ using other variables, termed $\widehat{SKEW}$. This table reports the results of forecasting returns on HML using innovations in $\widehat{SKEW}$ and the market using $\widehat{SKEW}$ from 1963 - 1996.

Dependent Variable	$\hat{\varepsilon}_{skew,t-1}$	$R_{m,t}$	$\widehat{SKEW}_{t-1} \cdot R_{m,t}$	$\widehat{SKEW}_{t-1}$	$R_{m,t-1}$	(Intercept)	R^2	N
$R_{hml,t}$	**-0.519**					**0.461**	1.49%	396
	[-2.472]					**[3.078]**		
$R_{hml,t}$	**-0.413**	**-0.198**				**0.551**	12.70%	396
	[-2.274]	**[-5.239]**				**[3.936]**		
$R_{hml,t}$	**-0.423**	**-0.217**	0.006			**0.548**	12.50%	396
	[-2.069]	**[-2.400]**	[0.228]			**[3.977]**		
$R_{m,t}$				**0.443**		-0.781	0.85%	396
				[2.107]		[-1.277]		
$R_{m,t}$				**0.479**	0.071	-0.914	1.09%	396
				[2.360]	[1.364]	[-1.512]		

Table 6: Corporate Bond Returns and ε_{skew}

We document that AAA bonds perform well when $SKEW$ increases while CCC bonds perform poorly. Thus the trade that goes long CCC and short AAA bonds behaves like HML with respect to innovations in $SKEW$.

Dependent Variable	$\varepsilon_{skew,t}$	$\varepsilon_{vix,t}$	$R_{m,t}$	(Intercept)	R^2	N
$R_{aaa,t}$	0.228	-0.049	-0.006	**0.271**	1.08%	201
	[1.699]	[-0.532]	[-0.143]	**[2.741]**		
$R_{aa,t}$	0.154	-0.066	0.006	**0.277**	2.65%	201
	[1.527]	[-0.876]	[0.142]	**[2.734]**		
$R_{a,t}$	0.167	-0.113	0.021	**0.298**	8.28%	201
	[1.565]	[-1.053]	[0.419]	**[2.478]**		
$R_{bbb,t}$	-0.117	-0.055	0.072	**0.338**	11.48%	201
	[-0.798]	[-0.688]	[1.506]	**[2.547]**		
$R_{bb,t}$	-0.296	-0.117	**0.166**	**0.392**	39.26%	190
	[-1.454]	[-1.789]	**[2.948]**	**[2.384]**		
$R_{b,t}$	**-0.427**	**-0.115**	**0.259**	0.258	46.08%	190
	[-2.167]	**[-2.216]**	**[5.063]**	[1.549]		
$R_{ccc,t}$	**-0.720**	-0.121	**0.454**	0.337	46.06%	190
	[-2.259]	[-1.532]	**[3.696]**	[1.247]		
$R_{ccc,t} - R_{aaa,t}$	**-0.945**	-0.070	**0.465**	-0.181	44.34%	190
	[-2.413]	[-0.854]	**[3.810]**	[-0.650]		

Table 7: Bond Return Forecasts Using $\varepsilon_{skew,t-1}$

This table shows that lagged innovations in $SKEW$ are able to forecast corporate bond returns highlighting that this asset class is also slow to incorporate information from the options market into prices.

Dependent Variable	$\varepsilon_{skew,t-1}$	$R_{m,t}$	$SKEW_{t-1} \cdot R_{m,t}$	(Intercept)	R^2	N
$R_{aaa,t}$	**0.397**	0.034	-0.006	**0.276**	7.45%	200
	[2.374]	[0.493]	[-0.494]	**[2.636]**		
$R_{aa,t}$	**0.318**	0.051	-0.004	**0.271**	6.49%	200
	[2.165]	[0.761]	[-0.401]	**[2.653]**		
$R_{a,t}$	**0.365**	0.146	-0.014	**0.276**	10.04%	200
	[2.176]	[1.365]	[-0.954]	**[2.127]**		
$R_{bbb,t}$	0.233	0.283	-0.032	**0.330**	16.27%	200
	[1.856]	[1.946]	[-1.438]	**[2.327]**		
$R_{bb,t}$	0.073	**0.445**	-0.033	**0.334**	36.43%	190
	[0.693]	**[2.537]**	[-1.271]	**[2.030]**		
$R_{b,t}$	-0.262	**0.500**	-0.024	0.198	43.02%	190
	[-1.670]	**[3.386]**	[-1.063]	[1.090]		
$R_{ccc,t}$	-0.376	**0.569**	0.009	0.226	43.44%	190
	[-1.504]	**[2.036]**	[0.201]	[0.793]		
$R_{ccc,t} - R_{aaa,t}$	**-0.775**	**0.545**	0.014	-0.277	43.70%	190
	[-2.897]	**[2.090]**	[0.337]	[-0.914]		

Table 8: Flows Into Value and Growth Funds

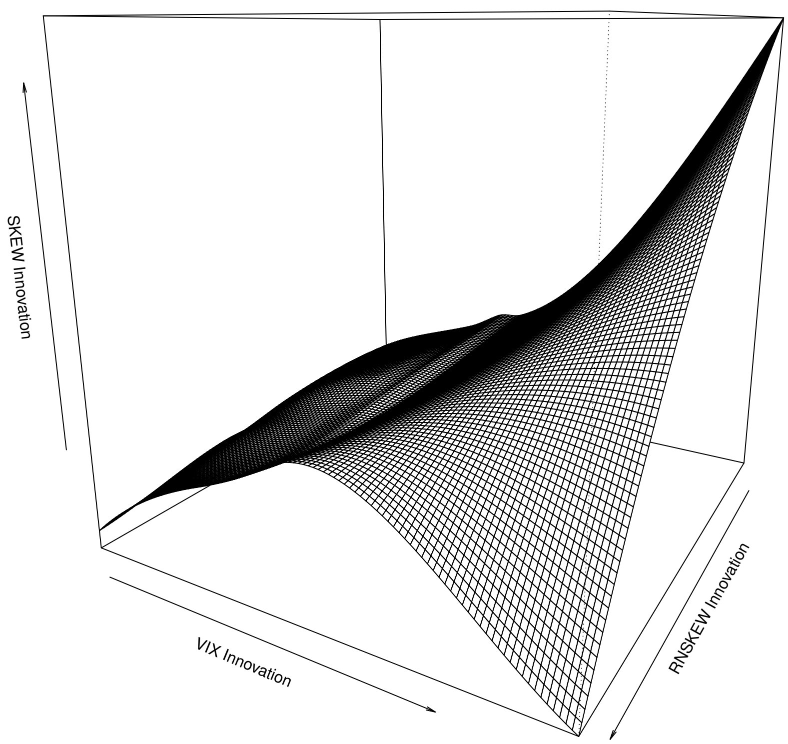
Mutual funds are sorted into style quintiles according to $\beta_{hml,t-1}$ in a regression of $R_{f,t} = a + \beta_{m,t} R^e_{m,t} + \beta_{smb,t} R_{smb,t} + \beta_{hml,t} R_{hml,t} + \beta_{umd,t} R_{umd,t}$ - where $R_{f,t}$ is the return of fund f at time t - as in Chan et al. (2002) among others. $FLOW_{f,t} \equiv \frac{TNA_{f,t} - TNA_{f,t-1}(1+R_{f,t})}{TNA_{f,t-1}}$ is computed for each fund f and month t. To control for the flow performance relationship cumulative returns over the past year are also computed and denoted by $R_{f,t-12\rightarrow t-1}$. Then for each quintile an asset (TNA_{t-1}) weighted average is taken across $FLOW_{b,t} \equiv \sum_{f\in b} w_{f,t-1} FLOW_{f,t}$ and $R_{b,t-12\rightarrow t-1} \equiv \sum_{f\in b} w_{f,t-1} R_{f,t-12\rightarrow t-1}$. Then for each quintile we regress $FLOW_t = a + \beta_{skew} \varepsilon_{skew,t-1} + \beta_{ret} R_{t-12\rightarrow t-1} + \nu_t$. The table shows that an increase in $SKEW_t$ causes investors to pull money away from value funds.

Value Style Quintile	$\varepsilon_{skew,t-1}$	$R_{t-12\rightarrow t-1}$	(Intercept)	R^2	N
1	0.007		-0.182	-0.50%	199
	[0.164]		[-1.036]		
	0.035	**0.016**	-0.362	16.88%	199
	[0.821]	**[2.678]**	[-3.111]		
2	-0.099		0.089	1.31%	199
	[-1.988]		[1.002]		
	-0.082	**0.010**	-0.019	5.22%	199
	[-1.592]	**[1.597]**	[-0.168]		
3	-0.027		0.007	-0.14%	199
	[-0.632]		[0.167]		
	-0.012	**0.008**	-0.066	4.30%	199
	[-0.258]	**[2.120]**	[-1.072]		
4	**-0.137**		-0.055	4.25%	199
	[-3.826]		[-0.518]		
	-0.117	**0.009**	-0.147	7.82%	199
	[-2.507]	**[2.192]**	[-1.535]		
5	**-0.208**		0.057	4.73%	199
	[-2.581]		[0.377]		
	-0.164	**0.017**	-0.139	12.76%	199
	[-2.039]	**[3.289]**	[-0.792]		
5-1	**-0.215**		0.239	1.66%	199
	[-2.076]		[0.675]		
	-0.163	**0.057**	0.215	53.75%	199
	[-1.980]	**[3.742]**	[1.387]		

Table 9: Unexpected Flows Into Value and Growth Funds

This table reports the results of equation (4.4) showing that innovations in $FLOW$ (relative to past values of $FLOW$) are predictable using lagged innovations in $SKEW$.

Value Style Quintile	$\varepsilon_{skew,t-1}$	$R_{t-12\rightarrow t-1}$	(Intercept)	R^2	N
1	**0.045**		-0.038	0.04%	199
	[2.108]		[-0.930]		
	0.042	-0.002	-0.020	-0.06%	199
	[1.208]	[-0.685]	[-0.412]		
2	-0.032		-0.019	-0.17%	199
	[-0.784]		[-0.421]		
	-0.035	-0.002	0.000	-0.44%	199
	[-0.868]	[-0.558]	[0.001]		
3	-0.017		-0.027	-0.36%	199
	[-0.364]		[-0.808]		
	-0.022	-0.003	-0.001	-0.17%	199
	[-0.479]	[-0.793]	[-0.011]		
4	-0.051		-0.025	0.62%	199
	[-1.600]		[-0.694]		
	-0.059	-0.003	0.009	1.02%	199
	[-1.490]	[-1.328]	[0.178]		
5	-0.050		0.007	0.32%	199
	[-0.961]		[0.175]		
	-0.047	0.001	-0.006	-0.09%	199
	[-0.895]	[0.826]	[-0.144]		
5-1	**-0.102**		0.013	1.40%	199
	[-2.328]		[0.238]		
	-0.104	-0.002	0.014	1.10%	199
	[-2.383]	[-0.372]	[0.259]		



Dependent Variable	$\varepsilon_{rnskew,t}$	$\varepsilon_{rnskew,t} * \varepsilon_{vix,t}$	$\varepsilon_{vix,t}$	(Intercept)	R^2	N
$\varepsilon_{skew,t}$	**-0.167**	**-0.266**	**0.516**	0.062	41.02%	201
	[-3.421]	**[-2.074]**	**[9.369]**	[1.013]		

Figure 1: Nonparametric Relationship Between $SKEW$, VIX and $RNSKEW$ Innovations

We show a nonparametric surface that relates innovations in $SKEW$ to innovations in the VIX and $RNSKEW$. The surface is the result of a local polynomial regression using second order polynomials and 75% span. Below the plot we present the parametric version of the relationship from equation (2.3).

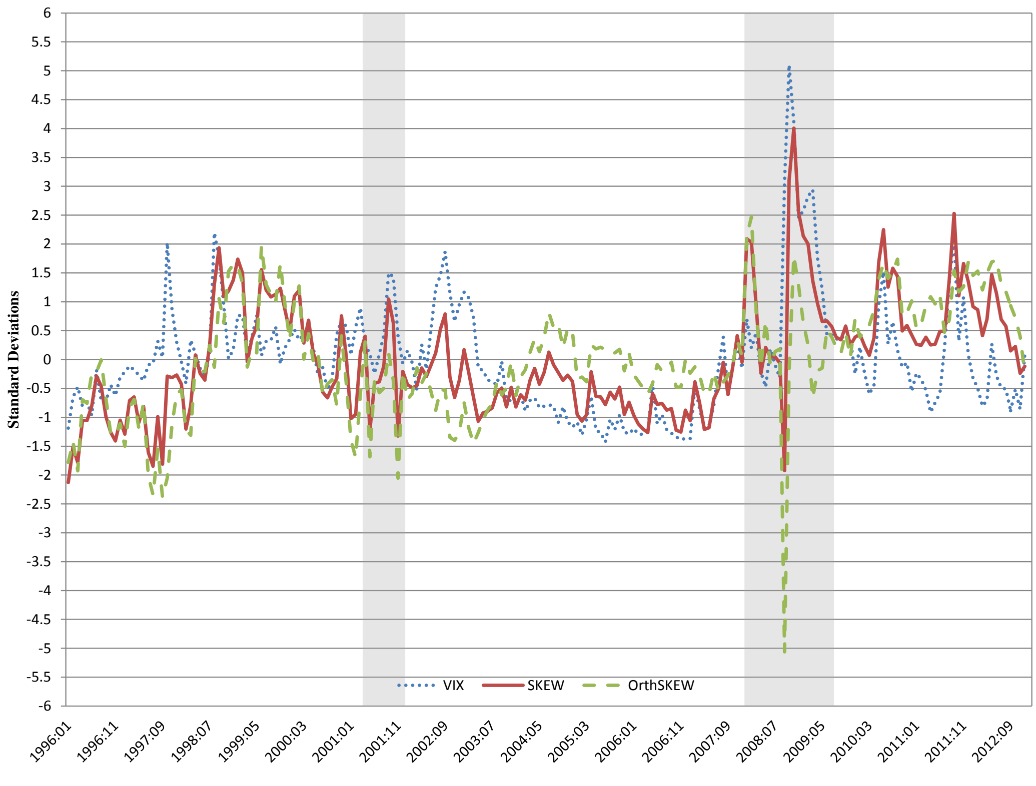


Figure 2: Time Series Plot of $SKEW$

Plot of $SKEW$, VIX and $OrthSKEW$ ($SKEW$ orthogonalized to the VIX through linear regression) from 1996-2012.

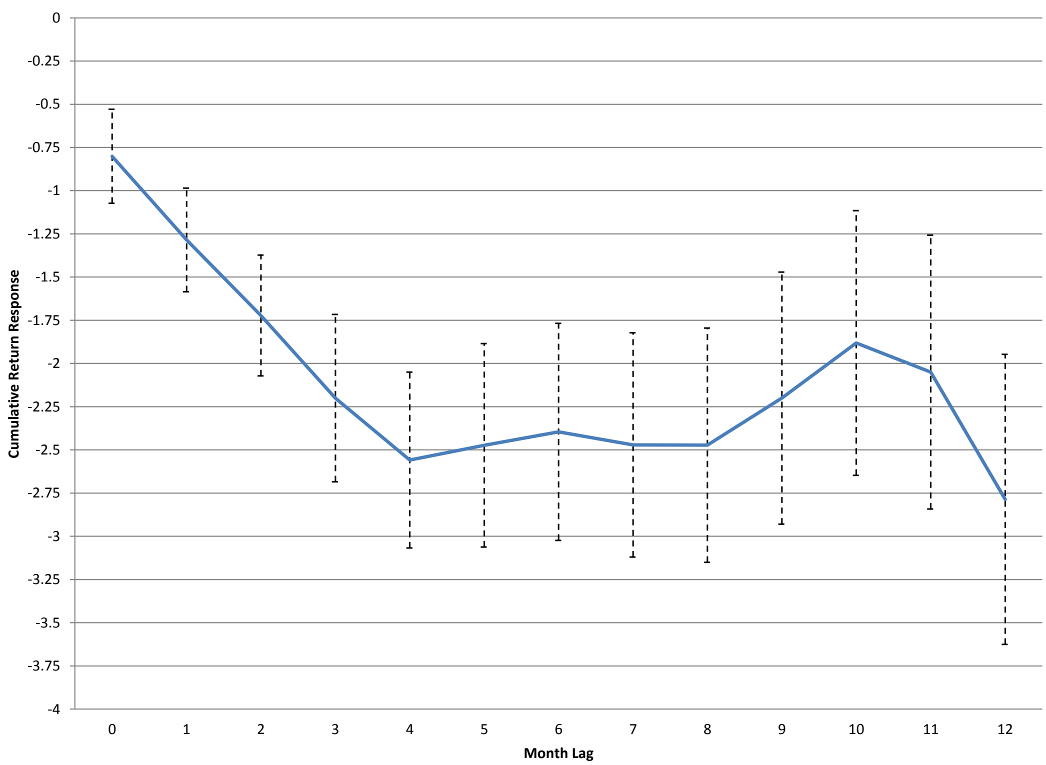


Figure 3: HML Underreaction to $SKEW$ Innovations

This plot demonstrates the underreaction of $R_{hml,t}$ to innovations in $SKEW_t$. We run regressions of $R_{hml,t} = a + \beta_m R_{m,t} + \beta_{\varepsilon,j}\varepsilon_{skew,t-j} + \epsilon_t$ for $j = 0...12$ and plot $\sum_{k=0}^{j} \beta_{\varepsilon,k}$. The error bars are plotted in dashes and assume that estimates of $\beta_{\varepsilon,j}$ are independent. As is clear from the plot, there is a significant predictability to $R_{hml,t}$ based on lagged innovations in $SKEW_t$.

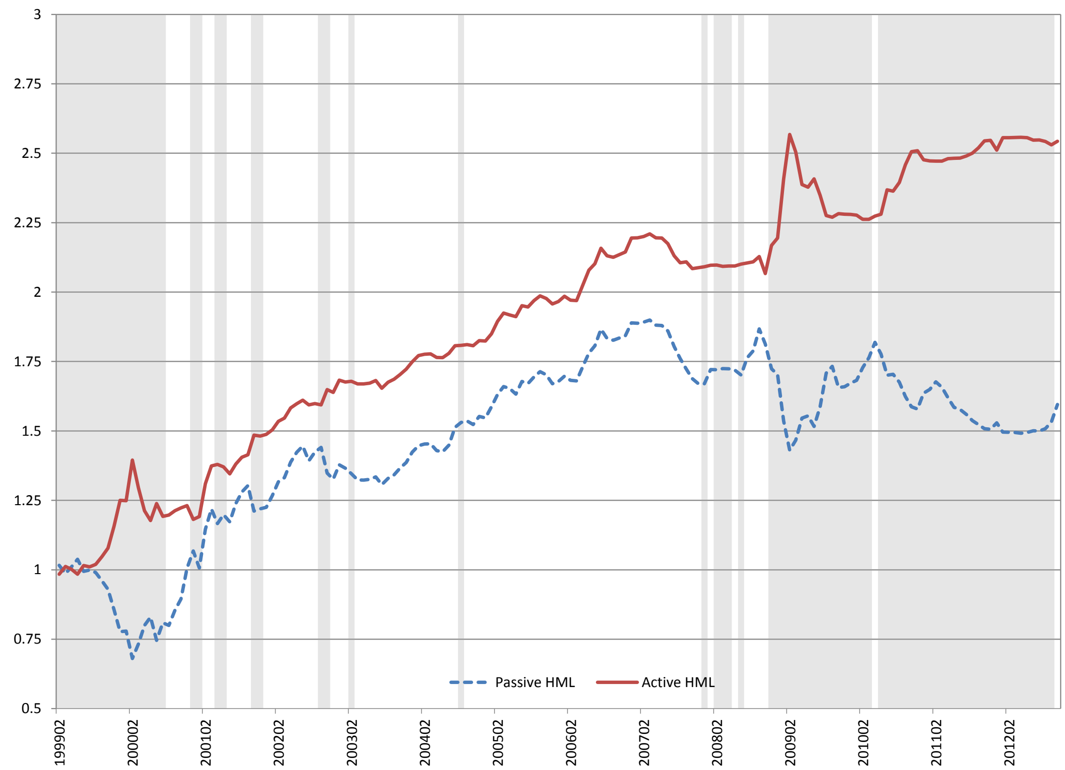


Figure 4: Cumulative Returns to Passive and Active HML Strategy

This plot demonstrates the out-of-sample forecasting performance of $SKEW_t$ in timing returns to $R_{hml,t}$. To construct the strategy we run a forecasting regression of $R_{hml,t-1} = a + \beta_s SKEW_{t-2} + \epsilon_{t-1}$ using 36 months of lagged data (this is the burn in period). Based on this model we compute the forecast for next month's HML return, $\hat{R}_{hml,t}$. To determine how much to invest each month we assume an endowment of $\mathcal{W}_{t-1}$ and Build a portfolio by putting $w_{hml,t-1}$ of it into HML and $(1 - |w_{hml,t-1}|)$ into the risk free rate where $w_{hml,t-1} = \tanh\left(\frac{\hat{R}_{hml,t}}{\sqrt{\frac{1}{J}\sum_{j=1}^{t}(\hat{R}_{hml,j} - \overline{\hat{R}}_{hml,t})^2}}\right)$. This is the hyperbolic tangent of the forecasted HML return scaled by the standard deviation of previous HML forecasts. The hyperbolic tangent is applied so that $w_{hml,t-1} \in [-1, 1]$. The return to this portfolio is $1 + R_{p,t} = 1 + w_{hml,t-1}R_{hml,t} + (1 - |w_{hml,t-1}|)R_{free,t}$. The mechanism described avoids look ahead bias in values and parameters. This cumulative return is plotted in the figure and labeled Active HML. Passive HML corresponds to monthly rebalancing strategy that invests equal weights into being long "H" and short "L".

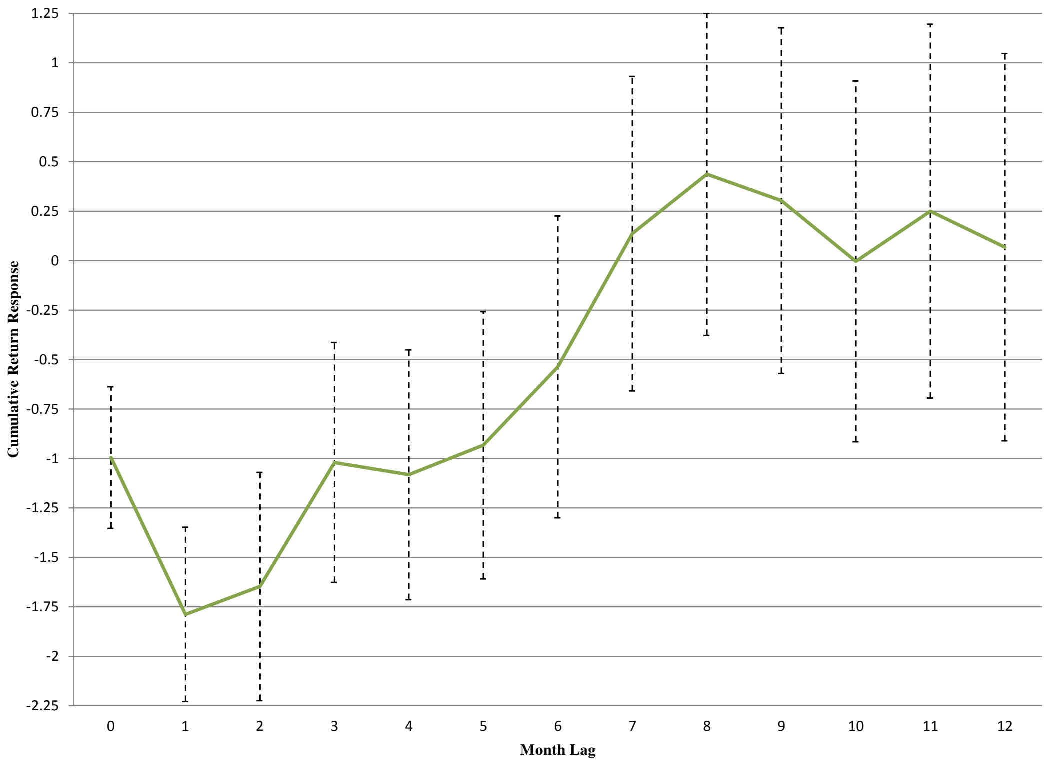


Figure 5: Cumulative CCC-AAA Response to ε_{skew}

Plot of the cumulative response to innovations in $SKEW$ of a trade that goes long CCC and short AAA bonds. Corporate bonds, like equities, are also slow to fully incorporate all information from $SKEW$.