

Limits of Arbitrage, Sentiment and Pricing Kernel: Evidence from S&P 500 Options *

Bing Han[†]

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[†]Correspondence to: Bing Han, Department of Finance; The Ohio State University; 838 Fisher Hall; 2100 Neil Avenue; Columbus, OH 43210-1144. Phone: (614) 292-1875. E-mail: han.184@osu.edu;

Abstract

This paper uses S&P 500 index options data to examine whether proxies of investor sentiment, or aggregate errors in investor beliefs, affect option prices and asset pricing kernel. I find that when market sentiment becomes more bearish (resp. bullish), both index option smile and asset pricing kernel are more (resp. less) negatively sloped. These relations are statistically and economically significant. They are robust and can not be explained by popular rational representative agent based option pricing models. Further, the impact of investor sentiment is stronger when there are more impediments to arbitrage in the index options. These findings suggest that sentiment matters for asset pricing.

1 Introduction

This paper studies whether market sentiment, or aggregate error in investors' beliefs, affects option prices. Previous studies have documented behavioral biases¹ and limits to arbitrage in the options market.² When some investors hold beliefs that deviate from the objective probability but the force of arbitrage is limited, market prices reflect a weighted average of the beliefs of the rational as well as irrational investors. Thus, investor sentiment can affect option prices.

This paper can also be viewed as examining whether asset pricing kernel depends on investor sentiment. The pricing kernel is the Arrow-Debreu state price per unit probability. If limits to arbitrage permit sentiment to affect option prices, then since options can be used to create Arrow-Debreu state contingent claims, states prices would be distorted by sentiment. Thus, pricing kernel would depend on investor sentiment, in addition to state variables that proxy for risks in the real economy.

The empirical analysis in this paper is motivated by recent advances in theoretical modelling of investor heterogeneity. The pricing kernel in such models looks fundamentally different from those in existing optional pricing models based on the assumption of a rational representative investor in a partial equilibrium setting. For example, the general equilibrium model of Shefrin (2005) shows that asset pricing kernel can be decomposed into a fundamental component pertaining to the growth rate of aggregate consumption, and a sentiment component capturing the aggregate belief errors in the market. Similarly, Evan, Ghysels and Juergens (2005) show that in a heterogeneous agent model, expected excess return of a risky asset contains a fundamental component and a heterogeneity component that reflects errors in individual investors' conditional mean beliefs about market return.

To test whether sentiment affects option prices and pricing kernel, I focus on the skewness

¹See, e.g., Stein (1989), Poteshman (2001), Poteshman and Serbin (2003), Lakonishok, Lee and Poteshman (2004), Mahani and Poteshman (2004).

²See, e.g., Phillips and Smith (1980), Figlewski (1989), Figlewski and Green (1999), Bollen and Whaley (2004), Ofek, Richardson and Whitelaw (2004).

of the risk-neutral density of monthly S&P 500 index return. Index risk-neutral skewness is substantially negative, although the empirical density of monthly index return is approximately symmetric [e.g., Jackwerth (2000), Rosenberg and Engle (2002)]. The difference is explained by the pricing kernel, which determines the transformation between the empirical objective probability and the risk-neutral measure. The risk-neutral skewness of index return depends on the slope of the pricing kernel, or the ratio of the value of pricing kernel at state of low index level to that at state of high index level. Index risk-neutral skewness becomes more negative when the pricing kernel is more negatively sloped. If sentiment affects option prices, then a more bearish sentiment should be associated with a more negatively sloped pricing kernel and thus a more negative index risk-neutral skewness. Similarly, index risk-neutral skewness should be less negative when market sentiment turns more bullish. This time-series relation between index risk-neutral skewness and sentiment is the key hypothesis that I test. This test can reveal whether asset pricing kernel depends on sentiment.

I focus on index risk-neutral skewness also because it is closely related to the option implied volatility smile³ [e.g., Bates (2001), Bakshi, Kapadia and Madan (2003), Bollen and Whaley (2004)]. Many papers try to explain the index option volatility smile within the rational representative agent framework, attributing any divergence between objective and risk-neutral probability measures solely to exogenously specified free risk-premium parameters.⁴ However, empirical tests uncover discrepancies between the properties of index return under the objective measure and the risk-neutral measure that are inconsistent with models' assumptions on the market prices of risks [e.g., Bakshi, Cao, and Chen (1997), Bates (2000), Pan (2002)]. There is also evidence that the S&P 500 options are not efficiently priced relative to a large class of rational option pricing models [e.g., Jackwerth (2000), Ait-Sahalia, Wang and Yared

³Index option volatility smile (or smirk) refers to the pattern that Black implied volatility for S&P 500 index option decreases monotonically with the strike price (e.g., Rubinstein (1994), Jackwerth and Rubinstein (1996)).

⁴See the extensive references contained in Bates (2003) and Whaley (2003). In other lines of recent research, Benzoni, Collin-Dufresne and Goldstein (2005), Liu, Pan and Wang (2005) study the implication of general equilibrium models for option smile; Constantinides (2001) and Constantinides, Jackwerth and Perrakis (2005) consider option pricing under market imperfection such as transaction costs; Benninga and Mayshar (2000), Bates (2001), Buraschi and Jiltsov (2005) study option pricing models with heterogeneous investors.

(2001), Bondarenko (2003)].

In this paper, I examine whether investor sentiment helps explain index option implied volatility smile. In the presence of limits to arbitrage, when market sentiment becomes more bearish, out-of-the-money index puts would be more expensive (measured in Black implied volatility) relative to at-the-money options and the implied volatility smile would be steeper. This is another hypothesis that I test.

Sentiment is not directly observable. In the empirical analysis, I use three proxies of investor sentiment. The first proxy is the proportion of bullish investors minus the proportion of bearish investors based on Investor's Intelligence's survey of newsletter writers. The second proxy is the net position in the S&P 500 index futures held by large speculators, obtained from the Commitments of Traders report published by the Commodity Futures Trading Commission. The third proxy is the deviation of the S&P 500 index level from that predicted by the log-linear dynamic growth model of Campbell and Shiller (1988) as implemented by Sharpe (2002).

I find strong and robust evidence that these sentiment proxies are significantly related to the risk-neutral skewness of index return and the slope of index option volatility smile in the manner hypothesized above. The risk-neutral density for index return is more negatively skewed, and the index option smile is steeper, when the market sentiment turns more bearish. On the other hand, a more bullish market sentiment is associated with less negative index risk-neutral skewness and flatter index option smile. These results hold after controlling for a set of rational factors that may be related to the sentiment proxies, and after controlling for variables that have recently been found to be related to the steepness of index option smile, including index volatility, recent index return [e.g., Amin, Coval and Seyhun (2004)], relative demand pressure of index options [e.g., Bollen and Whaley (2004), Garleanu, Pedersen and Poteshman (2005)], and dispersion of beliefs among investors [e.g., Buraschi and Jiltsov (2005)].

Limits to arbitrage play an important role for my results. I find that the relation between index risk-neutral skewness and sentiment proxies is stronger and statistically significant when there are more impediments to arbitrage in the index options market. In contrast, during periods of more effective arbitrage in the index options market, the rational factors become more important and the impact of sentiment becomes largely insignificant. Further, I find that several rational representative agent based option pricing models could not explain my findings. There is still a significant relation between index risk-neutral skewness and sentiment proxies after I control for the skewness under the rational models. Taken together, my findings support the idea that in the presence of limits to arbitrage, investor sentiment is an important determinant of option prices and asset pricing kernel.

This paper brings fresh evidence to the debate about whether investor sentiment matters for asset pricing. Previous studies on this question focus on the stock market.⁵ Since it is difficult to directly identify sentiment-driven stock price misvaluations, researchers usually test for patterns in stock returns that are consistent with sentiment-induced mispricing getting corrected over some horizon. However, this correction may not occur over the chosen horizon, due to limits of arbitrage and fluctuation in investor sentiment. This adds noises to the inferences about the pricing impact of sentiment based on realized stock returns.

I examine the asset pricing impact of investor sentiment using option prices. The advantage is that it is easier to identify sentiment-driven mispricing in option prices. First, option prices provide ex-ante measure of investors' belief. Second, there is a rich cross-section of options traded on the same underlying. Bullish investors tend to take long positions in calls, while bearish investors take long positions in index puts. In contrast, they may partially cancel each other in the stock market. A related point is that it is easy to create and destroy contracts in the option market while the supply of stock is fixed (at least in the short run). Thus, option market can provide a clearer picture of different groups of investors' absolute sentiment while

⁵See the following recent studies and the references therein: Fisher and Statman (2000), Baker and Wurgler (2005), Brown and Cliff (2004, 2005), Brown et al. (2003), Kaniel, Saar and Titman (2004), Kumar and Lee (2005), Lemmon and Portniaguina (2004).

stock market reflects investors' relative demand.⁶ Finally, the no arbitrage relation between stock and options, and the well-researched literature on rational option pricing models provide benchmark fair value for options. In the stock market, the fair value is more subjective and harder to pin down.

It is important to keep in mind that this paper is more than showing that market sentiment affects index option prices. Because of the link between index options prices and pricing kernel, and because pricing kernel is a unifying framework for the pricing of all financial assets, my findings have direct implication for the relevance of sentiment for asset valuation in other markets including the stock market.

My study is related to, but also distinct from, a large literature that estimates an *average* or *unconditional* pricing kernel from index option prices under some assumptions on the form of the pricing kernel [e.g., Ait-Sahalia and Lo (1998, 2000), Jackwerth (2000), Rosenberg and Engle (2002), Bliss and Panigirtzoglou (2004)]. Different from these studies, I extract *conditional* information about the slope of pricing kernel as encoded by index risk-neutral skewness and examine whether its time variation is related to change in sentiment. I obtain model-free estimate of index risk-neutral skewness from a cross-section of index option prices without making any assumptions on the form of the pricing kernel.⁷ This is important since I want to study the determinants of asset pricing kernel.

This paper contributes to a growing body of research outside the rational representative agent approach to option pricing as recently called for by several authors. Bates (2003) points out that the representative agent approach is inconsistent with the industrial organization of the stock index option market. He also argues that financial economists should not blithely attribute divergence between objective and risk-neutral probability measure to the free “risk-premium” parameters. Whaley (2003) suggests that “spending more resources developing more elaborate theoretical models (with even more parameters) and more sophisticated com-

⁶See Lakonishok, Lee and Poteshman (2004) for a similar argument.

⁷The origin of risk-neutral skewness measure is Bakshi and Madan (2000) and Bakshi, Kapadia and Madan (2003). See Section 3.2 for details.

putational techniques seems imprudent, at least in the short-run. Perhaps, a more promising avenue of investigation is the study of two related “fundamentals”—price pressure and limits to arbitrage.”

The rest of this paper is organized as follows. Section 2 discusses the theory background. Section 3 describes the data and measurement of main variables used in the tests. Empirical results are presented in Section 4. Section 5 concludes the paper.

2 Theory

The fundamental theorem in asset pricing states that in the absence of riskless arbitrage opportunities, assets can be valued under an equivalent martingale measure as if investors were risk neutral. Such measure is called a risk-neutral measure. The ratio of the risk-neutral probability density and the empirical probability density, discounted at the riskless rate, is referred to as the pricing kernel or stochastic discount factor. Equivalently, the value of pricing kernel at a given state is the corresponding Arrow-Debreu state price per unit probability.

Pricing kernel provides a unifying framework for all asset pricing theories [e.g., Harrison and Kreps (1979), Cochrane (2001)]. The behavioral finance literature documents numerous asset pricing findings that are difficult to explain under fully rational models. But none of them are riskless arbitrage opportunities. Thus, the pricing kernel framework continues to apply for behavioral finance models.

However, behavioral models and traditional rational models differ in what determines the asset pricing kernel. Traditional models, motivated by the marginal rate of substitution for a rational representative agent, specify the pricing kernel as a function of the aggregate consumption growth, return on the market portfolio, or more generally state variables that proxy for risks in the real economy. If the pricing kernel is disconnected from the marginal rates of substitution or transformation in the real economy, markets can be irrational or inefficient without requiring arbitrage opportunities.

A necessary condition for non-fundamental variables such as investor sentiment to affect the pricing kernel is that there are limits to arbitrage in the financial markets. I focus on the index options which enable me to extract valuable information about the pricing kernel [e.g., Breeden and Litzenberger (1978)]. Limits to arbitrage exist because of noise traders risk, trading frictions, short investment horizon and limited capital on the part of arbitrageurs [e.g., Shleifer and Vishny (1997), Liu and Longstaff (2004)]. In the index options market, in addition to these considerations, the industrial organization of the market and the high risks in trading options also limit the effectiveness of arbitrage activities.

A large clientele of assorted institutional investors predominantly buy stock index options, but there are no natural sellers of index options.⁸ Market-makers provide liquidity in option trading by risking their own capital and take the opposite side of public orders. However, the costs of setting up and unwinding an option hedge often outweigh the possible profits of selling options [e.g., Phillips and Smith (1980)]. Dynamic hedging of an option with the underlying asset and rebalancing would entail large risk and transaction costs that is impractical even for an option market maker [e.g., Figlewski (1989)]. Even if option sellers can perfectly delta-hedge an option's exposure to the underlying asset, they are still exposed to substantial volatility risk which can produce very large losses [e.g., Figlewski and Green (1999)]. Bollen and Whaley (2004) show that steeply sloped smile curve for index options does not present a profitable arbitrage opportunity once the costs of vega hedging have been considered.

Given limits to arbitrage in the index options market, there are at least two channels for sentiment to affect option prices. One, sentiment can affect investors' demand for various options. For example, if sentiment about the stock market shifts to more bearish, there would be higher demand for the out-of-the-money index put options as they provide "portfolio insurance." Recent studies document that demand pressures in the options market affect prices [e.g., Bollen and Whaley (2004), Cheng, Chan and Lung (2004), Garleanu, Pedersen

⁸See, e.g., Bates (2003). Bollen and Whaley (2004) find a net customer buying pressure for the out-of-the-money index puts. Garleanu, Pedersen and Poteshman (2005) also find that non-market makers have a net long position in S&P 500 index options with the largest net position in out-of-the-money puts.

and Poteshman (2005)].⁹ Thus, a more bearish sentiment can lead to more expensive out-of-the-money index puts, and hence a steeper implied volatility smile and a more negative index risk-neutral skewness.

I focus on a more direct channel for sentiment to manifest itself within asset prices through its influence on the pricing kernel. Recent studies show that in general equilibrium models with both rational investors and investors holding mistaken beliefs, the pricing kernel contains a sentiment component [e.g., Evan, Ghysels and Juergens (2005), Shefrin (2005)]. This second channel for sentiment to affect option prices does not require the price pressure effect of option demand. In fact, it works even in a perfect and complete market where options are redundant, perfect substitutes of each other, and in net zero supply. In this case, options can be priced by no-arbitrage just as in the rational option pricing models based on a representative investor such as the Black-Scholes model. But because of investor heterogeneity, aggregate belief error or investor sentiment enters into the pricing kernel and affects option prices.

In general, introducing heterogeneous beliefs about asset returns and consumption growth would have two effects on asset prices. One effect comes from errors in the conditional mean beliefs about asset returns and consumption growth, and another effect comes from the dispersion of beliefs. Evan, Ghysels and Juergens (2005) assume in the empirical analysis that the economy as a whole is correct on average about its expectation of consumption growth and stock returns. Therefore, Evan, Ghysels and Juergens (2005) zero out the first effect (first moment), and focus on dispersion in belief (second moment). They find that disagreement among analysts about expected stock earnings is a priced risk factor affecting both expected stock returns and volatility. My study complements Evan, Ghysels and Juergens (2005). I focus on how aggregate errors in investors' beliefs affect option prices, controlling for the impact of dispersion of beliefs.¹⁰

⁹In this case, the traditional no-arbitrage approach to pricing option does not apply. Garleanu, Pedersen and Poteshman (2005) propose a demand-based option pricing model, taking as given some exogenous and nonzero demand for each option. In their model, option prices are determined by utility maximizing dealers.

¹⁰To appreciate the difference between sentiment (aggregate error in investor beliefs) and dispersion of beliefs, compare the following two scenarios. In the first, 70% of the investors are bullish and 30% are bearish. In the

To examine whether the pricing kernel depends on sentiment, I infer the skewness of the risk-neutral density of index return from index option prices and investigate whether it is significantly related to proxies of investor sentiment. Time variations in the risk-neutral index skewness reflect changes in the state variables that determine the pricing kernel. If the projection of the pricing kernel on index return is a decreasing function, then index return is negatively skewed under the risk-neutral measure. The more downward sloped the projected pricing kernel is as a function of the index return, the more negative the risk-neutral skewness.

A more bearish sentiment about the stock index would increase investors' willingness to pay for hedging securities that pay off when the stock index level is low such as out-of-the-money index puts (i.e., a higher state price when index is low than when index achieves a high level). This leads to a more negatively sloped pricing kernel and thus a more negative index risk-neutral skewness. To see the argument more formally and directly based on the pricing kernel, consider the general equilibrium Shefrin (2005), where agents have power utility, some of whom hold mistaken belief about the aggregate consumption growth (or market return). Market is complete and the pricing kernel, described in terms of the representative investor constructed by Shefrin (2005), looks like

$$M(x_1|x_0) = \delta_R \Psi(x_1) g(x_1)^{-\gamma_R} \quad (1)$$

where x_0 and x_1 are the current and future aggregate consumption level (or stock index level), g is the growth rate, δ_R and γ_R are the time discount and risk aversion parameter of the representative agent, and Ψ reflects deviation of the probability belief P_R of the representative agent from the objective probability π :

$$\Psi(x_1) = P_R(x_1)/\pi(x_1)$$

second, 30% of the investors are bullish and 70% are bearish. The dispersion in beliefs is the same in the two cases, but not the sentiment. I examine whether the first scenario is associated with a flatter volatility smile and less steeped pricing kernel than the second case.

In particular, when everyone is rational, Ψ is reduced to identity. In general, the slope of the pricing kernel does depend on the aggregate belief error:

$$\frac{\partial M}{M \partial x} = \Lambda'(x) - \frac{\gamma}{g(x)}$$

where $\Lambda = \ln(\Psi)$. The Λ term, which is zero when everyone is rational, captures the impact of investor heterogeneity and mistaken belief on the pricing kernel. So when market sentiment becomes more bearish (giving a higher weight to states where x is low, and lower probability to states where x is high), then Λ' would be more negative, leading to a more negatively sloped pricing kernel and more negative risk-neutral skewness.

3 Data and Variables

3.1 Option Data

I use a dataset provided by the Chicago Board Options Exchange on the S&P 500 index options (with ticker symbol SPX). The SPX options are among the most actively traded derivatives in the world. They are European-style and cash-settled. The data contain trading date, expiration month, strike price, trading volume, open interest, high price, low price, last sale price as well as closing index level. Expiration are three near-term months followed by three additional months from the March quarterly cycle (March, June, September and December).¹¹ Strike prices are spaced at 5 index points increment for short maturity options, and 25 index points for the far months. This rich cross-section of index options helps estimate index risk-neutral skewness more precisely. The options data are daily frequency from January 4, 1988 to June 24, 1997.

¹¹The SPX options mature on the third Friday of the contract month. Trading ceases on the business day preceding the day on which the exercise-settlement value is calculated. However, before August 24, 1992, these options expired at market close. Therefore, until August 24, 1992, option's time to maturity is measured as the number of calendar days between trade date and the expiration date, but after that date, I use the number of calendar days remaining less one.

Following Ait-Sahalia and Lo (1998), Dumas, Fleming, and Whaley (1998), Poteshman (2001) and others, I apply the put-call parity (using calls and puts that are closest to being at-the-money) to infer an implied futures price on each date, and for each option maturity. Using standard cash-futures price relation, I then obtain, for each option, the corresponding dividend-adjusted index level S as interest rate deflated futures price.¹² I exclude all option observations that violate obvious no-arbitrage conditions such as $S \geq C \geq \max(0, S - Ke^{-rT})$ for a call option where S is the dividend-adjusted index level corresponding to maturity T . To avoid microstructure related bias, I exclude options whose prices are less than \$1/8, as well as options with maturities less than 1 week or more than 1 year.

3.2 Risk-Neutral Skewness of Index Return

The origin of my measure for the risk-neutral skewness is Bakshi and Madan (2000) and Bakshi, Kapadia and Madan (2003). Bakshi and Madan (2000) show that the continuum of characteristic functions of the risk-neutral return density and the continuum of options are equivalent classes of spanning securities: Any payoff function with bounded expectation can be spanned by out-of-the-money (OTM) European calls and puts. Based on this insight, Bakshi, Kapadia and Madan (2003) formalize a mechanism to extract the skewness (and other moments) of the risk-neutral return density from a contemporaneous collection of OTM calls and puts. More precisely, on date t , the skewness of the risk-neutral density of the index return over the period $[t, t + \tau]$ can be obtained as:

$$Skew(t, \tau) = \frac{e^{r\tau}W(t, \tau) - 3\mu(t, \tau)e^{r\tau}V(t, \tau) + 2\mu(t, \tau)^3}{[e^{r\tau}V(t, \tau) - \mu(t, \tau)^2]^{3/2}} \quad (2)$$

where

$$\mu(t, \tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V(t, \tau) - \frac{e^{r\tau}}{6}W(t, \tau) - \frac{e^{r\tau}}{24}X(t, \tau) \quad (3)$$

¹²I collect from Datastream the LIBOR rates with maturities of one-week, one-month, three-months, six-months, and one-year. LIBOR rates are quoted in annual yields. On each date, I first translate the annual yields into continuously compounded rates, and then linearly interpolate these rates to find the continuously compounded interest rates for all maturities between one week and one year.

and $V(t, \tau)$, $W(t, \tau)$ and $X(t, \tau)$ are weighted sums of prices of OTM call options $C(t, \tau, K)$ and put options $P(t, \tau, K)$ with time-to-maturity τ and strike price K , given the underlying asset price S_t :

$$V(t, \tau) = \int_{S_t}^{\infty} \frac{2(1 - \ln(\frac{K}{S_t}))}{K^2} C(t, \tau, K) dK + \int_0^{S_t} \frac{2(1 + \ln(\frac{S_t}{K}))}{K^2} P(t, \tau, K) dK \quad (4)$$

$$W(t, \tau) = \int_{S_t}^{\infty} \frac{6\ln(\frac{K}{S_t}) - 3[\ln(\frac{K}{S_t})]^2}{K^2} C(t, \tau, K) dK - \int_0^{S_t} \frac{6\ln(\frac{S_t}{K}) + 3[\ln(\frac{S_t}{K})]^2}{K^2} P(t, \tau, K) dK \quad (5)$$

$$X(t, \tau) = \int_{S_t}^{\infty} \frac{12[\ln(\frac{K}{S_t})]^2 - 4[\ln(\frac{K}{S_t})]^3}{K^2} C(t, \tau, K) dK + \int_0^{S_t} \frac{12[\ln(\frac{S_t}{K})]^2 + 4[\ln(\frac{S_t}{K})]^3}{K^2} P(t, \tau, K) dK \quad (6)$$

It is important to note that the Bakshi, Kapadia and Madan (2003) measure of the risk-neutral skewness is *model-free* since it does not require any assumption on the state variables that determine the pricing kernel or the functional form of the pricing kernel. It is an *ex-ante* measure of the *conditional* skewness of the index return since it is inferred from the contemporaneous index option prices which embed investors' expectation of future path of the S&P 500 index. Using this model-free measure of the conditional risk-neutral skewness of index return, I examine whether its time variation is related to changes in investor sentiment.

On each date t , I estimate the risk-neutral index skewness using equations (2) through (6) and the date- t last sale prices of OTM index puts and calls. To avoid stale prices, I use only index options that have positive trading volume on that date. I approximate the integrals in (4), (5) and (6) using the trapezoidal method. Given the fine grid of available strike prices for index options, and the fact that the integrand functions rapidly declines towards zero as the strike price deviates from the spot index level, the approximation error due to the discreteness of available strike prices is negligible [e.g., Dennis and Mayhew (2003)]. I use monthly return horizon (i.e., $\tau = 1/12$ year). This choice gives me enough non-overlapping observations to do time-series regressions. In addition, options with approximately one month to maturity are the most actively traded. On some dates, there are no traded options with maturity

exactly equal to one month. In such cases, I first compute the risk-neutral skewness for two horizons that are nearest to one month, and then linearly interpolate to get the risk-neutral skewness for one-month index return. Section 4.3 shows that my empirical results are robust to variations in the implementation of the Bakshi, Kapadia and Madan (2003) measure of risk-neutral skewness.

Figure 1 top left panel plots the monthly time series of risk-neutral skewness of S&P 500 index return over the next month inferred from contemporaneous index option prices. It shows that index risk-neutral skewness fluctuates substantially over time from one month to the next. This is confirmed by the high sample standard deviation of the risk-neutral skewness as reported in Table 1. One can see that index risk-neutral skewness is also positively autocorrelated. For this reason, I will include lagged skewness as a control variable in my regressions that have index risk-neutral skewness as the dependent variable.

3.3 Sentiment Proxies

I use three proxies of the sentiment for large, sophisticated investors. A large clientele of assorted institutional investors predominately buy stock index options [e.g., Bates (2003)]. Lakonishok, Lee and Poteshman (2004) find that option open interest and trading volume primarily originate from sophisticated traders such as firm proprietary traders and full-service brokerage customers rather than discount customers. Because of the large positions required in the index options market, individual investors tend not to use index options. Thus, I do not use small investors' sentiment since they are not important players in the index options market. Results in an earlier version of this paper show that proxies of individual investors' sentiment are not significantly related to index risk-neutral skewness, and their inclusions do not change the relation between proxies of large investors' sentiment and index risk-neutral skewness reported in Section 4.

The first proxy is a popular sentiment index based on Investor's Intelligence's weekly

surveys of approximately 150 investment newsletter writers. Each newsletter is read and marked as bullish, bearish or neutral based on the expectation of future market movements.¹³ Following Brown and Cliff (2004, 2005), I use the bull-bear spread, or the fraction of bullish investors minus the fraction of bearish investors, as a proxy for sentiment of large investors such as institutions, since many of the authors of these newsletters are current or retired market professionals. The bull-bear spread is published weekly in Barron's and is often mentioned in financial press. It is related to many other measures of investor sentiment [e.g., Brown and Cliff (2004)]. It is also positively related to deviations of large sized firms from their intrinsic values [e.g., Brown and Cliff (2005)].¹⁴

The second sentiment proxy is derived from trading activity in the S&P 500 index futures market. The Commodity Futures Trading Commission (CFTC) requires large traders holding positions above a specified level to report their positions on a daily basis. The open interest of large traders are broken down into "commercial" and "non-commercial" categories. Commercial traders are required to register with the CFTC by showing a related cash business for which futures are used as a hedge. The non-commercials are large speculators. The CFTC aggregates reported data and releases the breakdown of each Tuesday's open interest in the Commitments of Traders (COT) report.¹⁵ The report contains the number of long positions and the number of short positions separately for each category of traders. My second sentiment proxy is the net position of large speculators in the S&P 500 futures, computed as the number of long non-commercial contracts minus the number of short non-commercial contracts, scaled by the total open interest in the S&P 500 index futures.

The third sentiment proxy I use is the valuation errors of the S&P 500 index obtained by

¹³Since the newsletters are not written with the survey in mind, they may differ somewhat in forecast horizon and thus may require interpretation in the categorization. The temporal consistency in interpretation is maintained because there have been only two editors of Investors' Intelligence since its inception (Abe Cohen and Michael Burke). Investor's Intelligence indicates that the typical forecast horizon of the newsletter is one to three months.

¹⁴Brown and Cliff (2005) point out that other sentiment measure (primarily for the individual investors) predict small stock premiums is complementary, not contrary, to their finding of the importance of institutional sentiment for large firms and the market as a whole.

¹⁵The COT report for the S&P 500 index futures is available each Friday since October 1992. Prior to that, they are available at mid-month and month-end. I use the latest available COT report in my analysis.

Sharpe (2002). These errors are the fractional deviation of the S&P 500 index from the level predicted by the log-linear dynamic growth model of Campbell and Shiller (1988). They are the residuals of the log price-earnings ratio of the index regressed on earnings growth expectations, log dividend payout and several other variables such as expected inflation and real 30-year Treasury bond yield. Positive (negative) error means that according to the Campbell-Shiller model, the S&P 500 index was overvalued (undervalued) relative to the fundamentals. For example, according to Sharpe (2002), the stock index was grossly overvalued during August and September of 1987, just prior to the stock market crash. On the other hand, the S&P 500 index was undervalued by more than 10% between late 1990 to early 1991, from late 1995 to early 1996, and around September 1998.¹⁶

The three sentiment proxies are positively correlated with each other. The correlation of the bull-bear spread and the net position of large speculators in the S&P 500 index futures is 0.26. The correlation of these two variables with the valuation errors of the S&P 500 index is 0.35 and 0.15 respectively. Thus, the S&P 500 index is more overvalued relative to the fundamental when newsletter writers and large speculators in the S&P500 index futures are more bullish.

All three sentiment proxies display significant temporal movements, which can be seen from their time series plots in Figure 1. They also tend to move in lockstep with the index risk-neutral skewness. The correlation between the sentiment proxies and the index risk-neutral skewness ranges from 0.29 to 0.48. In Section 4, I study this relation in more detail using regressions.

¹⁶March 1991 is a NBER business cycle trough during the 1990-1991 recession. In the fall of 1998, the stock market dropped significantly out of concerns about the Russian financial crisis and Long Term Capital Management debacle.

4 Empirical Results

I find that index risk-neutral skewness is significantly related to sentiment proxies (Section 4.1). This relation is robust to a variety of control variables that are related to the index skewness or the sentiment variables (Section 4.2). It is also robust to variations in the measurement of skewness (Section 4.3). It can not be explained by several popular rational option pricing models (Section 4.4). It is stronger when there are higher limits to arbitrage in the index options (Section 4.5). Sentiment proxies also affect the relative valuation of index options and are significant determinants of the slope of the index option smile (Section 4.6).

4.1 Basic Results

Table 2 reports the results for regression models that study the relation between index risk-neutral skewness and the sentiment proxies. The regressions employ monthly time-series observations. The dependent variable for all regressions is the risk-neutral skewness of index return over the next month inferred from contemporaneous index option prices, evaluated on the last trading day of each month. The sentiment proxies are measured on or prior to that date, using the latest available data. Lagged dependent variable is included as a regressor to control for its positive autocorrelation. The t -statistics of the parameter estimates are obtained from standard errors that have been adjusted for heteroscedasticity and serial correlation according to Newey and West (1987).

Table 2 shows that all three sentiment proxies are significantly and positively related to index risk-neutral skewness. Thus, a more bearish market sentiment (lower values for the sentiment proxies) is related to a more negative index risk-neutral skewness. The impacts of sentiment proxies are also economically significant. For example, a one-standard deviation drop in the bull-bear spread (i.e., bearish shift in sentiment) is associated with a 0.23 standard deviation decrease in the index risk-neutral skewness (it becomes more negative). If investors become more bullish causing the S&P 500 index mispricing to increase by 1 sample standard

deviation (which is about 4.38%), then index risk-neutral skewness increases (i.e., becomes less negative) by about 0.38 sample standard deviation.

4.2 Robustness to Control Variables

I do a variety of robustness check on the relation between index risk-neutral skewness and sentiment proxies, by adding several variables that may be related to index risk-neutral skewness or sentiment. The first control variable is the instantaneous volatility of index return. Theoretically, this variable is the key determinant of the risk-neutral skewness under rational models with stochastic volatility (see Section 4.4). (In fact, it is the only driver of index risk-neutral skewness under the stochastic volatility model if model parameters are treated as constants.) Empirically, Li and Pearson (2005) find that the slope of the S&P 500 index option implied volatility depends on the at-the-money volatility. I use CBOE's Volatility Index (*VIX*) as a proxy for the instantaneous volatility of index return. During my sample period, *VIX* represents the average implied volatility of the at-the-money index options 30 days before expiration.¹⁷

The second control variable is stock market momentum, measured by the most recent six-month index return (similar results are obtained with three-month or twelve-month index return). On the one hand, recent market return is the most important determinant of market sentiment [e.g., Brown and Cliff (2004)]. On the other hand, it also affects the relative valuation of index options [e.g., Amin, Coval and Seyhun (2004)].

I also control for the relative demand of index options. Bollen and Whaley (2004) find that an option's implied volatility increases with its net buying pressure. Garleanu, Pedersen and Poteshman (2005) find that the level of net end-user demand impacts the level of implied volatility and the shape of implied volatility smile. Given the close relation between the slope of option smile and risk-neutral skewness, option demand pressure can be expected to

¹⁷Results are the same when I use the volatility state variable obtained by fitting the Heston (1993) stochastic volatility model to the index options as the proxy for the instantaneous volatility of index return.

be related to index risk-neutral skewness. To control for such effect, Table 3 includes as a regressor the ratio of the open interest for the out-of-the-money index put options to the open interest for the near and at-the-money index options. (Similar results are obtained using the put-call ratio of open interest or trading volume to proxy for the relative demand of options.) Following Bollen and Whaley (2004), I classify out-of-the-money puts as those options whose delta satisfy $-\frac{3}{8} < \Delta_P \leq -\frac{1}{8}$. The near and at-the-money options include call options with $\frac{1}{2} < \Delta_C \leq \frac{5}{8}$ and put options with $-\frac{1}{2} < \Delta_P \leq -\frac{3}{8}$.

Model (1) of Table 3 shows that these control variables are significantly related to index risk-neutral skewness. For example, index risk-neutral skewness is less negative when market volatility is higher. This is consistent with the prediction of stochastic volatility models (see Section 4.4, especially equation (7)). Further, consistent with Bollen and Whaley (2004) and Garleanu, Pedersen and Poteshman (2005), I find that index risk-neutral skewness becomes more negative when there is a higher demand for the out-of-the-money index put options relative to the near- and at-the-money index options. Finally, consistent with the finding of Amin, Coval and Seyhun (2004) that the index option volatility smile becomes flatter following an up-market, I find that index risk-neutral skewness is positively related to past six-month return of the S&P 500 index.

More interestingly, Model (2), (3) and (4) of Table 3 show that the relation between index risk-neutral skewness and sentiment proxies remains significant both statistically and economically after controlling for index return volatility, stock market momentum and the option demand-pressure effect. The coefficient estimates and their t -statistics in these regressions are about the same as or even somewhat stronger than those in the basic regressions of Table 2. This suggests that the sentiment proxies and the control variables largely capture different aspects of movements in the risk-neutral skewness of index return. It also provide support for the direct channel for sentiment to affect option prices and pricing kernel (see Section 2) beyond pure price pressure of option demand that may be induced by sentiment.

Each of the sentiment proxies is likely to include a sentiment component and non-sentiment

related components. In Table 3 Model (4), I address the concern that the explanatory power of sentiment proxies for the temporal movements in index risk-neutral skewness may come from the non-sentiment related components: sentiment proxies may be correlated with variables that proxy for investment opportunities and predict market return. Following Chen (1991), and Ferson and Harvey (1991), I control for the logarithmic growth in the aggregate industrial production over the last year, the one-month treasury bill rate, the spread between yields on the ten-year Treasury bond and the three-month treasury bill, and difference in yields on Baa and Aaa corporate bonds. Intuitively, Table 3 Model (4) is similar to first regress each sentiment proxy on a set of rational predictors of index return, and then regress index risk-neutral skewness on residuals of the sentiment proxies (obtained from the first pass regressions).¹⁸ If the relation between index risk-neutral skewness and sentiment proxies is driven by the non-sentiment related components, then it will weaken substantially or disappear in the presence of these additional control variables. However, Table 3 Model (4) indicates that this is not the case. Two of the three sentiment proxies, the bear-bear spread and the index misvaluation, are still significantly related to index risk-neutral skewness. The magnitudes of their coefficient estimates barely change in the presence of the rational control variables.

I have also run the regressions reported in Table 3 with an additional regressor that proxy for dispersion of beliefs among investors. Buraschi and Jiltsov (2005) estimate a heterogeneous-belief model using index option prices and option trading volume. They find that a higher value for the option-implied difference in beliefs leads to a steeper volatility smile, although this effect fads out over time quickly, and becomes statistically insignificant after about 9 days. They find that option trading volume is an excellent proxy for dispersion of beliefs, better than the trading volume of the underlying asset. Thus, I control for dispersion of beliefs among investors by the total trading volume in the SPX options (divided by 100,000 contracts and adjusted for a deterministic time trend). In unreported monthly regressions, I find that index risk-neutral skewness tends to be more negative when the dispersion proxy takes a larger

¹⁸Baker and Wurgler (2005) have used a similar approach to decompose sentiment proxies in studying the pricing effect of sentiment in the stock markets.

value, although the relation is not statistically significant. In weekly time-series regressions (see Table 6), the coefficient for the dispersion proxy becomes statistically significant, especially when there are more limits to arbitrage in the index options. In Section 4.5, I will explore in more detail how the results documented so far depend on limits to arbitrage.

4.3 Robustness to Measurement of Skewness

Table 4 provides further robustness check on the relation between the risk-neutral skewness of index return and investor sentiment. The focus here is how much noises in the measurement of index risk-neutral skewness can affect the results. All the regressions reported in Table 4 have the same specification as Table 3 Model (4): the dependent variable is index risk-neutral skewness; the independent variables include three sentiment proxies and control variables such as proxies for index volatility, stock market momentum and relative demand of index options. The only difference across the regressions in Table 4 as well as between Table 4 and Table 3 Model (4) is the measurement of index risk-neutral skewness.

Till now, I have used the last sale prices of index options and applied the Bakshi, Kapadia and Madan (2003) approach to infer index risk-neutral skewness. I continue to apply the same technique, but use different options data input. Note that in general, any noise in the dependent variable (index risk-neutral skewness) works against finding statistically significant coefficients in the regression (unless the noises happen to be correlated with the regressors). The goal here is to make sure that the significant relation between index risk-neutral skewness and sentiment proxies is not driven by measurement errors in index risk-neutral skewness somehow being correlated with sentiment proxies.

Table 4 Model (1) examines the impact of potential measurement errors in the index options data (including option bid-ask spread, non-synchronicity of last trade across different index options) on my results via simulations. For each round of simulation, I independently shock the last sale price of each index option on each date, by either +3% or -3%, and

then recompute the index risk-neutral skewness on each date using the simulated data. The simulation is done 10,000 times. I find that these errors in option prices only introduce very small variations in the risk-neutral skewness estimates. For example, the time-series average of the cross-sectional (i.e., across 10,000 simulations) standard deviation in the risk-neutral skewness estimates is 0.0197. In comparison, the average (median) absolute monthly change in the skewness during my sample period is 0.5129 (0.4151). When I use the average risk-neutral skewness (averaged across the 10,000 simulations on each date) as the dependent variable in regression Model (1) of Table 4, the result is similar to those reported previously (e.g., Table 3 Model (4)). In the same vein, Table 4 Model (2) shows that using the average of daily high price and low price (instead of last sale price) of each index option to compute index risk-neutral skewness does not alter my results.

In all the previous regressions, the risk-neutral skewness is estimated once a month using options data on the last trading day of each month. To make sure that my results are not special to the month end, in Table 4 Model (3) I use as the dependent variable the monthly average skewness which is the mean (over all trading days in a month) of the risk-neutral skewness computed from each trading day's cross-section of index option prices. Further, in Table 4 Model (4), index risk-neutral skewness is computed using index options data sampled around the middle of each month when there are options with exactly one-month time-to-maturity. Besides testing the robustness of the monthly regressions results to when the data is sampled, Model (4) also tests the robustness with respect to the linear interpolation that is used in computing the risk-neutral skewness of index return over a one-month horizon (interpolation is needed due to the lack of traded index options with exactly one-month maturity at month end; see Section 3.2). Table 4 shows that in both Model (3) and (4), there is still a significant relation between index risk-neutral skewness and all the sentiment proxies, just as in Table 2 and Table 3.

To summarize, results in Table 4 shows that the relation between index risk-neutral skewness and sentiment proxies is robust to measurement errors in index risk-neutral skewness.

4.4 Can the Results Be Explained by Rational Models?

Here I examine whether a class of rational option pricing models can explain the significant time-series relation between index risk-neutral skewness and investor sentiment. These models extend the Black-Scholes-Merton model by proposing richer factor dynamics while maintaining the assumptions of perfect market and homogeneous beliefs. Previous studies have examined whether these models can fit the average shape of index option smile, or equivalently, whether they can match the average amount of negative index risk-neutral skewness. But it has not been researched whether these rational models can explain time variation in index risk-neutral skewness.

One way to generate negative skewness in return under rational models is to allow the instantaneous volatility of return to be stochastic and negatively correlated with the innovation in return. For example, the Heston (1993) model assumes the following risk-neutral dynamics for asset price S_t and the instantaneous variance V_t of asset return:

$$\begin{aligned}dS_t &= r_t S_t dt + \sqrt{V_t} S_t dW_t \\dV_t &= \kappa(\theta - V_t)dt + \eta\sqrt{V_t}dB_t,\end{aligned}$$

where dW_t and dB_t are two correlated Brownian motions with correlation ρ . When $\rho < 0$, variances tend to be high when returns are low. The left tail of the return distribution is more spread out than the right tail, and this creates a negative skewness.

The possibility of a negative jump in the return process also generates negative skewness for the return density. Pure jump models such as Merton (1976) augment the lognormal return process under the Black-Scholes model with a Poisson jump process. Recent models include asymmetric jumps. For example, in Dupoyet (2004), the instantaneous asset return is determined by the following risk-neutral process:

$$\frac{dS_t}{S_t} = \left(r - \frac{\lambda_u}{\gamma_u - 1} + \frac{\lambda_d}{\gamma_d + 1} \right) dt + \sigma dW_t + J_u(t)dq_u(t) + J_d(t)dq_d(t),$$

where λ_u and λ_d are respectively the frequency of upward and downward jumps per year for the Poisson jump counters $q_u(t)$ and $q_d(t)$; $J_u(t)$ and $J_d(t)$ are the percentage up-jump and down-jump size conditionally on a jump occurring:

$$\begin{aligned} J_u(t) &= x_u(t) - 1, \quad x_u(t) \sim \text{Pareto}(r_u) \\ J_d(t) &= x_d(t) - 1, \quad x_d(t) \sim \text{Beta}(r_d, 1). \end{aligned}$$

Stochastic volatility and jump can also be combined. For example, Bakshi, Cao and Chen (1997) consider a jump-diffusion model with the following risk-neutral dynamics:

$$\begin{aligned} dS_t &= (r_t - \lambda\mu_J)S_t dt + \sqrt{V_t}S_t dW_t + J_t dq_t \\ dV_t &= (\theta_v - \kappa_v V_t)dt + \sigma_v \sqrt{V_t} dB_t \\ \ln(1 + J_t) &\sim \mathcal{N}(\ln(1 + \mu_J) - 0.5\sigma_J^2, \sigma_J^2), \end{aligned}$$

where q_t is a Poisson jump counter with constant intensity λ , and J_t is the percentage jump size with time-invariant lognormal distribution. $q(t)$ and $J(t)$ are uncorrelated with each other or with Brownian motions W_t and B_t , while $\text{Cov}[dW, dB] = \rho dt$. This model has been further extended. For example, Pan (2002) allows time-varying jump intensity that is linear in the instantaneous return variance V_t .

Under the rational models, European option prices and thus the risk-neutral skewness of the underlying asset return are completely determined by the specified risk factors. No other variables (e.g., sentiment) can have incremental power explaining the risk-neutral skewness. For example, under the Heston (1993) model, the date t risk-neutral skewness of the underlying asset return over the horizon $[t, t + \tau]$ is [see Das and Sundaram (1999)]:

$$\text{Skew}(t, \tau) = \left(\frac{3\eta\rho e^{0.5\kappa\tau}}{\sqrt{\kappa}} \right) \left[\frac{\theta(2 - 2e^{\kappa\tau} + \kappa\tau + \kappa\tau e^{\kappa\tau}) - V_t(1 + \kappa\tau - e^{\kappa\tau})}{(\theta[1 - e^{\kappa\tau} + \kappa\tau e^{\kappa\tau}] + V_t[e^{\kappa\tau} - 1])^{3/2}} \right]. \quad (7)$$

Given the model parameters, date- t risk-neutral skewness is uniquely determined by V_t . This

observation also applies to Bakshi, Cao and Chen (1997), Pan (2002) and others. I have shown that the significant relation between sentiment proxies and risk-neutral skewness persists after controlling for V_t .¹⁹

There is another possibility that rational models may explain the significant relation between index risk-neutral skewness and sentiment proxies which does not rely on the correlation of sentiment proxies and the risk factors in rational models (such as stochastic volatility). Rather, the sentiment proxies may be correlated with some model parameters that importantly affect the skewness of return density, such as the correlation between index return and its instantaneous volatility in stochastic volatility models, or the jump intensity parameters in jump-diffusion models. Allowing model parameters to be time-varying introduces extra state variables (although outside the model) and extra explanatory power for time-variation of risk-neutral skewness. Thus, if the hypothesized correlation exists, it may “explain away” the relation between index risk-neutral skewness and sentiment proxies.²⁰

To examine this possibility, I add, as additional control variables in Table 5, the conditional risk-neutral skewness of index return implied by Heston (1993) stochastic volatility model, Bakshi, Cao, and Chen (1997) jump-diffusion model and Dupoyet (2004) asymmetric jump model. The dependent variable for all monthly regressions reported in Table 5 is the Bakshi, Kapadia and Madan (2003) model-free estimate of the risk-neutral skewness of index return over the next month inferred from index options around the middle of each month when there are traded options with one-month to maturity. On each of these dates, I recalibrate each model to minimize the sum of squared fitted pricing errors (following Bakshi, Cao, and Chen (1997) and many others) for the same index options used to compute index risk-neutral

¹⁹By Equation (7), risk-neutral skewness is monotonically decreasing in V_t under the stochastic volatility model of Heston (1993). However, Li and Pearson (2005) suggest a quadratic relation between the slope of the S&P 500 index option implied volatility and the at-the-money volatility. In unreported tables, I only find a weak and insignificant quadratic relation between index risk-neutral skewness and V_t . Further, the relation between sentiment proxies and index risk-neutral skewness is about the same with or without the quadratic term in V_t .

²⁰Even then, one can argue that time varying model parameters are proxying for missing state variables, such as investor sentiment. From the modelling perspective, it is better to rigorously incorporate the missing state variables rather than using simplistic models with time varying parameters.

skewness. Model parameter estimates are then used to compute the skewness of one-month index return based on the assumed risk-neutral return dynamics for the S&P 500 index under each model.²¹

Table 5 Model (2), (4), and (6) show that the risk-neutral skewness implied by each of the three (recalibrated) models is significantly and positively related to the model-free skewness estimate. Compared to Table 5 Model (1), the addition of the model-implied skewness raises the regression R^2 , but only slightly reduces the magnitude of the regression coefficients for the sentiment proxies. Model (3), (5), and (7) show that there is still a significant relation between index risk-neutral skewness and the sentiment proxies after controlling for the rational models. This suggests that the influence of investor sentiment on index risk-neutral skewness and asset pricing kernel is largely independent of the risk factors under the rational models considered.

4.5 Relation to Limits to Arbitrage

The presence of limits to arbitrage is a necessary condition for investor sentiment to matter for asset pricing. The impact of investor sentiment on option prices and asset pricing kernel can be expected to be higher when limits to arbitrage in the index options market are more severe. Therefore, if the relation between index risk-neutral skewness and sentiment proxies manifests the impact of sentiment on pricing kernel, then the relation should be stronger when there are larger impediments to arbitrage in the index options market.

Table 6 tests this hypothesis in two ways. One, the sample is split into two subperiods: the first half from January 1988 to September 1992, and the second half from October 1992 to June 1997. It is reasonable to expect limits to arbitrage to be reduced in the second half of the sample as the index options market matures. Thus, a weaker relation between index risk-neutral skewness and sentiment proxies is expected during the second half of the sample.

²¹The risk-neutral skewness under the Heston (1993) model is computed using equation (7). To compute the risk-neutral skewness of index return over the next month under other models on each date, I use Monte-Carlo simulations to generate 10,000 paths of index level one-month into the future.

Two, arbitrage in the index options is more limited when there is higher uncertainty about market volatility. Arbitrageurs in the index options market need to form accurate forecast of market volatility, which becomes more difficult during periods of higher uncertainty about market volatility. Mistakes in forecasting volatility cause both option value and hedge ratio to be wrong. In addition, when there is a lot of uncertainty about market volatility, arbitrageurs face higher delta-hedging errors and greater volatility risk exposure. The impact on hedging accuracy is most significant for the out-of-the-money options [e.g., Figlewski (1989)]. Thus, there are more severe limits to arbitrage in the index options (especially for the out-of-the-money options) when uncertainty about market volatility is higher. Thus, a stronger relation between index risk-neutral skewness and sentiment proxies is expected during periods of high uncertainty about market volatility.

The regressions reported in Table 6 employ weekly time series observations (as opposed to monthly data used in the rest of the paper) in order to increase the statistical power of subsample tests and also to show the robustness of the results to the sample frequency. The index risk-neutral skewness is computed on the last trading day of each week from contemporaneous index option prices.²² All independent variables are measured on or prior (but as close as possible) to the last trading day of each week. Since the index mispricing variable is available only at monthly frequency, it is omitted from the weekly regressions in Table 6.

Table 6 Model (1) shows that the significant relation between index risk-neutral skewness and sentiment proxies also holds in weekly regressions. Model (2) and (3) show that this relation mostly comes from the first half of the sample when there are more limits to arbitrage in the index options market. In contrast, the parameter estimate and t -statistic for the coefficient of index return volatility are stronger in the second half of the sample. Recall from Section 4.4 that index return volatility is the key determinant for index risk-neutral skewness

²²In unreported regressions, I verify that using weekly data sampled on Wednesdays instead of Fridays does not change any of the results in Table 6. Further, using weekly data, I still find that the relation between index risk-neutral skewness and sentiment proxies is robust to measurement errors in the skewness, similar to the results reported in Table 4.

under several popular rational option pricing models. Thus, results above are consistent with sentiment (resp. rational factors) mattering more for option prices when arbitrage in index options is relatively less (resp. more) effective.

Table 6 Model (4) provides further evidence that the relation between index risk-neutral skewness and sentiment proxies depends importantly on limits to arbitrage considerations. Model (4) includes as additional regressors the interaction of sentiment proxies (and other control variables) with a dummy variable that takes value 1 on dates when a proxy for limits to arbitrage in the index options market is higher than the sample median. This proxy is the volatility of instantaneous variance of index return, obtained by recalibrating the Heston (1993) stochastic volatility model. (Similar results are obtained when uncertainty about short term market volatility is computed from daily high's and low's of *VIX* index using the extreme value method of Parkinson (1992).)

I find that when the amount of uncertainty about market volatility is higher than normal, the relation between index risk-neutral skewness and sentiment proxies is stronger. On the other hand, the relation is no longer statistically significant in low volatility uncertainty environment. During such periods, the rational factor (index volatility) becomes a more important determinant of index risk-neutral skewness. These results are difficult to understand under fully rational option pricing models. At the same time, they are consistent with the idea that limits to arbitrage allow sentiment to affect option prices and asset pricing kernel.

4.6 Sentiment and Index Options Smile

I now examine whether investor sentiment matters for index options valuation by testing whether change in sentiment is related to fluctuation in the steepness of index option volatility smile. The slope of index option smile is known to change dramatically from month to month [e.g., Bollen and Whaley (2004)]. Recent studies have found several factors that are related to the steepness of index option volatility smile, such as stock market momentum [e.g.,

Amin, Coval and Seyhun (2004)], demand pressure for index options [e.g., Garleanu, Pedersen and Poteshman (2005)], and dispersion of beliefs among investors [e.g., Buraschi and Jiltsov (2005)].

Table 7 reports the results for regressing the slope of index option smile on sentiment proxies and control variables. Following Bollen and Whaley (2004), I measure the smile slope as the ratio of average implied volatility for the out-of-the-money puts (those with $-\frac{3}{8} < \Delta_P \leq -\frac{1}{8}$) to the average implied volatility for the near and at-the-money options (including call options with $\frac{1}{2} < \Delta_C \leq \frac{5}{8}$ as well as put options with $-\frac{1}{2} < \Delta_P \leq -\frac{3}{8}$). This measure takes positive values larger than 1. I multiply it by -1 so that the slope of index options smile takes negative values just like index risk-neutral skewness.

Table 7 shows that in both monthly and weekly regressions, the sentiment proxies are significantly and positively related to the slope of index option smile: More bullish investor sentiment is associated with a flatter index option smile, and more bearish sentiment is related to a steeper smile. This relation is robust to controlling for index return volatility, the demand-pressure effect, the stock-momentum effect, and dispersion of investors' beliefs.²³ These results are consistent with the significant relation between risk-neutral skewness and sentiment. They further confirm that investor sentiment matters for asset pricing.

²³In unreported regressions, I use another measure for the smile slope and find similar results as those reported in Table 7. Following Bakshi, Kapadia and Madan (2000), I first fit the following regression to each date's cross-section of index option implied volatilities

$$\ln(\sigma_{\tau,K}) = \alpha + \beta_1 \ln(K/S) + \beta_2 \tau + \beta_3 \tau \ln(K/S) + \epsilon_{\tau,K},$$

where τ and K are the time-to-maturity (in years) and strike price of the option and S is the spot level of the underlying index. Using the parameters estimated from date t 's cross-section of index options, the second measure of smile slope at date t is $\hat{\beta}_1 + \hat{\beta}_3/12$, which is just the elasticity of option implied volatility to the moneyness for options with time to maturity of one month. Using alternative specifications for the structure of option implied volatilities (such as the quadratic function in moneyness used by Dumas, Fleming and Whaley (1998)) does not materially change the results.

5 Summary and Conclusions

Limits to arbitrage in the options market make it possible for sentiment or aggregate errors in investors' beliefs to affect option prices and asset pricing kernel. I test this possibility by examining whether changes in investor sentiment are related to time variation in the risk-neutral skewness of index return and the shape of the index option smile.

I find that index risk-neutral skewness becomes more negative, and the index option volatility smile tends to be steeper, when survey indicates that more market advisors are bearish, when large speculators take bigger short positions in the S&P 500 index futures, and when the S&P 500 index level is more depressed relative to the fundamentals. The relation between index risk-neutral skewness and sentiment proxies is robust. It can not be explained by several popular rational option pricing models based on homogeneous-agent and perfect market assumptions. On the other hand, the impact of investor sentiment becomes stronger when there are larger impediments to arbitrage in the index options.

These results support the idea that limits to arbitrage permit investor sentiment to affect option prices and asset pricing kernel. Traditional perfect-market homogeneous-agent based rational models need to be extended to incorporate this paper's findings. Such research has been called for by Bates (2003) and Whaley (2003). A promising approach is to follow recent models by Evan, Ghysels and Juergens (2005), Garleanu, Pedersen and Poteshman (2005), and Shefrin (2005) that explicitly incorporate investor heterogeneity, irrationality and market imperfection.

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Table 1: Summary Statistics of Variables

This table reports the summary statistics for the variables used in the regressions reported in subsequent tables. There are 114 monthly observations on each variable, measured as closely as possible to the month end. The sample period is from January 1988 to June 1997. “*Skew*” is the risk-neutral skewness of the S&P 500 index return over the next month inferred from index option prices according to Bakshi, Kapadia and Madan (2003). *BullBear_{Survey}* is the proportion of bullish investors minus the proportion of bearish investors based on the survey done by the Investor’s Intelligence. *LongShort_{Futures}* is the net position of large speculators in the S&P 500 index futures based on Commodity Futures Trading Commission’s Commitments of Traders report. It is measured as the number of long “non-commercial” contracts minus the number of short “non-commercial” contracts, scaled by the total open interest in the S&P 500 index futures. “*Mispricing_{Index}*” is the percent deviation of the S&P 500 index level from that predicted by the log-linear dynamic growth model of Campbell and Shiller (1988) as implemented by Sharpe (2002). “*IndexVolatility*” is CBOE’s Volatility Index. “*RelativeDemand*” is the ratio of total open interest for out-of-the-money index put options (defined by $-\frac{3}{8} < \Delta_P \leq -\frac{1}{8}$) to that for near and at-the-money index options (defined as call options with $\frac{1}{2} < \Delta_C \leq \frac{5}{8}$ and put options with $-\frac{1}{2} < \Delta_P \leq -\frac{3}{8}$). “*SmileSlope*” is the ratio of the average Black implied volatility of out-of-the-money index options to the average Black implied volatility of near- and at-the-money index options. “*IndexRet*” is the S&P 500 index return over the last six months. “*Dispersion*” is the total trading volume for the S&P 500 index options (adjusted for a deterministic time trend, and then divided by 100,000). “*ModelSkew_{SV}*”, “*ModelSkew_{SVJ}*”, and “*ModelSkew_{AJ}*” are the model-implied risk-neutral skewness for one-month index return according to respectively a stochastic volatility model, a stochastic volatility model with random jump and an asymmetric jump model.

Variable	Mean	Standard Deviation	Percentile			Serial Correlation
			25%	50%	75%	
<i>Skew</i>	-1.6475	0.6181	-2.0982	-1.6033	-1.1208	0.4115
<i>BullBear_{Survey}</i>	0.0370	0.1419	-0.0460	0.0405	0.1470	0.5815
<i>LongShort_{Futures}</i>	-0.0638	0.0415	-0.0891	-0.0545	-0.0322	0.7645
<i>Mispricing_{Index}</i>	-0.0157	0.0438	-0.0423	-0.0142	0.0128	0.7384
<i>IndexVolatility</i>	0.1782	0.0535	0.1344	0.1713	0.2057	0.8168
<i>RelativeDemand</i>	2.3850	1.2447	1.5167	2.2251	2.9574	0.1760
<i>IndexRet</i>	0.0554	0.0853	0.0152	0.0590	0.1115	0.7694
<i>Dispersion</i>	-0.1054	0.3324	-0.3004	-0.1363	-0.0035	0.3213
<i>ModelSkew_{SV}</i>	-1.2474	0.5075	-1.6406	-1.2360	-0.9442	0.4170
<i>ModelSkew_{SVJ}</i>	-1.1597	0.5533	-1.4575	-1.1612	-0.8676	0.3477
<i>ModelSkew_{AJ}</i>	-2.2773	1.3947	-3.7166	-2.6122	-1.6162	0.2853
<i>SmileSlope</i>	-1.2194	0.0735	-1.2727	-1.2189	-1.1661	0.2891

Table 2: Investor Sentiment and Index Risk-Neutral Skewness

This table reports the results for regression models that study the relation between the risk-neutral skewness of the S&P 500 index return and measures of investor sentiment. The dependent variable for all regressions is the risk-neutral skewness of index return over the next month implied from index option prices according to Bakshi, Kapadia and Madan (2003). $BullBear_{Survey}$ is the proportion of bullish investors minus the proportion of bearish investors from Investor’s Intelligence. $LongShort_{Futures}$ is the net position of large speculators in the S&P 500 index futures, measured as the number of long contracts they hold minus the number of short contracts they hold and scaled by the total open interest in the S&P 500 index futures. “ $Mispricing_{Index}$ ” is the percent deviation of the S&P 500 index level from that predicted by the log-linear dynamic growth model of Campbell and Shiller (1988) as implemented by Sharpe (2002). The data consist of 114 month-end observations on each variable from January, 1988 to June, 1997. Standard errors are adjusted for heteroscedasticity and serial correlation according to Newey and West (1987) and the t -statistics are reported in parentheses below the coefficients.

Variable	(1)	(2)	(3)	(4)
$BullBear_{Survey}$	0.9793 (3.0107)			0.8727 (2.6747)
$LongShort_{Futures}$		2.4612 (1.9190)		2.0202 (1.6207)
$Mispricing_{Index}$			5.2963 (3.4562)	3.5744 (2.3045)
<i>Lagged Dependent</i>	0.3799 (4.6703)	0.3889 (4.3918)	0.2428 (2.5169)	0.2386 (2.4718)
Adjusted R^2	0.2098	0.1863	0.2175	0.2605

Table 3: Investor Sentiment and Index Risk-Neutral Skewness: Robust to Control Variables

This table reports results of monthly regressions that examine the robustness of the relation between index risk-neutral skewness and sentiment proxies to control variables including index return volatility, past six-month index return, and relative demand of out-of-the-money index put options to near- and at-the-money index options. Model (5) includes the following variables as additional regressors: the logarithmic growth in aggregate industrial production over the last 12 months, the 1-month treasury bill rate, the spread between yields on the 10-year Treasury bond and the 3-month treasury bill, and difference in yields on Baa and Aaa corporate bonds. The regression coefficients for these additional control variables are omitted for brevity. $BullBear_{Survey}$ is the proportion of bullish investors minus the proportion of bearish investors from Investor's Intelligence. $LongShort_{Futures}$ is the net position of large speculators in the S&P 500 index futures. $Mispricing_{Index}$ is index pricing errors obtained by Sharpe (2002). The dependent variable for all regressions is the risk-neutral skewness of index return over the next month as implied from index option prices. The data consist of 114 month-end observations on each variable from January, 1988 to June, 1997. Standard errors are adjusted for heteroscedasticity and serial correlation according to Newey and West (1987) and the t -statistics are reported in parentheses below the coefficients.

Model	(1)	(2)	(3)	(4)	(5)
<i>BullBear_{Survey}</i>		1.1924 (4.0042)	1.3822 (4.6135)	1.0343 (3.1331)	1.1505 (3.0518)
<i>LongShort_{Futures}</i>		2.5734 (1.9208)	3.2373 (2.5141)	2.9837 (2.3816)	1.9274 (1.3857)
<i>Mispricing_{Index}</i>		4.1568 (2.9950)	3.7379 (2.7289)	3.1183 (2.4541)	3.1613 (2.4749)
<i>IndexVolatility</i>	4.3747 (4.6975)	4.9232 (6.0679)	4.0693 (4.8529)	4.5342 (5.4389)	4.5353 (3.4466)
<i>RelativeDemand</i>	-0.3342 (-3.0143)		-0.2953 (-2.7720)	-0.3525 (-3.1850)	-0.3184 (-2.4873)
<i>IndexRet</i>	3.0327 (4.2366)			1.4971 (2.4124)	1.7415 (2.2455)
<i>Lagged Dependent</i>	0.2141 (2.2957)	0.0612 (0.6313)	0.0555 (0.5821)	0.0461 (0.4869)	0.0231 (0.2217)
Adjusted R^2	0.3639	0.3976	0.4365	0.4534	0.4442

Table 4: Investor Sentiment and Index Risk-Neutral Skewness: Robust to Measurement of the Skewness

All the regressions reported in this table have identical specification (also the same as Table 3 Model (4)). They only differ in the measurement of the dependent variable, index risk-neutral skewness. All skewness measures are obtained using the Bakshi, Kapadia and Madan (2003) approach, but with different data input. In Table 3 Model (4), the index risk-neutral skewness is inferred from the last sale prices of index options on the last trading day of each month. Model (1) of this table uses 10,000 simulated data sets to examine how much measurement errors in option prices affect the regression result. In each simulation, a +3% or -3% observation error is randomly added to the last sale price of each index option on each date. In Model (1), the risk-neutral skewness on a given date is the average (over all simulations) of the risk-neutral skewness extracted from each set of simulated index option prices. In Model (2), the average of daily high price and low price of each index option on the last trading day of each month is used to compute index risk-neutral skewness on that date. Model (3) uses the monthly average risk-neutral skewness as the dependent variable. Model (4) uses data sampled around the middle of each month when there are options with exactly one-month time-to-maturity. There are 114 monthly observations on each variable from January, 1988 to June, 1997. Standard errors are adjusted for heteroscedasticity and serial correlation according to Newey and West (1987) and the t -statistics are reported in parentheses below the coefficients.

Model	(1)	(2)	(3)	(4)
<i>BullBear_{Survey}</i>	0.7752 (1.7896)	0.9918 (2.0986)	0.6044 (2.1566)	1.5163 (2.9888)
<i>LongShort_{Futures}</i>	3.4973 (2.4077)	3.2720 (2.1579)	2.4972 (2.7139)	2.6949 (1.9906)
<i>Mispricing_{Index}</i>	2.7071 (2.0736)	2.7374 (1.9940)	3.2366 (3.5146)	3.1765 (2.4454)
<i>IndexVolatility</i>	4.5214 (5.3881)	3.5864 (4.2715)	3.6009 (5.1378)	5.3565 (6.7348)
<i>RelativeDemand</i>	-0.3377 (-3.0498)	-0.2852 (-2.6150)	-0.2383 (-2.6213)	-0.2001 (-1.9351)
<i>IndexRet</i>	1.5766 (2.4596)	0.2838 (0.4767)	1.2548 (2.3096)	1.6564 (2.6842)
<i>Lagged Dependent</i>	0.0696 (0.7421)	0.1259 (1.3479)	0.2243 (2.4425)	0.0802 (0.9303)
Adjusted R^2	0.3999	0.3287	0.4175	0.4266

Table 5: Investor Sentiment and Index Risk-Neutral Skewness: Controlling for Rational Option Pricing Models

Regressions presented in this table examine whether the relation between investor sentiment and index risk-neutral skewness can be explained by three rational models based on representative-agent and perfect-market assumptions: the stochastic-volatility model of Heston (1992), the stochastic-volatility random-jump model of Bakshi, Cao, and Chen (1997), and the asymmetric jump model of Dupoyet (2004). All regressions use monthly data sampled around the middle of each month when there are traded options with one-month time-to-maturity. On each date, these models are recalibrated to best fit the prices of index options with one-month time-to-maturity. Model parameter estimates are then used to compute the skewness of one-month index return (“*ModelSkew*”) based on the assumed risk-neutral return dynamics for the S&P 500 index under each model. The dependent variable in all regressions reported in this table is the risk-neutral skewness of one-month index return extracted from prices of one-month maturity index options according to Bakshi, Kapadia and Madan (2003). Model (1) is identical to Table 4 Model (4) and is presented for ease of comparison. The data consist of 114 monthly observations on each variable from January, 1988 to June, 1997. Standard errors are adjusted for heteroscedasticity and serial correlation according to Newey and West (1987) and the *t*-statistics are reported in parentheses below the coefficients.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Stochastic Volatility		Stochastic Volatility with Jump		Asymmetric Jump	
<i>BullBearSurvey</i>	1.5163 (2.9888)		1.4756 (3.6270)		1.5006 (3.0999)		1.5380 (2.9755)
<i>LongShortFutures</i>	2.6949 (1.9906)		1.3810 (1.5149)		2.2650 (1.9130)		2.6696 (1.9678)
<i>MispricingIndex</i>	3.1765 (2.4454)		3.0290 (2.9138)		3.1199 (2.7336)		3.1462 (2.4395)
<i>IndexVolatility</i>	5.3565 (6.7348)		5.9346 (8.2866)		4.5398 (4.6558)		4.9403 (5.7405)
<i>RelativeDemand</i>	-0.2001 (-1.9351)		-0.1670 (-1.9502)		-0.2282 (-2.3109)		-0.2147 (-2.0314)
<i>IndexRet</i>	1.6564 (2.6842)		0.1237 (0.1703)		1.0604 (1.4897)		1.5836 (2.4433)
<i>ModelSkew</i>		0.6299 (4.7532)	0.6072 (4.4941)	0.4558 (3.5191)	0.3076 (2.0667)	0.1396 (3.3645)	0.0379 (1.3281)
<i>Lagged Dependent</i>	0.0802 (0.9303)	0.3644 (4.5091)	0.0635 (0.7817)	0.3368 (3.9793)	0.0670 (0.7745)	0.3245 (3.4090)	0.0825 (0.9250)
Adjusted R^2	0.4266	0.3407	0.5541	0.2650	0.4641	0.2209	0.4364

Table 6: Investor Sentiment and Index Risk-Neutral Skewness: Interaction with Limits to Arbitrage

All regressions reported in this table employ weekly time-series data. Model (1) uses the full sample from January 4, 1988 to June 27, 1997, while Model (2) and Model (3) use respectively the first half and the second half of the sample. The dependent variable in all models is the risk-neutral skewness of the S&P 500 index return over the next month computed from contemporaneous index option prices on the last trading day of each week. The independent variables include two proxies for investor sentiment (bull-bear spread based on investor surveys and net position of large speculators in index futures), index return volatility, relative demand for out-of-the-money to at-the-money index options, past six-month return on the S&P 500 index, and a proxy for dispersion of beliefs among investors. All independent variables are measured on or prior (but as close as possible) to the last trading day of each week. Model (4) adds the interaction of all independent variables (except lagged dependent variable) with a dummy that takes value 1 on dates when a proxy for limits to arbitrage in the index options market is higher than the sample median. This proxy captures the amount of uncertainty about market volatility and is taken to be the parameter denoting volatility of instantaneous variance of index return under the Heston (1993) stochastic volatility model, recalibrated each date. Standard errors are adjusted for heteroscedasticity and serial correlation according to Newey and West (1987) and the t -statistics are reported in parentheses below the coefficients.

Model	(1)	(2)	(3)	(4)		
	Full Sample	First Half	Second Half	Uncertainty about Low	Volatility High	Difference
<i>BullBearSurvey</i>	0.5965 (2.9488)	0.6646 (2.8628)	0.4382 (1.3022)	0.1735 (0.6139)	0.8834 (3.8433)	0.7099 (2.0912)
<i>LongShortFutures</i>	1.5741 (2.1698)	2.0255 (2.6942)	1.2981 (1.1724)	0.7847 (0.9116)	1.3563 (1.4137)	0.5716 (0.4749)
<i>IndexVolatility</i>	3.1871 (7.3602)	2.9831 (4.2294)	5.2581 (5.1288)	4.9010 (5.6678)	3.6813 (6.2946)	-1.2197 (-1.8303)
<i>RelativeDemand</i>	-0.2045 (-3.4404)	-0.1298 (-1.9386)	-0.2466 (-3.8997)	-0.1495 (-3.0781)	-0.2517 (-3.7482)	-0.1022 (-1.3689)
<i>IndexRet</i>	1.1570 (3.5240)	1.2347 (3.1263)	0.6514 (1.0443)	0.9193 (1.5379)	1.2079 (2.7189)	0.2885 (0.3656)
<i>Dispersion</i>	-0.1855 (-2.1668)	-0.3608 (-1.7210)	-0.1745 (-1.8377)	-0.1218 (-1.1089)	-0.2639 (-2.7834)	-0.1420 (-0.9489)
<i>Lagged Dependent</i>	0.4114 (9.2849)	0.3630 (6.5308)	0.3831 (6.4966)	0.3969 (9.5340)		
Adjusted R^2	0.4883	0.3230	0.5230	0.5198		

Table 7: Investor Sentiment and Slope of Index Volatility Smile

This table reports the results for regression models that study the relation between the slope of index options volatility smile and investor sentiment. The dependent variable in all regressions is the slope of the index option volatility smile, measured as (-1) times the ratio of average implied volatility for out-of-the-money puts (those with $-\frac{3}{8} < \Delta_P \leq -\frac{1}{8}$) to the average implied volatility for near and at-the-money options (including call options with $\frac{1}{2} < \Delta_C \leq \frac{5}{8}$ as well as put options with $-\frac{1}{2} < \Delta_P \leq -\frac{3}{8}$). $BullBear_{Survey}$ is the proportion of bullish investors minus the proportion of bearish investors based on the surveys done by Investor's Intelligence. $LongShort_{Futures}$ is the net position of large speculators in the S&P 500 index futures. $Mispricing_{Index}$ is index pricing errors obtained by Sharpe (2002). Other independent variables are index volatility, past six-month index return, and relative demand of out-of-the-money index put options to near- and at-the-money index options, and a proxy of investors' disagreement. Model (1) through (4) use 114 monthly observations on each variable from January, 1988 to June, 1997. Model (5) and (6) use 497 weekly observations on each variable during the same period. $Mispricing_{Index}$ is omitted from the weekly regressions since it is available only monthly. Standard errors are adjusted for heteroscedasticity and serial correlation according to Newey and West (1987) and the t -statistics are reported in parentheses below the coefficients.

Model	Monthly Regressions				Weekly Regressions	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>BullBear_{Survey}</i>	0.1195 (2.5183)			0.0601 (1.1349)	0.0994 (3.3784)	0.0739 (2.5241)
<i>LongShort_{Futures}</i>		0.4419 (2.5824)		0.4603 (2.7135)	0.3123 (3.0789)	0.2978 (2.9966)
<i>Mispricing_{Index}</i>			0.3901 (3.0507)	0.3203 (2.0997)		
<i>IndexVolatility</i>				0.2897 (1.9061)		0.2245 (3.0601)
<i>RelativeDemand</i>				-0.0237 (-1.8187)		-0.0106 (-2.0087)
<i>IndexRet</i>				0.0914 (0.8037)		0.1563 (3.7995)
<i>Dispersion</i>				-0.0378 (-1.2665)		-0.0298 (-2.6569)
<i>Lagged Dependent</i>	0.2223 (2.1707)	0.2218 (1.9512)	0.2202 (2.3522)	0.1465 (1.7948)	0.2785 (4.4909)	0.2360 (3.7459)
Adjusted R^2	0.1159	0.1245	0.1152	0.2451	0.1957	0.2400

Figure 1: **Time Series of Index Risk-Neutral Skewness and Investor Sentiment**

This figure plots the monthly time series of the index risk-neutral skewness and three measures of investor sentiment between January, 1988 and June, 1997. The top left panel plots the risk-neutral skewness of the S&P 500 index return over the next month inferred from index option prices according to Bakshi, Kapadia and Madan (2003). The top right panel plots the proportion of bullish investors minus the proportion of bearish investors based on the survey done by the Investor’s Intelligence. The bottom left panel plots the number of long non-commercial contracts minus the number of short non-commercial contracts in the S&P 500 index futures (scaled by the total open interest) based on the Commodity Futures Trading Commission’s Commitments of Traders report. The bottom right panel plots the fraction deviation of the S&P 500 index level from that predicted by the log-linear dynamic growth model of Campbell and Shiller (1988) as implemented by Sharpe (2002).

