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Asymmetric Volatility, Skewness, and Downside Risk in Different Asset Classes: Evidence from Futures Markets

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Abstract

This study examines the cross-sectional variation of futures returns from different asset classes. The monthly returns are positively correlated with downside risk and negatively correlated with coskewness. The asymmetric volatility effect generates negatively skewed returns. Assets with high coskewness and low downside betas provide hedges against market downside risk and offer low returns. The high returns offered by assets with low coskewness and high downside betas are a risk premium for bearing downside risk. The asset pricing model that incorporates downside risk partially explains the futures returns. The results indicate a unified risk perspective to jointly price different asset classes.

Keywords: asymmetric volatility, skewness, coskewness, downside risk, international futures

JEL Classifications: C22, G10, G13

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1. Introduction

A stylized fact of stock markets is that volatility tends to be higher following negative return shocks than it does following positive shocks, as first noted by Black (1976) and Christie (1982). Engle (2004) points out that this asymmetric volatility effect induces negatively skewed returns. Earlier work by Kraus and Litzenberger (1976) and Rubinstein (1973) shows that investors dislike stocks with negative skewness, and, therefore, they require higher returns on these assets. Harvey and Siddique (2000) further show that coskewness with a U.S. stock market volatility portfolio explains the cross-sectional variation in expected returns. Stocks with low coskewness (i.e., assets delivering low returns when market volatility is high) earn higher average returns.

Investors indicate a different level of concern about downside losses versus upside gains. Ang, Chen and Xing (2006a) report that stocks with higher downside betas have higher returns, indicating a premium for bearing downside risk in the cross-section. Ang, Chen and Xing (2006b, p. 260) provide an intuitive description of how market volatility risk is related to downside risk, coskewness, and asset returns:

> Risk averse agents demand stocks that hedge against [market volatility] risk. Periods of high volatility also tend to coincide with downward market movements. . . . As Bakshi and Kapadia (2003) comment, assets with high sensitivities to market volatility risk provide hedges against market downside risk. The higher demand for assets with high systematic volatility loadings increases their price and lowers their average return. Finally, stocks that do badly when volatility increases tend to have negatively skewed returns over intermediate horizons, while stocks that do well when volatility rises tend to have positively skewed returns. If investors have preferences over coskewness (see Harvey and Siddique, 2000), stocks that have high sensitivities to innovations in market volatility are attractive and have low returns.

I provide a systematic approach for describing these relations in diverse asset classes, represented by 55 futures contracts, including indexes, bonds, commodities, and currencies. I test two hypotheses: (1) asymmetric volatility results in negative long-run skewness and (2) downside risk is priced in the cross-section of different asset classes. I start with the relation between asymmetric volatility and long-run skewness and then look at the relation among skewness, downside beta, and coskewness. Finally, I examine the risk premium for downside risk. The results provide insight into risk management with international multiple asset classes represented by futures contracts.

Futures contracts with lower transaction costs facilitate an examination of the relationship among asymmetric volatility, risks, and returns. The index and bond futures comprise all the major international markets, including Germany, Japan, the United Kingdom, and the United States. Although investors can take a long or short position in futures, like Gorton and Rouwenhorst (2006) and Lettau, Maggiori and Weber (2014) in commodities futures, this study examines returns on long positions in futures contracts. Gorton and Rouwenhorst (2006) study the diversification benefits of commodities futures (not the underlying assets) as an asset class from the perspective of investors holding Standard & Poor's (S&P) 500 index.

The study is closely related to Lettau, Maggiori and Weber (2014), who report that the downside-risk-CAPM (capital-asset pricing model) can jointly explain the cross-sectional returns of currencies, commodities, sovereign bonds, and U.S. stocks, but the authors do not consider asymmetric volatility. They test their models on sorted portfolios that capture a characteristic (e.g., the interest rate differential among currencies) associated with expected returns. In contrast, I use futures returns directly without sorting them into portfolios. More specifically, Lettau, Maggiori and Weber (2014) focus on the in-sample explanation of cross-sectional returns. I use the asset pricing model in an out-of-sample test with time-varying betas of different measures for downside risk. Results of my study can be easily used by practitioners with lower transaction costs and fewer procedures for portfolio formation. Unlike Lettau, Maggiori and Weber (2014) and other studies, my data are all international futures returns, which show excess returns without detailed estimations. My results provide an international perspective for conditional risk premia of different asset classes. Models that have been developed for stocks or a particular asset class may not be able to jointly price other classes.

Two popular generalized autoregressive heteroskedasticity (GARCH)-type models, the exponential GARCH (EGARCH) model of Nelson (1991) and the GJR-GARCH model of Glosten, Jagannatha and Runkle (1993), have been used to describe the asymmetric volatility process of stock returns. Following negative return shocks, both models correctly predict an increase in volatility. However, estimations of these two models also predict an increase in volatility following large positive return shocks (albeit a much smaller increase than a negative shock of the same magnitude), but Ederington and Guan (2010) show that both implied and realized volatilities generally fall after positive return shocks. Considering different dynamics of the long-run and short-run components of volatility, I use Engle and Lee's (1999) component GARCH (CGARCH) model to describe the asymmetric volatility process of both positive and negative shocks using daily returns. As shown by Wang and Ghysels (2014), volatility component models can capture complex dynamics in a simple model specification and are not significantly influenced by structural breaks or nonstationarities in volatilities.

The CGARCH model shows that international stock indexes and investment currencies in carry trades exhibit significant asymmetric volatility but not government bonds, most commodities, and funding currencies. Foreign exchange (FX) carry trades involve borrowing a low-interest currency (a funding currency, e.g., Japanese yen) and using the funds to purchase a high-interest currency (an investment currency, e.g., Australian dollars). Burnside, Eichenbaum, Kleshchelski and Rebelo (2011) and other studies show that carry trades offer excess profits.

Why do assets with asymmetric volatility generally offer higher returns? The asymmetric volatility effect generates negative skewness of monthly returns. Negative skewness increases for longer horizons (Engle, 2004). This negative skewness means the probability of a large sustained decline in asset prices is substantial. Investors will seek to hedge against this and other types of long-term risk. High unexpected volatility typically coincides with low returns, so high-coskewness assets that covary negatively with market volatility innovations provide a good hedge and therefore are expected to earn a lower average return. By the same token, low-downside-beta assets, which perform relatively well during market downturns, should yield lower returns.

The results show that monthly returns on futures positively correlate with asymmetric volatility and downside risk and negatively correlate with unconditional skewness and conditional coskewness. Futures contracts with large downside betas offer higher average monthly returns and exhibit asymmetric volatility, negative skewness, and negative coskewness. In contrast, contracts with small downside beta yield opposite results. Using the Fama-MacBeth procedures with time-varying betas, downside beta and coskewness partially explain the cross-sectional variation of futures returns. The overall results support the two hypotheses stated above and suggest a unified risk perspective on different asset classes. Investors who view the U.S. stock index as the benchmark portfolio and want to hedge the downside risk should include international asset classes with low downside beta and high coskewness in their portfolios. Likewise, investors who invest in high downside beta and low coskewness must realize that the higher returns are simply compensation for the high downside risk.

Previous research in asset pricing models does not examine the impact of asymmetric volatility on returns. In the following section, I present econometric models of asymmetric volatility, skewness, volatility beta, downside beta, and coskewness.

2. Theoretical and econometric models

Long-term negative skewness is a consequence of asymmetric volatility models (Engle, 2004). Skewness is defined in terms of long horizon T at time t and continuously compounded returns as

$$skew_t\,(T) = \frac{E_t(r_{t+T} - \mu_{t+T})^3}{\left[E_t(r_{t+T} - \mu_{t+T})^2\right]^{3/2}}, \qquad \mu_{t+T} = E\,(r_{t+T})\,, \tag{1}$$

where r_{t+T} is the long-term log returns (or monthly returns in the current paper). Using log returns, $skew_t(T)$ focuses on the asymmetry of return distributions (Engle, 2011; Engle and Mistry, 2014). Long-term negative skewness resulting from asymmetric volatility increases the downside risk and investors will pursue strategies to hedge against this risk. Therefore, it is important to correctly model the asymmetric volatility of returns, as shown in the following.

In Engle (2004, 2011) and Engle and Mistry (2014), a hedge asset is considered an asset that hedges against the unconditional negative skewness of stock returns.

For traditional asset allocations, a hedge asset is considered an asset that negatively correlates with stocks (e.g., bonds) and, therefore, diversifies the risk of stock returns. In the current study, I specify a hedge asset that hedges against the downside risk of stocks.

2.1. Asymmetric volatility and unconditional skewness

Nelson (1991) proposes the following EGARCH model to allow for asymmetric volatility.

$$log\left(\sigma_t^2\right) = \omega + \alpha\,|z_{t-1}| + \theta z_{t-1} + \gamma log\left(\sigma_{t-1}^2\right), \qquad z_t \equiv \varepsilon_t/\sigma_t, \tag{2}$$

where ε_t is the returns residual that follows a zero-mean independent and identically distributed process with conditional variance, ${\sigma_t}^2$, and z_t is the standardized residual. In Equation (2), asymmetric volatility is captured by the coefficient θ. A negative θ indicates that negative return shocks will increase volatility more than positive return shocks. ω is a constant term, α describes the impact of a volatility shock on the conditional variance, and γ measures the volatility persistence.

Another popular asymmetric GARCH model is the GJR-GARCH model introduced by Glosten, Jagannatha and Runkkle (1993) or the threshold model of Zakoian (1994).

$$\sigma_t^2 = \omega + (\alpha + \delta I_{t-1})\,\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2\,, \tag{3}$$

where I_t is an indicator variable $= 1$ if $\varepsilon_t < 0$. α $(\alpha+\delta)$ describes the impact of a volatility shock on the conditional variance if the return is positive (negative). In Equation (3), the asymmetric volatility coefficient δ is positive and has the same economic meaning of a negative θ in Equation (2), although the magnitudes of θ and δ cannot be compared directly; (see, for example, Engle and Mistry (2014) and Girard and Biswas (2007). The volatility persistence is measured by $\alpha + \gamma + \delta/2$.

Two major explanations for this asymmetric volatility are the leverage effect and the volatility feedback. In their discussions about the leverage effect, both Black (1976) and Christie (1982) suggest that a firm's stock volatility changes due to changes in its financial leverage. With a negative realized return, the firm value declines, making the equity riskier and increasing its volatility. In their discussions about the volatility feedback effect, both French, Schwert and Stambaugh (1987) and Pindyck (1984) argue that an anticipated increase in volatility raises the required return on equities, thereby causing an immediate decline in stock prices (see also Bekaert and Wu, 2000; Wu, 2001). However, Avramov, Chordia and Goyal (2006) provide evidence that undermines these two explanations. They show that selling trading activity governs the asymmetric volatility effect in daily stock returns. Following a negative return, selling is dominated by investors who are uninformed or herding, leading to an increase in volatility. Engle (2004) discusses the effect of this volatility asymmetry on multiperiod returns. Even though each period has a symmetric distribution, the multiperiod return distribution will be negatively skewed. Using a simple two-step binomial tree, he shows that if the price goes down in the second period, the variance will be higher, so the outcomes will be further apart and "the bad outcome is far worse than if the variance had been constant" (Engle, 2004, p. 415).

The asymmetric volatility process of daily returns means that long-run monthly returns will have significant negative unconditional skewness. As pointed out by Berd, Engle and Voronov (2007) and Engle (2004, 2011), negative skewness means that the probability of a large sustained decline in asset prices is substantial. Therefore, an asset with significant asymmetric volatility should have higher returns to warrant the risk of negative skewness. In contrast, investors will seek to hedge against this risk, resulting in lower expected returns for assets with insignificant asymmetric volatility (i.e., θ in EGARCH and δ in GJR-GARCH are close to zero) or even reverse asymmetric volatility (i.e., $\theta > 0$ and $\delta < 0$). More specifically, for a hedge asset, positive returns predict higher volatility than negative returns, and, therefore, the return distribution will be positively skewed.

In the setting of Merton's (1973) intertemporal CAPM with conditional variance, Engle and Mistry (2014) find theoretical time series predictions on the relationship among volatility, returns, and skewness for priced risk factors. They link individual stock skewness to the skewness of the market and conclude that firms with higher systemic risk have more negatively skewed returns.[1]

Ederington and Guan (2010) note that, following large positive return shocks, both the EGARCH and GJR-GARCH models predict an increase in volatility (albeit a much smaller increase than following a negative shock of the same magnitude). The reason is that the ARCH coefficient, α, is positive in both models. A positive return shock will still increase the future variance. However, Ederington and Guan (2010) and prior research in the U.S. stock markets (e.g., Fleming, Ostdiek and Whaley, 1995; Whaley, 2000; Low, 2004; Whaley, 2000) show that implied and realized volatilities generally *fall* following positive shocks, contrary to the predictions of the two asymmetric GARCH models.

Ghysels, Santa-Clara and Valknov (2005) state that EGARCH and GJR-GARCH models constrain the persistence of both positive and negative shocks so they are the same, although they find that negative shocks have lower persistence. Ghysels, Santa-Clara and Valknov (2005) report that the CGARCH model of Engle and Lee (1999) obtains persistent estimates of conditional variance more consistently with the observed results by allowing positive and negative shocks to have different degrees of persistence.

More important, the persistence of volatility tends to decrease after temporary extreme events (Lamourex and Lastrapes, 1993). Allowing for different degrees of persistence for long-run and short-run processes may mitigate the influence of the

[1] Engle and Mistry (2014) prove that the skewness of an individual stock is the sum of the market skewness and the skewness of the stock's idiosyncratic component, weighted by the proportion of stock volatility and idiosyncratic components. Moreover, they find that firm size, value, debt ratio, and credit rating explain stock skewness in the U.S. market.

extreme events on the volatility estimates. As shown by Wang and Ghysels (2014, p. 1), "volatility component models have received considerable attention recently to capture the complex volatility dynamics via a parsimonious parameter structure, but also because it is believed that they can handle well structural breaks or nonstationarities in asset price volatility."

The CGARCH model is also better than standard GARCH models in explaining the long-range dependence of time series volatility (Maheu, 2005), the risk-return relation in stock markets (Guo and Neely, 2008), and market volatility (Engle and Rosenberg, 2000). In the FX market, Ahmed and Valente (2015) use the CGARCH model to investigate the cross-sectional pricing ability of the short- and long-run components of global volatility for carry trade returns.

Therefore, I use the following asymmetric CGARCH model for the volatility asymmetry:

$$\sigma_t^2 = q_t + (\alpha + \delta I_{t-1})\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \gamma\left(\sigma_{t-1} - q_{t-1}\right), \tag{4a}$$

$$q_t = \omega + \rho\left(q_{t-1} - \omega\right) + \varphi\left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right), \tag{4b}$$

where q_t represents the long-run component of conditional variance. The short-run component of conditional variance is obtained using $({\sigma_t}^2 - q_t)$. The persistence of the long-run component is measured by ρ and the short-run component by $\alpha + \gamma + \delta/2$. The parameter φ represents the initial effect of a shock to the long-run component. If $1 > \rho > \alpha + \gamma + \delta/2$, the long-run component of volatility has a higher persistence than the short-run component. The coefficient δ in Equation (4a) captures the asymmetric volatility effect on the short-run component of variance. As in the GJR-GARCH model, the more positive the asymmetric volatility coefficient δ, the more negative skewness, and, accordingly, the higher expected returns.

The CGARCH model does not have all nonnegative coefficients—a condition that is often assumed for the stationarity of GARCH models. See Wang and Ghysels (2014) for further information. If α is negative in Equation (4a), a positive shock will reduce volatility in the short run. This important issue is discussed in detail in the empirical results of the volatility models.

2.2. *Asset pricing with conditional skewness and downside risk*

The seminal work of Kraus and Litzenberger (1976) extends the CAPM to incorporate the effect of skewness on valuation. Investors are found to have a preference for positive skewness. But for a diversifying investor, it is coskewness with the market that matters.

Expected returns, $R_{i,t+1}$, of all assets follow the standard Euler condition

$$E_t\left[\left(1 + R_{i,t+1}\right) m_{t+1}\right] = 1, \tag{5}$$

where m_{t+1} is the marginal rate of substitution or a stochastic discount factor that prices all asset payoffs. Harvey and Siddique (2000) assume a quadratic form of m_{t+1} in the market return, $R_{M,\mathrm{t}+1}$:

$$m_{t+1} = a_t + b_t R_{M,t+1} + c_t R^2_{M,t+1} \tag{6}$$

with the weights a_t, b_t, and c_t being the functions of period t information set. Discarding the last term produces the traditional CAPM. According to Equation (6), the expected return is determined by its conditional covariance with both market returns and market volatility measured by the square of market returns (conditional coskewness). From Equations (5) and (6), Harvey and Siddique (2000) show that the expected excess returns of asset i over the risk-free rate depend on two risk premia:

$$E_t\left[r_{i,t+1}\right] = \lambda_1 Cov_t\left(r_{t+1}, r_{M,t+1}\right) + \lambda_2 Cov_t\left(r_{i,t+1}, r^2_{M,t+1}\right), \tag{7}$$

where λ_1 and λ_2 describe the prices of risk. $\lambda_1 > 0$ follows the traditional CAPM that an asset with higher covariance with market returns (or beta) should have a higher expected return.

$\lambda_2 < 0$ in Equation (7) indicates that an asset with lower covariance with squared market returns (lower coskewness) has higher volatility risk and, therefore, should have a higher expected return. This reflects the asymmetric volatility modeled by the asymmetric GARCH models with $\delta > 0$ in the CGARCH model. In contrast, a hedge asset should have returns that increase when volatility is expected to increase (high coskewness) and have asymmetric volatility of the opposite sign, $\delta < 0$.

Equation (7) indicates that a simple approach to estimating coskewness of asset i is to regress the asset return on the square of the market return. I denote the coefficient obtained from regressing the excess return on the square of the market return as $\beta_{V,i}$, volatility beta.

Harvey and Siddique (2000) formulate a direct measure of standardized coskewness,

$$\beta_{SKD,i} = \frac{E\left[\xi_{i,t+1}\xi^2_{M,t+1}\right]}{\sqrt{E\left[\xi^2_{i,t+1}\right]}E\left[\xi^2_{M,t+1}\right]} \,. \tag{8}$$

$\xi_{i,t+1}$ is the residual from the regression of excess returns, $r_{i,t+1}$, on contemporaneous market excess returns, $r_{M,t+1.}$ $\xi_{M,t+1} = r_{M,t+1} - \mu_M$, where μ_M is the average market return. High unexpected volatility typically coincides with low returns, so assets that covary positively with market volatility innovations provide a good hedge, and are therefore expected to earn a lower return. Motivated by these insights, several recent papers study how exposure to market volatility risk is priced in the cross-section of returns on the stock market. Harvey and Siddique (2000, p. 1276) point out that $\beta_{SKD,i}$ is better than $\beta_{V,i}$ for two reasons: $\beta_{SKD,i}$ is constructed from residuals (that are independent of the market return) and $\beta_{SKD,i}$ is standardized, unit free, and analogous to a factor loading. Therefore, I use $\beta_{SKD,i}$ in the following asset pricing model while reporting the estimates of $\beta_{V,i}$ to show the close relation between these two estimates of coskewness.

Harvey and Siddique (2000) note that coskewness captures asymmetry in risk, particularly downside risk. Investors have a preference for assets with lower downside risk for reasons similar to those for higher coskewness. Investors are more sensitive to downside losses than to upside gains. They require a premium not only for the higher beta but also when assets covary more with market returns conditional on low market returns. Several papers, for example, Conrad, Dittmar and Ghysels (2013), show that stocks with more ex ante negative skewness (estimated from option prices) yield higher returns. This paper estimates realized skewness only from futures returns.

Ang, Chen and Xing (2006a) show that expected returns are related to downside risk, represented by a downside beta, β_i^-, much more than they are related to the usual beta, β_i.[2] Lettau, Magggiori and Weber (2014) capture the relative importance of downside risk in the following downside risk CAPM, DR-CAPM, as follows:

$$E\left[r_i\right] = \beta_i \lambda + \left(\beta_i^- - \beta_i\right) \lambda^-, \tag{9a}$$

$$\beta_i = \frac{\operatorname{cov}\left(r_i, r_M\right)}{\operatorname{var}\left(r_M\right)}, \tag{9b}$$

$$\beta_i^- = \frac{\operatorname{cov}\left(r_i, r_M | r_M < \kappa\right)}{\operatorname{var}\left(r_M | r_M < \kappa\right)}, \tag{9c}$$

where β_i is the unconditional beta, β_i^- is the downside risk beta defined by an exogenous threshold (κ) for market returns, and λ and $\lambda^-$are the unconditional and downside prices of risk, respectively. The difference between the unconditional beta and downside beta, $\beta_i^- - \beta_i$, is called the relative downside beta. $\lambda > 0$ is the same as λ_1 in Equation (7) and λ^- (which is positive and larger than λ) is inversely related to λ_2 in Equation (7). Therefore, assets should have higher expected returns if they have higher relative downside beta and lower volatility beta and coskewness because these assets offer a poor hedge against a bad economy when the marginal utility of wealth is high.

Downside beta, β_i^-, explicitly conditions for market downside movements, whereas volatility beta, $\beta_{V,i}$, and coskewness, $\beta_{SKD,i}$, not subscipt do not distinguish asymmetries across market downside and upside movements. Nevertheless, high market volatility usually occurs during market downturns. $\beta_{V,i}$, β_i^-, and $\beta_{SKD,i}$ measure downside risk in different ways and, therefore, are related.

3. Data and related research

I collect daily settlement prices for 55 futures markets of six financial and commodity classes for the period January 1988 (or the start of contract trading) through December 2013 from Commodity Systems, Inc. (CSI). A particular asset is

[2] Downside beta has long been used in risk management for hedge funds (Lo, 2001).

represented by a futures contract, not the underlying spot market. I start the sample period after the stock market crash in October 1987. All these futures contracts are actively traded and provide a good representation of six financial and commodity classes as listed in Table 1: agriculture (11 contracts), energy (6), metals (7), bonds (13), stocks (9), and currencies (9). The agriculture contracts are further classified as grains (5), livestock (2), and softs (4); and the metal contracts as industry (4) and precious metals (3). Detailed information on contract symbols and futures exchanges are summarized in Appendix Table A1.

The data are similar to those of Moskowitz, Ooi and Pedersen (2012, table 1) with some minor differences. The authors find significant time series momentum in these contracts. My data are all futures contracts, but Moskowitz, Ooi and Pedersen (2012) use currency forward contracts.[3] Individual and institutional investors can readily use the liquid futures contracts in my sample. I compute the daily returns as log price changes using the nearest contracts until the first trading day of the month of maturity. Like Bessembinder (1992), Tse (1996), and others, this study calculates futures returns before they roll over to the next nearest contracts. That is, each daily return (or log price changes) is calculated using successive prices on a contract for delivery on a specific date and never across contracts with different delivery dates.

Monthly returns are constructed by linking the daily returns. In particular, the daily returns, r_d, and monthly returns, r_m, are calculated as

$$r_d = log(P_d/P_{d-1}), \tag{10a}$$

$$r_m = r_1 + r_2 + \ldots + r_d + \ldots + r_{D_m}, \tag{10b}$$

where P_d is the daily settlement price of the nearest contract on day d, P_{d-1} is the previous settlement price, and D_m is the number of days in a given month m. Both P_d and P_{d-1} are collected from the same contract for any given day d.[4]

Lettau, Maggiori and Weber (2014) use the downside-risk-CAPM to explain the cross-section of these asset classes' log excess returns. I examine a similar issue, but I also consider how asymmetric volatility is related to downside risk. Moreover, Lettau, Maggiori and Weber (2014) categorize the assets of a given class into portfolios based on a characteristic that is potentially related to expected returns, while I consider each futures contract a portfolio. The authors sort the currencies by interest rate differential, commodities by basis between spot and futures prices for commodities, government bonds by credit rating, and U.S. stocks by book-to-market ratio. They allow for

[3] I use futures data available from CSI for the assets used by Moskowitz, Ooi and Pedersen (2012) as close as possible. Examining their results is not an issue in this study. Instead, I follow Moskowitz, Ooi and Pedersen (2012) as a guide to obtain a balanced mix of different class assets represented by futures contracts.

[4] Some studies calculate compound monthly returns as $r_m = (1+r_1)(1+r_2)\ldots(1+r_d)\ \ldots(1+ r_{D_m}) - 1$, where the daily return, $r_d = (P_d/P_{d-1} - 1)$, is the simple percentage price change.

predictability generated by variation over time in these characteristics. Because I use individual futures returns directly, my approach is easier to implement, with lower transaction costs and no portfolio formation. However, using unsorted assets lowers the explanatory power of the pricing model used in this paper.

It is also important to note that futures returns are excess returns per se. According to Pukthuanthong-Le, Levich and Thomas (2007), changes in spot rates are only one component of profit and loss on a currency trade. It is essential to consider the interest earned on the long currency and the funding cost of the short currency, but futures prices do this automatically. Similar arguments apply to other asset classes. The index and bond futures comprise all the major international markets, including Germany, Japan, the United Kingdom, and the United States. In sum, my results provide a more international perspective on conditional risk premia than prior research does.

Several recent studies investigate the relation between volatility risk and returns for a particular asset class. Menkhoff, Sarno, Schmaling and Schrimf (2012) find that high returns to carry trades negatively relate to global currency volatility shocks and, therefore, come with a risk premium for their high currency volatility risk. Dobrynskaya (2014) reports that carry trade returns are required for their high downside global stock market risk. As reported in Brunnermeier, Nagel and Pedersen (2009), Christiansen, Ranaldo and Söderlind (2011), and others, the popular funding currencies are the Japanese yen and Swiss franc and the investment currencies are the Australian dollar and New Zealand dollar. None of these papers consider futures returns, asymmetric volatility, or multiple asset classes.

It is worth noting two empirical issues before discussing the results in the next section. First, I use daily returns to estimate the CGARCH model and monthly returns to calculate skewness, beta, downside beta, and coskewness. Using monthly data to estimate beta is most common in practice as well as in academic research (Ibbotson, Kaplan and Peterson, 2011). Market imperfections (e.g., nonsynchronous trading and gradual information diffusion) will result in biased estimates of beta, downside beta, and coskewness using daily data. Skewness in the context of downside risk should also be estimated by longer term returns, as discussed in Engle (2004).[5] The two papers that I follow closely, Harvey and Siddique (2000) and Lettau, Maggiori and Weber (2014), use monthly returns to estimate skewness, beta, downside beta, and coskewness. The five-year rolling window estimator using monthly returns is widely used in the asset pricing literature and also represents the first-stage estimates in my implementation of the Fama and MacBeth (1973) and Ferson and Harvey (1991) procedures.

Estimation errors due to volatility model mis-specification decrease as data frequency increases (Nelson, 1992). Daily returns, but not monthly returns, capture the persistence and clustering of stock volatility (Zivot, 2009). French, Schwert and

[5] Engle and Mistry (2014) show that one-day stock returns are slightly negative and grow more negative with time aggregation.

Stambaugh (1987) is one of the earliest papers to use *daily* returns to estimate stock market volatility with a GARCH model and examine the relation between *monthly* returns and volatility. Prior research, for example, Adrian and Rosenberg (2008) and Ahmed and Valente (2015), also uses daily returns for the CGARCH volatility process and monthly returns in asset pricing.

The second issue is the choice of the market. The market is often chosen to be similar to the assets held by the investor. It is natural to assume that an investor's benchmark portfolio is the stock index. Rapach, Strauss and Zhou (2013) identify a leading role for the U.S. stock market represented by the S&P 500 index: lagged U.S. monthly returns significantly predict returns in other industrialized countries, but not the reverse.[6] The S&P 500 index is the most active stock index worldwide, both in mutual funds and futures contracts. Examining commodities futures and currencies futures in asset allocations, respectively, Gorton and Rouwenhorst (2006) and Das, Kadapakkam and Tse (2013) represent the market by the U.S. index. Nevertheless, the current asset pricing results concerning downside risk may be specifically applied to the investors who use the U.S. index as their benchmark portfolio.

4. Empirical results

The 26-year sample period covers various financial events in the world: the tech bubble of the late 1990s, the Asian financial crisis in 1997, the Russian financial crisis in 1998, the bursting of the bubble in 2000, the exceptionally high volatility in commodity markets in 2006–2008, and the global financial crisis in 2008. All these events are likely to create complex structures in the asset price series.[7]

However, the CGARCH model handles these complex structures better than traditional GARCH models do. The CGARCH allows the temporary component of the volatility process less persistence than the permanent component, consistent with the observation that the volatility persistence tends to decrease after extreme events. Moreover, the Fama-MacBeth procedures with time-varying betas and coskewness with a rolling-period out-of-sample estimation will also lessen the bias induced by the structural changes. Structural changes are not considered in Lettau, Maggiori and Weber (2014), and they use in-sample estimation.

Furthermore, although extreme events may influence the econometric results, these events are excellent examples for showing the relation between asset returns

[6] Rapach, Strauss and Zhou (2013, p. 1658) "posit that many investors focus more intently on the U.S. market, which, in the presence of information-processing limitations, creates a gradual diffusion of relevant information on macroeconomic fundamentals across countries, thereby generating predictive power for lagged U.S. returns."

[7] Extending the Perron (1997) model, which allows only one possible break point for a single series, Bai and Perron (1998) introduce two tests, *Udmax* and *Wdmax* of the null hypothesis of no structural break against an unknown number of breaks given an upper bound (five in the current study). Note that the Bai-Perron model tests structural breaks in the price level and the variance is treated as a nuisance parameter (Bai and Perron, 2003). I report the number of significant structural changes estimated by these two tests in Appendix Table A2. Forty-eight assets have multiple structural changes. I also find that the changes occurred on different dates for different assets.

and downside risk. For instance, stocks usually offer higher average returns than other asset classes. But stocks also experienced much greater loss during the 2008 global financial crisis. This is consistent with the main theme of this study: The higher average return offered by an asset class is compensation for the downside risk. Therefore, excluding or adjusting for the extreme events will lower the power of the statistical tests for downside risk.

4.1. Summary statistics

Table 1 reports summary statistics for monthly returns of the 55 futures contracts. Most contracts (42) offer positive mean returns. Maximum and minimum mean returns are both offered by energy futures—unleaded gasoline (1.6%) versus natural gas (−1.3%). I observe a wide range of volatility across the 55 contracts. Energy futures have a higher standard deviation than other futures, with natural gas being the most volatile (16.6%). Bond futures have the lowest standard deviation, with Australian 10-year bonds the least volatile (0.35%). The other classes in the middle range are agriculture, metal, index, and currency in descending order of volatility, while live cattle and gold have lower volatility than other futures in their corresponding classes.

The table shows 41 futures (including all the index futures) that have negative unconditional skewness, with an average of −0.228. Contracts that have positive skewness or minimal negative skewness, with a magnitude of less than 0.1, are traditional hedge assets, such as U.S. Treasury bonds, gold, Japanese yen, and some commodities. In the following sections, I use S&P 500 index futures as the market. Compared with most contracts, the S&P index returns are much more negatively skewed (−0.808). The overall results are similar if I use the value-weighted CRSP equity portfolio (which has a correlation of 0.98 with the S&P 500).

The last column of Table 1 reports the correlation of each asset with the S&P 500. All the stock indexes are significant and positively correlate with the U.S. index (with an average of 0.7). Bonds generally negatively correlate with the stock index, consistent with the fact that bonds are traditionally used to diversify stock returns. Most of the commodities moderately correlate with the index.[8] Although most currencies positively correlate with the S&P 500, the Japanese yen and Swiss franc experience slightly negative correlation with the index.

4.2. Asymmetric volatility

Table 2 reports the results of the asymmetric CGARH model of Engle and Lee (1999) with the return residual, $\varepsilon_t \,|\Phi_{t-1} \sim N(0, \sigma_t{}^2)$, where $\sigma_t{}^2$ is the conditional

[8] Commodities futures have been effective as an asset class to diversify stock risks and hedge against inflation for earlier decades, as examined in Gorton and Rouwenhorst (2006). But in recent years, correlated returns with other assets and increasing volatility have made commodities less attractive in asset allocation.

Table 1

Summary statistics of monthly futures returns

I compute the daily returns as log price changes using the nearest contracts to the first trading day of the month of maturity. Monthly returns are constructed by linking the daily returns. Unconditional skewness is calculated using Equation (1) in text. All the monthly futures returns end in December 2013.

Contract	Class	Start month	Mean (%)	Std dev (%)	Skew	Min (%)	Max (%)	Corr. with S&P
Corn	Agriculture: Grain	1988.01	−0.476	7.807	0.127	−25.88	37.72	0.232
Soybeans	Agriculture: Grain	1988.01	0.298	7.107	−0.500	−26.64	21.15	0.210
Soybean meal	Agriculture: Grain	1988.01	0.815	7.695	−0.135	−31.68	23.97	0.149
Soybean oil	Agriculture: Grain	1988.01	−0.275	7.259	−0.288	−29.03	23.79	0.218
Wheat	Agriculture: Grain	1988.01	−0.699	7.841	0.088	−29.10	32.02	0.197
Lean hogs	Agriculture: Livestock	1988.01	−0.185	7.503	−0.444	−30.06	26.39	−0.011
Live cattle	Agriculture: Livestock	1988.01	0.217	3.951	−0.957	−26.23	11.80	0.038
Cocoa	Agriculture: Soft	1988.01	−0.298	8.649	0.200	−28.78	29.69	0.044
Coffee	Agriculture: Soft	1988.01	−0.569	10.441	0.502	−36.23	40.94	0.130
Cotton	Agriculture: Soft	1988.01	−0.303	8.011	−0.107	−25.67	22.11	0.242
Sugar	Agriculture: Soft	1988.01	0.310	9.594	0.204	−35.24	34.19	0.038
Brent oil	Energy	1988.07	1.176	9.621	−0.148	−43.01	43.05	0.089
Crude oil	Energy	1988.01	0.759	10.072	−0.277	−42.29	40.68	0.064
Gasoline	Energy	1988.01	0.911	9.150	−0.062	−35.88	34.44	0.056
Heating oil	Energy	1988.01	0.932	9.970	0.295	−36.66	49.96	0.077
Natural gas	Energy	1990.04	−1.337	16.592	0.122	−51.29	58.01	0.022
Unleaded gasoline	Energy	1988.01	1.630	10.701	−0.221	−53.37	43.31	0.136
Aluminum	Metal: Industry	1988.01	−0.018	5.936	−0.112	−23.51	17.78	0.243
Copper	Metal: Industry	1988.01	0.588	8.145	−0.466	−44.69	30.32	0.317
Nickel	Metal: Industry	1988.01	0.143	10.464	0.389	−31.83	58.09	0.306
Zinc	Metal: Industry	1988.09	0.125	7.272	−0.492	−40.10	23.69	0.293
Gold	Metal: Precious	1988.01	−0.012	4.551	−0.045	−20.41	14.88	−0.027
Platinum	Metal: Precious	1988.01	0.382	6.172	−1.062	−38.37	21.17	0.156
Silver	Metal: Precious	1988.01	0.018	8.140	−0.252	−32.83	24.87	0.144
Two-year Treasury note	Bond	1990.07	0.135	0.486	0.211	−1.23	1.64	−0.148
Five-year Treasury note	Bond	1988.06	0.248	1.209	0.006	−3.35	5.23	−0.065
10-year Treasury note	Bond	1988.01	0.333	1.775	0.040	−5.98	8.32	−0.020
30-year Treasury bond	Bond	1988.01	0.386	2.738	−0.021	−10.52	12.79	−0.016
Australian three-year bond	Bond	1988.06	0.056	0.416	−0.196	−1.73	1.34	−0.045
Australian 10-year bond	Bond	1988.01	0.044	0.352	−0.200	−1.06	1.17	0.011
British gilt long bond	Bond	1988.01	0.196	1.992	−0.069	−5.57	6.42	0.036
Canadian 10-year bond	Bond	1989.10	0.303	1.734	−0.128	−5.27	5.08	0.065
Euro-Schatz German two-year	Bond	1997.03	0.081	0.390	0.131	−0.97	1.55	−0.419
Euro-Bobl German five-year	Bond	1991.10	0.239	0.939	−0.069	−2.00	2.48	−0.237
Euro-Bund German 10-year	Bond	1990.12	0.321	1.508	−0.074	−3.65	4.67	−0.171
Euro-Buxl German 30-year	Bond	1998.10	0.314	2.931	0.777	−8.40	12.12	−0.272
Japanese govt bond	Bond	1990.04	0.307	1.258	−0.668	−6.10	4.81	−0.003
AEX (Netherlands)	Index	1992.11	0.473	5.904	−1.041	−23.55	15.19	0.758
CAC 40 Index	Index	1988.09	0.313	5.653	−0.559	−20.11	12.53	0.731
DAX	Index	1990.12	0.428	6.196	−0.890	−28.47	18.40	0.749
FTSE / MIB (Italy)	Index	1994.12	0.112	6.655	−0.082	−19.11	19.31	0.670

(*Continued*)

Table 1 (*Continued*)

Summary statistics of monthly futures returns

Contract	Class	Start month	Mean (%)	Std dev (%)	Skew	Min (%)	Max (%)	Corr. with S&P
FTSE 100	Index	1988.01	0.278	4.333	−0.472	−13.98	12.85	0.795
IBEX 35 (Spain)	Index	1992.05	0.473	6.397	−0.495	−24.55	16.15	0.668
Nikkei 225	Index	1988.01	−0.148	6.444	−0.561	−28.83	19.42	0.528
S&P 500	Index	1988.01	0.492	4.268	−0.808	−18.94	10.39	N/A
SPI ASE 200 Index	Index	1988.01	0.304	4.124	−0.619	−14.91	10.44	0.658
Australian dollar	Currency	1988.01	0.277	3.384	−0.596	−16.96	9.29	0.412
British pound	Currency	1988.01	0.098	2.835	−0.686	−12.55	8.52	0.102
Canadian dollar	Currency	1988.01	0.116	2.174	−0.483	−12.43	8.67	0.495
Euro	Currency	1988.01	0.017	3.121	−0.364	−11.10	9.20	0.125
Japanese yen	Currency	1988.01	−0.171	3.225	0.330	−10.21	15.99	−0.041
New Zealand dollar	Currency	1997.06	0.298	3.895	−0.390	−14.39	12.69	0.445
Norwegian krone	Currency	2002.06	0.293	3.482	−0.578	−13.52	7.86	0.452
Swedish krona	Currency	2002.06	0.324	3.535	−0.203	−11.37	9.22	0.557
Swiss franc	Currency	1988.01	−0.007	3.323	−0.165	−12.01	12.19	−0.008
Average			0.201	5.442	−0.228	−21.48	19.27	0.203
Maximum			1.630	16.592	0.777	−0.97	58.09	0.795
Minimum			−1.337	0.352	−1.062	−53.37	1.17	−0.419

variance and Φ_{t-1} is the information set. For the sake of simplicity, the mean equations of an autoregressive order 1, AR(1), model are not reported. The AR(1) lagged term allows the autocorrelation of returns. I estimate the asymmetric volatility model using daily returns with the Bollerslev-Wooldridge robust standard errors. Daily data are used to improve the estimation precision and monthly returns for the cross-sectional analysis. I use the S&P 500 index futures as an example:

$$\sigma_t^2 = q_t + (-0.048 + 0.125 I_{t-1}) \left(\varepsilon_{t-1}^2 - q_{t-1}\right) + 0.924 \left(\sigma_{t-1} - q_{t-1}\right), \quad (11a)$$

$$q_t = 0.782 + 0.990 \left(q_{t-1} - 0.782\right) + 0.035 \left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right). \quad (11b)$$

The persistence of the long-run volatility component (estimated by ρ) is 0.990, larger than that of the short-run volatility component ($\alpha + \gamma + \delta/2$), 0.939. The asymmetric volatility coefficient, $\delta = 0.125$ ($t = 6.99$), is consistent with the asymmetric volatility effect. Note that the ARCH coefficient in the short-run component is $\alpha = -0.048$ ($t = -3.38$), indicating that a positive return shock will decrease volatility. The results of the conditional variance are similar for different lag lengths of the mean equation. For example, $\delta = 0.120$ and 0.126 for two lags and no lag, respectively.

Comparing the EGARCH and GJR-GARCH results (not reported in the table):

$$log\left(\sigma_t^2\right) = -0.092 + 0.120 \left|z_{t-1}\right| - 0.113 z_{t-1} + 0.977 log\left(\sigma_{t-1}^2\right), \; z_t \equiv \varepsilon_t / \sigma_t, \quad (12)$$

$$\sigma_t^2 = 0.022 + (0.001 + 0.145 I_{t-1})\, \varepsilon_{t-1}^2 + 0.906 \sigma_{t-1}^2. \quad (13)$$

Table 2

Estimation of CGARCH model

$$\sigma_t^2 = q_t + (\alpha + \delta I_{t-1})(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\sigma_{t-1} - q_{t-1}),$$

where q_t represents the long-run component of conditional variance, ${\sigma_t}^2$ I_t is an indicator variable = 1 if $\varepsilon_t < 0$. α (α+δ) describes the impact of a volatility shock on the conditional variance if the return is positive (negative). The parameter of interest is δ, which captures the asymmetric volatility. The results of δ and α presented are ranked by the value of δ. Daily returns are used to estimate the model and the *t*-statistics are calculated with the Bollerslev-Wooldridge robust standard errors.

	δ		α	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.
DAX	0.137	3.84	−0.125	−6.46
AEX (Netherlands)	0.131	6.78	−0.044	−3.40
S&P 500	0.125	6.99	−0.048	−3.38
Nikkei 225	0.120	9.14	−0.135	−4.78
SPI ASE 200	0.105	6.06	−0.011	−0.94
Australian dollar	0.083	2.49	−0.043	−1.79
New Zealand dollar	0.078	1.89	−0.054	−2.17
Canadian dollar	0.076	3.36	−0.036	−3.00
Live cattle	0.073	6.11	−0.032	−4.08
CAC 40 Index	0.063	1.95	−0.107	−5.17
Silver	0.055	3.11	0.081	6.38
30-year Treasury bond	0.051	1.61	−0.035	−1.46
Euro-Bobl five-year	0.047	1.88	−0.022	−1.39
FTSE / MIB (Italy)	0.046	1.24	−0.093	−3.28
Cotton	0.044	1.27	0.046	2.08
FTSE 100	0.044	1.25	−0.044	−1.42
Canada 10-year bond	0.040	1.94	−0.007	−0.53
Norwegian krone	0.036	0.72	0.006	0.19
Copper	0.036	2.00	0.012	1.08
Sugar	0.033	0.95	0.030	1.23
Euro-Bund 10-year	0.028	1.35	−0.022	−1.47
Soybeans	0.026	0.95	−0.038	−1.82
Gold	0.025	2.68	0.047	7.25
Australian 10-year bond	0.021	1.10	0.020	1.06
Australian three-year bond	0.015	1.99	0.015	2.93
Lean hogs	0.012	0.62	−0.011	−0.73
Gasoline	0.010	0.53	−0.038	−2.99
10-year Treasury note	0.009	0.61	−0.022	−2.41
Japanese govt bond	0.008	0.11	0.076	1.11
Swedish krona	0.007	0.41	−0.319	−0.35
Crude oil	0.004	1.74	−0.216	−2.58
Two-year Treasury note	0.004	0.22	0.037	2.94
Five-year Treasury note	0.003	0.38	0.019	3.34
IBEX 35 (Spain)	0.001	0.07	−0.020	−1.82
Heating oil	-0.004	−0.31	0.058	4.68
Nickel	−0.004	−0.32	−0.001	−0.16
Aluminum	−0.012	−0.81	0.056	4.75
Zinc	−0.013	−0.21	0.118	2.19

(*Continued*)

Table 2 (*Continued*)

Estimation of CGARCH model

	δ		α	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.
British pound	−0.014	−0.75	0.009	0.75
Soybean oil	−0.020	−0.75	−0.006	−0.29
Wheat	−0.024	−1.70	0.043	3.84
Platinum	−0.025	−0.61	0.076	2.37
British gilt long bond	−0.029	−1.52	0.041	2.80
Soybean meal	−0.031	−1.86	0.071	5.51
Corn	−0.033	−1.19	0.043	1.98
Deutschmark / euro	−0.033	−1.54	0.010	0.78
Cocoa	−0.038	−2.65	0.036	2.89
Swiss franc	−0.049	−1.22	0.029	0.82
Euro−Schatz two-year	−0.052	−2.20	0.076	4.01
Brent oil	−0.060	−2.00	0.064	2.51
Euro-Buxl 30-year	−0.063	−2.23	0.031	1.99
Unleaded gasoline	−0.067	−2.41	0.080	3.08
Coffee	−0.078	−1.76	0.084	2.14
Japanese yen	−0.142	−3.14	0.124	3.10
Natural gas	−0.156	−2.44	0.074	1.22

The asymmetric volatility coefficients are significant with the correct signs, $\theta = -0.113$ ($t = -10.6$) for EGARCH and $\delta = 0.145$ ($t = 8.68$) for GJR-GARCH. Note that the ARCH coefficients, α, are positive, 0.120 ($t = 9.16$) and 0.001 ($t = 0.08$), for both models, suggesting that a positive return shock still increases future volatility (although less than a negative shock of equal size), a finding contrary to the results of realized and implied volatilities examined by Ederington and Guan (2010). Therefore, the CGARCH model describes the U.S. stock market volatility process better than the EGARCH and GJR-GARCH models do.

I sort the results of the CGARCH in descending order of the value of the asymmetric volatility parameter and, for brevity, present the results of δ and α in Table 2. The top five assets that have the largest asymmetric volatility are index futures, followed by the Australian dollar (with a significantly positive δ). In contrast, the bottom five assets are commodities, bonds, and the Japanese yen (with a significantly negative δ). The table shows that δ is either insignificantly positive or negative for most of the bond futures.[9] As noted previously, the Japanese yen-Australian dollar is the most popular pair of funding and investment currencies in

[9] I obtain similar results if I estimate the model from 1988 to 2007, before the 2008 financial crisis. Fourteen assets, including the S&P 500, experienced the largest price changes in October 2008. The top five assets with the highest values of asymmetric volatility are stock indexes and the Australian dollar, and the bottom five are commodities and the Japanese yen.

carry trades. These results suggest that risky assets that offer high average returns have asymmetric volatility and hedge assets that offer low average returns have the reverse effect. As discussed in Engle and Mistry (2014, p. 136), "a hedge portfolio should have the opposite characteristics since a short position in a risk[y] portfolio is the hedge portfolio. It should have returns that increase when volatility is expected to increase and have asymmetric volatility of the opposite sign." That is, negative (positive) returns of risky (hedge) assets predict higher volatility than comparable positive (negative) returns.

All the index futures also have a negative α, but I do not observe a consistent pattern in other asset classes. Not reported in Table 2, all the futures returns have a higher persistence for the long-run component of the volatility, ρ, than for the short-run component, indicating slower mean reversion in the long run.

Although the asymmetric CGARCH model may be a better model than the EGARCH and GJR-GARCH models for describing the volatility dynamics of stock indexes, its performance with respect to other asset classes is not confirmed until further examination. Therefore, I also discuss the main results using these two popular asymmetric volatility models. The asymmetric volatility coefficients in the EGARCH and GJR-GARCH models generally parallel the results given by the CGARCH model, but α is positive for all futures contracts. The correlations of the CCARCH asymmetric volatility coefficient with the asymmetric volatility coefficients of EGARCH and GJR-GARCH are 0.68 and 0.69, respectively.

4.3. Coskewness and downside beta

I estimate the beta and downside beta in the following regressions:

$$r_{it} = a_i + \beta_i r_{Mt} + \varepsilon_{it}, \tag{14}$$

$$r_{it} = a_i^- + \beta_i^- r_{Mt} + \varepsilon_{it}^- \; if \; r_{Mt} \leq \kappa, \tag{15}$$

where r_{it} and r_{Mt} are the monthly futures returns of asset *i* and the market (i.e., the S&P 500). As in Lettau, Maggiori and Weber (2014), the threshold $\kappa = (\mu_M - \sigma_M)$ is used to estimate the downside risk beta in Equation (15), where σ_M is the standard deviation of market returns. Equations (14) and (15) correspond to the first-stage regressions of the Fama and MacBeth (1973) procedure with time-invariant betas.

I report beta, downside beta, and coskewness in Table 3. I report the volatility beta for reference. All index futures, commodity futures (except gold and lean hogs), and currency futures (except the Japanese yen and Swiss franc) have a positive beta, while most bonds have a negative beta. Focusing on index futures and other futures with a positive beta, I observe that the downside betas are generally larger than the regular beta. For example, corn (the first commodity futures listed in the table) has a beta of 0.42 ($t = 3.44$) and a downside beta of 1.14 ($t = 4.34$); the AEX (Netherlands)

Table 3

Estimation of beta, volatility beta, downside risk beta, and coskewness

The beta, volatility beta, and downside beta are estimated using the following regressions:

$$r_{it} = a_i + \beta_i r_{Mt} + \varepsilon_{it},$$
$$r_{it} = a_{V,i} + \beta_{V,i} r_{Mt}^2 + \varepsilon_{it},$$
$$r_{it} = a_i^- + \beta_i^- r_{mt} + \varepsilon_{it}^- \; if \; r_{Mt} \leq \kappa,$$

where r_{it} and r_{Mt} are the monthly futures returns of asset i and the market (i.e., the S&P 500). The threshold $\kappa = \mu_M - \sigma_M$ is used to estimate the downside risk beta, β^-, where μ_M are σ_M are the sample average and standard deviation of market returns. Harvey and Siddique (2000) formulate a direct measure of standardized coskewness, β_{SKD}. The t-statistics are calculated using the Newey-West correction of standard errors for heteroskedasticity and autocorrelation.

	Beta β	t-Stat.	Volatility beta β_V	t-Stat.	Downside beta β^-	t-Stat.	Coskewness β_{SKD}
Corn	0.424	3.44	−0.033	−2.21	1.141	4.34	−0.129
Soybeans	0.350	3.31	−0.019	−1.50	0.869	4.71	−0.048
Soybean meal	0.268	2.50	−0.012	−1.07	0.710	3.04	−0.009
Soybean oil	0.372	2.91	−0.031	−1.46	1.107	2.11	−0.143
Wheat	0.362	3.06	−0.028	−1.55	1.083	2.46	−0.109
Lean hogs	−0.020	−0.16	−0.021	−1.21	0.374	0.62	−0.183
Live cattle	0.035	0.55	−0.015	−2.50	0.309	1.80	−0.217
Cocoa	0.089	0.66	−0.005	−0.23	0.160	0.21	−0.011
Coffee	0.319	2.79	−0.020	−1.51	0.508	1.42	−0.042
Cotton	0.454	3.50	−0.029	−1.44	0.938	1.87	−0.088
Sugar	0.085	0.54	−0.005	−0.23	0.815	2.20	−0.009
Brent oil	0.199	0.78	−0.064	−2.13	1.431	1.59	−0.363
Crude oil	0.151	0.65	−0.058	−2.17	1.253	1.51	−0.324
Gasoline	0.121	0.56	−0.058	−2.46	1.184	1.47	−0.361
Heating oil	0.181	0.83	−0.053	−1.97	1.320	1.77	−0.283
Natural gas	0.084	0.40	−0.023	−1.10	−0.011	−0.02	−0.074
Unleaded gasoline	0.341	1.32	−0.053	−1.26	1.421	1.14	−0.234
Aluminum	0.338	3.19	−0.013	−0.79	0.589	1.58	0.001
Copper	0.605	3.58	−0.046	−1.40	1.616	2.23	−0.179
Nickel	0.750	4.94	−0.036	−1.58	0.771	1.48	−0.041
Zinc	0.496	3.68	−0.040	−1.46	1.422	2.01	−0.185
Gold	−0.029	−0.37	−0.016	−1.18	0.708	1.81	−0.229
Platinum	0.225	1.64	−0.027	−1.44	0.812	1.81	−0.181
Silver	0.275	2.12	−0.029	−1.77	1.086	3.56	−0.140
Two-year Treasury note	−0.017	−1.87	0.003	3.86	−0.055	−1.59	0.273
Five-year Treasury note	−0.018	−0.86	0.005	2.88	−0.095	−1.19	0.231
10-year Treasury note	−0.008	−0.26	0.004	1.08	−0.017	−0.11	0.135
30-year Treasury bond	−0.010	−0.21	0.001	0.11	0.147	0.61	0.004
Australian three-year bond	−0.004	−0.59	0.001	1.39	−0.008	−0.31	0.138
Australian 10-year bond	0.001	0.16	0.000	0.60	0.010	0.55	0.063
British gilt bond	0.017	0.54	0.004	1.10	−0.025	−0.21	0.139
Canada 10-year bond	0.026	0.92	0.000	0.16	0.026	0.28	0.053
Euro-Schatz two-year	−0.035	−5.16	0.003	4.98	−0.065	−4.02	0.330
Euro-Bobl five-year	−0.051	−3.43	0.006	4.95	−0.095	−2.50	0.242
Euro-Bund 10-year	−0.060	−2.49	0.006	2.34	−0.068	−0.60	0.154
Euro-Buxl 30-year	−0.174	−3.49	0.004	1.19	0.291	1.27	−0.083
Japanese govt bond	−0.001	−0.04	0.000	0.11	0.008	0.22	−0.013

(*Continued*)

Table 3 (*Continued*)

Estimation of beta, volatility beta, downside risk beta, and coskewness

	Beta β	t-Stat.	Volatility beta β_V	t-Stat.	Downside beta β^-	t-Stat.	Coskewness β_{SKD}
AEX (Netherlands)	1.028	11.06	−0.060	−4.99	1.168	5.32	−0.224
CAC 40 Index	0.962	15.07	−0.050	−5.10	0.990	4.72	−0.193
DAX	1.082	11.98	−0.057	−4.20	1.302	3.23	−0.196
FTSE / MIB (Italy)	0.987	13.62	−0.053	−4.97	1.101	8.04	−0.096
FTSE 100	0.807	20.87	−0.031	−3.43	0.694	6.02	0.011
IBEX 35 (Spain)	0.990	14.53	−0.059	−5.10	1.444	5.70	−0.200
Nikkei 225	0.798	9.57	−0.059	−4.35	0.973	2.92	−0.308
SPI ASE 200	0.636	13.68	−0.033	−3.83	0.599	4.31	−0.150
Australian dollar	0.326	4.97	−0.023	−1.93	0.700	2.96	−0.195
British pound	0.068	1.28	−0.002	−0.22	0.174	0.61	0.009
Canadian dollar	0.252	6.89	−0.017	−2.24	0.385	2.17	−0.215
Euro	0.091	1.52	−0.007	−0.69	0.335	1.36	−0.063
Japanese yen	−0.031	−0.55	0.014	2.54	−0.107	−0.57	0.247
New Zealand dollar	0.370	5.38	−0.022	−2.31	0.494	1.88	−0.096
Norwegian krone	0.350	3.59	−0.017	−1.05	0.638	2.29	−0.016
Swedish krona	0.438	5.24	−0.018	−1.33	0.699	4.54	0.067
Swiss franc	−0.006	−0.11	0.002	0.34	0.087	0.49	0.040
Average	0.283	3.12	−0.022	−1.04	0.618	1.76	−0.065
Max	1.082	20.87	0.014	4.98	1.616	8.04	0.330
Min	−0.174	−5.16	−0.064	−5.10	−0.107	−4.02	−0.363

index has a beta of 1.03 ($t = 11.1$) and a downside beta of 1.17 ($t = 5.32$); and the Australian dollar has a beta of 0.33 ($t = 4.97$) and a downside beta of 0.70 ($t = 2.96$). The t-statistics are calculated using the Newey-West correction of standard errors for heteroskedasticity and autocorrelation.

An observation for coskewness is that all the bond futures offer positive coskewness (except the German 30-year Buxl and Japanese government bond). In contrast, all the commodity (except aluminum) and index (except the FTSE 100) futures yield negative coskewness. Half the currency futures show positive coskewness (particularly the Japanese yen, Swedish krona, and Swiss franc) and half have negative coskewness (particularly the Canadian dollar, Australian dollar, and New Zealand dollar). The Japanese yen and Swiss franc are considered safe-haven currencies that appreciate against the U.S. dollar when U.S. stock prices drop and U.S. bond prices and currency volatility increase (Ranaldo and Söderlind, 2010).

Consider the futures contract that has the lowest coskewness (Brent oil) and the contract that has the highest downside beta (copper). These two contracts have much higher average returns than other contracts, indicating that the higher returns reflect a fair compensation for investors who tolerate higher downside risk.

Table 4

Correlation analysis

β, β^-, and $(\beta^- - \beta)$ denote the beta, the downside risk beta, and the relative downside risk beta, respectively. The mean return, betas, skewness, and coskewness are calculated by monthly returns. The asymmetric volatility effect is represented by the coefficient δ in the CGARCH model using daily returns. The p-values in parentheses are reported below the correlation coefficients.

	Return	Skewness	δ	β	β^-	$\beta^- - \beta$	Coskewness
Return	1.000	−0.230	0.245	0.084	0.361	0.415	−0.267
		(0.091)	(0.072)	(0.544)	(0.007)	(0.002)	(0.051)
Skewness	−0.230	1.000	−0.606	−0.417	−0.263	0.003	0.379
	(0.091)		(0.000)	(0.002)	(0.055)	(0.985)	(0.005)
δ	0.245	−0.606	1.000	0.466	0.220	−0.102	−0.265
	(0.072)	(0.000)		(0.000)	(0.111)	(0.462)	(0.052)
β	0.084	−0.417	0.466	1.000	0.673	0.053	−0.438
	(0.544)	(0.002)	(0.000)		(0.000)	(0.705)	(0.001)
β^-	0.361	−0.263	0.220	0.673	1.000	0.774	−0.779
	(0.007)	(0.055)	(0.111)	(0.000)		(0.000)	(0.000)
$\beta^- - \beta$	0.415	0.003	−0.102	0.053	0.774	1.000	−0.677
	(0.002)	(0.985)	(0.462)	(0.705)	(0.000)		(0.000)
Coskewness	−0.267	0.379	−0.265	−0.438	−0.779	−0.677	1.000
	(0.051)	(0.005)	(0.052)	(0.001)	(0.000)	(0.000)	

4.4. Correlation analysis

Engle (2004, 2011) and Engle and Mistry (2014) focus on the relation between asymmetric volatility and unconditional skewness. They consider long-term negative skewness the downside risk that investors want to hedge; accordingly, asymmetric volatility and downside risk should be positively correlated. However, Harvey and Siddique (2000) argue that coskewness (or the component of an asset's skewness relative to the market portfolio's skewness) matters more than unconditional skewness for expected returns. Adding an asset with negative coskewness to a portfolio makes the resultant portfolio more negatively skewed; therefore, assets with negative coskewness must have higher expected return. Coskewness and downside beta should negatively correlate across markets.

I examine the cross-market correlations for all the asset characteristics: average monthly return, skewness, coskewness, beta, downside beta, relative downside beta $(\beta^- - \beta)$, and the asymmetric volatility coefficient (δ). The first column of Table 4 shows correlations of average returns with all the other asset characteristics. Returns negatively correlate with skewness, −0.23 ($p = 0.091$), and coskewness, −0.27 ($p = 0.051$). Returns positively correlate with the asymmetric volatility coefficient, 0.25 ($p = 0.072$).[10] Although the correlation between returns and beta is not significant, the returns significantly positively correlate with the downside beta, 0.36 ($p = 0.007$).

[10] The correlations are −0.23 ($p = 0.097$) and 0.19 ($p = 0.172$) for the EGARCH and GJR-GARCH models. The correlation between returns and the volatility beta is −0.33 ($p = 0.016$).

The correlations are even more significant with the relative downside beta, 0.42 ($p =$ 0.002).

Other important results include the negative correlation between skewness and asymmetric volatility, −0.61 ($p < 0.001$), and the negative correlation between coskewness and downside beta, 0.78 ($p < 0.001$), and relative downside beta, −0.68 ($p < 0.001$). Beta negatively correlates with skewness and coskewness and positively correlates with downside beta and asymmetric volatility.

These results are consistent with the theory that investors have a preference for assets with higher skewness and coskewness and lower downside beta. Asymmetric volatility induces negative skewness. Assets that have high covariance with the market during market downturns exhibit high average returns over the same period.

4.5. Fama-MacBeth estimation with time-varying betas

Following Lettau, Maggiori and Weber (2014), I use the two-stage procedure of Fama and MacBeth (1973) to examine the futures returns in the cross-section. Lettau, Maggiori and Weber (2014) use the following second-stage cross-sectional regression

$$\bar{r}_i = \beta_i \lambda + \left(\beta_i^- - \beta_i\right) \lambda^- + c_i, \tag{16}$$

where $\bar{r}_i$ is the average futures returns of asset i and c_i is the pricing error. However, Equations (14), (15), and (16) assume time-invariant betas and downside betas throughout the sample period. Since Lettau, Maggiori and Weber (2014) test their model on sorted portfolios that capture a characteristic associated with expected returns, they recognize predictability generated by variation over time in this characteristic.

I allow time-varying betas of unsorted futures in an out-of-sample test as Dobrynskaya (2014) finds variation in betas and downside betas. In the first step, Equations (14) and (15) are estimated in a five-year rolling window, and in the second step, Equation (16) is estimated with betas and downside betas in the preceding five years. There is a one-month gap between a given month and the preceding five-year period to allow different time zones for the contracts. Specifically, I estimate the beta and downside beta during the period January 1988 through December 1992 in Equations (14) and (15) for the return of the first month used in Equation (16), February 1993. The second month is March 1993, using the preceding period of February 1988 and January 1993, and so on.

The unconditional price of risk (or beta premium), λ, and the relative downside price of risk (or relative downside beta premium), λ^-, are the averages of the time series estimates from Equation (16). I use the same two-stage five-year rolling estimation for coskewness by replacing $(\beta_i{}^- - \beta_i)$ with the time-varying coskewness in Equation (17).

$$\bar{r}_i = \beta_i \lambda + \beta_{SKD,i} \lambda_{SKD} + c_i, \tag{17}$$

where λ_{SKD} measures the price of risk premium of coskewness.

Table 5

Estimation of risk premium using Fama-MacBeth procedures with time-varying betas

Time-varying betas in an out-of-sample test are used to examine the futures returns in the cross-section. The unconditional beta risk premium, λ, the relative downside beta premium, λ^-, and the coskewness premium, λ_{SKD}, are the averages of the time series estimates from the following regressions:

$$\bar{r}_i = \beta_i \lambda + (\beta_i^- - \beta_i)\lambda^- + c_i,$$
$$\bar{r}_i = \beta_i \lambda + \beta_{SKD,i}\lambda_{SKD} + c_i,$$

where $\bar{r}_i$ is the average futures returns of asset i. The last column presents the results with both the relative downside beta and coskewness as independent variables in the same regressions. The t-statistics in parentheses are calculated using the Newey-West standard errors.

	Return	Return	Return
Constant	0.144	0.167	0.119
	(0.95)	(1.04)	(0.81)
λ	−0.066	−0.085	−0.022
	(−0.20)	(−0.25)	(−0.07)
λ^-	0.227		0.154
	(1.75)		(0.87)
λ_{SKD}		−0.919	−0.734
		(−2.29)	(−1.40)
R-square	0.160	0.137	0.197

Table 5 shows that the beta premium, λ, in Equations (16) and (17) is insignificant for the second-stage estimation. In contrast, the risk premia of relative downside beta and coskewness are significant with the expected signs: $\lambda^- = 0.227$ ($t = 1.75$) and $\lambda_{SKD} = -0.919$ ($t = -2.29$).[11]

Including the relative downside beta and coskewness in the same second-stage regressions, λ^- and λ_{SKD} become insignificant (albeit with correct signs). The high magnitude of correlation between the relative downside beta and coskewness, as reported in Table 4, may create the problem of collinearity and make it difficult to separate the impact of downside beta and coskewness on asset returns.[12] Put another way, downside beta and coskewness measure similar risks.

The average R^2 is small, ranging from 14% to 20%. Nevertheless, the premium for downside risk is positive and the premium for (positive) coskewness risk is negative in multiple asset classes. To ensure that these out-of-sample results are not driven by a particular year with an extreme event, I estimate the results by removing

[11] The market volatility premium, λ_V, using $\beta_{V,i}$ is estimated for comparison purposes; $\lambda_V = -8.04$ ($t = -2.6$). If I use compound monthly returns without taking log for the second step of the out-of-sample test, the results do not change qualitatively: $\lambda^- = 0.326$ ($t = 2.4$), $\lambda_{SKD} = -1.03$ (-2.6), and $\lambda_V = -9.03$ (-2.8).

[12] Engle and Mistry (2014, p. 141) find the same problem for the effects of systematic risk and firm size (with a correlation of 0.54) on skewness.

one year each time from the sample period. The results (available on request) are similar to those reported in Table 5.

The results in general add to the recent literature of joint cross-section of returns in multiple asset classes. In particular, Asness, Moskowitz and Pedersen (2013) report consistent value and momentum return premia across diverse asset classes and a strong common factor structure among their returns.

5. Conclusions

I examine the cross-sectional returns of diverse international asset classes using 55 liquid futures contracts for the period 1988–2013. I find that futures returns positively correlate with asymmetric volatility and downside risk and negatively correlate with unconditional skewness and conditional coskewness. The asymmetric volatility effect described by a CGARCH model generates negative long-run skewness. This long-run skewness is closely related to the downside risk of asset returns as measured by downside beta and coskewness. Futures contracts are considered risky (e.g., international stock indexes and investment currencies) if they have a large downside beta and negative coskewness and the contracts offer higher average returns. Investors do not favor risky assets with higher downside beta and lower coskewness and, therefore, require higher returns for assets with these characteristics. In contrast, hedge contracts (international government bonds and safe-haven currencies) of low downside risk yielding lower average returns have a small downside beta, reverse asymmetric volatility, and positive skewness and coskewness.

I find a positive premium for downside risk and negative premium for coskewness risk. The relative downside beta and coskewness partially explain the cross-sectional variation of futures returns. The overall results suggest that returns of different asset classes should be considered in a unified approach with a downside-risk-based model.

Appendix

Table A1

Contract specifications

All data are obtained from Commodity Systems, Inc. (CSI).

Contract	Symbol	Exchange	Contract	Symbol	Exchange
Corn	C	CBOT	Two-year Treasury note	TU	CME
Soybeans	S	CBOT	Five-year Treasury note	FV	CME
Soybean meal	SM	CBOT	10-year Treasury note	TY	CME
Soybean oil	BO	CBOT	30-year Treasury bond	US	CME
Wheat	W	CBOT	Australian three year bond	YTT	SFE
Lean hogs	LH	CME	Australian 10-year bond	YT2	SFE
Live cattle	LC	CME	British gilt long bond	FLG	Eurex

(*Continued*)

Table A1 (*Continued*)

Contract specifications

Contract	Symbol	Exchange	Contract	Symbol	Exchange
Cocoa	CC	ICE	Canada 10-year bond	CGB	ME
Coffee	KC	ICE	Euro-Schatz German two-year	EBS	Eurex
Cotton	CT	ICE	Euro-Bobl German five-year	EBM	Eurex
Sugar	SB	ICE	Euro-Bund German 10-year	EBL	Eurex
Brent oil	LCO	ICE	Euro-Buxl German 30-year	EBX	Eurex
Crude oil	CL	NYMEX	Japanese govt bond	JGB	TSE
Gasoline	LGO	ICE	AEX (Netherlands)	AEX	EOE
Heating oil	HO	NYMEX	CAC 40 Index	FCH	Euronext
Natural gas	NG	NYMEX	DAX	FDX	Eurex
Unleaded gasoline	RB	NYMEX	FTSE / MIB (Italy)	IFS	MIF
Aluminum	MHA	LME	FTSE 100	FFI	LIFFE
Copper	HG	NYMEX	IBEX 35 (Spain)	MFX	MEFF
Nickel	MNI	LME	Nikkei 225	SSI	SGX
Zinc	MZS	LME	S&P 500	SP	CME
Gold	GC	NYMEX	SPI ASE 200 Index	YAP	SFE
Platinum	PL	NYMEX	Australian dollar	AD	CME
Silver	SI	NYMEX	British pound	BP	CME
			Canadian dollar	CD	CME
			Deutschmark/euro	EU	CME
			Japanese yen	JY	CME
			New Zealand dollar	NE	CME
			Norwegian krone	NOK	CME
			Swedish krona	SEK	CME
			Swiss franc	SF	CME

Table A2

Structural changes of asset prices

Bai and Perron (1998) introduce two tests, *Udmax* and *Wdmax*, of the null hypothesis of no structural break against an unknown number breaks given an upper bound (five in the current study). I use end-of-the-month log prices for these two tests. The numbers under the columns of *Udmax* and *Wdmax* are the numbers for significant structural break at the 10% level. The results are virtually the same using the 1% and 5% levels.

	Udmax	*Wdmax*		*Udmax*	*Wdmax*
Corn	3	5	Two-year Treasury note	5	5
Soybeans	1	3	Five-year Treasury note	3	3
Soybean meal	1	1	10-year Treasury note	3	3
Soybean oil	3	5	30-year Treasury bond	4	5
Wheat	5	5	Australian three-year bond	0	0
Lean hogs	1	1	Australian 10-year bond	0	5
Live cattle	4	4	British gilt long bond	2	3
Cocoa	2	4	Canada 10-year bond	3	5
Coffee	4	4	Euro-Schatz two-year	4	5
Cotton	3	5	Euro-Bobl five-year	3	5
Sugar	1	1	Euro-Bund 10-year	2	3
Brent oil	3	5	Euro-Buxl 30-year	5	5
Crude oil	3	5	Japanese govt bond	4	4
Gasoline	3	5	AEX (Netherlands)	5	5
Heating oil	4	5	CAC 40 Index	5	5
Natural gas	3	4	DAX	4	5
Unleaded gasoline	3	5	FTSE / MIB (Italy)	5	5
Aluminum	0	0	FTSE 100	2	5
Copper	4	4	IBEX 35 (Spain)	0	0
Nickel	1	1	Nikkei 225	4	5
Zinc	5	5	S&P 500	3	3
Gold	4	5	SPI ASE 200 Index	4	5
Platinum	2	5	Australian dollar	3	3
Silver	2	5	British pound	2	5
			Canadian dollar	5	5
			Deutschmark/euro	2	5
			Japanese yen	2	3
			New Zealand dollar	4	4
			Norwegian krone	4	5
			Swedish krona	0	5
			Swiss franc	5	5

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