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A New Predictor of Real Economic Activity: The S&P 500 Option Implied Risk Aversion*

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Abstract

We propose a new predictor of real economic activity (REA), namely the representative investor's implied relative risk aversion (IRRA) extracted from S&P 500 option prices. IRRA exploits the forward-looking information in option prices. It increases as risk averse investors enter the market, leading to a decrease in market risk premium thus predicting a REA improvement. In line with our hypothesis, IRRA predicts U.S. REA even when we control for well-known REA predictors. Results hold over both short and long horizons and regardless of the way we conduct inference. Moreover, IRRA forecasts REA out-of-sample over the 2008-2009 great economic recession peak.

Keywords: Option prices, Risk aversion, Risk-neutral moments, Real Economic Activity.

JEL Classification: E44, G13, G17

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1. Introduction

The question whether real economic activity (REA) can be predicted is of particular importance to policy makers, firms and investors. Monetary and fiscal policy as well as the firms' business plans and investors' decisions are based on forecasts of REA. There is an extensive literature which studies whether REA can be predicted by employing a number of financial variables (for a review, see Stock and Watson, 2003). This literature has become even more topical recently when the 2007 turbulence in the financial markets was followed by a significant economic recession which caught investors and academics by surprise (Gourinchas and Obstfeld, 2012). These facts highlight the link between financial markets and the real economy as well as the need to develop new accurate REA predictors based on financial markets' information.

In this paper, we explore whether the cross-section of index option market prices conveys information for future REA. To this end, we propose a new predictor of REA. We investigate whether the representative investor's relative risk aversion (RRA) extracted from the S&P 500 market option prices (implied RRA, IRRA) predicts U.S. REA. The motivation for the choice of our predictor is threefold. First, S&P 500 options are inherently REA forward-looking contracts. Their payoff depends on the future state of the economy because the underlying stock index is a broad one that eliminates idiosyncratic risk. Hence, option prices are expected to be superior REA predictors to other financial variables for which their relation with future REA may not be clear and their predictive ability has been questioned empirically.[1] In addition, evidence suggests that informed traders tend to prefer option markets rather than the underlying spot market to exploit their informational advantage (e.g., Easley et al., 1998, Pan and Poteshman, 2006, and references therein) thus making option-based measures even more appealing for forecasting REA. Second, IRRA

[1] For instance, stock variables have also been claimed to be forward-looking instruments based on the rationale that their values depend on future cash flows (i.e. dividends). However, the correlation between dividends and REA is weak (Subrahmanyam and Titman, 2013).

synopsizes the information in market index option prices trading across the spectrum of strikes by construction. Third, from an asset pricing perspective, RRA determines discount rates which are related to future REA (Fama, 1990, Cochrane, 2011). Therefore, it is appealing to summarize the options' information in a RRA measure.

We extract a time series of IRRA values using Kang et al. (2010) formula which employs the S&P 500 risk-neutral volatility, risk-neutral skewness, risk-neutral kurtosis and the physical variance as inputs. We calculate the risk-neutral moments via the Bakshi et al. (2003) method which uses the cross-section of traded S&P 500 option prices. Hence, IRRA incorporates information from all traded options by construction. Our estimated IRRA values are positive and their magnitude is plausible and within the range of values reported by previous literature. In addition, IRRA is positively correlated with the S&P 500.

Next, we investigate whether IRRA forecasts future REA. To this end, we use three alternative measures to proxy REA: industrial production, nonfarm private payroll employment and the Kansas financial stress index. We test IRRA's forecasting ability across different forecasting horizons up to one year both in a stand-alone setting as well as jointly with a large set of variables documented by the previous literature to predict REA. This set comprises the "traditional" interest rate spreads (default, term and TED spreads) and equity asset pricing factors as well as the more recently documented REA predictors such as the forward variances inferred from option prices, variance risk premium, Baltic dry index, commodity open interest and commodity-specific factors. We conduct statistical inference carefully by coping with small sample biases, overlapping observations and persistence of regressors.

We find that an increase (decrease) in IRRA predicts an increase (decrease) in REA. Most importantly, we find that IRRA predicts future REA over and above these predictors regardless of the REA measure. Therefore, IRRA contains information that has not already been incorporated by other financial predictors. Depending on the REA proxy, the addition of our proposed predictor increases the adjusted R^2 by 20% to 65% relative to a model which uses only the predictors proposed by the previous literature. The adjusted R^2 increases (decreases) with the forecasting horizon when REA is measured by the industrial production index (nonfarm private payroll employment and the Kansas financial stress index). These results are robust and they hold regardless of the way we conduct statistical inference. In addition, within an out-of-sample setting, IRRA predicts REA more accurately than other financial predictors do over the 2008-2009 peak of the recent financial crisis and the subsequent great economic recession. Finally, we explore the origin of the statistical significance of IRRA by attributing it to its inputs. We find that IRRA's forecasting ability stems from the option information based inputs used to estimate it, and more specifically from the risk-neutral moments of the S&P 500 distribution.

The fact that an increase (decrease) in IRRA predicts an increase (decrease) in REA can be explained as follows. Wilson (1968, Theorems 4 and 5) and Hara et al. (2007, Lemma 1) show that the representative agent's RRA is a weighted average of the individual agents RRAs. Notice that the representative agent's IRRA takes into consideration *only* the risk aversion of the individual agents who participate in the stock market, thus ignoring the risk aversion of the non-market participants. Therefore, in the case where investors expect an improvement (deterioration) in REA, the more risk averse investors return (exit) to (from) the market and as a result IRRA increases (decreases). At the same time, the stock market does well (badly) because of buying (selling) orders and as a result the expected returns decrease (increase). This will lead to an improvement (deterioration) of REA.

Our explanation for the relation between IRRA and REA is consistent with our finding that IRRA is positively correlated with the S&P 500. Barone-Adesi et al. (2014) and Duan and Zhang (2014) also report a positive correlation between IRRA and the stock market. [2] This may seem to be

[2] Barone-Adesi et al. (2014) offer an alternative behavioral finance explanation for the positive correlation between the option implied RRA and the S&P 500. Prospect theory suggests that risk aversion will be lower after market losses than after market gains.

a counterintuitive result at a first glance. Asset pricing theory suggests that an increase in RRA increases expected return and so it should decrease the stock index price. However, the discussed above relation between the representative agent's and the individuals investors' RRAs as well as the nature of IRRA estimates which is distinct from that of RRA estimated via standard consumption asset pricing models explains this seemingly counterintuitive result. The RRA estimated from standard consumption asset pricing models does not confine itself only to stock market investors. Hence, it does not depend only on investors' entry-exit behavior in the stock market and as a result its time series behavior differs from IRRA's. Typically, it is reported to be countercyclical (e.g., Campbell and Cochrane, 1999, Xiouros and Zapatero, 2010). We verify the IRRA dependence on individual investor's entry/exit in the stock market by documenting a positive relation between IRRA and U.S. equity mutual funds net flows. The latter reflect individual investors' risk attitudes because they are determined primarily by individual investors. In 2013, U.S. households held 90 percent of total mutual fund assets (Investment Company Institute, 2014).

As a by-product of our analysis, we also find that commonly perceived measures of risk aversion such as VIX, the variance risk premium, put/call ratio and risk-neutral skewness are not correlated with IRRA. This is not surprising though. Some of the previously proposed variables to proxy risk aversion are expected to do so only under strong modeling assumptions (Bollerslev et al., 2011) and some others are based on intuition thus rendering the use of these variables as a proxy of the unobservable RRA questionable (Coudert and Gex, 2008).

Related literature: Our paper ties three strands of literature. The first strand has to do with the use of financial variables to predict REA. The rationale is that financial markets reflect investors' perceptions about the future state of the economy and hence they can predict REA. The term spread (Estrella and Hardouvelis, 1991) and default spread (Stock and Watson, 2003) are two prominent predictors of REA. An increase (decrease) in the term spread predicts an expansion (recession) of REA whereas an increase in the default spread signifies a recession. More recently, other financial variables such as asset pricing factors (Liew and Vassalou, 2000), the TED spread (Chiu, 2010), forward variances inferred from options (Bakshi et al., 2011), the Baltic dry index (Bakshi et al., 2012), commodity futures open interest (Hong and Yogo, 2012), and commodity-specific factors (Bakshi et al., 2014) have been found to predict REA.

The second strand of literature has to do with the estimation of the representative agent's risk aversion from index options market prices. This is possible due to the theoretical relation of risk aversion to the ratio of the risk-neutral distribution and the subjective distribution of the option's underlying index; the former can be recovered from option prices (for a review, see Jackwerth, 2000). Ait-Sahalia and Lo (2000) Jackwerth (2000), Bliss and Panigirtzoglou (2004) and Kang and Kim (2006) obtain single IRRA estimates. Rosenberg and Engle (2002), Bakshi and Madan (2006), Kang et al. (2010), Kostakis et al., (2011), Barone-Adesi et al., (2014) and Duan and Zhang (2014) estimate a time series of IRRA. We choose the Kang et al., (2010) methodology to estimate IRRA because it is parsimonious in terms of the required inputs. Most importantly, these inputs can be estimated accurately from the cross-section of market option prices which are readily available.

The third strand of literature uses the informational content of market option prices to address a number of topics in economics and finance. The rationale is that market option prices convey information which can be used for policy making (Söderlind and Svensson, 1997), risk management (Chang et al., 2012, Buss and Vilkov, 2012), asset allocation (Kostakis et al., 2011, DeMiguel et al., 2013) and stock selection purposes (for reviews, see Chang et al., 2012, Giamouridis and Skiadopoulos, 2012). Surprisingly, there is a paucity of research on whether the information embedded in *index* option prices can be used to predict REA, too. To the best of our knowledge, Bakshi et al. (2011) is the only paper which explores this and it documents that forward variances extracted from index options forecast REA.[3]

The rest of the paper is structured as follows. Section 2 describes the data and Section 3 explains IRRA's estimation, required inputs and results on its time variation. Section 4 presents the testable hypothesis and evidence on the IRRA as a predictor of REA. Section 5 verifies that IRRA's predictive ability stems from option prices informational content. Section 6 concludes.

2. Data and key variables

For the purposes of our analysis, we use monthly (end-of-month) data.

2.1 Options data

We obtain S&P 500 European style index option data (quotes prices) for the period January 1996 to December 2012 from the Ivy DB database of OptionMetrics. We use the S&P 500 implied volatilities provided by Ivy DB for each traded contract. These are calculated based on the midpoint of bid and ask prices using Merton's (1973) model. In addition, we obtain the closing price of the S&P 500 and the continuously paid dividend yield from Ivy DB. We filter the options data to remove any noise. We only consider out-of-the-money and at-the-money options with time-to-maturity 5 to 270 days. We also discard options with zero open interest and zero trading volume. Furthermore, we retain only option contracts that do not violate Merton's, 1973, no-arbitrage condition and have implied volatilities less than 100%. We also eliminate options that form vertical and butterfly spreads with negative prices and option contracts with zero bid prices and premiums. As a proxy for the risk-free rate, we use the continuously compounded U.S. LIBOR rates with maturities one to

[3] Bali et al. (2012) find that a measure of the stock market riskiness constructed from individual equity options predicts future economic downturns. Neumann (2014) finds that the prices of options written on bank stocks predict future REA. In the context of bond markets, Mueller et al. (2013) find that the variance risk premium extracted from bond option prices also forecasts REA.

six months taken from Bloomberg. To obtain the rate for any other required maturity, we use linear interpolation across the closest available maturities. In addition, we obtain the history of expected dividend payments over the life of each option contract and their timing provided by IvyDB. These expected dividend payments have been calculated based on the assumption of constant dividend yields over the life of the option.

Finally, we construct two measures of the forward variances inferred from option prices, in accordance with Bakshi et al. (2011). We construct at time t the forward variance $FV_t^1(30)$ between t and $t+30$ and the forward variance $FV_t^2(30)$ between $t+30$ and $t+60$. Appendix A describes the calculation of the forward variances from the market prices of call and put option portfolios.

2.2 Other variables

We collect data on a number of variables for the period July 2002 to December 2012. We obtain the net cash flows of all U.S. equity funds calculated as the difference of inflows minus the outflows from Bloomberg. In addition, we obtain the VIX implied volatility index and the put/call ratio from Bloomberg. We also obtain data on Moody's BAA and AAA corporate bond spreads and the 3-month and 10- year U.S. government treasury yields from the Federal Reserve Bank of St. Louis (FRED) website to calculate the default and term spreads, respectively. We calculate the TED spread as the difference between the 3-month U.S. LIBOR rate and the 3-month U.S. Treasury Bill. Furthermore, we obtain the monthly Fama-French (1996) high minus low (HML) and small minus big (SMB) factors from Kenneth R. French's website.

We also obtain data on 22 individual commodity futures from Bloomberg and we construct the three Daskalaki et al. (2014) commodity-specific factors (hedging-pressure, momentum and basis factors); Appendix B provides a detailed description of the construction of these factors. Table 1 lists the employed commodities categorized in five sectors (grains and oilseeds, energy, livestock, metals and softs). In addition, we construct a commodity futures open interest variable following the approach of Hong and Yogo (2012). First, we compute the growth rate of open interest for each commodity futures. Then, we compute the median of the growth rates of open interest for all commodities futures of each sector. Last, we compute the equally weighted average of the medians growth rates of all sectors.

We proxy REA by three alternative measures. We use the non-farm payroll (Payroll) in line with Beber and Brandt (2006) and Bakshi et al. (2011). We also follow Allen et al. (2012) and Neumann (2014) and we use the industrial production (IPI) growth rate and the Kansas City Financial Stress Index (KCFSI). IPI measures the amount of the industries output. Nonfarm payroll is an indicator of the state of the labour market. KCFSI measures the financial stress in the U.S. economy. A positive value indicates that financial stress is above the long-run average, while a negative value signifies that financial stress is below the long-run average. KCFSI is associated with REA through three channels (Hakkio and Keeton, 2009). First, an increase in financial stress increases the uncertainty about the asset prices, agents reduce their spending, and thus REA decreases. Second, it increases the agents' cost of financing spending which leads again to a decrease in REA. Third, it decreases the lending opportunities, as a result REA decreases too. The IPI and non-farm-payroll time series are seasonally adjusted obtained from the FRED website. KCFSI is downloaded from the Federal Reserve Bank of Kansas City website. We collect data for all three proxies for the period July 2002 to November 2013.

Finally, we obtain daily realized variances from the Realized Library of the Oxford-Man Institute of Quantitative Finance. Realized variances are the sum of intra-day squared 5-minute returns within each day and they are available for the period January 2000- December 2012.

3. Extraction of risk aversion from option prices

3.1 Formula and estimation method

Assuming that the representative agent's preferences are described by a power utility function, Bakshi and Madan (2006) derive a formula which can be used to extract RRA from European options market prices. Let γ be the coefficient of relative risk aversion, and $\sigma^2_{q,t}(\tau), \sigma^2_{p,t}(\tau), \theta_{p,t}(\tau)$ and $\kappa_{p,t}(\tau)$ denote the risk-neutral variance, physical variance, physical skewness and physical kurtosis of the index continuously compounded returns distribution at time t with horizon τ, respectively. Then,

$$\frac{\sigma^2_{q,t}(\tau) - \sigma^2_{p,t}(\tau)}{\sigma^2_{p,t}(\tau)} \approx -\gamma \times \left(\sigma^2_{p,t}(\tau)\right)^{1/2} \times \theta_{p,t}(\tau) + \frac{\gamma^2}{2} \times \sigma^2_{p,t}(\tau) \times \left(\kappa_{p,t}(\tau) - 3\right) \tag{1}$$

RRA can be estimated from equation (1). However, the RRA estimation requires estimation of the higher order physical moments first. Their estimation is challenging. On the one hand, a long time series is required to estimate them accurately. On the other hand, a small sample size is needed to capture their time variation (Jackwerth and Rubinstein, 1996). To avoid the problem of estimating the physical higher order moments, we resort to the Kang et al. (2010) formula which is a variant of equation (1), i.e.

$$\frac{\sigma^2_{p,t}(\tau) - \sigma^2_{q,t}(\tau)}{\sigma^2_{q,t}(\tau)} \approx \gamma \times \left(\sigma^2_{q,t}(\tau)\right)^{1/2} \times \theta_{q,t}(\tau) + \frac{\gamma^2}{2} \times \sigma^2_{q,t}(\tau) \times \left(\kappa_{q,t}(\tau) - 3\right) \tag{2}$$

where $\theta_{q,t}(\tau)$ and $\kappa_{q,t}(\tau)$ is the skewness and kurtosis, respectively, of the risk-neutral index distribution at time t with horizon τ. Kang et al. (2010) derive equation (2) by also assuming that the representative agent's preferences are described by a power utility function. Then, they use the moment generating functions of the risk-neutral and physical probability distributions and they truncate their expansion series appropriately.

Equation (2) shows that to estimate RRA, estimates of the risk-neutral and the physical variance as well as of the higher order risk-neutral rather than physical moments are required as inputs.[4] This is in contrast to equation (1) which requires the estimation of the higher order physical moments and hence it circumvents the discussed above estimation challenges. This is because the estimation of the higher order risk-neutral moments is model-free as it will be explained in Section 3.3. Moreover, the risk-neutral moments can be estimated at time *t* from the market option prices at time *t* and hence they are forward-looking whereas the physical moments estimates are backward-looking since they rely on past historical data.

In line with Bakshi and Madan (2006), Kang et al. (2010) and Duan and Zhang (2014), we use the generalized method of moments (GMM, Hansen, 1982) to estimate RRA. We minimize the following objective function with respect to γ:

$$
\begin{aligned}
&J_T \equiv \min_{\gamma} g'_T H_T g_T \\
&g_T \equiv \frac{1}{T}\sum_{t=1}^{T} \varepsilon_t \otimes Z_t \\
&\varepsilon_t \equiv \frac{\sigma^2_{p,t}(\tau)-\sigma^2_{q,t}(\tau)}{\sigma^2_{q,t}(\tau)} - \gamma \times \left(\sigma_{q,t}(\tau)\right) \times \theta_{q,t}(\tau) - \frac{\gamma^2}{2} \times \sigma^2_{q,t}(\tau) \times \left(\kappa_{q,t}(\tau)-3\right)
\end{aligned}
\tag{3}
$$

where J_T is the objective function, g_T denotes the sample mean estimate of the orthogonality condition of the instruments, H_T is the inverse of the variance-covariance matrix of the function g_T

[4] Note that the risk-neutral and physical variances should not be annualized when it comes to be used as inputs in equations (1) and (2). To prove this statement, we multiply and divide equation (2) by 252,

$$\frac{\sigma^{*2}_{p} - \sigma^{*2}_{q}}{\sigma^{*2}_{q}} \approx \frac{\gamma}{\sqrt{252}} \times \left(\sigma^{*2}_{q}\right)^{1/2} \times \theta_q + \frac{1}{2}\left(\frac{\gamma}{\sqrt{252}}\right)^2 \times \sigma^{*2}_{q} \times \left(\kappa_q - 3\right) = \gamma^* \times \left(\sigma^{*2}_{q}\right)^{1/2} \times \theta_q + \frac{1}{2}\gamma^{*2} \times \sigma^{*2}_{q} \times \left(\kappa_q - 3\right)$$

where * denotes the annualized values. Hence, if we use the annualized instead of the raw variance as input, the risk aversion coefficient we obtain from the estimation is the annualized, $\gamma^* = \frac{\gamma}{\sqrt{252}}$, which differs from the raw risk aversion estimate γ. Hence, we use the raw values of the variances as inputs to estimate the risk aversion coefficient.

and Z_T are the instruments. In equation (3), there are as many moment conditions as instruments. In line with Bakshi and Madan (2006), Kang et al. (2010) and Duan and Zhang (2014), we use three different sets of instruments for robustness. The first set consists of a constant and one lag of the risk-neutral variance $\sigma^2_{q,t-1}(\tau)$. The second set consists of a constant and two lags of the risk-neutral variance [$\sigma^2_{q,t-1}(\tau)$, $\sigma^2_{q,t-2}(\tau)$]. The third set contains a constant and three lags of the risk-neutral variance [$\sigma^2_{q,t-1}(\tau)$, $\sigma^2_{q,t-2}(\tau)$, $\sigma^2_{q,t-3}(\tau)$]. We extract RRA for a constant time horizon τ=30 days. All three studies document that the moment restrictions imposed by equation (3) are not rejected by the data for the S&P 100 and S&P 500 markets for any given set of instruments.

3.2 Inputs estimation

We extract the S&P 500 risk-neutral moments from market option prices following the Bakshi et al. (2003) methodology. The advantage of this methodology is that it is model-free because it does not require any specific assumptions for the underlying's asset price stochastic process.

Let $S(t)$ be the price of the underlying asset at time t, r the risk-free rate and $R(t,\tau) \equiv \ln\left[S\left(t+\tau\right)\right] - \ln\left[S\left(t\right)\right]$ the τ-period continuously compounded return. The computed at time t model-free risk-neutral volatility (IV), skewness ($SKEW$) and kurtosis ($KURT$) of the log-returns $R(t,\tau)$ distribution with horizon τ are given by:

$$IV(t,\tau) = \sqrt{E_t^Q\left\{R(t,\tau)^2\right\} - \mu(t,\tau)^2} = \sqrt{V(t,\tau)e^{r\tau} - \mu(t,\tau)^2} \tag{4}$$

$$\begin{aligned} SKEW(t,\tau) &= \frac{E_t^Q\left\{(R(t,\tau) - E_t^Q\left[R(t,\tau)\right])^3\right\}}{\left\{E_t^Q(R(t,\tau) - E_t^Q\left[R(t,\tau)\right])^2\right\}^{\frac{3}{2}}} \\ &= \frac{e^{r\tau}W(t,\tau) - 3\mu(t,\tau)e^{r\tau}V(t,\tau) + 2\mu(t,\tau)^3}{\left[e^{r\tau}V(t,\tau) - \mu(t,\tau)^2\right]^{\frac{3}{2}}} \end{aligned} \tag{5}$$

$$KURT(t,\tau)=\frac{E_t^Q\left\{(R(t,\tau)-E_t^Q\left[R(t,\tau)\right])^4\right\}}{\left\{E_t^Q(R(t,\tau)-E_t^Q\left[R(t,\tau)\right])^2\right\}^2}$$
$$=\frac{e^{r\tau}X(t,\tau)-4\mu(t,\tau)e^{r\tau}W(t,\tau)+6e^{r\tau}\mu(t,\tau)^2V(t,\tau)-3\mu(t,\tau)^4}{\left[e^{r\tau}V(t,\tau)-\mu(t,\tau)^2\right]^2} \tag{6}$$

where $V(t, \tau)$, $W(t,\tau)$ and $X(t,\tau)$ are the fair values of three artificial contracts (volatility, cubic and quartic contract) defined as:

$$V(t,\tau)\equiv E_t^Q\left\{e^{-r\tau}R(t,\tau)^2\right\},\ W(t,\tau)\equiv E_t^Q\left\{e^{-r\tau}R(t,\tau)^3\right\},\ X(t,\tau)\equiv E_t^Q\left\{e^{-r\tau}R(t,\tau)^4\right\} \tag{7}$$

and $\mu(t, \tau)$ is the mean of the log return for period τ defined as:

$$\mu(t,\tau)\equiv E_t^Q\left\{ln\left[\frac{S(t+\tau)}{S(t)}\right]\right\}\approx e^{r\tau}-1-\frac{e^{r\tau}}{2}V(t,\tau)-\frac{e^{r\tau}}{6}W(t,\tau)-\frac{e^{r\tau}}{24}X(t,\tau) \tag{8}$$

The prices of the three contracts can be computed as a linear combination of out-of-the-money call and put options:

$$V(t,\tau)=\int_{S(t)}^{\infty}\frac{2\left(1-ln\left[\frac{K}{S(t)}\right]\right)}{K^2}C\left(t,\tau;K\right)dK+\int_0^{S(t)}\frac{2\left(1+ln\left[\frac{S(t)}{K}\right]\right)}{K^2}P\left(t,\tau;K\right)dK \tag{9}$$

$$W(t,\tau)=\int_{S(t)}^{\infty}\frac{6\,ln\left[\frac{K}{S(t)}\right]-3\left(ln\left[\frac{K}{S(t)}\right]\right)^2}{K^2}C\left(t,\tau;K\right)dK-\int_0^{S(t)}\frac{6\,ln\left[\frac{S(t)}{K}\right]+3\left(ln\left[\frac{S(t)}{K}\right]\right)^2}{K^2}P\left(t,\tau;K\right)dK \tag{10}$$

$$X(t,\tau)=\int_{S(t)}^{\infty}\frac{12\left(ln\left[\frac{K}{S(t)}\right]\right)^2-4\left(ln\left[\frac{K}{S(t)}\right]\right)^3}{K^2}C\left(t,\tau;K\right)dK$$
$$+\int_0^{S(t)}\frac{12\left(ln\left[\frac{S(t)}{K}\right]\right)^2+4\left(ln\left[\frac{S(t)}{K}\right]\right)^3}{K^2}P\left(t,\tau;K\right)dK \tag{11}$$

where $C(t,\tau;K)$ ($P(t,\tau;K)$) are the call and put prices with strike price K and time to maturity τ.

Equations (9) - (11) show that to compute the risk-neutral moments, a continuum of out-of-the- money calls and puts across strikes is required. However, options trade for discrete strikes. We also need constant-maturity risk-neutral moments to extract IRRA corresponding to a 30-days constant horizon. We estimate the risk-neutral moments of the S&P 500 returns distribution in line with Jiang and Tian (2005), Carr and Wu (2009), Chang et al. (2013), and Neumann and Skiadopoulos (2013). First, we keep only maturities for which there are at least two out-the-money puts and two out-the-money calls. Next, for any given maturity and date t, we convert strikes into moneyness $(K/S(t))$ levels. Then, we interpolate across the implied volatilities to obtain a continuum of implied volatilities as a function of moneyness levels. To compute constant maturity moments, for each moneyness level, we interpolate across implied volatilities in the time dimension using a cubic smoothing spline. We keep the implied moments with a constant maturity 30 days. Finally, implied volatilities are converted to option prices using Merton's (1973) model. Using trapezoidal approximation, we compute the prices for the three contracts which we then use to compute the risk-neutral moments. To account for any dividends expected to be paid over the life of the constant maturity option, we adjust the underlying price by the present value of the expected dividends.

Figure 1 shows the time series variation of the S&P 500 risk-neutral volatility, skewness and kurtosis and Table 2 reports their descriptive statistics. We can see that the risk-neutral skewness is negative and the kurtosis is greater than 3. Our findings are consistent with these reported by the previous literature (e.g., Neumann and Skiadopoulos, 2013).

Finally, the variance of the S&P 500 index under the physical probability measure is also required as an input in equation (2) to estimate IRRA. In line with Andersen and Bollerslev (1998), at any point in time t, we estimate the $\tau = 30$ days physical variance using 5-minutes high frequency S&P 500 returns by assuming that the physical variance follows a random walk. Therefore, the 30-

calendar-days physical variance $\sigma^2_{p,t}(\tau)$ equals the realized variance $RV_{t-\tau,t}$ computed as the sum of the daily realized variances and the sum of the overnight squared returns (OR) of the S&P 500 over the last 30 days:

$$RV_{t-\tau,t} = \sum_{i=t-\tau}^{t} \sigma_i^2 + \sum_{i=t-\tau}^{t} OR_i^2 \tag{12}$$

Daily realized variances are obtained from the Realized Library of the Oxford-Man Institute of Quantitative Finance. Overnight returns are calculated as the log difference of each day's opening price minus the closing price of the previous day: $OR = \ln S_t^{Op} - \ln S_{t-1}^{Cl}$, where S^{Op}, S^{Cl} are the opening and the closing prices of the index, respectively.

3.3 IRRA: Results

We record the risk-neutral moments and the realized variance at the last trading day of each month and we use equation (2) to estimate the monthly IRRA series with a rolling GMM estimation using a rolling window of size 30 months.[5] As a result, we extract the IRRA series for the period July 2002 - December 2012 given that our option dataset spans the period January 1996 to December 2012.

We use three different sets of instruments. Each set includes a constant and one to three lags of the risk-neutral variance, respectively. First, we estimate IRRA over the full sample to check whether its magnitude would be in line with the IRRA estimates provided by the previous literature. We find that the full sample IRRA coefficient is 9.49, 8.84 and 8. 95 for the three respective sets of instruments. These values fall within the range of IRRA values reported by the previous literature.

[5] We have also estimated IRRA with rolling windows of sizes 45 and 60 months. The results are similar to the IRRA estimated with a 30 months rolling window.

Ait-Sahalia and Lo (2000) report a full IRRA of 12.7, Rosenberg and Engle (2002) report values from 2.26 to 12.55, Bakshi et al. (2003) report values between 1.76 and 11.39, Bliss and Panigirtzoglou (2004) report a full sample estimate of 4.08, Bakshi and Madan (2006) report values from 12.71 to 17.33, Kang and Kim (2006) report values between 2 and 4, Kang et al. (2010) 1.2 to 1.4, Barone-Adesi et al. (2014) report values between -0.5 and 3, and Duan and Zhang (2014) obtain values from 1.8 to 7.1.

Regarding the monthly times series of IRRA extracted from the rolling GMM, Figure 2 shows IRRA's time variation for each one of the three sets of instruments. The values are all positive and they range between 1.71 to 12.15. Each one of IRRA's time variation is similar across all three sets of instruments. In the remainder of the paper, we report results for the case of the IRRA estimated by the second set of instruments comprising the constant and two lags of the risk-neutral variance.

Two remarks are in order regarding IRRA's time series behavior. First, IRRA is quite persistent. This is a feature that we will take into account in the statistical inference we will conduct subsequently by means of bootstrapping estimators' standard errors.[6] Second, IRRA co-moves with the S&P 500 (Figure 2). This implies that in periods when the S&P 500 rises (falls), risk aversion rises (falls) too. Barone-Adesi et al. (2014) and Duan and Zhang (2014) also extract IRRA that are positively correlated with the stock market. We will comment further on this IRRA's property in Section 4.1. In addition, IRRA is procyclical. Figure 3 shows the time variation of IRRA with the three REA proxies. We can see that IRRA is positively correlated with the procyclical proxies of REA (correlation of 0.30 and 0.70 with the growth rates of the industrial production index and the

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[6] Standard unit root tests indicate that IRRA is non-stationary. However, Cochrane (1999) shows that these tests cannot distinguish between a stationary and a non-stationary series in finite samples. In addition, IRRA is expected to be bounded from an economic theory perspective. Therefore, we do not difference IRRA to avoid discarding valuable information and instead we take its persistence into account when conducting statistical inference.

nonfarm payroll employment, respectively) and negatively correlated with the countercyclical Kansas City Financial Stress Index (KCFSI) (correlation of -0.74).

As a by-product of our analysis, IRRA can be used to test whether variables proposed by the previous literature to proxy the representative agent's RRA actually do so. We consider four such variables: VIX, the variance risk premium, put call ratio and risk-neutral skewness. VIX is commonly considered as a measure of investor's fear (Whaley, 2000). Bollerslev et al. (2011) and Bekaert and Hoerova (2013) use VRP as a proxy of risk aversion. Finally, put call ratio is considered to be a proxy for investor's sentiment and risk-neutral skewness may proxy risk aversion (Bakshi et al., 2003). To investigate whether these variables proxy risk aversion, we calculate the pairwise correlations of the implied RRA with them (we use the variables in their first differences). We measure VRP as the difference of the conditional expectations of the physical variance $E_{p,t}[\sigma_t^2(\tau)]$ and that of the risk-neutral variance $E_{q,t}[\sigma_t^2(\tau)]$.

$$\mathrm{VRP}_t(\tau) = E_{p,t}[\sigma_t^2(\tau)] - E_{q,t}[\sigma_t^2(\tau)] \tag{13}$$

We estimate the conditional expectation of the physical variance as the realized variance from time t to τ. We measure the conditional expectation of the variance under the risk-neutral measure by equating it to the squared VIX index (Jiang and Tian, 2007). We find that none of these variables is highly correlated with the option implied RRA. The correlation of IRRA with VIX, VRP, put/call ratio and risk-neutral skewness is -0.06, -0.06, -0.02 and -0.02, respectively. This shows that commonly perceived measures of risk aversion are not correlated with the option implied RRA. This is not surprising given that the above variables have been used by the previous literature as RRA proxies based either on intuition (VIX, put/call ratio, risk-neutral skewness) or on specific modeling assumptions (Bollerslev et al., 2011 assume that VRP is linear in volatility to establish the relation between VRP and RRA).

4. Predicting REA

First, we formulate our testable hypothesis by explaining why we expect that IRRA would forecast REA. Then, we test our hypothesis by examining whether IRRA predicts REA first over monthly horizons and subsequently over longer horizons. We employ an in-sample setting and then an out-of-sample one.

4.1 IRRA and REA: Testable hypothesis

We expect that an increase (decrease) in IRRA will lead to an increase (decrease) in REA. This testable hypothesis stems from (a) the relation between the representative investor's RRA and the individual investors' RRAs, and (b) the fact that IRRA takes into consideration *only* the risk aversion of the individuals that participate in the market, ignoring the risk aversion of the non-market participants. In particular, Wilson (Theorems 4 and 5, 1968) and Hara et al. (Lemma 1, 2007) show that the representative agent's RRA is a weighted average of the individual agents' RRAs. Investors decide whether to participate in the stock market, according to their degree of risk aversion and given their expectations about the future state of the economy. In the case where stock investors expect an improvement (deterioration) in REA, then IRRA will increase (decrease) because the more risk averse investors will enter (exit) the market. As a result, the stock index price will increase (decrease) because of buying (selling) orders and thus the equity premium will decrease (increase) leading to an increase (decrease) in REA.

Our testable hypothesis is consistent with our finding in Section 3.3 where we document that IRRA is positively correlated with the stock market. For instance, Duan and Zhang (2014) document a high equity risk premium for the S&P 500 over the 2007-2009 subprime crisis where IRRA decreases as the S&P 500 decreases. This would be expected to slow down REA. Indeed, this was the case as experienced with the 2008-2009 great economic recession. Moreover, we test our conjecture that market participants exit (participate in) the stock market in bad (good) times and this decreases (increases) the representative agents' IRRA. To this end, we explore the relation of net flows to U.S. equity mutual funds and the extracted IRRA. This relation should be positive under our hypothesis. The representative agent's IRRA should decrease (increase) when the more risk-averse investors exit (return to) the market, i.e. when the net flows decrease (increase). We regard mutual funds flows as an informative proxy of individual investors' risk attitudes. The Investment Company Institute (ICI, 2014) reports that 96 million individual U.S. investors or 46 percent of all U.S. households owned mutual funds and held 90 percent of total mutual fund assets directly or through retirement plans at year-end in 2013. Therefore, mutual funds flows are decided predominantly by individual investors and hence they are expected to reflect their risk aversion to a reasonable extent; this is not the case for the flows of other institutional investors.

Figure 4 shows the representative agent's IRRA and the net fund flows to U.S. equity mutual funds time variation. We can see that IRRA co-moves with the equities net funds flows in most of the sample period, i.e. in the case where IRRA is high, the net flows of the equity funds are also high. Next, we regress IRRA on the net fund flows. Table 3 reports the results of the regression. We can see that the funds flows coefficient is statistically significant and it has a positive sign, i.e. an increase in funds net flows increases IRRA. This finding is in line with our argument that risk aversion co-moves with the market because of the entry/exit of institutional investors in the market depending on market conditions. In good (bad) times, investors become less (more) risk averse, i.e. they enter (exit) the market by investing more (less) in equity funds and as a result IRRA increases (decreases).

4.2 Single predictor models

To identify whether IRRA predicts REA over monthly horizons, first we regress each one of the employed measures of REA on IRRA. For a start, we run single predictor regressions to investigate the marginal effect of IRRA on each REA proxy, i.e.

$$\text{REA}_{i,t+1} = c + b\text{RRA}_t + \varepsilon_{t+1} \tag{14}$$

where $REA_{i,t+1}$ denotes the *i*=1, 2, 3 proxies of real economic activity at *t+1* (one month ahead) and RRA_t the IRRA at *t*.

The sample spans the period August 2002- December 2012. This yields 125 observations. To address the potential presence of small sample bias on the statistical inference of the obtained results, we report both Newey-West (1994) *p*-values as well as bootstrapped *p*-values. We calculate the latter by implementing a stationary bootstrap estimation by modifying Politis and Romano (1994) method. We introduce the modification to correct for the Stambaugh (1999) bias. This arises because we perform predictive regressions on a lagged stochastic variable which is a persistent regressor and as a result any bias in the autocorrelation coefficient will map to a bias in the beta coefficient; we test and we find that the IRRA regressor follows an autoregressive process of order one (AR(1)). Appendix C provides a detailed description of the bootstrap methodology.

Column (1) in Tables 4, 5, 6 reports the results from the single predictor OLS predictive regressions using the respective three REA proxies. The forecasting horizon is one month. The coefficient estimates, Newey-West (1994) *p*-values estimated with a Bartlett kernel and a lag in the autocorrelation process for the error term (ARMA(*p*, *q*)) (Newey-West, 1994, Theorem 1), the two-sided *p*-values obtained from the stationary bootstrap (within parenthesis) and the adjusted R^2 for each REA proxy are reported.

We can see that IRRA predicts REA. This holds regardless of the way we measure REA. Moreover, we find that the adjusted R^2's are high in most cases. This varies between 10.5% and 41.0% for all proxies of REA but the IPI growth rate (adjusted R^2 of 2.5%). Moreover, we find that the IRRA estimated coefficients are positive for IPI and nonfarm payroll employment and negative for the KCFSI. In particular, an increase (decrease) in IRRA predicts an increase (decrease) in IPI and the nonfarm payroll employment. Similarly, an increase (decrease) in IRRA predicts an increase (decrease) in the KCFSI index and hence an increase (decrease) in REA. KCFSI is a measure of financial stress in the economy. In good times, markets are more secure and the index falls. The fact that an increase (decrease) in IRRA predicts an increase (decrease) in REA is in line with our hypothesis.

4.3 Multiple predictors models

In the previous section, we document that IRRA predicts REA over monthly horizons when it is used as a stand-alone predictor. Next, we investigate whether IRRA still predicts REA when we control for a set **x** of financial variables documented to predict REA. **x** comprises the Bakshi et al. (2011) forward variances $FV_t^1(30)$ and $FV_t^2(30)$, VRP (Bollerslev et al., 2009, find that VRP predicts discount rates and hence it may predict REA, too), Baltic dry index (BDI, Bakshi, et al., 2012), term spread (Estrella and Hardouvelis, 1991), default spread (Gilchrist and Zakrajšek, 2012), TED spread that proxies for funding liquidity (Chiu, 2010), SMB and HML Fama-French (1996) factors (Liew and Vassalou, 2000), commodity-specific factors (momentum, basis and hedging-pressure, Bakshi et al., 2014), and the growth rate of the commodity futures market open interest (Hong and Yogo, 2012).

First, to verify that the considered variables in **x** predict REA as the earlier studies document, we run predictive regressions of REA_i on **x** for each i, i.e.

$$REA_{i,t+1} = c + b'\mathbf{x}_t + \varepsilon_{t+1} \tag{15}$$

We shall term constrained model the one described by equation (15). Note that that the variables included in **x** are not highly correlated, and hence there are no multicollinearity concerns. Column (2) of Tables 4, 5 and 6 reports the constrained model results. We can see that the computed at time t forward variance $FV_t^1(30)$ to prevail between t and $t+30$ consistently predicts REA across all proxies of REA. The computed at time t forward variance $FV_t^2(30)$ to prevail between $t+30$ and $t+60$, , the variance risk premium and the term and the default spreads predict the industrial production index whereas the commodity basis factor predicts the nonfarm payroll employment. Last, the growth of commodity market open interest forecasts both the nonfarm payroll employment and the KCFSI index. These results are robust to both Newey- West (1994) and bootstrapped two sided p-values and they confirm that the chosen variables predict REA as it has also been documented by the previous literature.

Next, we examine the predictive power of IRRA and of the other predictors *jointly* by running the following regression

$$\text{REA}_{i,t+1} = c + b\text{RRA}_t + c'\mathbf{x}_t + \varepsilon_{t+1} \tag{16}$$

We shall term full model the one described by equation (16). Column (3) in Tables 4, 5, 6 reports results. Three remarks can be drawn. First, we can see that IRRA continues to predict REA even once we control for the other predictors. Moreover, in the case where IRRA is included as a predictor in the joint predictive regressions, the adjusted R^2 increases significantly compared to the adjusted R^2 obtained from the constrained model. In particular, the adjusted R^2 increases from 15% to 23.5%, from 18.9% to 76.9% and from 43.5% to 88%, when REA is measured by the industrial production index, nonfarm payroll and KCFSI, respectively. These findings imply that IRRA contains more information than the one contained in the other financial variables to predict REA. Second, there is strong evidence on the statistical significance of IRRA. IRRA predicts future REA even when we consider the two-sided p-values obtained from the stationary bootstrap (reported within parenthesis). This occurs for all three REA proxies. Third, the sign of the IRRA coefficient is again positive (negative) when REA is proxied by IPI and non-farm payroll (KCFSI). An increase in IRRA by one unit predicts an increase in the growth rates of IPI and nonfarm payroll employment by 0.1% and 0.03%, respectively, and it predicts a decrease in KCFSI by 2%. Its statistical significance is strong; it prevails regardless of the way we conduct statistical inference and it holds for all REA proxies.

4.4 Longer horizons predictability

In Sections 4.2 and 4.3 we provided strong evidence that IRRA forecasts REA over a one month horizon even when we control for other well-known REA predictors. In this section, we examine whether this predictability survives over longer horizons.

We construct the h-period continuously compounded growth rates of IPI and Payroll as $Y_{t+h} = \ln\left(\frac{X_{t+h}}{X_t}\right)$. KCFSI measures the change in financial stress of the economy relative to the long-run average, so there is no need to construct its growth rate. We set h=3, 6, 9, 12 months. Once again, we estimate single predictor models with IRRA acting as the only predictor as well as multiple predictors' models to explore whether IRRA predicts REA once we control for other REA predictors. Notice that in the long horizons case, we use overlapping observations of REA. Thus, in addition to the Newey-West (1994) and bootstrapped p-values employed in the one-month horizon forecasts, we also employ Hodrick's (1992) standard errors to address any bias concerns regarding the statistical inference of the obtained results (i.e. t-statistics could have been overestimated in the presence of overlapping observations). Tables 7, 8 and 9 report results using the industrial production, the non-farm payroll and the KCFSI as REA proxies, respectively. Panels A and B report results for the single and multiple predictor models, respectively. Coefficient estimates, Newey-West (1994) t-statistics estimated with a Bartlett kernel, Hodrick's (1992) t-statistics and the two-sided p-values obtained from the stationary bootstrap (within brackets) are reported.

Regarding the single predictor models (Panel A) we can see that IRRA predicts REA, thus extending the evidence from the one-month results. This holds for either REA proxy and for every forecasting horizon. Most importantly, IRRA continues to predict REA even once we control for multiple predictors (Tables 7 and 8, Panel B) just as was the case with one-month forecasting horizon. The predictability of IRRA is again robust and it holds regardless of the way we conduct statistical inference. The adjusted R^2 increases (decreases) with the forecasting horizon when REA is measured by the industrial production index (growth of the nonfarm private payroll employment and the Kansas financial stress index). Regarding the significance of the other predictors used in the joint regressions, there is no robust evidence with the exception of the TED spread that predicts REA for most long horizons and for all REA proxies but the nonfarm payroll employment in the 3 months horizon.

4.5 Predicting REA: Out-of-sample evidence

In the previous section we documented that IRRA forecasts REA in an in-sample setting. In this section, we assess the forecasting ability of IRRA in a real time out-of-sample setting over the period October 2007 - December 2012. This is a period of particular interest because it includes the onset and develpment of the recent financial crisis and the subsequent significant economic recession (also termed Great Recession). For each REA proxy, we estimate equations (15) and (16) recursively by employing an expanding rolling window; the first estimation sample window contains 63 observations spanning the period July 2002 - September 2007. At each point in time, we form h=1, 3, 6, 9, 12 months ahead -ahead REA forecasts.

Figure 5 shows the out-of-sample forecasts formed by the constrained and full models as well as the realized REA value for the case where REA is proxied by IPI. We depict results for the various forecasting horizons h. We can see that both models yield forecasts with a similar time pattern for any given h. However, the constrained model cannot track the REA proxies over late 2008 – late

2009 period that marked the peak of the financial crisis and part of the subsequent Great Recession.[7] The superiority of the full model during that crucial period holds for all forecasting horizons. We obtain similar results for the other two REA proxies, too (results are not reported due to space constraints).

5. Sources of IRRA‘s predictive power

In the previous sections, we found that the index option IRRA predicts REA for different forecasting horizons. Next, we investigate the sources of IRRA's predictive power. IRRA‘s estimation is based on the risk-neutral variance, skewness and kurtosis as well as on the physical variance (equation (2)). We examine whether the forecasting ability of IRRA is due to the information embedded in option prices (i.e. the risk-neutral moments) or it is also due to the information embedded in the physical variance. We structure our approach as follows. First, we orthogonalize IRRA with respect to the physical variance, by regressing it on the contemporaneous physical variance to obtain the pure effect of the option-based inputs of IRRA. Then, we use the *orthogonalized* IRRA as a predictor for REA by controlling for the other variables used in the previous Sections. In the case where we find that the orthogonalized IRRA predicts REA, then this will imply that option prices convey information for future REA. In addition, if we also find that the adusted R^2 of the regression that employs the orthogonalized IRRA as a predictor is similar to the adjusted R^2 of the regression that employs the “raw“ implied RRA as a predictor, this will confirm that the predictive power of the implied RRA is *solely* due to the informational content of index option prices.

First, we investigate the one-month forecasting ability of the orthogonalized IRRA. Table 10 reports results across the three REA proxies for the multiple predictors models. We can see that the

[7] According to the U.S. National Bureau of Economic Research (the official arbiter of U.S. recessions), the U.S. recession began in December 2007 and ended in June 2009.

orthogonalized IRRA is statistically significant in all cases and regardless of the way we conduct statistical inference. Furthermore, if we compare the adjusted R^2 of the multiple predictors models of the previous sections where RRA is included as a predictor, with the ones obtained when the orthogonalized RRA acts as a predictor, we can see that their values are very similar. These findings confirm that the predictability of the option implied RRA stems from the index options market and not from the physical variance. Once again, an increase in (orthogonalized) IRRA increases REA for the procyclical REA proxies, whereas it decreases KCFSI.

Regarding the sources of IRRA predictive power in the longer horizons, Table 11 reports the results for the 3, 6, 9 and 12 months horizons. Panels A, B and C report results in the case where the industrial production, the non-farm payroll and the KCFSI index are used as REA proxies, respectively. We can see that that the predictability of REA is mostly based on the option implied measures just as it was the case in the one-month horizon. The orthogonalized IRRA is significant in almost all horizons for all REA proxies (except for the 12-months horizon when KCFSI proxies for REA). Regarding the values of the adjusted R^2, they are again close to the adjusted R^2 of the previous sections where RRA was included as a predictor, and they range between 48.9% and 53.2% for the industrial production index, 69.8% and 75.9% for the nonfarm payroll and 46.7% and 71.9% for the KCFSI. Moreover, Table 11 shows that the orthogonalized IRRA prevails its statistical significance even if we consider Hodrick *t* statistics and the bootstrapped two sided *p*-values (numbers reported within parenthesis and within brackets, respectively). In sum, the reported predictability of IRRA for REA stems from the information content of the S&P 500 option prices. This holds for both short and long horizons when we control for other variables which may predict REA.

6. Conclusions

The recent financial crisis and the subsequent economic recession has revived the debate about the usefulness of financial variables to forecast future real economic activity (REA). We propose a new predictor of REA, namely the representative agent's implied relative risk aversion (IRRA) extracted from index option market prices. Thus, IRRA is forward-looking by construction and hence it is a natural choice to predict REA. Our testable hypothesis is that in the light of market participants' expectations for an improvement of REA, the more risk averse investors enter the stock market leading to an increase in IRRA, an increase in stock prices, a decrease in expected returns and hence to an increase in REA.

We extract IRRA from S&P 500 index options. Our findings verify our hypothesis. We conduct statistical inference carefully and we find that IRRA predicts U.S. REA. An increase (decrease) in IRRA predicts an increase (decrease) in REA. This holds either in a stand alone or in a multiple predictors setting where we control for other long standing as well as more recently proposed REA predictors. Moreover, the values of the adjusted R^2 of all models increase remarkably when IRRA is included as a predictor in the multiple predictors setting. Our results are robust regardless of the REA proxy and the method to conduct statistical inference. They also pertain over short and longer forecasting horizons. Interestingly, IRRA helps forecasting REA more accurately even out-of-sample over the 2008-2009 peak of the recent economic recession. Finally, we confirm that IRRA's forecasting ability stems from the information content of option prices rather than from the backward-looking physical variance which is also used as an input for its estimation. Our results are in line with the empirically documented positive correlation of IRRA with the S&P 500 and the equity mutual funds net flows.

Our results imply that the informational content of S&P 500 option prices synopsized by IRRA contains more information than that already contained in other financial variables to predict

REA and hence IRRA should be added to the existing list of U.S. REA predictors. Future research should examine whether IRRA extracted from other countries' option markets can also serve predicting the respective REAs.

References

Ait-Sahalia, Y., and A. W. Lo (2000), "Nonparametric Risk Management and Implied Risk Aversion", *Journal of Econometrics,* 94, 9-51.

Allen, L., T. G. Bali, and Y. Tang (2012), "Does Systemic Risk in the Financial Sector predict Future Economic Downturns?", *Review of Financial Studies* 25, 3000-3036.

Andersen, T. G., and T. Bollerslev (1998), "Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts", *International Economic Review,* 39, 885-905.

Bakshi, G., N. Kapadia, and D. Madan (2003), "Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options", *Review of Financial Studies,* 16, 101-143.

Bakshi, G., and D. Madan (2006), "A Theory of Volatility Spreads", *Management Science*, 52, 1945-1956.

Bakshi, G., G. Panayotov, and G. Skoulakis (2011), "Improving the Predictability of Real Economic Activity and Asset Returns with Forward Variances Inferred from Option Portfolios", *Journal of Financial Economics,* 100, 475-495.

Bakshi, G., G. Panayotov, and G. Skoulakis (2012), "The Baltic Dry Index as a Predictor of Global Stock Returns, Commodity Returns, and Global Economic Activity", *Chicago Meetings Paper,* AFA.

Bakshi, G., X. Gao, and A. Rossi (2014), "A Better Specified Asset Pricing Models to explain the Cross-section and Time-Series of Commodity Returns", University of Maryland, Working Paper.

Bali, T.G., Cakici, N. and F., Chabi-Yo (2012), "Does Aggregate Riskiness Predict Future Economic Downturns?" McDonough School of Business, Georgetown University, Working Paper.

Barone-Adesi, G., Mancini, L., and H., Shefrin (2014), "Sentiment, Risk Aversion and Time Preference", University of Lugano, Working Paper.

Beber, A., and M. W. Brandt (2006), "The Effect of Macroeconomic News on Beliefs and Preferences: Evidence from the Options Markets", *Journal of Monetary Economics*, 53, 1997-2039.

Bekaert, G., and M. Hoerova (2013), "The VIX, the Variance Premium and Stock Market Volatility", *Journal of Econometrics*, forthcoming.

Bliss, R. R., and N. Panigirtzoglou (2004), "Option-Implied Risk Aversion Estimates", *Journal of Finance,* 59, 407-446.

Bollerslev, T., G. Tauchen, and H. Zhou (2009), "Expected Stock Returns and Variance Risk Premia", *Review of Financial Studies*, 22, 4463-4492.

Bollerslev, T., M. Gibson, and H. Zhou (2011), "Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option-Implied and Realized Volatilities", *Journal of Econometrics* 160, 235-245.

Buss, A., and G. Vilkov (2012), "Measuring Equity Risk with Option-implied Correlations", *Review of Financial Studies*, 25 (10), 3113-3140.

Campbell, J. Y., and J. H. Cochrane (1999), "By Force of Habit: A Consumption-based explanation of Aggregate Stock Market Behavior", *Journal of Political Economy,* 107, 205-251.

Carr, P., and L. Wu (2009), "Variance Risk Premiums", *Review of Financial Studies*, 22, 1311-1341.

Chang, B. Y., P. Christoffersen, K. Jacobs, and G. Vainberg (2012), "Option-Implied Measures of Equity Risk", *Review of Finance*, 16, 385-428.

Chiu, C.W. (2010), "Funding Liquidity, Business Cycles and Asset Pricing in the U.S.", Working Paper, Duke University.

Cochrane, J. H. (1999), "A Critique of The Application of Unit Root Tests", *Journal of Economic Dynamics and Control*, 15, 275-284.

Cochrane, J. H. (2011), "Discount Rates", *Journal of Finance,* 66, 1047-1108.

Coudert, V. and M. Gex (2008), “Does Risk Aversion Drive Financial Crises? Testing the Predictive Power of Empirical Indicators”, *Journal of Empirical Finance* 15, 167-184.

Daskalaki C., A. Kostakis and G. Skiadopoulos. (2014), “Are there Common Factors in Individual Commodity Futures Returns?”, *Journal of Banking and Finance,* 40, 346-363.

DeMiguel, V., Y. Plyakha, R. Uppal, and G. Vilkov (2013), “Improving Portfolio Selection using Option-Implied Volatility and Skewness”, *Journal of Financial and Quantitative Analysis*, 48(6), 1813-1845.

Duan, J. C., and W. Zhang (2014), “Forward-Looking Market Risk Premium”, *Management Science,* 60, 521-538.

Easley, D., M. O’Hara, and P. Srinivas (1998), “Option Volume and Stock Prices: Evidence on where Informed Traders Trade”, *Journal of Finance*, 53, 431–465.

Estrella, A., and G. A. Hardouvelis (1991), “The Term Structure as a Predictor of Real Economic Activity”, *Journal of Finance,* 46, 555-576.

Fama, E. F. (1990), “Stock Returns, Expected Returns, and Real Activity”, *Journal of Finance,* 45, 1089-1108.

Fama, E. F. and K. French (1996), “Multifactor Explanations of Asset Pricing Anomalies”, *Journal of Finance,* 51, 55-84.

Giamouridis, D., and G. Skiadopoulos (2012), “The Informational Content of Financial Options for Quantitative Asset Management: A Review”. In *Handbook of Quantitative Asset Management*, 243-265. 243-265, B. Scherer and K. Winston (Editors), Oxford University Press.

Gorton, G.B., F. Hayashi, and K.G. Rouwenhorst (2012), “The Fundamentals of Commodity Futures Returns”, *Review of Finance*, 17, 35–105.

Gourinchas, P-O., and M. Obstfeld (2012), “Stories of the Twentieth Century for the Twenty-First", *American Economic Journal: Macroeconomics*, 4, 226-65.

Hakkio, C., and W. Keeton (2009), "Financial Stress: What is it, How can it be Measured, and Why does it Matter?", *Federal Reserve Bank of Kansas City,* Economic Review.

Hansen, L. P. (1982), "Large Sample Properties of Generalized Method of Moments Estimators", *Econometrica,* 50, 1029-1084.

Hara, C., J. Huang, and C. Kuzmics (2007), "Representative Consumer's Risk Aversion and Efficient Risk-Sharing Rules", *Journal of Economic Theory* 137, 652-672.

Harvey, D., S. Leybourne, and P. Newbold (1997) "Testing the Equality of Prediction Mean Squared Errors." *International Journal of Forecasting*, 13, 281-291.

Hodrick, R. (1992), "Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement", *Review of Financial Studies* 5, 357-386.

Hong, H., and M. Yogo (2012), "What does Futures Market Interest Tell us about the Macroeconomy and Asset Prices?", *Journal of Financial Economics* 105, 473-490.

Investment Company Fact Book (2014), "A Review of Trends and Activity in the U.S. Investment Company Industry", 54rth Edition.

Jackwerth, J. C., and M. Rubinstein (1996), "Recovering Probability Distributions from Option Prices", *Journal of Finance*, 51, 1611-1631.

Jackwerth, J. C. (2000), "Recovering Risk Aversion from Option Prices and Realized Returns", *Review of Financial Studies,* 13, 433-451.

Jiang, G. J., and Y. S. Tian (2005), "The Model-Free Implied Volatility and its Information Content", *Review of Financial Studies*, 18, 1305-1342.

Jiang, G.J., and Y.S. Tian (2007), "Extracting model-free Volatility from Option Prices: An Examination of the VIX index", *Journal of Derivatives*, 14, 35-60.

Kang B. J., and T. S. Kim (2006), "Option-Implied Risk Preferences: An Extension to wider Classes of Utility Functions", *Journal of Financial Markets*, 9, 180-198.

Kang, B. J., T. S. Kim, and S-J. Yoon (2010), “Information Content of Volatility Spreads”, *Journal of Futures Markets*, 30, 533-558.

Kostakis, A., N. Panigirtzoglou, and G. Skiadopoulos (2011), “Market Timing with Option-Implied Distributions: A Forward-Looking Approach”, *Management Science* 57, 1231-1249.

Liew, J., and M. Vassalou (2000), “Can Book-to-Market, Size and Momentum be Risk Factors that Predict Economic Growth?”, *Journal of Financial Economics*, 57, 221-245.

Merton, R. C. (1973), “Theory of Rational Option Pricing”, *Bell Journal of Economics and Management Science*, 4, 141-183.

Mueller, P., A, Vedolin and Y-M. Yen (2013), “Bond Variance Risk Premia”, London School of Economics, Working Paper.

Neumann, M., and G. Skiadopoulos (2013), “Predictable Dynamics in Higher Order Risk-Neutral Moments: Evidence from the S&P 500 Options”, *Journal of Financial and Quantitative Analysis* 48, 947-977.

Neumann, M. (2014), “Financial Sector Tail Risk and Real Economic Activity: Evidence from the Option Market”, Queen Mary, University of London, Working Paper.

Newey, W., and K. West (1994), “Automatic Lag Selection in Covariance Matrix Estimation”, *Review of Economic Studies,* 61, 631-653.

Pan, J. and A. Poteshman (2006), “The Information in Options volume for future Stock Prices,” *Review of Financial Studies*, 19, 871–908.

Politis, D. N., and J. P. Romano (1994), “The Stationary Bootstrap”, *Journal of the American Statistical Association,* 89, 1303-1313.

Rosenberg, J. V., and R. F. Engle (2002), “Empirical Pricing Kernels”, *Journal of Financial Economics,* 64, 341-372.

Söderlind, P., and L. Svensson (1997), “New Techniques to Extract Market Expectations from Financial Instruments”, *Journal of Monetary Economics*, 40, 383–429.

Stambaugh, R. F. (1999), "Predictive Regressions", *Journal of Financial Economics,* 54, 375-421.

Stock, J. H. and M. H. Watson (2003), "Forecasting Output and Inflation: The Role of Asset Prices", *Journal of Economic Literature*, 41, 788-829.

Subrahmanyam, A. and S., Titman (2013), "Financial Market Shocks and the Macroeconomy", *Review of Financial Studies* 26, 2687-2717.

Xiouros, C. and F. Zapatero (2010), "The Representative Agent of an Economy with External Habit-Formation and Heterogeneous Risk-Aversion", *Review of Financial Studies*, 23, 3017-3047.

Whaley, R. E. (2000). "The Investor Fear Gauge," *Journal of Portfolio Management*, Spring, 12-17.

Wilson, R. (1968), "The Theory of Syndicates", *Econometrica,* 36, 119-132.

Appendix A: Extraction of Forward Variances from Option Prices

We extract the forward variances from option prices along the lines of Bakshi, Panayotov and Skoulakis (2011). We compute the price $H(t,\tau)$ of exponential claims at time *t* with horizon τ in terms of the prices of call and put options as

$$H(t,\tau) = e^{-r\tau} + \int_{S(t)}^{\infty} \omega(K)C(t,\tau;K)dK + \int_{0}^{S(t)} \omega(K)P(t,\tau;K)dK, \quad \text{(A.1)}$$

$$\omega(K) = -\frac{\frac{8}{\sqrt{14}}\cos\left\{\arctan(1/\sqrt{7}) + \frac{\sqrt{7}}{2}\ln\left(\frac{K}{S(t)}\right)\right\}}{\sqrt{S(t)}K^{3/2}} \quad \text{(A.2)}$$

where $C(t,\tau;K)$ and $P(t,\tau;K)$ are the prices of call and put options at time *t*, respectively, τ is the time to maturity and *K* is the strike price. We compute $H(t,\tau)$ for maturities 30 and 60 calendar days respectively. The integrals are computed using trapezoidal approximation following the same methodology as the one applied for the calculation of the risk-neutral moments described in Section 3.3.

We then compute two forward variances at time *t* with horizon 30 calendar days as:

$$FV_t^1(30) = -\ln H_t^{t,30} \quad \text{(A.3)}$$

$$FV_t^2(30) = \ln H_t^{t,30} - \ln H_t^{t,60} \quad \text{(A.4)}$$

Appendix B: Construction of the Commodity Factors

We construct the three commodity risk factors (the hedging-pressure risk factor, the basis risk factor and the momentum risk factor) along the lines of Daskalaki, Kostakis and Skiadopoulos (2014).

Hedging-pressure risk factor

We denote as $HP_{i,t}$ the hedging pressure for any commodity *i* at time *t* and it is the number of short hedging positions minus the number of long hedging positions, divided by the total number of hedgers in the respective commodity market. The more risk averse speculators take futures positions only if they receive compensation and they share the price risk with hedgers (hedging pressure hypothesis). So, if $HP_{i,t}$ is positive (negative), hedgers are net short (long) in the futures contract. Speculators are willing to take the long (short) position only if they receive a positive risk premium. We then construct a zero cost mimicking portfolio for the above strategy. First, we calculate the *HP* for each futures contract at each month *t*. We then define two portfolios; the portfolio H that contains all commodities with positive *HP* and the portfolio L that contains all commodities with negative *HP*. We construct the high minus low *HP* risk factor by going long in portfolio H and short in portfolio L. Last, we calculate the mimicking portfolio return at time *t*+1, i.e. the next month.

Momentum risk factor

According to Gordon, Hayashi and Rouwenhorst (2012), a negative shock to inventories leads to an increase in prices which is then followed by a short period of high expected futures returns for the respective commodity. This happens because the demand exceeds the supply for the commodity for that period and thus a price momentum is created. We define two portfolios; portfolio H that contains all commodities with positive prior 12- month average return and portfolio L that contains those with negative prior 12-month average return. We then construct the high minus low momentum risk factor at each month t, by going long in portfolio H and short in portfolio L. Last, we calculate the mimicking portfolio return at time *t*+1, i.e. the next month.

Basis risk factor

According to the theory of storage, a positive basis is associated with low inventories for any given commodity. In addition, Gordon, Hayashi and Rouwenhorst (2012) find that a portfolio of commodities with a high basis outperforms the portfolio of commodities with a low basis. We construct again two portfolios; portfolio H that contains all commodities with positive basis and portfolio L that contains all commodities with negative basis. We then construct the high minus low basis risk factor at each month t, by going long in portfolio H and short in portfolio L. Last, in order to obtain the time series of the factor returns, we calculate the mimicking portfolio return at time $t+1$, i.e. the next month.

Appendix C: Parametric bootstrap for the significance of the predictors

We consider the following predictive regression with *k*-predictors:

$$\text{REA}_{t\to t+1} = c_0 + c_1 X_{1t} + ... + c_k X_{kt} + e_{t+1} \tag{C.1}$$

where $REA_{t\to t+1}$ is the growth rate of REA from t to $t+h$ and X_{it} is the *i*th predictor (i=1,..,14) where predictors dynamics are given by

$$X_{it} = a_i + \rho_i X_{it-1} + u_{it} \tag{C.2}$$

For most variables, Akaike criterion dictates an autoregressive process of order one (AR(1)). We apply the stationary bootstrap of Politis and Romano (1994) to assess the statistical significance of the predictors. We test the null hypothesis that c_i is statistical insignificant, against the alternative that it is significant $(H_0 : c_i = 0, \text{against } H_a = c_i \neq 0)$.

We construct the bootstrapped *p*-values in seven steps. First, we estimate equation (C.1) and obtain the estimated coefficients $(c_0, c_1, ..., c_k)$, their *t*-statistics $(t_{c_0}, t_{c_1}, ..., t_{c_k})$ and the regression residuals (e_{t+1}). Second, we estimate equation (C.2) and obtain the estimated coefficients (a_i, ρ_i) and the residuals (u_{it}). Third, we bootstrap the residuals obtained in the first two steps in a pairwise manner. We sample with replacement rows from a matrix that contains the residuals of equations (C.1) and (C.2) in each column. This way, we construct our first bootstrap sample of residuals (e_{t+1}^{Boot} and u_{it}^{Boot}) whose size is equal to the original sample size. Fourth, we construct the first sample of bootstrapped predictor(s) (X_{it}^{Boot}), using equation (C.2), the estimated coefficients and the bootstrapped u_{it}^{Boot} residuals. Fifth, we construct the bootstrapped dependent variable, $\text{REA}_{t\to t+1}^{Boot}$, under the null hypothesis that $c_i = 0$. To this end, we impose $c_i = 0$ on equation (C.1) and we use the bootstrapped residuals e_{t+1}^{Boot}. Sixth, we re-estimate the predictive regression (C.1) using the bootstrapped variables and save the *t*-statistic of the tested parameter $(t_{c_i}^{Boot})$. Seventh, we repeat steps one to six N=2,000 times. This yields 2,000 $t_{c_i}^{Boot}$. Finally, we calculate the *p*-value as the number of times where $\left|t_{c_i}^{Boot}\right|$ exceeds $\left|t_{c_i}\right|$ i=1,…, k.

Tables

Table 1: List of Commodities

Panel A	**Commodities**
Grains and Oilseeds	Corn
	Kansas Wheat
	Oats
	Soybean Meal
	Soybean Oil
	Soybeans
	Wheat
Panel B	
Energy	Crude Oil
	Heating Oil
Panel C	
Livestock	Feeder Cattle
	Pork Bellies
	Lean Hogs
	Live Cattle
Panel D	
Metals	Copper
	Gold
	Palladium
	Platinum
	Silver
Panel E	
Softs	Cocoa
	Coffee
	Cotton
	Sugar

Entries report the 22 commodities used in the analysis categorized in five broad sectors.

Table 2: Descriptive Statistics of S&P 500 Risk-Neutral Moments

	30 days horizon		
	IV	SKEW	KURT
# Observations	3576	3576	3576
Mean	0.06	-1.32	5.94
Median	0.06	-1.32	5.85
Max	0.23	-0.34	15.00
Min	0.03	-3.11	3.01
Standard Dev.	0.03	0.33	1.19
Skewness	1.95	-0.24	1.06
Kurtosis	6.54	0.63	3.84

Entries report the descriptive statistics of the daily S&P 500 risk-neutral moments with horizon 30 calendar days. The estimation period is from January 4^{th} 1996 to December 31^{st} 2012.

Table 3: Representative Agent's Implied Relative Risk Aversion and U.S. Equity Funds Net Flows

		$IRRA_t$
C	Coef.	8.06*
	NW, t-stat	16.09
Net Funds Flows$_t$	Coef.	0.0000001*
	NW, t-stat	2.85
% Adj. R^2		10.51

Entries report results from the OLS regressions of implied risk aversion (IRRA) on the U.S. equity funds net flows. All variables are reported in levels. IRRA is estimated using equation (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *t*-statistics estimated with a Bartlett kernel and the adjusted R^2 are reported. Asterisk denotes rejection of the null hypothesis of a zero coefficient at a 5% level. The sample spans the period July 2002-December 2012.

Table 4: Predicting Industrial Production Index with Implied Risk Aversion and Other Predictors

One Month Horizon

IPI_{t+1}	(1)	(2)	(3)
$IRRA_t$	0.0002		0.001
	0.005 (0.000)		0.000 (0.000)
FV_t^1		-0.50	-0.39
		0.005 (0.010)	0.017 (0.003)
FV_t^2		0.51	0.17
		0.036 (0.031)	0.436 (0.093)
VRP_t		-0.07	-0.06
		0.061 (0.056)	0.006 (0.008)
BDI_t		-0.03	-0.04
		0.240 (0.242)	0.173 (0.385)
$Term_t$		0.002	0.001
		0.011 (0.000)	0.036 (0.012)
$Default_t$		-0.004	-0.01
		0.068 (0.069)	0.011 (0.000)
TED_t		-0.0002	-0.0001
		0.928 (0.954)	0.934 (0.824)
SMB_t		-0.0004	-0.0003
		0.333 (0.351)	0.398 (0.883)
HML_t		0.0002	0.0001
		0.286 (0.223)	0.571 (0.535)
$Momentum_t$		-0.01	-0.01
		0.600 (0.598)	0.595 (0.798)
$Basis_t$		-0.02	-0.01
		0.147 (0.142)	0.276 (0.013)
HP_t		0.01	0.01
		0.392 (0.413)	0.376 (0.885)
$Open\ Interest_t$		0.03	0.02
		0.110 (0.101)	0.224 (0.954)
% Adj. R^2	2.54	14.98	23.54

Entries report results from the OLS predictive regressions of growth in industrial production index on previous month implied relative risk aversion (RRA) and a set of other predictors. The forecasting horizon is one month. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *p*-values estimated with a Bartlett kernel, the stationary bootstrapped *p*-values (within parenthesis) and the adjusted R^2 for each model are reported. The sample spans the period August 2002- January 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, $Open\ Interest_t$ and IPI_{t+1} denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), the variance risk premium, the growth of the Baltic dry index, the term, the default and the TED spreads, the Fama- French (1996) SMB and HML factors, the momentum, basis and hedging-pressure commodity risk factors and the growth of commodity market open interest from time (*t*-1) to *t*, and the industrial production index growth rate from *t* to (*t+1*), respectively.

Table 5: Predicting Nonfarm Payroll Employment with Implied Risk Aversion and Other Predictors

One Month Horizon

$Payroll_{t+1}$	(1)	(2)	(3)
$IRRA_t$	0.0001 0.000 (0.000)		0.0003 0.000 (0.000)
FV_t^1		-0.13 0.074 (0.066)	-0.05 0.388 (0.000)
FV_t^2		0.13 0.147 (0.138)	-0.11 0.060 (0.000)
VRP_t		-0.004 0.730 (0.738)	0.00001 0.988 (0.869)
BDI_t		-0.01 0.511 (0.515)	-0.01 0.039 (0.016)
$Term_t$		0.001 0.103 (0.030)	0.0001 0.363 (0.847)
$Default_t$		-0.001 0.361 (0.325)	-0.001 0.002 (0.000)
TED_t		-0.0002 0.810 (0.810)	-0.0001 0.738 (0.005)
SMB_t		-0.00001 0.224 (0.251)	-0.00004 0.359 (0.436)
HML_t		0.00001 0.449 (0.537)	-0.000001 0.868 (0.700)
$Momentum_t$		-0.004 0.212 (0.208)	-0.004 0.030 (0.002)
$Basis_t$		-0.01 0.061 (0.068)	-0.002 0.139 (0.367)
HP_t		0.003 0.505 (0.534)	0.003 0.032 (0.979)
$Open\ Interest_t$		0.01 0.043 (0.050)	0.0003 0.893 (0.733)
% Adj. R^2	10.47	18.89	76.90

Entries report results from the OLS predictive regressions of growth in nonfarm payroll employment on previous month implied relative risk aversion (RRA) and a set of other predictors. The forecasting horizon is one month. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *p*-values estimated with a Bartlett kernel, the stationary bootstrapped *p*-values (within parenthesis) and the adjusted R^2 for each model are reported. The sample spans the period August 2002- January 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, $Open\ Interest_t$ and $Payroll_{t+1}$ denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), variance risk premium, growth of the Baltic dry index, term, the default and the TED spreads, Fama- French (1996) SMB and HML factors, momentum, basis and hedging-pressure commodity risk factors, growth of commodity market open interest from time (*t*-1) to *t*, and the nonfarm payroll employment growth rate from *t* to (*t+1*), respectively.

Table 6: Predicting the Kansas City Financial Stress Index with Implied Risk Aversion and Other Predictors

One Month Horizon

$KCFSI_{t+1}$	(1)	(2)	(3)
$IRRA_t$	-0.32 0.001 (0.000)		-0.02 0.000 (0.000)
FV_t^1		87.67 0.034 (0.027)	45.75 0.223 (0.000)
FV_t^2		-78.38 0.137 (0.139)	49.03 0.044 (0.853)
VRP_t		2.26 0.635 (0.658)	0.73 0.810 (0.555)
BDI_t		-4.78 0.531 (0.539)	-2.86 0.460 (0.000)
$Term_t$		-0.16 0.315 (0.168)	0.04 0.396 (0.000)
$Default_t$		0.38 0.501 (0.494)	0.55 0.009 (0.000)
TED_t		0.68 0.131 (0.112)	0.67 0.047 (0.019)
SMB_t		0.05 0.120 (0.144)	0.02 0.074 (0.041)
HML_t		-0.07 0.241 (0.410)	-0.03 0.266 (0.000)
$Momentum_t$		0.09 0.952 (0.959)	0.31 0.662 (0.295)
$Basis_t$		2.12 0.250 (0.261)	0.10 0.878 (0.886)
HP_t		0.86 0.663 (0.681)	0.48 0.425 (0.101)
$Open\ Interest_t$		-4.33 0.031 (0.034)	-0.12 0.862 (0.031)
% Adj. R^2	40.99	43.53	87.98

Entries report results from the OLS predictive regressions of KCFSI index on previous month implied relative risk aversion (RRA) and a set of other predictors. The forecasting horizon is one month. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *p*-values estimated with a Bartlett kernel, the stationary bootstrapped *p*-values (within parenthesis) and the adjusted R^2 for each model are reported. The sample spans the period August 2002- January 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, $Open\ Interest_t$ and $KCFSI_{t+1}$ denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), the variance risk premium, the growth of the Baltic dry index, the term, the default and the TED spreads, the Fama- French (1996) SMB and HML factors, the momentum, basis and hedging-pressure commodity risk factors and the growth of commodity market open interest from time (*t*-1) to *t*, and the Kansas city financial stress index from *t* to (*t+1*), respectively.

Table 7: Predicting Industrial Production Index with Implied Risk Aversion and Other Predictors

Long Horizons

Panel A

IPI_{t+h}		3 M	6 M	9 M	12 M
	Coefficients	0.001	0.001	0.001	0.002
$IRRA_t$	NW t-stats	2.93	2.75	2.36	2.04
	Hodrick t-stats	(2.81)	(3.04)	(2.73)	(2.45)
	Bootstrap p-values	[0.000]	[0.000]	[0.000]	[0.000]
% Adj. R^2		4.28	4.19	3.38	2.59

Table 7 (Cont'd)

Panel B

IPI_{t+h}	3 M	6 M	9 M	12 M
$IRRA_t$	0.001 3.45 (2.28) [0.000]	0.002 2.83 (1.68) [0.000]	0.002 2.26 (1.13) [0.000]	0.002 1.77 (0.72) [0.000]
FV_t^1	-1.43 -3.16 (-1.83) [0.005]	-1.50 -1.69 (-0.93) [0.091]	-1.23 -0.87 (-0.80) [0.383]	0.03 0.02 (0.02) [0.990]
FV_t^2	0.78 1.34 (0.77) [0.180]	0.92 0.94 (0.58) [0.346]	0.74 0.59 (0.50) [0.564]	-0.69 -0.62 (-0.46) [0.544]
VRP_t	-0.10 -2.47 (-1.65) [0.016]	-0.16 -1.97 (-1.14) [0.045]	-0.17 -1.45 (-1.25) [0.133]	-0.08 -0.61 (-0.56) [0.537]
BDI_t	0.01 0.08 (0.04) [0.937]	-0.09 -0.61 (-0.47) [0.547]	-0.22 -0.98 (-1.23) [0.333]	-0.46 -1.43 (-2.72) [0.156]
$Term_t$	0.002 1.54 (1.05) [0.034]	0.001 0.70 (0.46) [0.318]	0.001 0.31 (0.20) [0.656]	0.001 0.29 (0.19) [0.684]
$Default_t$	-0.01 -0.98 (-0.76) [0.312]	0.002 0.20 (0.15) [0.831]	0.02 1.34 (0.95) [0.186]	0.03 2.55 (1.40) [0.011]
TED_t	-0.01 -1.80 (-1.02) [0.073]	-0.03 -2.69 (-2.03) [0.017]	-0.06 -3.30 (-2.68) [0.009]	-0.08 -4.20 (-3.44) [0.003]
SMB_t	-0.001 -1.68 (-1.31) [0.091]	-0.002 -1.46 (-1.45) [0.142]	-0.003 -1.64 (-1.93) [0.095]	-0.003 -1.49 (-1.65) [0.137]
HML_t	0.0003 0.51 (0.30) [0.579]	0.001 0.48 (0.45) [0.561]	0.001 0.44 (0.54) [0.599]	0.002 1.21 (1.30) [0.158]
$Momentum_t$	-0.01 -0.82 (-0.52) [0.425]	-0.03 -0.96 (-1.02) [0.328]	-0.04 -0.99 (-1.09) [0.312]	-0.08 -1.63 (-2.00) [0.103]
$Basis_t$	-0.03 -1.75 (-0.94) [0.079]	-0.03 -1.25 (-0.84) [0.223]	-0.07 -1.43 (-1.75) [0.153]	-0.06 -0.96 (-1.22) [0.344]
HP_t	0.04 1.74 (1.29) [0.081]	0.05 1.21 (1.34) [0.218]	0.08 1.18 (1.67) [0.234]	0.09 1.03 (1.66) [0.295]
$Open\ Interest_t$	0.04 1.40 (0.89) [0.176]	0.07 1.32 (1.31) [0.198]	0.05 0.68 (0.98) [0.512]	0.03 0.37 (0.66) [0.716]
% Adj. R^2	48.62	49.55	50.64	53.37

Panel A reports results from the OLS predictive regressions of growth in industrial production index on previous months implied relative risk aversion (RRA). Panel B reports results from the OLS predictive regressions of growth in industrial production index on previous months implied relative risk aversion and a set of other predictors. The forecasting horizon is 3 to 12 months ahead. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *t*-statistics with a Bartlett kernel, the Hodrick (1992) *t*-statistics (within parenthesis), the stationary bootstrapped *p*-values (within brackets) and the adjusted R^2 for each model are reported. The sample spans the period August 2002- November 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, *Open Interest*$_t$ and IPI_{t+h} denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), variance risk premium, growth of the Baltic dry index, term, the default and the TED spreads, Fama- French (1996) SMB and HML factors, momentum, basis and hedging-pressure commodity risk factors, growth of commodity market open interest from time (*t*-*1*) to *t*, and the growth rate of the industrial production index with horizon 3-12 months, respectively.

Table 8: Predicting Nonfarm Payroll Employment with Implied Risk Aversion and Other Predictors

Long Horizons

Panel A

Payroll$_{t+h}$		3 M	6 M	9 M	12 M
IRRA$_t$	Coefficients	0.002	0.003	0.004	0.005
	NW *t*-stats	3.34	3.11	2.94	2.77
	Hodrick *t*-stats	(1.67)	(1.68)	(1.66)	(1.59)
	Bootstrap *p*-values	[0.045]	[0.058]	[0.063]	[0.086]
% Adj. R^2		43.60	40.21	36.03	30.34

Table 8 (Cont'd)

Panel B

Payroll$_{t+h}$	3 M	6 M	9 M	12 M
IRRA$_t$	0.001	0.002	0.002	0.003
	12.30 (2.04) [0.000]	11.65 (1.70) [0.000]	10.34 (1.35) [0.000]	9.10 (1.13) [0.000]
FV_t^1	-0.26	-0.52	-0.53	-0.20
	-1.55 (-0.26) [0.123]	-1.44 (-0.33) [0.147]	-0.93 (-0.30) [0.341]	-0.29 (-0.11) [0.768]
FV_t^2	-0.22	-0.31	-0.52	-0.95
	-1.18 (-0.17) [0.240]	-0.96 (-0.20) [0.344]	-1.29 (-0.33) [0.209]	-2.10 (-0.59) [0.041]
VRP_t	-0.01	-0.03	-0.05	-0.03
	-0.81 (-0.15) [0.414]	-1.06 (-0.25) [0.296]	-0.88 (-0.35) [0.374]	-0.45 (-0.23) [0.635]
BDI_t	-0.02	-0.05	-0.11	-0.20
	-1.46 (-0.22) [0.147]	-1.57 (-0.30) [0.123]	-2.12 (-0.60) [0.038]	-2.35 (-1.08) [0.025]
$Term_t$	0.0003	0.0004	0.001	0.001
	0.79 (0.16) [0.147]	0.61 (0.15) [0.351]	0.57 (0.15) [0.385]	0.75 (0.20) [0.249]
$Default_t$	-0.003	-0.004	-0.003	0.001
	-2.60 (-0.46) [0.232]	-1.59 (-0.31) [0.079]	-0.72 (-0.13) [0.426]	0.19 (0.03) [0.831]
TED_t	-0.002	-0.01	-0.02	-0.03
	-1.10 (-0.22) [0.004]	-2.09 (-0.53) [0.027]	-2.79 (-0.80) [0.010]	-3.68 (-1.07) [0.002]
SMB_t	-0.0002	-0.001	-0.002	-0.001
	-1.86 (-0.40) [0.225]	-1.88 (-0.56) [0.055]	-1.72 (-0.62) [0.084]	-1.53 (-0.57) [0.126]
HML_t	-0.000004	-0.00001	-0.0002	-0.000001
	-0.03 (-0.01) [0.059]	-0.34 (-0.09) [0.683]	-0.44 (-0.16) [0.609]	-0.03 (-0.01) [0.966]
$Momentum_t$	-0.01	-0.02	-0.03	-0.04
	-2.08 (-0.39) [0.976]	-1.90 (-0.45) [0.052]	-2.37 (-0.71) [0.017]	-3.19 (-0.98) [0.002]
$Basis_t$	-0.01	-0.01	-0.01	-0.01
	-1.10 (-0.16) [0.037]	-0.56 (-0.13) [0.583]	-0.92 (-0.33) [0.359]	-0.67 (-0.31) [0.494]
HP_t	0.01	0.02	0.03	0.04
	2.33 (0.32) [0.271]	1.81 (0.44) [0.070]	1.52 (0.59) [0.131]	1.40 (0.68) [0.160]
Open Interest$_t$	0.001	0.001	0.002	-0.002
	0.12 (0.02) [0.018]	0.10 (0.03) [0.928]	0.08 (0.04) [0.932]	-0.07 (-0.04) [0.939]
% Adj. R^2	76.87	74.55	72.12	71.14

Panel A reports results from the OLS predictive regressions of growth in nonfarm payroll employment on previous months implied relative risk aversion (RRA). Panel B reports results from the OLS predictive regressions of growth in nonfarm payroll employment on previous months implied relative risk aversion and a set of other predictors. The forecasting horizon is 3 to 12 months ahead. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *t*-statistics estimated with a Bartlett kernel, the Hodrick (1992) *t*-statistics (within parenthesis), the stationary bootstrapped *p*-values (within brackets) and the adjusted R^2 for each model are reported. The sample spans the period August 2002- November 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, *Open Interest$_t$* and $Payroll_{t+h}$ denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), the variance risk premium, the growth of the Baltic dry index, the term, the default and the TED spreads, the Fama- French (1996) SMB and HML factors, the momentum, basis and hedging-pressure commodity risk factors and the growth of commodity market open interest from time (*t*-1) to *t*, and the growth rate of the nonfarm payroll employment with horizon 3-12 months, respectively.

Table 9: Predicting KCFSI with Implied Risk Aversion and Other Predictors

Long Horizons

Panel A

$KCFSI_{t+h}$		3 M	6 M	9 M	12 M
$IRRA_t$	Coefficients	-0.30	-0.26	-0.18	-0.12
	NW *t*-stats	-3.11	-2.64	-2.16	-1.74
	Hodrick *t*-stats	(-2.05)	(-2.80)	(-1.85)	(0.96)
	Bootstrap *p*-values	[0.000]	[0.000]	[0.000]	[0.000]
% Adj. R^2		43.69	32.03	15.63	5.65

Table 9 (Cont'd)

Panel B

$KCFSI_{t+h}$	3 M	6 M	9 M	12 M
	-0.14	-0.10	-0.06	-0.03
$IRRA_t$	-9.37 (-2.79) [0.000]	-4.72 (-1.07) [0.000]	-2.31 (-0.43) [0.000]	-0.97 (-0.13) [0.072]
	30.65	-16.96	-72.36	-128.76
FV_t^1	0.78 (0.27) [0.397]	-0.40 (-0.10) [0.671]	-1.70 (-0.45) [0.097]	-4.47 (-0.71) [0.000]
	23.53	17.60	48.97	95.45
FV_t^2	1.06 (0.16) [0.275]	0.66 (0.10) [0.509]	1.72 (0.30) [0.094]	2.61 (0.55) [0.012]
	3.04	-0.20	-4.28	-8.22
VRP_t	0.81 (0.46) [0.400]	-0.06 (-0.02) [0.947]	-1.08 (-0.33) [0.284]	-2.43 (-0.54) [0.016]
	-0.93	5.59	13.23	10.20
BDI_t	-0.33 (-0.06) [0.744]	0.92 (0.33) [0.369]	1.27 (0.76) [0.206]	1.13 (0.62) [0.248]
	0.10	0.14	0.04	-0.05
$Term_t$	1.87 (0.64) [0.010]	1.51 (0.51) [0.036]	0.36 (0.10) [0.609]	-0.43 (-0.09) [0.517]
	0.26	-0.20	-0.28	-0.54
$Default_t$	1.05 (0.38) [0.241]	-0.63 (-0.19) [0.509]	-0.76 (-0.19) [0.434]	-1.54 (-0.29) [0.105]
	1.18	1.80	1.87	2.21
TED_t	3.46 (0.94) [0.005]	3.43 (0.86) [0.006]	3.27 (0.65) [0.013]	4.05 (0.67) [0.000]
	0.04	0.06	0.01	-0.03
SMB_t	0.96 (0.55) [0.365]	1.32 (0.50) [0.185]	0.30 (0.10) [0.759]	-1.20 (-0.28) [0.225]
	-0.02	-0.02	-0.0003	-0.07
HML_t	-0.46 (-0.17) [0.586]	-0.82 (-0.19) [0.312]	-0.01 (-0.003) [0.994]	-1.71 (-0.52) [0.055]
	0.47	0.62	2.13	1.75
$Momentum_t$	0.44 (0.17) [0.641]	0.59 (0.22) [0.538]	1.45 (0.65) [0.136]	1.21 (0.43) [0.206]
	-1.03	0.83	-0.49	-1.18
$Basis_t$	-1.16 (-0.58) [0.259]	0.43 (0.22) [0.679]	-0.26 (-0.13) [0.786]	-0.71 (-0.28) [0.479]
	-0.19	-2.41	0.27	3.09
HP_t	-0.22 (-0.08) [0.840]	-0.91 (-0.53) [0.363]	0.09 (0.05) [0.928]	1.02 (0.60) [0.318]
	-0.49	-1.50	-0.07	3.55
$Open\ Interest_t$	-0.26 (-0.13) [0.800]	-0.77 (-0.29) [0.448]	-0.03 (-0.01) [0.984]	1.18 (0.64) [0.231]
% Adj. R^2	71.78	55.32	36.99	47.02

Panel A reports results from the OLS predictive regressions of KCFSI index on previous months implied relative risk aversion (RRA). Panel B reports results from the OLS predictive regressions of KCFSI index on previous months implied relative risk aversion (RRA) and a set of other predictors. The forecasting horizon is 3 to 12 months ahead. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *t*-statistics with a Bartlett kernel, the Hodrick (1992) *t*-statistics (within parenthesis), the stationary bootstrapped *p*-values (within brackets) and the adjusted R^2 for each model are reported. The sample spans the period August

2002- November 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, $Open\ Interest_t$ and $KCFSI_{t+h}$ denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), the variance risk premium, the growth of the Baltic dry index, the term, the default and the TED spreads, the Fama- French (1996) SMB and HML factors, the momentum, basis and hedging-pressure commodity risk factors and the growth of commodity market open interest from time (*t*-1) to *t*, and the Kansas city financial stress index with horizon 3-12 months, respectively.

Table 10: Predicting Real Economic Activity with Orthogonalized Implied Risk Aversion

One Month Horizon

	IPI$_{t+1}$	**Payroll$_{t+1}$**	**KCFSI$_{t+1}$**
	(1)	(2)	(3)
$IRRA\_Orthog._t$	0.001	0.0003	-0.15
	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
FV_t^1	-0.11	0.14	-59.48
	0.584 (0.006)	0.029 (0.000)	0.140 (0.000)
FV_t^2	0.06	-0.18	93.59
	0.806 (0.082)	0.002 (0.000)	0.000 (0.851)
VRP_t	-0.05	0.01	-4.88
	0.034 (0.012)	0.062 (0.856)	0.149 (0.584)
BDI_t	-0.04	-0.01	-2.09
	0.159 (0.384)	0.025 (0.014)	0.561 (0.000)
$Term_t$	0.001	0.0002	0.01
	0.018 (0.026)	0.106 (0.949)	0.845 (0.000)
$Default_t$	-0.04	-0.001	0.42
	0.015 (0.002)	0.009 (0.000)	0.030 (0.000)
TED_t	-0.0004	-0.0003	0.77
	0.780 (0.817)	0.430 (0.016)	0.020 (0.003)
SMB_t	-0.0003	-0.0001	0.03
	0.390 (0.890)	0.319 (0.424)	0.038 (0.034)
HML_t	0.0001	-0.00001	-0.02
	0.589 (0.452)	0.765 (0.683)	0.323 (0.000)
$Momentum_t$	-0.005	-0.004	0.30
	0.598 (0.788)	0.023 (0.004)	0.649 (0.288)
$Basis_t$	-0.01	-0.003	0.18
	0.258 (0.016)	0.122 (0.364)	0.769 (0.891)
HP_t	0.013	0.003	0.40
	0.370 (0.889)	0.029 (0.984)	0.481 (0.075)
$Open\ Interest_t$	0.02	0.0001	0.09
	0.240 (0.954)	0.977 (0.722)	0.899 (0.027)
% Adj. R^2	23.29	75.44	88.97

Entries report results from the OLS predictive regressions of growth in industrial production index, growth in nonfarm payroll employment and KCFSI index on previous month orthogonalized implied relative risk aversion (RRA_Orthog.) and a set of other predictors. The forecasting horizon is one month. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *p*-values estimated with a Bartlett kernel, the stationary bootstrapped *p*-values (within parenthesis) and the adjusted R^2 for each model are reported. The sample spans the period August 2002- January 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, $Open\ Interest_t$, IPI_{t+1}, $Payroll_{t+1}$ and $KCFSI_{t+1}$ denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), the variance risk premium, the growth of the Baltic dry index, the term, the default and the TED spreads, the Fama- French (1996) SMB and HML factors, the momentum, basis and hedging-pressure commodity risk factors and the growth of commodity market open interest from time (*t*-1) to *t*, the industrial production index growth rate from *t* to (*t+1*), the nonfarm payroll employment growth rate from *t* to (*t+1*), and the Kansas city financial stress index from *t* to (*t+1*), respectively.

Table 11: Predicting Real Economic Activity with Orthogonalized Implied Risk Aversion

Long Horizons

Panel A: $\mathbf{IPI_{t+h}}$

	3 M	6 M	9 M	12 M
$IRRA\_Orthog._t$	0.001	0.002	0.002	0.002
	3.86 (2.42) [0.000]	3.16 (1.71) [0.000]	2.47 (1.11) [0.000]	1.85 (0.70) [0.000]
FV_t^1	-0.71	-0.38	-0.08	1.03
	-1.24 (-0.76) [0.200]	-0.35 (-0.25) [0.713]	-0.05 (-0.05) [0.961]	0.58 (0.58) [0.559]
FV_t^2	0.47	0.45	0.27	-1.07
	0.80 (0.45) [0.417]	0.45 (0.30) [0.642]	0.22 (0.19) [0.828]	-0.95 (-0.72) [0.342]
VRP_t	-0.06	-0.10	-0.11	-0.03
	-1.46 (-0.91) [0.143]	-1.28 (-0.77) [0.198]	-0.88 (-0.86) [0.370]	-0.20 (-0.21) [0.844]
BDI_t	-0.001	-0.09	-0.23	-0.46
	-0.01 (-0.01) [0.991]	-0.67 (-0.52) [0.506]	-1.00 (-1.30) [0.324]	-1.44 (-2.77) [0.155]
$Term_t$	0.002	0.002	0.001	0.001
	1.85 (1.23) [0.016]	0.92 (0.60) [0.209]	0.48 (0.31) [0.495]	0.43 (0.27) [0.563]
$Default_t$	-0.004	0.003	0.02	0.03
	-0.84 (-0.63) [0.385]	0.38 (0.28) [0.684]	1.54 (1.08) [0.121]	2.78 (1.55) [0.007]
TED_t	-0.01	-0.03	-0.06	-0.09
	-1.94 (-1.08) [0.056]	-2.78 (-2.06) [0.013]	-3.35 (-2.68) [0.003]	-4.21 (-3.40) [0.000]
SMB_t	-0.001	-0.002	-0.003	-0.003
	-1.69 (-1.32) [0.087]	-1.46 (-1.47) [0.146]	-1.64 (-1.93) [0.100]	-1.49 (-1.65) [0.133]
HML_t	0.0002	0.001	0.001	0.002
	0.47 (0.27) [0.576]	0.45 (0.42) [0.599]	0.42 (0.52) [0.603]	1.21 (1.28) [0.127]
$Momentum_t$	-0.01	-0.03	-0.04	-0.08
	-0.82 (-0.52) [0.407]	-0.96 (-1.04) [0.343]	-0.99 (-1.11) [0.333]	-1.63 (-2.02) [0.113]
$Basis_t$	-0.03	-0.04	-0.07	-0.06
	-1.78 (-0.98) [0.083]	-1.27 (-0.87) [0.221]	-1.44 (-1.83) [0.146]	-0.98 (-1.28) [0.355]
HP_t	0.04	0.05	0.08	0.09
	1.78 (1.31) [0.078]	1.23 (1.36) [0.221]	1.19 (1.69) [0.237]	1.04 (1.67) [0.293]
$Open\ Interest_t$	0.03	0.07	0.05	0.03
	1.31 (0.84) [0.192]	1.25 (1.28) [0.217]	0.65 (0.98) [0.507]	0.36 (0.67) [0.721]
% Adj. R^2	48.88	49.72	50.54	53.19

Table 11
(Cont'd)

Panel B: **$Payroll_{t+h}$**

	3 M	6 M	9 M	12 M
IRRA_Orthog.$_t$	0.001	0.002	0.002	0.002
	13.06 (2.02) [0.000]	12.78 (1.66) [0.000]	11.26 (1.31) [0.000]	9.63 (1.10) [0.000]
FV_t^1	0.29	0.48	0.78	1.30
	1.50 (0.28) [0.128]	1.24 (0.32) [0.215]	1.31 (0.44) [0.187]	1.75 (0.61) [0.081]
FV_t^2	-0.44	-0.71	-1.04	-1.53
	-2.25 (-0.34) [0.030]	-2.15 (-0.46) [0.034]	-2.56 (-0.68) [0.016]	-3.32 (-0.93) [0.002]
VRP_t	0.02	0.02	0.02	0.05
	0.88 (0.19) [0.379]	0.54 (0.15) [0.575]	0.43 (0.20) [0.665]	0.68 (0.40) [0.491]
BDI_t	-0.03	-0.06	-0.12	-0.21
	-1.69 (-0.25) [0.094]	-1.76 (-0.34) [0.087]	-2.20 (-0.67) [0.034]	-2.37 (-1.14) [0.022]
$Term_t$	0.001	0.001	0.001	0.002
	1.46 (0.29) [0.038]	1.21 (0.30) [0.084]	1.13 (0.29) [0.104]	1.29 (0.33) [0.060]
$Default_t$	-0.003	-0.003	-0.001	0.003
	-2.09 (-0.37) [0.018]	-1.13 (-0.22) [0.202]	-0.24 (-0.04) [0.779]	0.67 (0.11) [0.470]
TED_t	-0.002	-0.01	-0.02	-0.03
	-1.46 (-0.28) [0.110]	-2.36 (-0.59) [0.015]	-2.98 (-0.85) [0.006]	-3.83 (-1.12) [0.001]
SMB_t	-0.0002	-0.001	-0.001	-0.001
	-1.86 (-0.42) [0.071]	-1.87 (-0.58) [0.065]	-1.72 (-0.63) [0.089]	-1.54 (-0.59) [0.125]
HML_t	-0.00002	-0.0001	-0.0002	-0.0001
	-0.14 (-0.03) [0.846]	-0.44 (-0.12) [0.604]	-0.53 (-0.20) [0.522]	-0.12 (-0.05) [0.886]
$Momentum_t$	-0.01	-0.02	-0.03	-0.04
	-2.20 (-0.41) [0.036]	-2.00 (-0.51) [0.046]	-2.47 (-0.76) [0.014]	-3.24 (-1.08) [0.002]
$Basis_t$	-0.01	-0.01	-0.02	-0.02
	-1.19 (-0.19) [0.244]	-0.66 (-0.17) [0.521]	-0.98 (-0.39) [0.338]	-0.75 (-0.37) [0.469]
HP_t	0.01	0.02	0.03	0.04
	2.41 (0.34) [0.016]	1.83 (0.47) [0.062]	1.51 (0.62) [0.126]	1.39 (0.73) [0.163]
Open Interest$_t$	0.00002	-0.00001	0.0003	-0.003
	0.00 (0.00) [0.998]	0.00 (0.00) [0.995]	0.01 (0.01) [0.987]	-0.10 (-0.07) [0.909]
% Adj. R^2	75.88	73.66	70.92	69.79

Table 11 (Cont'd)

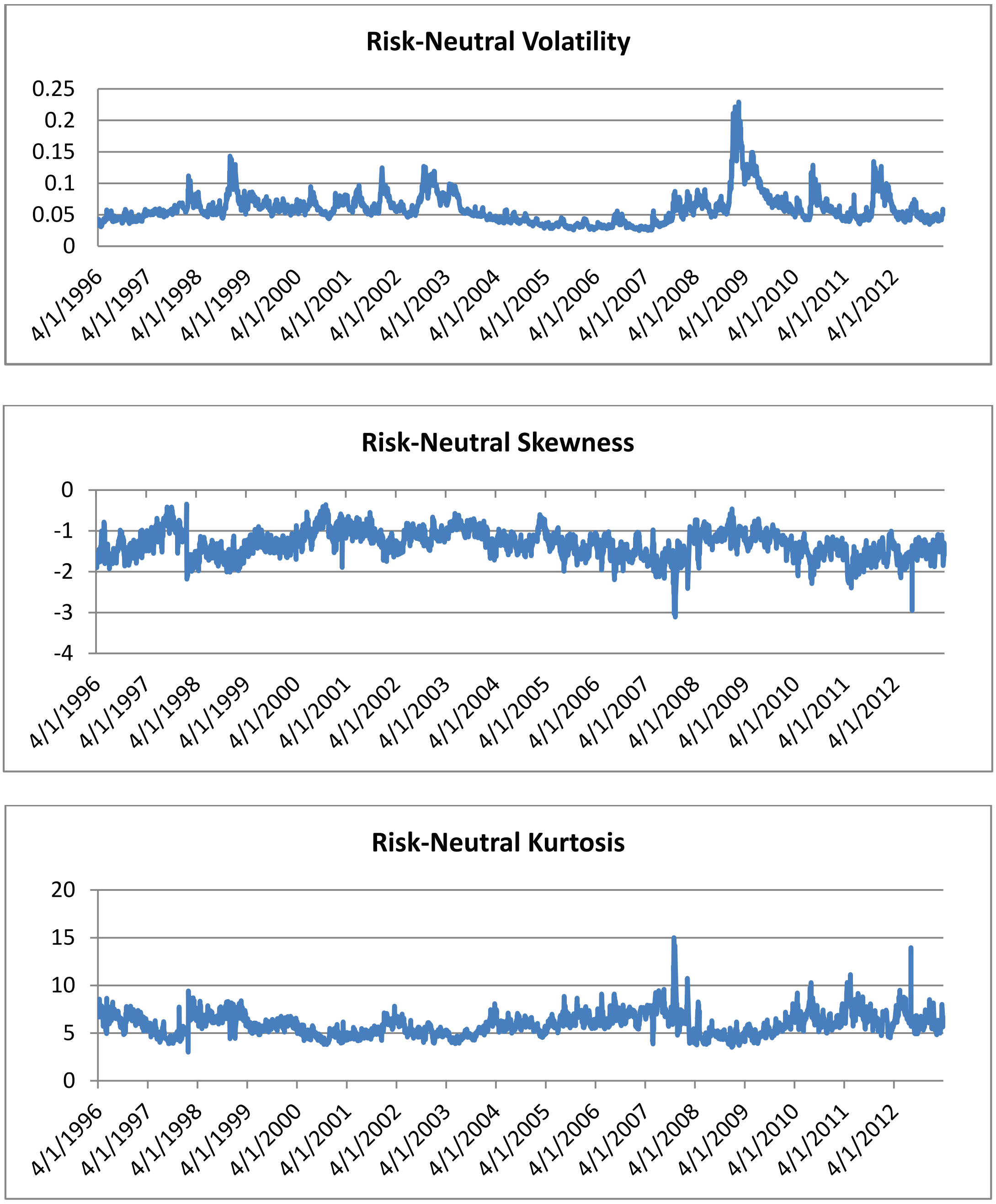
Panel C: KCFSI$_{t+h}$

	3 M	6 M	9 M	12 M
IRRA_Orthog.$_t$	-0.13	-0.09	-0.05	-0.02
	-10.86 (-2.87) [0.000]	-4.75 (-1.02) [0.000]	-2.12 (-0.39) [0.000]	-0.79 (-0.11) [0.068]
FV_t^1	-57.42	-75.00	-106.81	-142.71
	-1.36 (-0.46) [0.162]	-1.58 (-0.47) [0.112]	-2.24 (-0.66) [0.028]	-3.83 (-0.67) [0.002]
FV_t^2	59.68	37.79	57.48	96.36
	2.80 (0.40) [0.011]	1.36 (0.23) [0.180]	1.83 (0.38) [0.074]	2.35 (0.55) [0.024]
VRP_t	-1.64	-3.28	-6.07	-8.92
	-0.41 (-0.26) [0.676]	-1.01 (-0.28) [0.307]	-1.52 (-0.53) [0.125]	-2.49 (-0.59) [0.010]
BDI_t	-0.32	5.94	13.38	10.20
	-0.11 (-0.02) [0.899]	0.96 (0.36) [0.338]	1.28 (0.77) [0.200]	1.14 (0.62) [0.242]
$Term_t$	0.07	0.12	0.02	-0.07
	1.35 (0.46) [0.045]	1.25 (0.43) [0.064]	0.19 (0.05) [0.797]	-0.55 (-0.12) [0.438]
$Default_t$	0.16	-0.26	-0.31	-0.55
	0.68 (0.24) [0.436]	-0.86 (-0.25) [0.379]	-0.85 (-0.21) [0.396]	-1.53 (-0.31) [0.111]
TED_t	1.26	1.85	1.91	2.22
	3.74 (0.98) [0.002]	3.50 (0.87) [0.004]	3.27 (0.66) [0.010]	4.02 (0.67) [0.003]
SMB_t	0.04	0.06	0.01	-0.03
	0.99 (0.58) [0.323]	1.32 (0.51) [0.190]	0.32 (0.10) [0.750]	-1.18 (-0.28) [0.236]
HML_t	-0.01	-0.02	-0.001	-0.07
	-0.38 (-0.15) [0.648]	-0.79 (-0.18) [0.334]	-0.01 (-0.01) [0.988]	-1.73 (-0.53) [0.055]
$Momentum_t$	0.45	0.61	2.12	1.75
	0.44 (0.17) [0.656]	0.58 (0.22) [0.560]	1.45 (0.65) [0.148]	1.21 (0.43) [0.225]
$Basis_t$	-0.95	0.95	-0.39	-1.11
	-1.09 (-0.54) [0.268]	0.48 (0.25) [0.633]	-0.20 (-0.10) [0.843]	-0.68 (-0.27) [0.488]
HP_t	-0.27	-2.44	0.25	3.09
	-0.31 (-0.11) [0.758]	-0.91 (-0.53) [0.369]	0.08 (0.05) [0.927]	1.02 (0.60) [0.288]
Open Interest$_t$	-0.35	-1.52	-0.19	3.45
	-0.17 (-0.09) [0.862]	-0.74 (-0.29) [0.443]	-0.08 (-0.03) [0.930]	1.15 (0.64) [0.249]
% Adj. R^2	71.91	54.14	35.97	46.66

Entries report results from the OLS predictive regressions of growth in industrial production index, growth in nonfarm payroll employment and KCFSI index on previous months orthogonalized implied relative risk aversion (RRA_Orthog.) and a set of other predictors. The forecasting horizon is 3 to 12 months ahead. Implied RRA is estimated using formula (2) with a window of size 30 months. Coefficient estimates, the Newey-West (1994) *t*-statistics with a Bartlett kernel, the Hodrick (1992) *t*-statistics (within parenthesis), the stationary bootstrapped *p*-values (within brackets) and the adjusted R^2 for each model are reported. The sample spans the period August 2002- November 2013. FV_t^1, FV_t^2, VRP_t, BDI_t, $Term_t$, $Default_t$, TED_t, SMB_t, HML_t, $Momentum_t$, $Basis_t$, HP_t, *Open Interest$_t$*, IPI_{t+h}, $Payroll_{t+h}$ and $KCFSI_{t+h}$ denote the Bakshi et al (2011) forward variances from time *t* to (*t*+30) and from (*t*+30) to (*t*+60), the variance risk premium, the growth of the Baltic dry index, the term, the default and the TED spreads, the Fama- French (1996) SMB and HML factors, the momentum, basis and hedging-pressure commodity risk factors and the growth of commodity market open interest from (*t*-1) to *t*, the industrial production index growth rate with horizon 3-12 months, the nonfarm payroll employment growth rate with horizon 3-12 months and the Kansas city financial stress index with horizon 3-12 months, respectively.

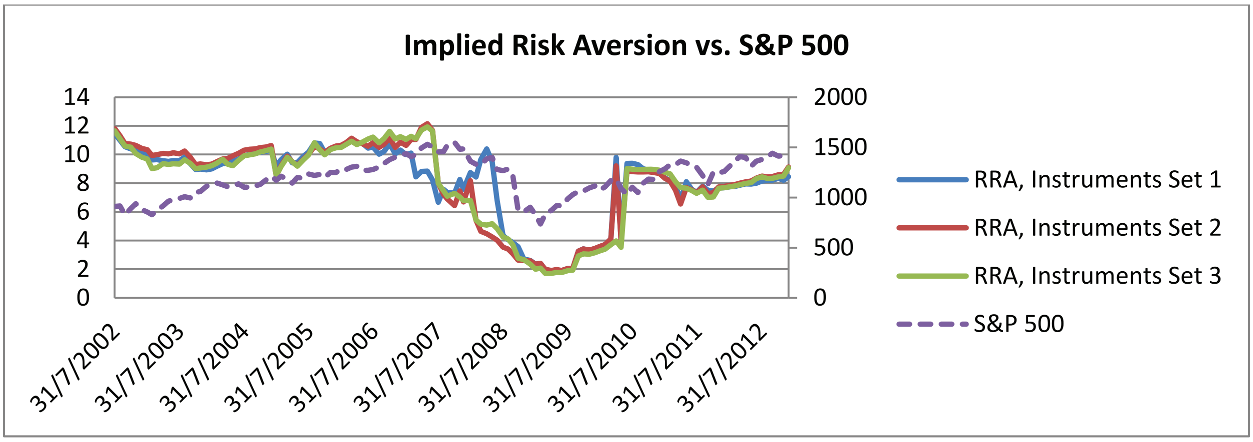
Figures

Figure 1: Time variation of Risk -Neutral Moments



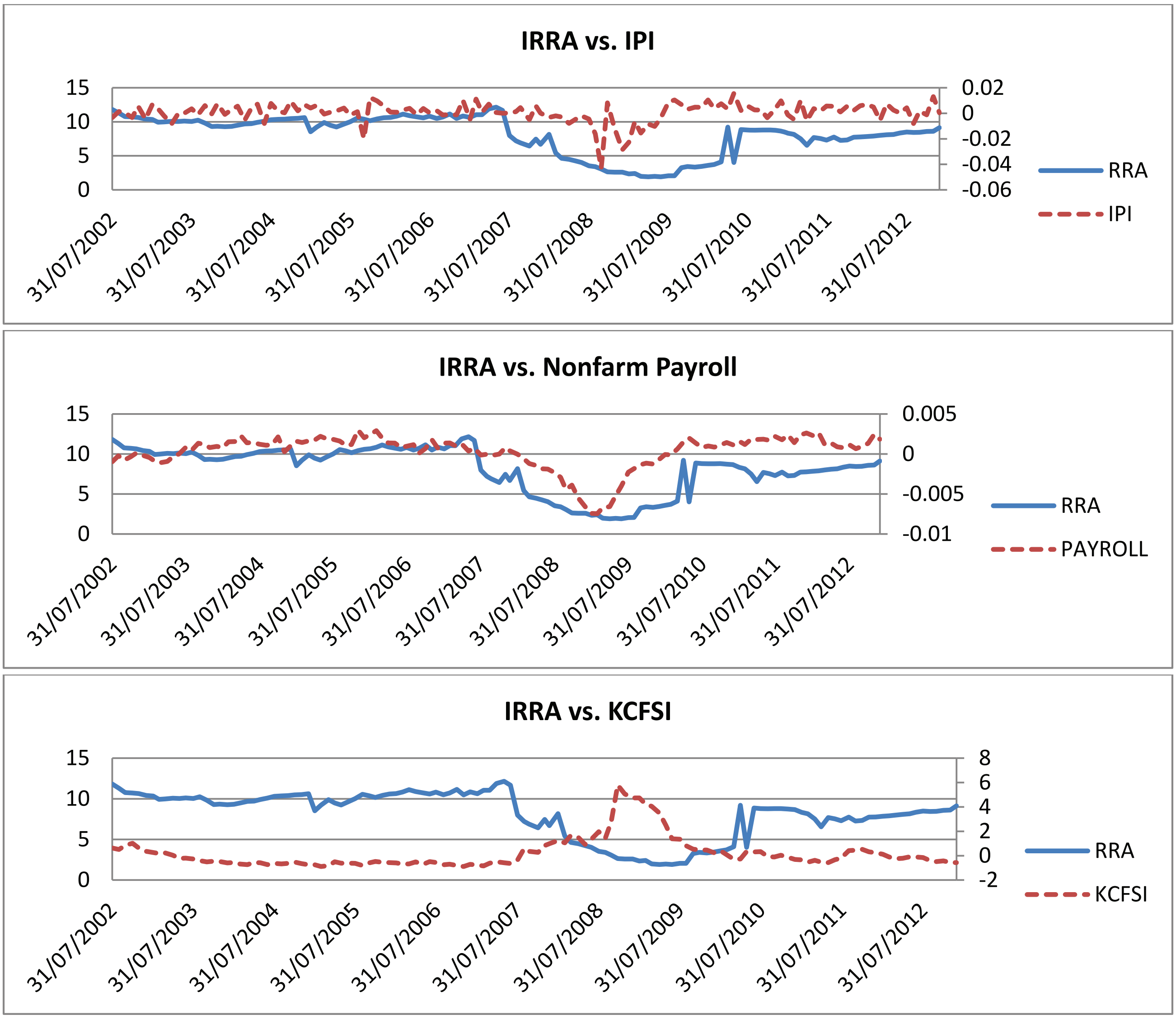
The figure shows the time evolution of the daily S&P 500 risk-neutral volatility, skewness and kurtosis with horizon 30 days over the period January 4th 1996 - December 31st 2012.

Figure 2: Implied Risk Aversion and S&P 500



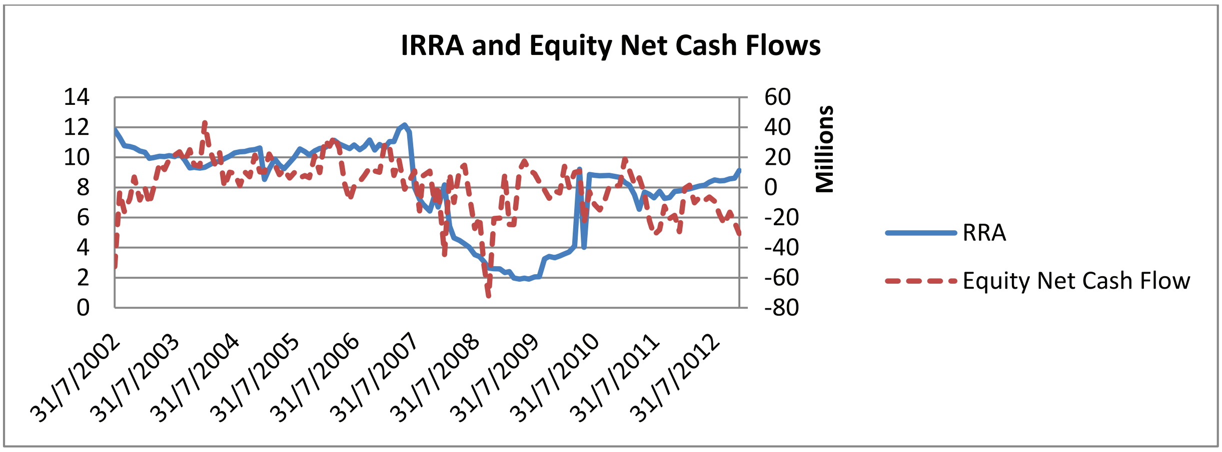
The figure depicts the monthly implied relative risk aversion (IRRA) with a 30 days constant horizon and the S&P 500 over the period July 2002 - December 2012. IRRA is estimated by the Kang, Kim and Yoon (2010) formula using an estimation window of size 30 months. Physical variance is estimated with high-frequency data.

Figure 3: Implied Risk Aversion (IRRA) and the Economy



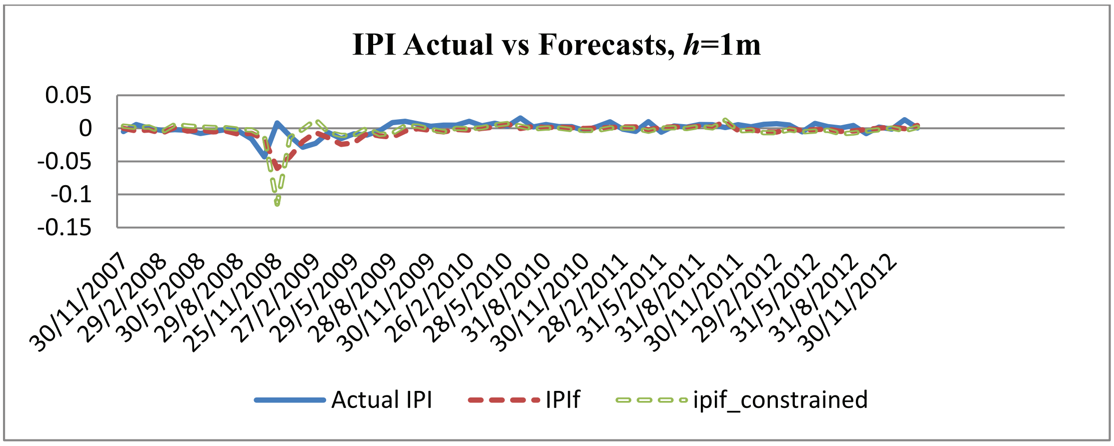
The figure shows the time evolution of the monthly implied relative risk aversion (IRRA) with a 30 days constant horizon and the three proxies of economy. IPI, Nonfarm Payroll and KCFSI denote the monthly growth rates of industrial production index, the nonfarm payroll employment and the Kansas City Financial Stress Index. The sample spans the period July 2002 to December 2012.

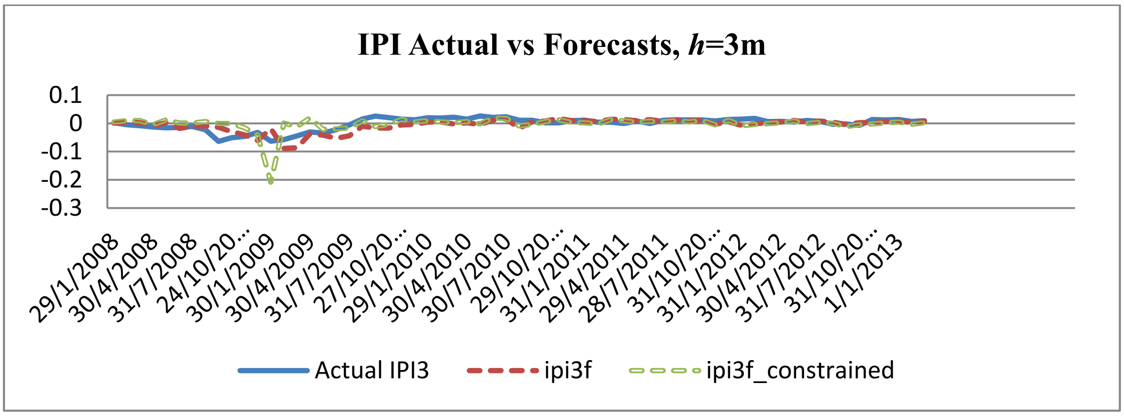
Figure 4: Implied Relative Risk Aversion (IRRA) and U.S. equity funds net flows

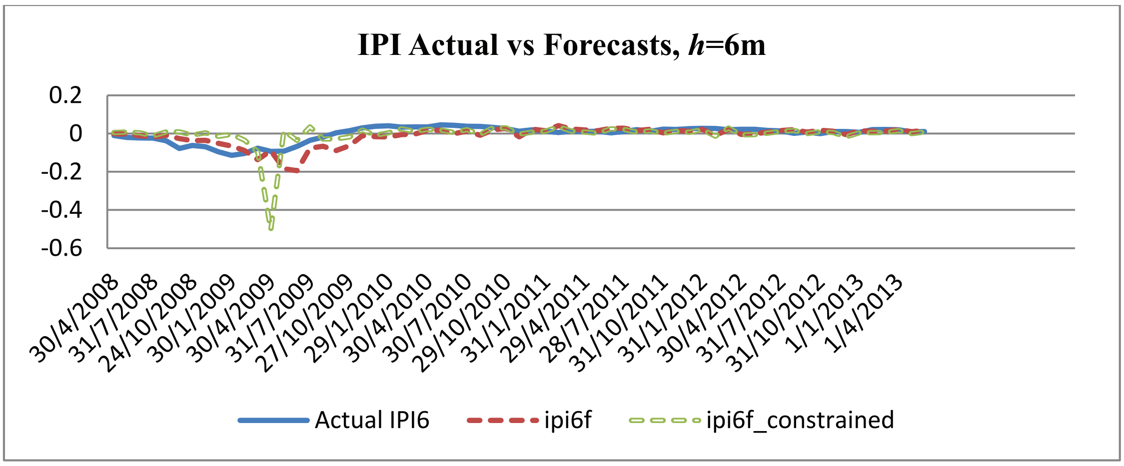


The figure shows the IRRA and the U.S. equities funds net flows time variation. IRRAis estimated using formula (2). Equity net flows are reported in millions U.S. dollars. The graph refers to the period July 2002 - December 2012.

Figure 5: Forecasting real economic activity out-of-sample

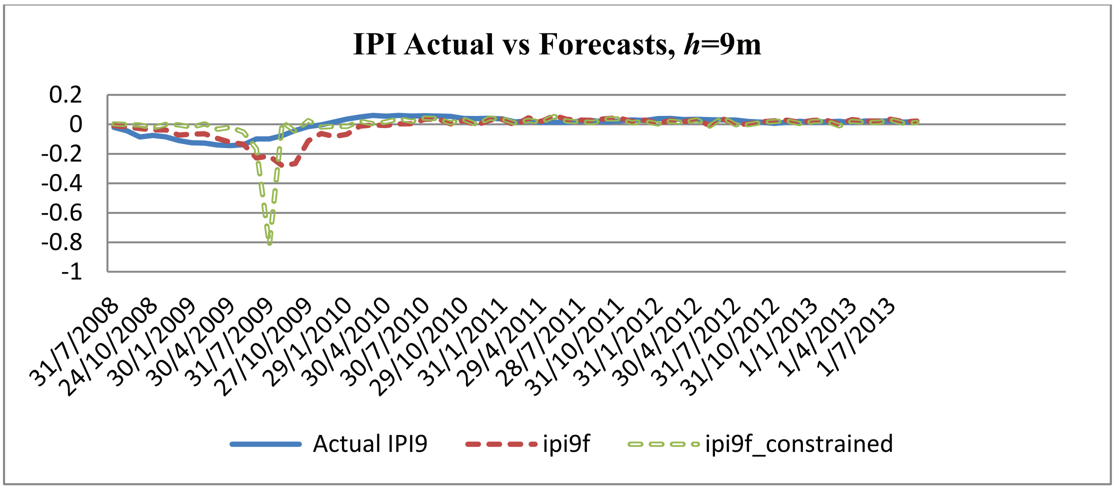


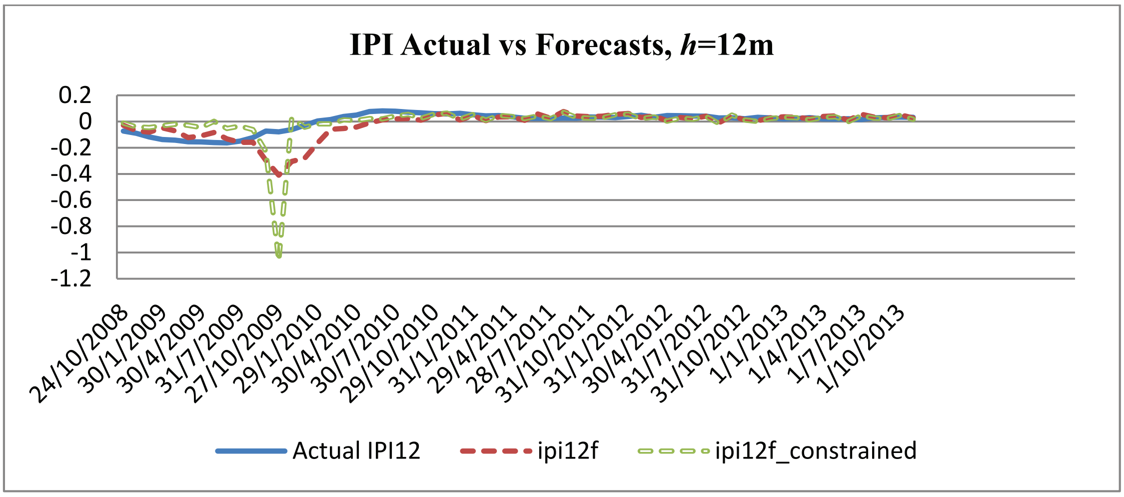




Figures show the out-of-sample forecasts of industrial production growth (IPI) formed by the constrained and full (which contains the option implied IRRA) models [equations (15) and (16), respectively] as well as the IPI realized values. Figures are drawn for forecasting horizons h=1, 3, 6, 9, 12 months.

Figure 5 (cont'd): Forecasting real economic activity out-of-sample





Figures show the out-of-sample forecasts of industrial production growth (IPI) formed by the constrained and full (which contains the option implied IRRA) models [equations (15) and (16), respectively] as well as the IPI realized values. Figures are drawn for forecasting horizons h=1, 3, 6, 9, 12 months.

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