Predictability of Co-movements in Commodity Prices: What is the Role of Technical Indicators

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Abstract: Taking oil futures market as an example, this paper investigates the forecasting ability of technical indicators based on returns and trading volumes (including both commercial and non-commercial positions) to directly forecast the co-movements in commodity prices, and compares their performance with macroeconomic variables. We find that technical indicators based on non-commercial positions do exhibit statistically and economically significant in-sample and out-of-sample forecasting power, clearly exceeding that of pairs based on commercial positions well-known macroeconomic variables. Moreover, the strength of the predictive evidence is robust during recessions and expansions and can detect the typical decline in the future premium near business-cycle peaks effectively, with relatively stronger performance during recessions. This paper therefore provides innovative evidence that index funds impact returns across commodity futures markets from the perspective of technical analysis.

Predictability of Structural Co-movements in Commodity Prices: What is the Role of Technical Indicators

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Keywords: Price predictability; Technical indicators; Commodity returns; Co-movements; Financialization of commodity

1. Introduction

The coincident rise in a broad set of commodity prices and increased numbers of financial participants in the commodity futures market from 2000~2008 has led to allegations that --a speculative bubble could have been partly responsible for the surge in commodity prices (De Schutter 2010; Baffes and Haniotis, 2010) or the commodity index investment directly or indirectly had an impact on commodity futures prices (Röthig and Chiarella, 2007; Brunetti and Buyuksahin, 2009; Gilbert 2009, 2010; Einloth 2009; Medlock III et al., 2009; Khanm, 2009; Robles et al., 2009; Sanders et al., 2010; Sanders and Irwin, 2010; Buyuksahinb and Robe, 2011;Du et al., 2011; Tang and Xiong 2012; Manera et al., 2013; Kilian and Murph, 2014).

However,there is still some opposition. One group of studies criticizes the data andmethods used in these studies, which are subject to criticisms that limit the confidenceone can place in their results. Moreover, another group of studies provides no systematicevidence of a relationship between positions of index funds and the levelof commodity futures prices statistically or economically. The lack of a direct empirical link between indexfund trading and commodity futures prices casts considerable doubt on the beliefthat index funds fueled a price bubble.

Besides, a number of market analysts and economists who attributes the boom-and-bust cycle to a matter of supply and demand express skepticism about the bubble argument, citing logical inconsistencies and contrary facts (e.g., Krugman 2008; Pirrong 2008; Wright 2009;Sanders and Irwin 2008; Trostle 2008; Smith 2009; Hamilton 2009; Harris and Buyuksahin, 2009; Kilian and Murphy 2010; Stoll and Whaley, 2010; Irwin and Sanders, 2010a, b, c; Büyüksahin and Harris, 2011; Capelle and Coulibaly, 2011; Sanders and Irwin, 2011; Bohl and Stephan, 2013; Morana, 2013). Popular explanations are regularly mentioned to explain the recent episodes of price increase of commodities: strong global growth (especially from emerging economies such as China and India), global liquidity imbalance (Caballero, Farhi, and Gourinchas, 2008), easy monetary policy or monetary instability (as reflected in low real interest rates or expected inflation), and risk (possibly resulting from geopolitical uncertainties).Even though over seven years have passed since the 2008 peak in commodity prices, the controversy surrounding index funds continues unabated.These statements illustrate the acrimonious and heated nature of the public policy debate surrounding the role of index funds in commodity futures markets.

In this paper, we aim to complement the existing literature byexploring the forecasting ability of technical indicators based on non-commercial positions (reflect index-based trading activity)and commercial positions (reflect hedge activity), respectively, to directly forecast the structural co-movements of commodityprices, which can test the relation between commodity prices and the trading positions of various types of traders.

Our analysis proceeds in two steps, and contributes to the existing empirical literature along several dimensions.First, wefit a factor model tocharacterize the co-movements in commodity prices.A substantial literature views co-movements as a central and distinctive characteristic of commodityprices, which mainly examine the co-movement in terms of types of commodities (See, Alquist and Coibion, 2013; Byrne, Fazio and Fiess, 2013; West and Wong, 2014).In contrast to the citedpapers, our focus is not on how this factor interacts with macroeconomic variables. Nor do we attemptto model dynamics through lagged factors.Rather,using a Bayesian dynamic latent factor model, we decompose commodity returns into global, sectoral(namely, indexed and off-index sector), and idiosyncratic components. This decomposition measures the extent to which global, sectoral, and commodity-specific components explain the variation in commodity prices, which provides new insights into the genesis of commodity price fluctuations in terms of the significance and the structure of the common dynamic properties of commodity price fluctuations.

In the second step, we aim to investigate the forecasting ability of technical indicators based on both returns andtrading activity to directly forecast the global, sectoral, and commodity-specific components estimated in the first step. Taking the predictability of macro variables as a benchmark, we first compare the predictive ability of technical indicators with that of well-known macroeconomic variables. To parsimoniously incorporate information from many predictors, we also estimate predictive regressionsbased on a small number of principal components extracted from the entire set of technical indicators and/or macroeconomic variables. Moreover, further evidence has also been obtained by comparing thepredictive performance of indexed components and with their off-index correspondents. If the predictive power of technical indicators outperformsthatofmacroeconomic variables, or if the forecasting power of technical indicatorsbased on non-commercial positions clearly exceeds that of pairs based on commercial positions, we therefore able to provide direct and systematic evidence of a relationship between index-basedtrading and the level of commodity futures prices statistically or economically.In comparing the technical andmacroeconomic predictors, we consider not only the level of returns but the level of volatilities as well. We generate all forecasts in a standard predictive regression framework, wherethe return or volatility is regressed on a constant and the lag of a technicalindicator or macroeconomic variable. We provide both in-sample and out-of-sample forecasts as well as evidence across recessions and expansions, including business-cycle peaks and troughs. Our results confirm the significance of direct effect between index-basedtrading and commodity futures prices from the perspective of technical analysis. It is of particular relevance for recent policy discussions about the potential role of speculation in commodity markets after 2004.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the dynamic latent factor model, and outlines how we estimate it and presents factor model estimation results. Section 4 reports the regression results relating the forecasting power of technical indicators. Section 5 provides robustness checks. Section 6 offers the conclusions.

2. Data and indicators

2.1Commodities

The empirical results are estimated using a broad monthly data set of commodities from six regions, including both indexed and off-index, starting in January 1991 and ending in December 2014. The data are obtained from DataStream. The commodities under consideration contain 26 kinds of first-month futures contracts, including energy, precious and industrial metals, industrials, livestocks, and softs.

We calculate monthly returns as the change in log price, using averagedprices during periods. Concerning volatility,we assume that it is fixed within periods (in this paper, months) but variable across periods. Thus, following Garman and Klass (1980) and Alizadeh et al. (2002), we calculate monthly volatilities based on weekly averages, and the weekly return volatilities are estimatedby using weekly high, low, opening and closing prices obtained from underlying daily high, low, open and close data from the Monday open to the Friday close:

$$\begin{aligned}\sigma_t^2 = {} & 0.511(H_t - L_t)^2 - 0.019\left[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)\right] \\ & - 0.383(C_t - O_t)^2\end{aligned}, \tag{7}$$

where H_t is the Monday-Friday high, L_t is the Monday-Friday low, O_t is the Monday open and C_t is the Friday close (all in natural logarithms). Descriptive statistics for returns and volatilities are provided in Tables 1.

[Insert Table 1 Here]

2.2 Technical indicators

To investigate the predictive ability of technical indicators, 22 technical indicators are established on unique data from the U.S. Commodity Futures Trading Commission (CFTC) following three popular trading rules, namely moving-average rule, momentum rule, and on-balance volume rule.These indicators are representative of quantitative strategies analyzed popularly in the academic literature (Sullivan et al., 1999; Miffre and Rallis, 2007; Szakmary et al., 2010; Fuertes et al., 2010).Due to limited space, we select indicators generated from WTI crude oil in details as a representative.

The moving-average (MA) rule is mechanical trading rule that attempt to capture trends. It generates a buy or sell signal ($S_{i,t} = 1$ or $S_{i,t} = 0$, respectively) at the end of t by comparing two moving averages:

$$S_{i,t} = \begin{cases} 1 & if \quad MA_{s,t} \geq MA_{l,t} \\ 0 & if \quad MA_{s,t} < MA_{l,t} \end{cases}, \tag{1}$$

where

$$MA_{j,t} = (1/j)\sum_{i=0}^{j-1} P_{t-i} \text{ for } j = s, l, \tag{2}$$

P_t is denoted as the level of a specific commodity futures price, and s or l is the length of the short or long MA ($s < l$), respectively. We set the MA indicator with short and long lengths s and l by MA(*s*,*l*). The MA rule is sensitive about changes in price trends through the formulas intuitively, for the short MA will be more sensitive to immediate price movement than the long MA. Specifically speaking, once prices have recently been falling, the short MA will lower quickly than the long MA; conversely, when prices begin to trend upward, the short MA responds faster than the long MA, eventually exceeding the long MA and generating a buy signal. In empirical analysis, we study monthly MA rules with s = 1, 2, 3, 6 and l = 9, 12, that is MA(1,9), MA(1,12), MA(2,9), MA(2,12), MA(3,9), MA(3,12), MA(6,9) and MA(6,12).

The second strategy is based on momentum (MOM), which generates a buy or sell signal ($S_{i,t} = 1$ or $S_{i,t} = 0$, respectively) at the end of t by comparing the current crude oil futures price and its level *m* periods ago:

$$S_{i,t} = \begin{cases} 1 & if \quad P_t \geq P_{t-m} \\ 0 & if \quad P_t < P_{t-m} \end{cases}, \tag{3}$$

Intuitively, this strategy is a simple trading rule whereby past returns on assets being investigates, then take long positions in assets that performed relatively well and short positions in assets that performed relatively poorly. In particular, if a crude oil futures price is higher than its level *m* periods ago, it indicates “positive” momentum and relatively high expected excess returns, thereby generating a buy signal; and vice versa. We denote the momentum indicators that compares P_t to P_{t-m} by MOM(*m*), and we use monthly signals for m = 1, 2, 3, 6, 9, 12, that is MOM(1), MOM(2), MOM(3), MOM(6), MOM(9) and MOM(12).

The third strategy is on-balance volume averages (Blume et al., 1994), which is combined with past prices to identify market trends. It involves subtracting from the indicator the entire amount of volume when the closing price increases (decreases). It forms a trading signal ($S_{i,t} = 1$

or $S_{i,t} = 0$, respectively) at the end of t by comparing two moving averages based on OBV_t as:

$$S_{i,t} = \begin{cases} 1 & if \quad MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0 & if \quad MA_{s,t}^{OBV} < MA_{l,t}^{OBV} \end{cases}, \tag{4}$$

where

$$MA_{j,t}^{OBV} = (1/j)\sum_{i=0}^{j-1} OBV_{t-i}, \tag{5}$$

$$OBV_t = \sum_{k=1}^{t} VOL_k D_k, \tag{6}$$

D_k is a binary variable that takes a value of 1 if $P_k - P_{k-1} \geq 0$ and -1 otherwise, and VOL_k is a measure of position data during period k .The position data utilized in this study comes from the CFTC's Large Trader Reporting System (LTRS) which is a collection of position-level information on the composition of open interest across all futures and options-on-futures contracts for each market. It is collected by the CFTC's market surveillance staff to help the Commission fulfill its mission of detecting and deterring futures market manipulation.

The CFTC publishes a weekly Commitment of Traders (COT) report in which traders are pooled into two broad categories: commercial and non-commercial. A trading entity is generally classified as "commercial" when it files a statement with the CFTC that indicates it is commerciallyengaged in business activities hedged by the use of the futures or option markets, consisted of dealers, producers, manufacturers, and other entities typically involved with commodities. "Non-commercials" are mostly financial traders, such as hedge funds, mutual funds, and floor brokers and traders whose positions are reported even though they are not registered with the CFTC under the Commodity Exchange Act. Therefore, the hedging and speculating are often considered opposing activities and are generally identified with commercial and non-commercial traders.Although the publicly available COT dataare widely used in academic research, we areaware of their shortcomings, most notably withrespect to the frequency, the high degree ofaggregation, and the trader classification (e.g., Büyüksahin and Harris, 2011). However, tomake our results comparable to previous studies,we stick to the COT data set and drawcareful conclusions.

As the formula indicates, relatively high recent volume together with recent price increasing illustrates a strong positive market trend and generates a buy signal. Like the moving-average strategy, we set monthly signals for s = 1, 2, 3, 6 and l = 9, 12, that is VOL(1,9), VOL(1,12),

VOL(2,9), VOL(2,12), VOL(3,9), VOL(3,12), VOL(6,9) and VOL(6,12).

2.3 Macroeconomic variables

To compare the performance of technical indicators to that of macroeconomic variables, we also investigate the capacity of macroeconomic indicators. As macroeconomic predictors, we consider a set of 22 macro variables. The first thirteen variables are from the literature on stock return predictability (Goyal and Welch, 2008):1) Book-to-market ratio, BM: book-to-market value ratio for the Dow Jones Industrial Average;2) Treasury bill rate, TBL: interest rate on a three-month Treasury bill (secondary market);3) Long-term yield, LGB: ten-year government bond yield;4) Term spread, TermS: long-term yield minus the Treasury bill rate;5) Inflation, CPI (log): calculated from the Consumer Price Index (CPI) for all urban consumers; 6) Dividend-price ratio (log), DP: log of a twelve-month moving sum of dividends paid on the S&P 500 index minus the log of the S&P 500 index; 7) Dividend yield (log), DY: log of a twelve-month moving sum of dividends minus the log of lagged stock prices;8) Earnings-price ratio (log), EP: log of a twelve-month moving sum of earnings on the S&P 500 index minus the log of stock prices; 9) Lettau-Ludvigson Consumption-wealth ratio, CAY, a successful predictorof forecastinglong-term income growth and stock returns; 10)Stock variance, SVAR: the sum of squareddaily returns on the S&P 500; 11)Net equity expansion, NTIS: the ratio of 12-monthmoving sums of net issues by NYSE listed stocks divided by the totalend-of-year market capitalization of NYSE stocks; 12) Default yield spread,DFY: the difference betweenBAA and AAA-rated corporate bond yields; 13)Investment to capital ratio, IK: theratio of aggregate (private nonresidential fixed) investment to aggregatecapital for the whole economy.These series are constructed by Goyal and Welch (2008), and are available and updated on the authors' website.

The second set of variables aims to measure the board state of the economy. Specifically, we use the following six macro variables: 14) The unemployment rate, UER: the unemployment rate in USA; 15) Money supply growth (log), MS2: the growth of the monthly US money supply (M2); 16) Growth in industrial production, IIP: the monthly growth in the USIndustrial Production Index; 17) Capacity utilization in manufactory, CUM: the capacity utilization in manufactory index; 18) Purchasing Managers' Index, PMI: the monthly PMI in USA, an indicator of the economic health of the manufacturing sector.To track the demand for commodities in global markets, we use19) Real global activity, KI: the Kilian's (2009) real global economic activity index.Becausetrading of commodityis dominated in the US dollars, we also include20) U.S. trade-weighted real exchange rate, USDX: Realtrade weighted U.S. Dollar Index(Broad).These series can be obtained from the Federal Reserve Bank of St. Louis.

The third set of variables refers to fluctuations in demand and supply pressures in commodity markets, taking oil as an example. As to supply, we consider 21) Production of crude oil, FPO: log of the U.S. field production of crude oil (thousand barrels), which is widely used in reports published by U.S. Energy Information Administration (EIA), International Energy Agency (IEA), etc. To capture information from financial markets, we include 22) Returns and excess returns on oil company stocks, OI: log of NYSE Arca oil index.

Table 2 reports summary statistics for the monthly data during January 1991 to December 2014 for22 macroeconomic variables. The KI has the highest volatility amongst the variables, while the CPI is the most stationary variable.With the exception of MS2, the auto-correlation of 21 macroeconomic variables are nearly 1. All the variables do not follow the normal distribution as evidenced by the Jarque-Bera statistics since the null hypothesis that the variables are normally distributed is rejected for all cases.

[Insert Table 2 Here]

3. The dynamic indexed and off-index factors

3.1 Econometric methodology

We extract indexed and off-index factors by applying a dynamic latent factor model proposed by Kose et al. (2003, 2008). This approach models co-variation among many variables in a unified framework, as a function of a small number of latent factors rather than using pair-wise correlations and related techniques that are difficult to summarize. Kose et al. (2008), among others, have recently widely used this method to study international co-movements in real macroeconomic variables. For example, Yin and Han (2015) characterizes the co-movements in commodity prices with this model that decomposes commodity returns into global, sectoral, and idiosyncratic components.

Following Kose et al. (2003), we suppose that there are three types of factors: the single global factor (f_t^w)[1], J sectoral factors ($f_{j,t}^s$, one each for each sector) and N commodity-specific factors ($f_{n,t}^c$, one per commodity). Therefore, the model is given by:

$$y_{i,t} = \beta_i^w f_t^w + \beta_i^s f_{j,t}^s + \beta_i^c f_{n,t}^c + \varepsilon_{i,t}\,, \tag{7}$$

where $y_{i,t}$ is the demeaned log returns for commodity i ($i = 1,..., N$) from month $t-1$ to t ($t = 1,...,T$). The global factor, f_t^w , is common across all of the $N = 26$ commodity returns. The sectoral factors, $f_{j,t}^s$ $(j = 1, 2, \cdots, J)$, are common to the commodities in each of $J = 2$ specific sectors, namely indexed commodities and off-index commodities. The $f_{n,t}^c$ is the specific component of commodity i 's return, which captures purely specific influences on return. The loadings, β_i^w , β_i^s and β_i^c , measure the responses of an individual commodity's return to changes in the global, sectoral and commodity-specific factors, respectively. To ensure that β_i^w , β_i^s and β_i^c sum to one, we follow Kose et al. (2003) and orthogonalize the factors (using the global, sectoral, commodity-specific factor ordering) whencomputing the variance decompositions at each replication. Since the sample correlations are small, this has little influence on the results. The idiosyncratic errors $\varepsilon_{i,t}$ are assumed to be normally distributed, butmay be serially correlated.We assume that $\varepsilon_{i,t}$ follows an AR(p) process:

$$\varepsilon_{i,t} = \rho_{i,1}\varepsilon_{i,t-1} + \cdots + \rho_{i,p}\varepsilon_{i,t-p} + u_{i,t}\,, \tag{8}$$

where $u_{i,t} \sim \left(0, \sigma_i^2\right)$, and $E\left(u_{i,t}u_{i,t-s}\right) = 0$ for $s \neq 0$ .The evolution of the factors f_t^w , $f_{j,t}^r$ and $f_{n,t}^c$ are likewise governed by an auto-regression, of order q with normal errors:

$$f_t^w = \rho_1^w f_{t-1}^w + \cdots + \rho_q^w f_{t-q}^w + u_t^w\,, \tag{9}$$

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[1] To attempt to discover whether there are really two global factors or more, we study a variety of dynamic systems with multiple global factors. However, we find no significant evidence of a second global factor. Therefore, we choose a simplified model which employs one global factor that all commodities share.

$$f_{j,t}^{s} = \rho_{j,1}^{s} f_{j,t-1}^{s} + \cdots + \rho_{j,q}^{s} f_{j,t-q}^{s} + u_{j,t}^{s}, \quad (j = 1, 2, \cdots, J), \tag{10}$$

$$f_{n,t}^{c} = \rho_{n,1}^{c} f_{n,t-1}^{c} + \cdots + \rho_{n,q}^{c} f_{n,t-q}^{c} + u_{n,t}^{c}, \quad (n = 1, 2, \cdots, N), \tag{11}$$

where $u_t^w \sim \left(0, \sigma_w^2\right)$, $u_{j,t}^s \sim \left(0, \sigma_{j,s}^2\right)$, $u_{n,t}^c \sim \left(0, \sigma_{n,c}^2\right)$ and $E\left(u_t^w u_{t-s}^w\right) = E\left(u_{j,t}^s u_{j,t-s}^s\right) = E\left(u_{n,t}^c u_{n,t-s}^c\right) = 0$ for $s \neq 0$.

Thus, Eq. (7) is a dynamic latent factor model. In line with standardin the literature, we assume that the shocks in (8)-(11) are uncorrelated contemporaneously and uncorrelated atall leads and lags, so that the global, sectoral, and commodity-specific factors are orthogonal. We setthe orders of the AR processes, p and q, equal to two whenestimating the dynamic factor model.Other non-zero values for p and q produce similar results.

We reiterate that the dynamic factor model attributes all of the co-movements in commodity returns to the global and sectoral factors via the factor loadings. In theextreme, a commodity with $\beta_i^w = \beta_i^s = 0$ will have a return that is completely idiosyncratic($y_{i,t} = \beta_i^c f_{n,t}^c + \varepsilon_{i,t}$), displaying no co-variation with other commodities' returns.To normalize the signs of the factors/loadings, we follow a strategy similar to Kose et al. (2003) and restrict the loading on the global factor for Corn andthe loadings on the sectoral factors for Corn and Oatto be positive. Tonormalize the scales, we also assume that each of the factor shock variances, σ_w^2 and $\sigma_{j,s}^2$ $(j = 1, 2, \cdots, J)$, is equal to one. The sign and scalenormalizations do not have any economic content and do not affect any economic inference.

To save space we do not report the procedure, interested readers can refer to Otrok and Whiteman (1998) and Kose et al. (2003) whichdetail the estimation procedure.To implement Bayesian analysis,we use the following conjugate priors, which are similar to those used in Kose et al. (2003):

$$\left(\beta_i^w, \beta_i^s, \beta_i^c\right)' \sim N\left(0, I_3\right), \ (i = 1, 2, \cdots, N), \tag{12}$$

$$\left(\rho_{i,1}, \cdots, \rho_{i,p}\right)' \sim N\left[0, diag\left(1, 0.5, \cdots, 0.5^{p-1}\right)\right], \ (i = 1, 2, \cdots, N), \tag{13}$$

$$\left(\rho_1^w, \cdots, \rho_q^w\right)' \sim N\left[0, diag\left(1, 0.5, \cdots, 0.5^{q-1}\right)\right], \tag{14}$$

$$\left(\rho_{j,1}^s, \cdots, \rho_{j,q}^s\right)' \sim N\left[0, diag\left(1, 0.5, \cdots, 0.5^{q-1}\right)\right], (j = 1, 2, \cdots, J), \tag{15}$$

$$\left(\rho_{n,1}^{c},\cdots,\rho_{n,q}^{c}\right)' \sim N\left[0, diag\left(1, 0.5, \cdots, 0.5^{q-1}\right)\right], \ (n=1,2,\cdots,N), \tag{16}$$

$$\sigma_i^2 \sim IG\left(6, 0.001\right), \ (i=1,2,\cdots,N). \tag{17}$$

where $IG(\ )$ denotes the inverse-gamma distribution, and the prior on the innovation variances is quite diffuse. Experimentation with tighter and looser priors for both the factor loadings and the autoregressive parameters do not produce qualitatively important changes in the results. As noted in Otrok and Whiteman (1998), Equations (13)-(17) imply that the prior distributions for the AR parameters become more tightly centered on zero as the lag length increases.

In particular, taking starting values of the parameters and factors as given, we *first* sample from the posterior distribution of the parameters conditional on the factors; *next* we sample from the distribution of the global factor conditional on the parameters and the commodity-specific and sectoral factors; *then* we sample each sectoral factor conditional on the global factor and the commodity-specific factors in that sector; *finally*, we complete one step of the Markov chain by sampling each commodity-specific factor conditioning on the global factor and the appropriate sectoral factor. This sequential sampling of the full set of conditional distributions is known as "Gibbs sampling". Under regularity conditions (Eqs.(12)-(17)), the Markov chain produces converges, and yields a sample from the joint posterior distribution of the parameters and the unobserved factors, conditioned on the data. The sampling order within each step is irrelevant. We in fact experimented with changing the order, and the results obtained are robustness.

We measure the extent of global influences on each commodity by computing the global factor's contribution to the total variability in a commodity's return. This variance decomposition is straightforward to compute for orthogonal factors:

$$\theta_i^w = \left(\beta_i^w\right)^2 \mathrm{var}\left(f_t^w\right) \big/ \mathrm{var}\left(y_{i,t}\right), \tag{18}$$

where

$$\mathrm{var}\left(y_{i,t}\right) = \left(\beta_i^w\right)^2 \mathrm{var}\left(f_t^w\right) + \left(\beta_i^s\right)^2 \mathrm{var}\left(f_{j,t}^r\right) + \left(\beta_i^c\right)^2 \mathrm{var}\left(f_{n,t}^c\right) + \mathrm{var}\left(\varepsilon_{i,t}\right), i=1,2,\cdots,N, \tag{19}$$

and θ_i^w is the proportion of the total variability in commodity i's return attributable to the global factor. The relative magnitudes of θ_i^w and θ_j^w depend on both the factor loadings and relative volatility of return in commodities i and j. θ_i^s and θ_i^c (the proportions of the total variability in commodity i's return attributable to the sectoral factor and specific factor, respectively) are defined similarly.

3.2 Properties of the dynamic factors

Figures 1 and 2 depict means of the posterior distributions for the global, indexed and off-index factors in term of price level and return. The estimated factor series is naturally interpreted as a normalized index of corresponding commodity returns.

[Insert Figure 1 Here]

[Insert Figure 2 Here]

According to Figure 1, the global factor is relatively steady before 2004s and spends a decline period during 1999~2004. At the beginning of 2005, it increases substantially with a notable uptick from 0.95 to 1.05, which could be explained by the emergence of commodity index investment. It also shows a sharp downturn during late 2008 financial crisis with 1.1 decreasing to 1.0, thus clearly supporting a synchronized fall in prices of a broad set of commodities. As the the US economy starts to recover from the recession in 2012, the global factor increases again from about 1.03 to 1.1, suggesting the surge of commodity index investment. The estimated indexed factor performs similarly to the global factor. The significant fluctuations generally help to detect significant co-movements across sectors, after accounting for global-wide co-movements, and 2004 can be regard as an interval. After 2004, the fluctuation of estimated indexed factor shows the same trend as the global factor with severe alteration and some portending change.

However, there are notable differences between off-index factor and the indexed factor, indicating that these two factors play different roles at different points over time and around the globe, which should be distinguished. The indexed factor shows broadly fluctuant and reveals the similar tendency with the global factor. On the contrary, the off-index factor seems to be more steady during the period in Figure 1 with it fluctuation less than 0.01.

Similar results can also be found in Figure 2, which further illustrates the complementary roles of these two types of factors. The movements in the indexed returns in are much more abrupt, whereas the off-index return displays a relatively smooth pattern. In accord with those preliminary results, it can be supported that the commodity prices may be driven by commodity index investment.

3.3 Variance decompositions

We turn next to the estimates of the variance decompositions, the key metric for assessing the degree of co-movements in commodity returns. Table 3 reports averages across various commodity sectors of the means, as well as 0.05 and 0.95quantiles for the posterior distributions.

On average, the global factor explains a significant fraction of the commodity prices fluctuations. The average estimate for global factor is 16.68%, while the average estimates for sectoral and commodity-specific factors are 18.53% (64.79%). The global and sectoral shocks together account for roughly one third (35.21%) of commodity prices fluctuations, indicating significant co-movements characteristic in commodity markets. However, these effects exhibit significant difference across sectors. Notably, the global and sectoral factors of indexed sector edge out their pairs of off-index sectoral as dominant, which explain roughly half (44.09%) of commodity prices fluctuations, though both play important roles. The high explanatory power for the global factors of indexed sector contrasts with the low explanatory power of global factor of off-index sector, which explains 22.04% of price volatility in indexed sectors. Similar to global factors, the sectoral factors also accounts for 22.05% of price variability for indexed sector, whereas it plays a relatively minor role in off-index sector, with the value of only 10.63%.

[Insert Table 3 Here]

4. The dynamic factors forecast based on technical indicators

Krugman (2008), Hamilton (2009) and Kilian and Murphy (2010) illustrate the acrimonious and heated nature of the public policy debate surrounding the role of index funds in commodity market. Thus, this part aims to compare the forecasting ability of technical indicators based on both returns and trading activity to directly forecast the global, sectoral, and commodity-specific components estimated in the first step. If the predictive power of technical indicators outperforms the effects of macroeconomic factors, therefore a direct empirical link between index fund trading and commodity futures prices is supported, casting considerable doubt on the belief that strong demand growth from emerging economies fuel a price bubble.

Our study focuses on three questions. First, do technical indicators possess stronger predictive power than that of macroeconomic variables for common factors of commodity returns? To address this issue, we explore both in-sample and out-of-sample predictability for the global and sector factors over the period 1991-2014, taking the predictability of macro variables as the benchmark. Employing both in-sample and out-of sample tests helps to establish the robustness of our results.

Second, does the predictability depend on the underlying economic state? The evidence obtained in traditional financial markets suggests that the predictability of asset returns is largely confined to economic recessions. Clearly, it is of interest to see whether a similar finding carries over to commodity markets, in which the state of the economy would be expected to play an important role. We address this question by considering the strength of the predictive evidence during recessions and expansions separately. Due to limited space, we report the forecast results by technical indicators generated from WTI crude oil in details as a representative, and the results for other indexed commodities are very similar.

4.1 In-sample analysis

4.1.1 Bivariate predicative regressions

Following studies on predictability, we first consider simple univariate prediction models, which could reveal the marginal predictive power of individual predictor variables. The regressions are specified as follows:

$$r_{t+1} = \alpha_i + \beta_i S_{t,i} + \varepsilon_{t+1,i}\ , \tag{20}$$

where r_{t+1}, is the factors from period to $t+1$; $S_{t,i}$ performs as a predictor (e.g., MA(1,9)) that is available at period t; and $\varepsilon_{t,i}$ is a zero-mean disturbance term. When the null hypothesis of no predictability is $\beta_i = 0$, Eq. (20) reduces to the constant expected oil return model.

To directly compare the macroeconomic variables with the factors forecasts based on technical indicators, we evaluate the macroeconomic variables by replacing $S_{t,i}$ in Eq. (20) with $x_{t,i}$, which takes the following formulation:

$$r_{t+1} = \alpha_i + \beta_i x_{t,i} + \varepsilon_{t+1,i}\ , \tag{21}$$

where the denotations of r_{t+1}, α_i, β_i, $\varepsilon_{t,i}$ are the same as those for Eq. (20).

Econometrically, in line with Inoue and Kilian (2004), who recommend a one-sided alternative hypothesis to increase the power of in-sample predictability tests, we define $x_{t,i}$

such that β_i is expected to be positive under the alternative, and we also test $H_0 : \beta_i = 0$ against $H_A : \beta_i > 0$ using a heteroskedasticity-consistent *t*-statistic that corresponds to $\hat{\beta}_i$, the OLS estimation of β_i in Eq. (21). Because $S_{t,i} = 1$ $\left(S_{t,i} = 0\right)$ represents a buy (sell) signal, we test $H_0 : \beta_i = 0$ against $H_A : \beta_i > 0$ using a heteroskedasticity-consistent *t*-statistic corresponding to $\hat{\beta}_i$, the OLS estimation of β_i in Eq. (20).

In addition, a wild bootstrap procedure is used to compute *p*-values in order to address the well-known Stambaugh (1999) bias because otherwise, the test size of the $\hat{\beta}_i$ *t*-statistic in Eqs. (20)-(21) would be distorted, especially when $x_{t,i}$ or $S_{t,i}$ is highly persistent. This procedure has been widely used because it accounts for not only the persistence in regressors and correlations between factors and predictor innovations but also general forms of heteroskedasticity. Furthermore, based on Elliott and Müller (2006), we adopt the $\widehat{qLL}$ statistic for in-sample regression, testing the null hypothesis that the intercept and slope coefficients are constant with Eq. (20).

[Insert Table 4 Here]

Panels A and B in Table 4 shows estimates of β_i for the bivariate predictive regressions given by Eqs. (20)-(21), together with heteroskedasticity-consistent *t*-statistics, and an R^2 statistic for Return Global Factor (Ret_g), Return indexed Factor (Ret_i) and Return offindex Factor (Ret_o), respectively. Generally speaking, technical indicators and macroeconomics variables show different forecast ability for three factors. For Ret_g and Ret_i, although there is reasonable evidence of predictive ability for macroeconomic variables, a large range of technical indicators clearly display stronger predictive power, especially for MOM indicators all significant. For three technical strategies, short period technical indicators seem to reveal better prediction capacity than long period. Values for the *R*-square statistic show similar evidence. The R^2 values for significant technical indicators are more than 0.5%[2]. Hence, the technical

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[2] As with stock returns, monthly commodity returns may inherently contain a substantial unpredictable component. Therefore, a monthly R^2 near 0.5% can represent economically significant predictability or can generate significant economic value (Kandel and Stambaugh,

indicators outperform all of the individual economic predictors in forecasting the monthly market returns in-sample. Compared with the technical indicators, the macroeconomic variables are less effective in intuitive forecasts. Out of the 22 macro variables, only less than 5 of which exhibit significant predictive abilities for Ret_gand Ret_i with relatively smaller R^2 values than technical indicators.

However, prediction for Ret_o seems manifest opposite results. The forecast ability of technical indicators is not strong for long term MA and VOL indicators are insignificant. The R^2 results also lower. The macroeconomics variables show relatively stronger forecasts for there are 7 variables, TermS, DFY, BM, SVAR, UER, KI and OI significant at 1% or 5% confidant level with the values of R^2 much larger.

4.1.2 Predictive regressions near cyclical peaks and troughs

Considering that many studies find that the predictive ability is related to the economic cycle, we are also interested in gauging the relative strength of factors' predictive ability during different states of the economy, namely, the popular NBER-based expansions and recessions (Nyberg, 2013). It is natural and feasible to compute R^2 statistics separately for cyclical expansions and recessions; however, the nature of the R^2 statistics has no clean decomposition of the full-sample R^2 statistic into subsample R^2 statistics based on the full-sample parameter estimates. In order to compare the degree of return predictability across expansions and recessions, we consider the following R^2 statistic:

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c \hat{\varepsilon}_{i,t}^2}{\sum_{t=1}^{T} I_t^c (r_t - \bar{r})^2}, \text{ for } c = EXP\left(REC\right), \tag{22}$$

where I_t^c, $c = EXP\left(REC\right)$ is an indicator variable that takes a value of 1 when month *t* is during an expansion (or recession) period and zero otherwise; $\hat{\varepsilon}_{i,t}^2$ is the fitted residual based on the full-sample estimates of the predictive regression model; $\bar{r}$ is the full-sample average of r_t; and T is the number of usable observations for the full sample.

[Insert Table 5 Here]

1996; Campbell and Thompson, 2008).

The Panel A and Panel B columns in Table 5 display the R^2 statistics during the business cycle. The R_c^2 (*c=EXP/REC*) statistics of technical indicators are much larger than macroeconomic variables for Ret_g and Ret_i. For short period MA and MOM indicators, MA(1,9), MA(1,12), MOM(1) and MOM(2), R_c^2 (c=*EXP*) is larger than in recession, and middle and long term MA and MOM indicators perform better during the recession period. For macroeconomic variables, TBL, LGB, TermS, DFY, BM, CPI, CUM, OI, KI and FPO show stronger prediction capacity during the expansion period, and DY, SVAR, USDX perform relatively larger R_c^2 during the recession period.

The results also manifest difference between Ret_i and Ret_o. The values R_c^2 of technical indicators intuitively are smaller for Ret_o than Ret_i, whereas macroeconomics variables are much larger with the maximum value to 76.47%. And with the exception of EP, NTIS, MS2, IIP, PMI, KI, USDX and FPO, macroeconomics variables are all above of 1%. TBL, LGB, TermS, BM, IK, CAY, UER, KI and USDX own higher R_c^2 (*c=EXP*), and others perform better during the recession period. Therefore, the forecast capacity of technical indicators and macroeconomic variables is robust whatever business cycle is considered.

4.1.3 Predictive regressions based on principal components

So far, we have analyzed the effects of individual technical predictors on forecast performance. It is natural to ask what happens if multivariate information is used. To this end, we incorporate information from all of the technical indicators by estimating a predictive regression based on principal component analysis. Principal components parsimoniously incorporate information from a large number of potential predictors in a predictive regression. The first few principal components identify the key co-movements among the entire set of predictors, which filters out much of the noise in individual predictors, thereby guarding against in-sample over-fitting.

We define $S_t = (S_{i,t}, ..., S_{N,t})'$, denoting the *N*-vector $(N = 22)$ of the entire set of technical indicators and with $\hat{F}_t^T = (\hat{F}_{i,t}^T, ..., \hat{F}_{k,t}^T)'$ representing the first *K* principal components extracted from S_t where $K \ll N$. Therefore, the principal component predictive regression for technical indicators can be given by:

$$r_{t+1} = \alpha + \sum_{k=1}^{K} \beta_k \hat{F}_{k,t}^{T} + \varepsilon_{t+1} . \tag{23}$$

Similarly, to incorporate information from all of the macroeconomic variables, we estimate the following principal component predictive regression:

$$r_{t+1} = \alpha + \sum_{h=1}^{H} \beta_h \hat{F}_{h,t}^{E} + \varepsilon_{t+1} , \tag{24}$$

where $\hat{F}_{t}^{E} = (\hat{F}_{i,t}^{E},...,\hat{F}_{H,t}^{E})'$ is the vector containing the first H principal components extracted from the N-vector $(N = 22)$ of the macroeconomic variables.

[Insert Table 6 Here]

We estimate Eqs. (23)-(24) via OLS, and compute heteroskedasticity-consistent *t*-statistics, and base inferences on wild bootstrapped *p*-values, respectively. Panel A to C in Table 6 report the estimation results for Eqs. (23) and (24) for Ret_g, Ret_i and Ret_o, respectively. For Ret_g, 2 of 3 $\hat{F}_{i,t}^{T}$ are significant at 1% confident level, and only 1 $\hat{F}_{1,t}^{E}$ is significant, with the R^2 and R_c^2 (*c=EXP/REC*) indicating that technical principle components show stronger forecasts. All technical principle components are significant for Indexed Factor in Panel B, yet only 1 of 3 macroeconomics variable is significant, revealing that technical principle components perform better than macroeconomics principle components. The much higher R^2 and R_c^2 (*c=EXP/REC*) of technical principle components also show the same results. However, macroeconomics principle components manifest better prediction ability than technical for Ret_oin Panel C, which show more significant principle components and higher R^2 and R_c^2 (*c=EXP/REC*).

[Insert Figure 3 Here]

Furthermore, Figure 3 illustrates the forecast capacity of technical indicators and macroeconomic variables more intuitively. The figure shows in-sample forecasts of the 3 factors for the technical or macroeconomics principle components models, which represent in-sample estimates of the expected factors. Real factors are also listed in each Panel. For Ret_g and Ret_i forecasts shown in Panel A to D, macroeconomics principle components only depict the trend, and describe the volatility relatively weakly. And technical principle components can both mimic the trend and fluctuation of Ret_g and Ret_i. However, technical principle components for Ret_o might not forecast as well as for Ret_g and Ret_i with exceeded volatility, whereas macroeconomics variables seems to perform better for prediction.

4.2 Out-of-sample analysis

Although the in-sample analysis provides more efficient parameter estimates and thus more precise forecasts by utilizing all available data, Welch and Goyal (2008), among others, argue that out-of-sample tests appear to be more relevant for assessing genuine factors predictability in real time and avoiding the in-sample over-fitting issue. In addition, out-of-sample tests are much less affected by small-sample size distortions such as the Stambaugh bias (Busetti and Marcucci, 2012) and the look-ahead bias concern with the PLS approach (Kelly and Pruitt, 2013).

Thus, our out-of-sample regression for the 22 technical indicators and 22 macroeconomic variables based on month ($t+1$) out-of-sample factors forecasts is given by:

$$\hat{r}_{t+1}=\hat{\alpha}_{t+1}+\hat{\beta}_{t,i}S_{t,i}\,, \tag{25}$$

where $S_{t,i}$ represents the 22 individual technical indicators and $\hat{\alpha}_{t+1}$ and $\hat{\beta}_{t,i}$ are OLS estimates from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{S_{i,s}\}_{s=1}^{t-1}$. For the 22 macroeconomic variables, $S_{t,i}$ is replaced by $X_{t,i}$, that is

$$\hat{r}_{t+1}=\hat{\alpha}_{t+1}+\hat{\beta}_{t,i}X_{t,i}\,, \tag{26}$$

where $\hat{\alpha}_{t+1}$ and $\hat{\beta}_{t,i}$ are OLS estimates from regressing $\{r_s\}_{s=2}^{t}$ on a constant and $\{x_{i,s}\}_{s=1}^{t-1}$. We set Dec2004 as an interval, using Jan1992 to Dec2004 as the initial estimation period, so that the forecast evaluation period spanned Jan2005 to Dec2013. Because out-of-sample tests of predictive ability have better size properties when the forecast evaluation period is a relatively large proportion of the available sample (Hansen and Timmermann, 2012), we use13 years as the out-of-sample period and 8 years as the in-sample period.

In addition, we also generate the out-of-sample forecasts based on principal components:

$$\hat{r}^{j}_{t+1}=\hat{\alpha}_t+\sum_{k=1}^{k}\hat{\beta}_{t,k}\hat{F}_{1:t,k,t}\ \text{ for } j=TECH,ECON\,, \tag{27}$$

where $\hat{F}_{1:t,k,t}$ is the k-th principal components extracted from the 22 technical indicators, 22 macroeconomic variables through period t. Additionally, the definitions of $\hat{\alpha}_t$ and $\hat{\beta}_{t,k}$ are the OLS estimations.

Relatively, we generate historical average forecasts as a benchmark based on Welch and Goyal (2008), Campbell and Thompson (2008), Ferreira and Santa-Clara (2011):

$$\hat{r}_{t+1}^{HA} = (1/t)\sum_{k=1}^{k} r_s \ . \tag{28}$$

The assumption of Eq. (28) is a constant expected log factors, and it is very strict (Welch and Goyal, 2008) for predictive regression forecasts based on individual macroeconomic variables that typically fail to outperform the historical averages.

In line with Campbell and Thompson (2008) and Clark and West (2007), we measure the $R_{os}{}^2$ and $MSFE-adjusted$ statistics to analysis forecasts performance. The R^2 statistic measures the proportional reduction in mean squared forecast errors (*MSFE*) for the predictive regression forecasts relative to the historical averages. Thus, a positive value indicates that the predictive regression forecast outperforms the historical average in terms of *MSFE*, whereas a negative value signals the opposite. The $MSFE-adjusted$ statistic tests the null hypothesis that the historical average *MSFE* is less than or equal to the predictive regression *MSFE* against the one-sided (upper-tail) alternative hypothesis that the historical average *MSFE* is greater than the predictive regression *MSFE*.

[Insert Table 7 Here]

Panel A and B of Table 7 report the out-of-sample results for the bivariate predictive regression forecasts based on the 22 individual technical indicators for three factors in Section 3. There are 13 technical indicators significant for Ret_g, showing strong predictions. The macroeconomics variables seems much weaker, only LGB, IK and CAY significant. And the values of $R_{c,os}{}^2$ also reflect the results: 18 technical indicators own the $R_{c,os}{}^2$ more than 0.5%, yet the macroeconomics variables only have 5. Technical indicators reveal better prediction power for Ret_i, 18 of which are significant and all $R_{c,os}{}^2$ of 22 indicators are more than 0.5%. And the macroeconomics variables are still weak, only 4 of which are significant and 7 $R_{c,os}{}^2$ values are more than 0.5%. However, macroeconomics variables manifest the strong prediction for Ret_o intuitively, 14 of which are significant at 1% and 5% confident level and 17 of whose $R_{c,os}{}^2$ valuesaremore than 0.5% with $R_{c,os}{}^2$ of TBL reaching 81.56%. On the contrary, technical indicators perform relatively weak with only MOM(1) and VOL(6,12) significant.

[Insert Table 8 Here]

We also consider the forecast capacity during the business cycle. The Panel A and Panel B columns in Table 8reveal the $R_{c,os}{}^2$ statistics during the business cycle for out-of-sample estimates. The $R_{c,os}{}^2$ (c=EX*P/REC*) statistics of technical indicators are much larger than macroeconomic variables for both Ret_g and Ret_i with largest $R_{c,os}{}^2$ 66.13%. The VOL indicators seem perform better during the recession period and the $R_{c,os}{}^2$ (*c=EXP*) of MOM are larger for Return Indexed Factor.Andthe values $R_{c,os}{}^2$ (c=EX*P/REC*) of macroeconomic variables are much smaller for Ret_g and Ret_i, while they are much larger when forecasting Ret_o. The values $R_{c,os}{}^2$ (c=EX*P/REC*) of technical indicators intuitively are smaller for Ret_o, which are about half of $R_{c,os}{}^2$ (c=EX*P/REC*) for Ret_i. And macroeconomics variables are larger than with maximum to 85.57%. TBL, LGB, TermS, BM, IK, CAY, UER, OI, KI and USDX show higher $R_{c,os}{}^2$ (c=EX*P/REC*) during the expansion period, andthe $R_{c,os}{}^2$ values of DFY, DP, DY, EP, SVAR, NTIS, CPI, MS2, IIP, CUM, PMI and FPO are larger during the recession period.

[Insert Table 9 Here]

The same as in-sample estimates, principle components forecasts are displayed in Table 9 with Panel A to C in reporting the estimation results for 3 factors, respectively. For Ret_g and Ret_i, all $\hat{F}_{i,t}^{T}$ are significant at 1% confident level, with the R^2 (*c=EXP/REC*) indicating that technical principle components show stronger forecasts while macroeconomics principle components show relatively weak prediction. However, macroeconomics principle components manifest better prediction ability than technical for Ret_o in Panel C, which show more significant principle components and higher R^2 and R_c^2 (*c=EXP/REC*).

[Insert Figure 4 Here]

Panel A to F in Figure 4 depict the expected factors by out-of-sample estimates with real factors during 2004 to 2013. Macroeconomics principle components mainly reflect trend, while technical principle components seems to mimic fluctuation better. For Ret_g and Ret_i, technical principles predict relatively better, and weakly for Ret_o comparing the macroeconomic principle components.

5. Robustness

We also investigate in terms of volatility as robust analysis and focus on the out-of-sample estimates for forecast capacity.

[Insert Figure 5 Here]

Panel A and B in Figure5 depict means of the posterior distributions for 3 factors interpreted as a normalized index of corresponding commodity volatility. Volatility Global Factor (Vola_g) and Indexed Factor (Vola_i) show more broadly fluctuation than Volatility Off-index Factor (Vola_o).

[Insert Table 10 Here]

Panel A and B of Table 10 reports the out-of-sample results for the bivariate predictive regression forecasts based on the 22 individual technical indicators for three factors in Section 3. 8 technical indicators are significant for Vola_g, which show strong predictions. The macroeconomics variables seems much weaker, and only TBL and IK reveal significance. The values of $R_{c,os}{}^2$ also reflect those results: 10 technical indicators own the $R_{c,os}{}^2$ more than 0.5%, while the macroeconomics variables only have 7 $R_{c,os}{}^2$ more than 0.5%. Technical indicators manifest still manifest prediction power for Vola_i, 8 of which are significant and $R_{c,os}{}^2$ of 10 indicators are more than 0.5%. And the macroeconomics variables also show strong as 11 macroeconomics variables are significant and 13 $R_{c,os}{}^2$ value are more than 0.5%. For Vola_o, macroeconomics variables manifest the strong prediction intuitively, 16 of which are significant at 1% and 5% confident level and 19 of whose $R_{c,os}{}^2$ value more than 0.5%, while technical indicators perform relative weaker with 8 indicators significant.

[Insert Table 11 Here]

Similarly, we consider the forecast capacity during the business cycle. The Panel A and Panel B columns in Table 11show the ${R_{c,os}}^2$ statistics during the business cycle for out-of-sample estimates. The ${R_{c,os}}^2$ (c=EX*P/REC*) statistics of technical indicators are relatively larger than macroeconomic variables forVola_g and Vola_i with ${R_{c,os}}^2$ of MOM(1) more than 60%, while they are much larger when forecasting Vola_o. The values ${R_{c,os}}^2$ (c=EX*P/REC*) of technical indicators intuitively are smaller for Vola_o. And macroeconomics variables are larger than with maximum reaching 86.39%.

[Insert Table 12 Here]

The same as Section 4, principle components forecasts are also listed in Table 12 with Panel A to C in reporting the estimation results for 3 factors, respectively. Both $\hat{F}_{i,t}^{T}$ are significant indicating that technical principle components show stronger forecasts while macroeconomics principle components show relatively weak prediction for Vola_g. Both technical and macroeconomics principle components are significant at the 1% confident level. However, macroeconomics principle components manifest better prediction ability than technical for Vola_o in Panel C.

Further, Panels A to F in Figure 6 describe the expected factors with real factors for 2004-2013. Technical principle components mimic relatively better than macroeconomics principle components for Vola_g and Vola_i. However, Technical principle components seem to predict the real curve trend for Vola_o.

6. Conclusion

This paper investigates the forecasting ability of technical indicators based on returns and trading volumes (including both commercial and non-commercial positions) to directly forecast the co-movements in commodity prices, and compares their performance with macroeconomic variables. By utilizing 22 technical indicators and 22 macroeconomic variables, we explore both in-sample and out-of-sample forecasting for co-movements in returns and volatilities over the period 1991-2014, and we evaluate the strength of the predictive evidence during recessions and expansions separately as well as around economic cycles.

Our paper suggests interesting findings. We find that technical indicators do exhibit statistically and economically significant in-sample and out-of-sample forecasting power, clearly exceeding that of well-known macroeconomic variables. Moreover, the strength of the predictive evidence based on technical indicators is robust during recessions and expansions with relatively stronger performance during recessions. Beside, the forecasts based on technical indicators can detect the typical decline in the oil returns near business-cycle peaks effectively. Overall, the substantial counter-cyclical fluctuations in the commodity prices appear well captured by technical indicators rather than macroeconomic variables. The results prove useful to commodity producers, consumers, and financial investors keen to enhance their understanding of commodity price movements.

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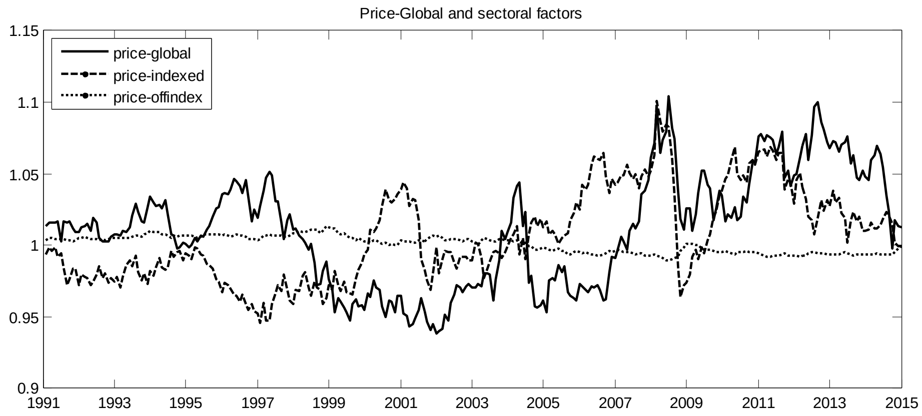


Figure 1 The mean for the posterior distributions for the global and sectoral factors in term of price level, 1991-2014.

Notes:This figure describes the means of the posterior distributions for the global, indexed and off-index factors in term of price level and return in Panel A and B for 1991-2014.

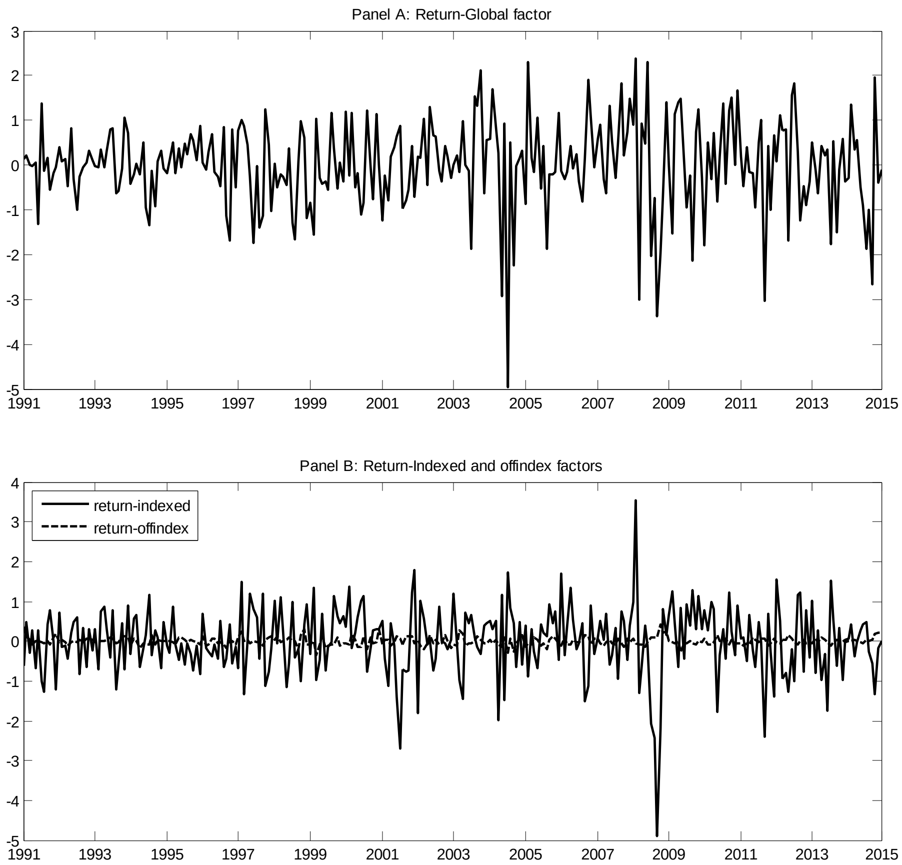
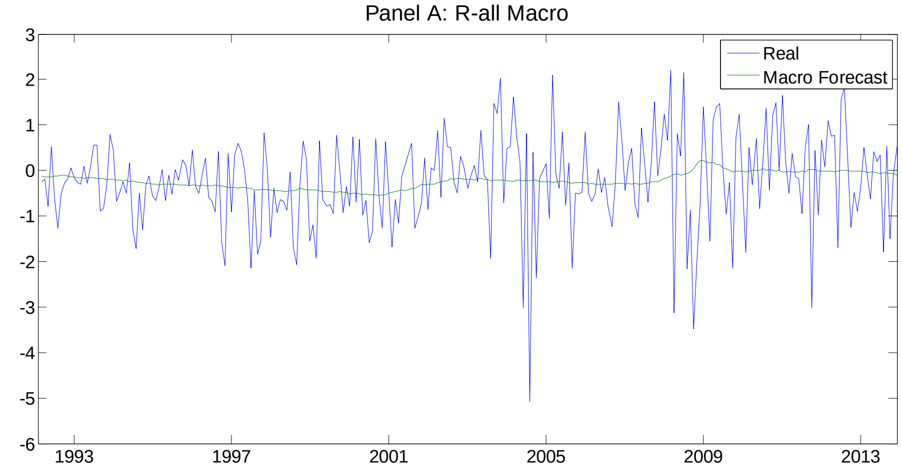
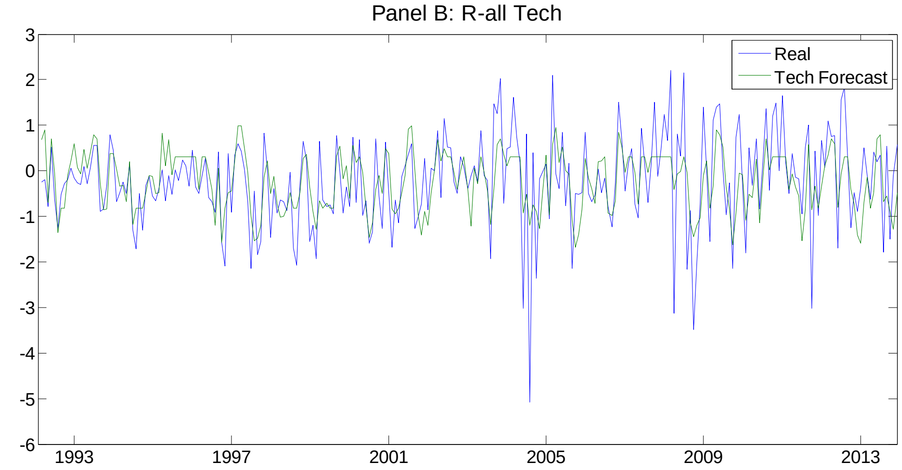
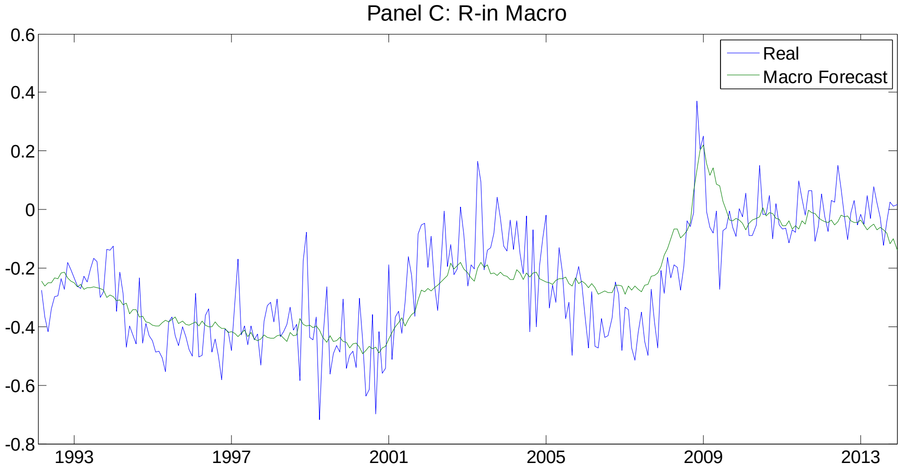


Figure 2 The mean for the posterior distributions for the global and sectoral factors in term of return, 1991-2014.

*Notes:*This figure describes the means of the posterior distributions for the global, indexed and off-index factors in term of price return in Panel A and B for 1991-2014. The estimated factor series is naturallyinterpreted as a normalized index of corresponding commodity returns.


Panel A: R-all Macro
Real
Macro Forecast
3
2
1
0
-1
-2
-3
-4
-5
-6
1993
1997
2001
2005
2009
2013


Panel B: R-all Tech
Real
Tech Forecast
3
2
1
0
-1
-2
-3
-4
-5
-6
1993
1997
2001
2005
2009
2013


Panel C: R-in Macro
Real
Macro Forecast
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1993
1997
2001
2005
2009
2013

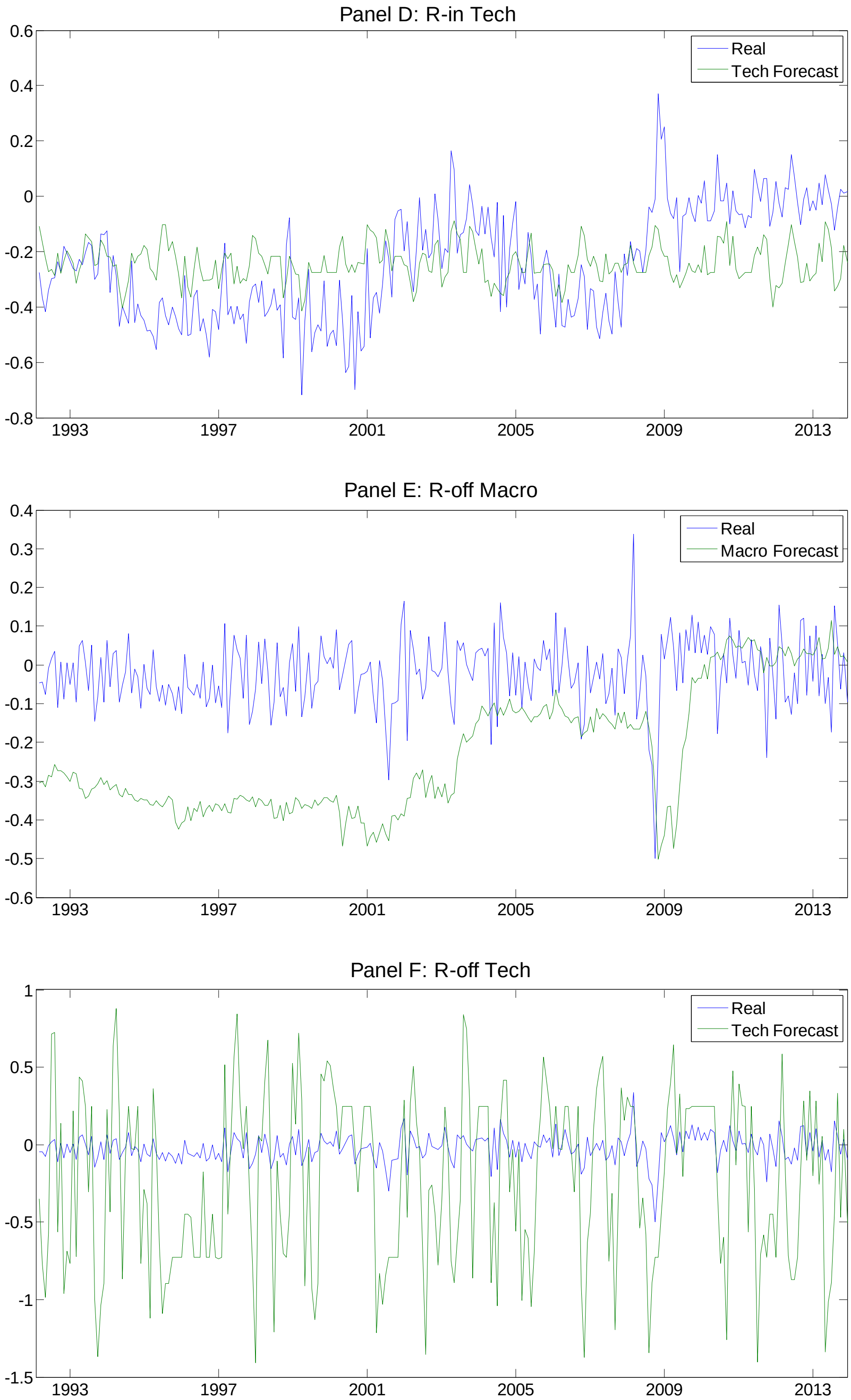
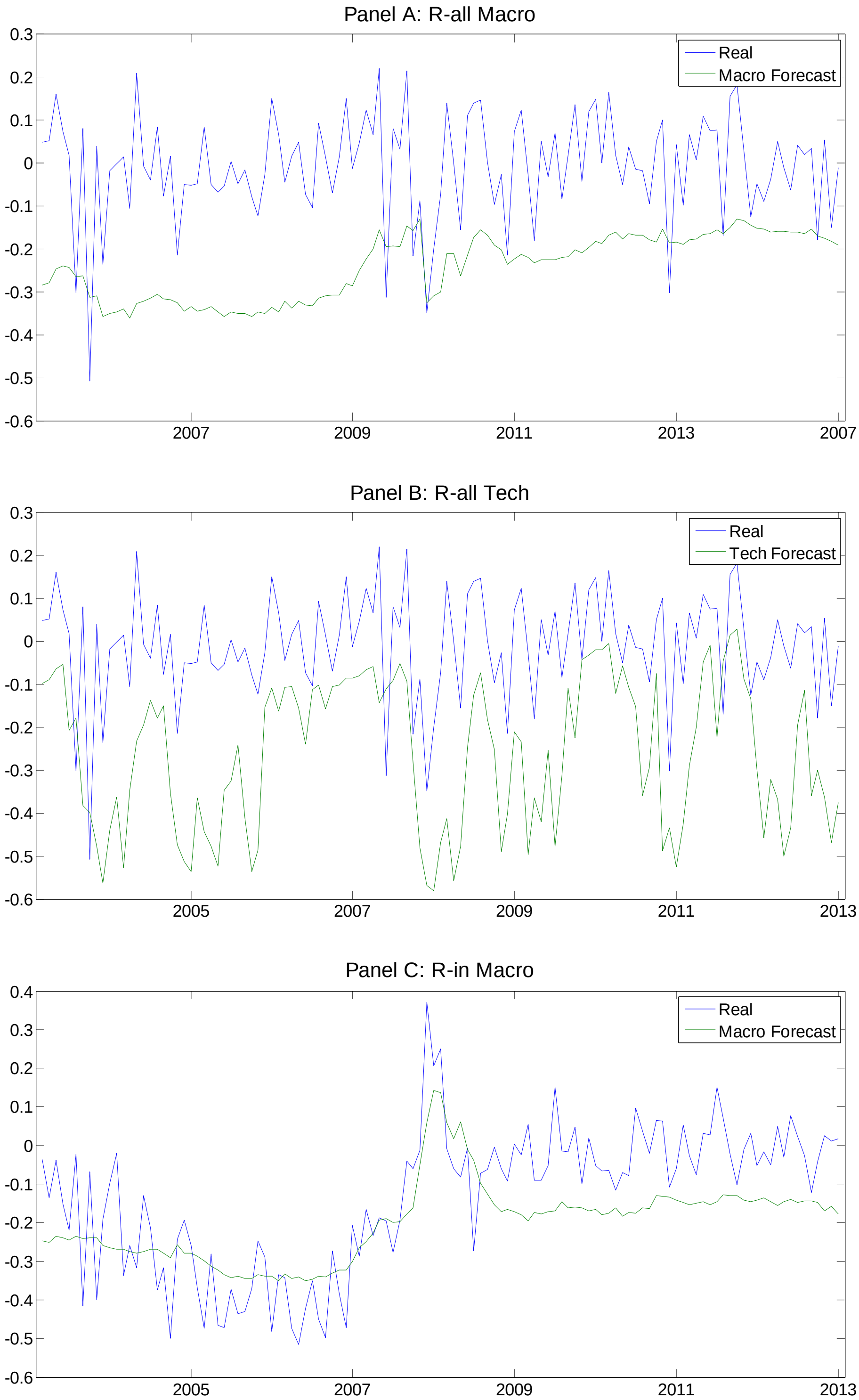


Figure 3 In-Sample return factors forecasts

Notes: This figure summarizes the in-sample results of principle components, consisting of 6 panels for the technical indicators defined in Section 2.2, the macroeconomic variables descried in Section 2.3 from 1992:01 to 2014:12, respectively. The principal components for the technical indicators ($\hat{F}_{c,t}^{T}=(\hat{F}_{c,1,t}^{T},...,\hat{F}_{c,3,t}^{T})'$) and the macroeconomic variables ($\hat{F}_{c,t}^{E}=(\hat{F}_{c,1,t}^{E},...,\hat{F}_{c,3,t}^{E})'$). Each Panel includes real factors (Real) and expected factors estimated by technical or macroeconomics principle components.



Panel A: R-all Macro
Real
Macro Forecast
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
2007
2009
2011
2013
2007
Panel B: R-all Tech
Real
Tech Forecast
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
2005
2007
2009
2011
2013
Panel C: R-in Macro
Real
Macro Forecast
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
2005
2007
2009
2011
2013

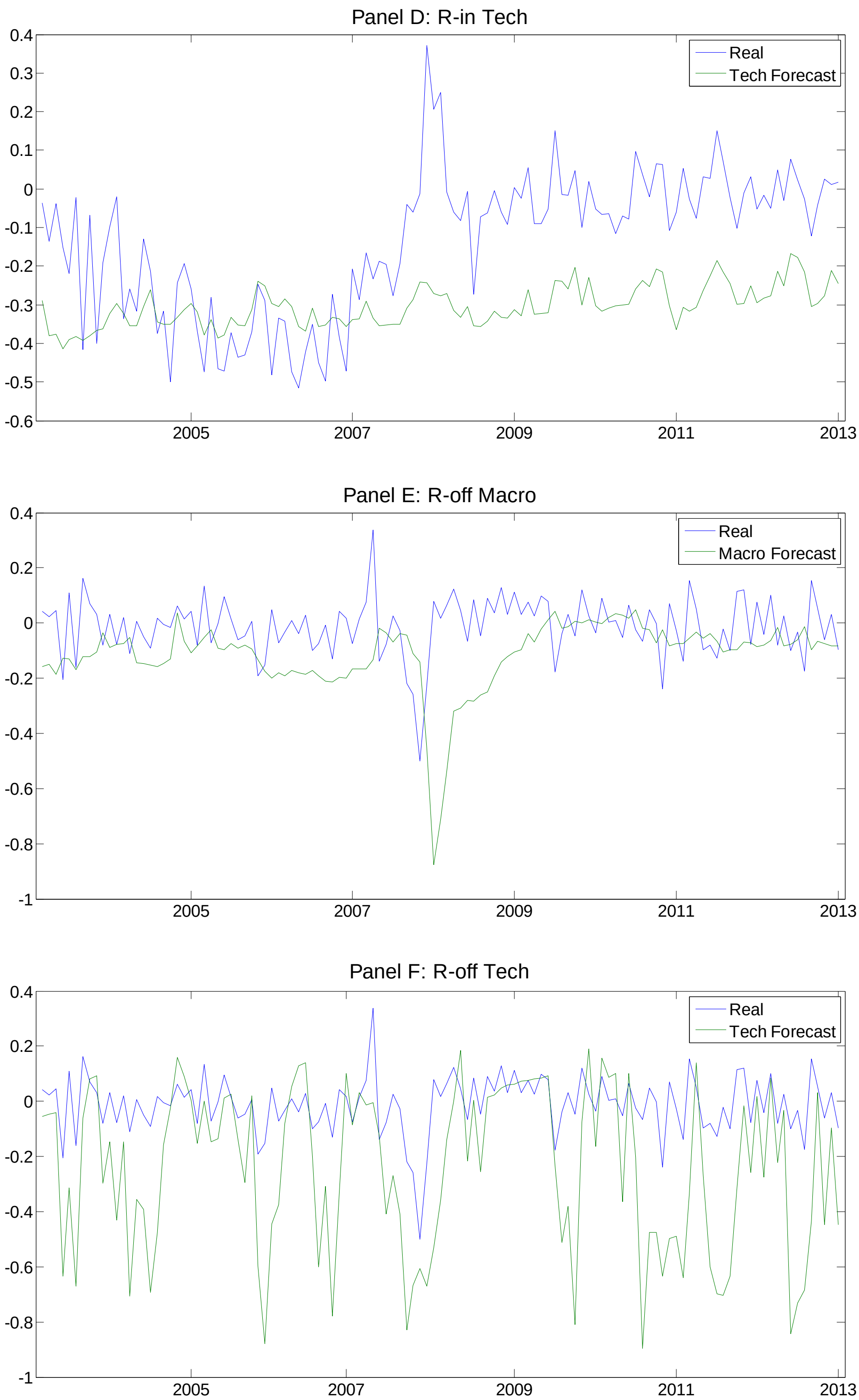


Figure 4 Out-of--sample return factors forecasts

Notes: This figure summarizes the out-of-sample results of principle components, consisting of 6 panels for the technical indicators defined in Section 2.2, the macroeconomic variables descried in Section 2.3 from 1992:01 to 2014:12 with 2004:01 as an interval, respectively. The principal components for the technical indicators ($\hat{F}^{T}_{c,t} = (\hat{F}^{T}_{c,1,t},...,\hat{F}^{T}_{c,3,t})'$) and the macroeconomic variables ($\hat{F}^{E}_{c,t} = (\hat{F}^{E}_{c,1,t},...,\hat{F}^{E}_{c,3,t})'$) defined in Section 4. Each Panel includes real factor(Real) and expected factor for 2004:02-2013:12 estimated by technical or macroeconomics principle components.

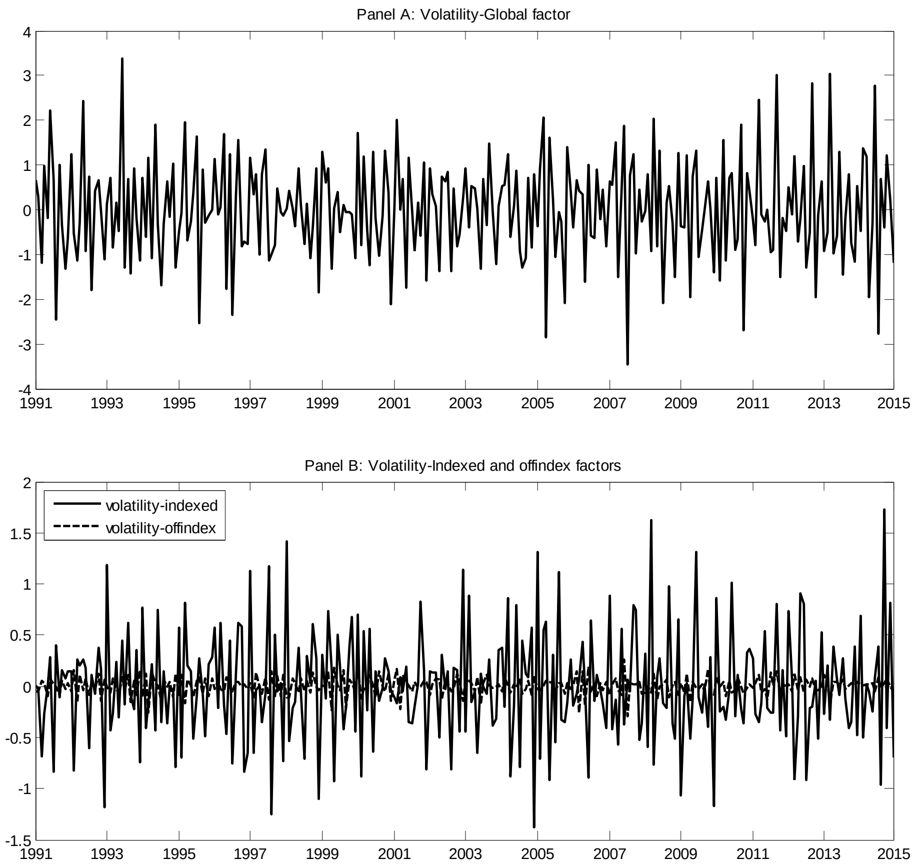
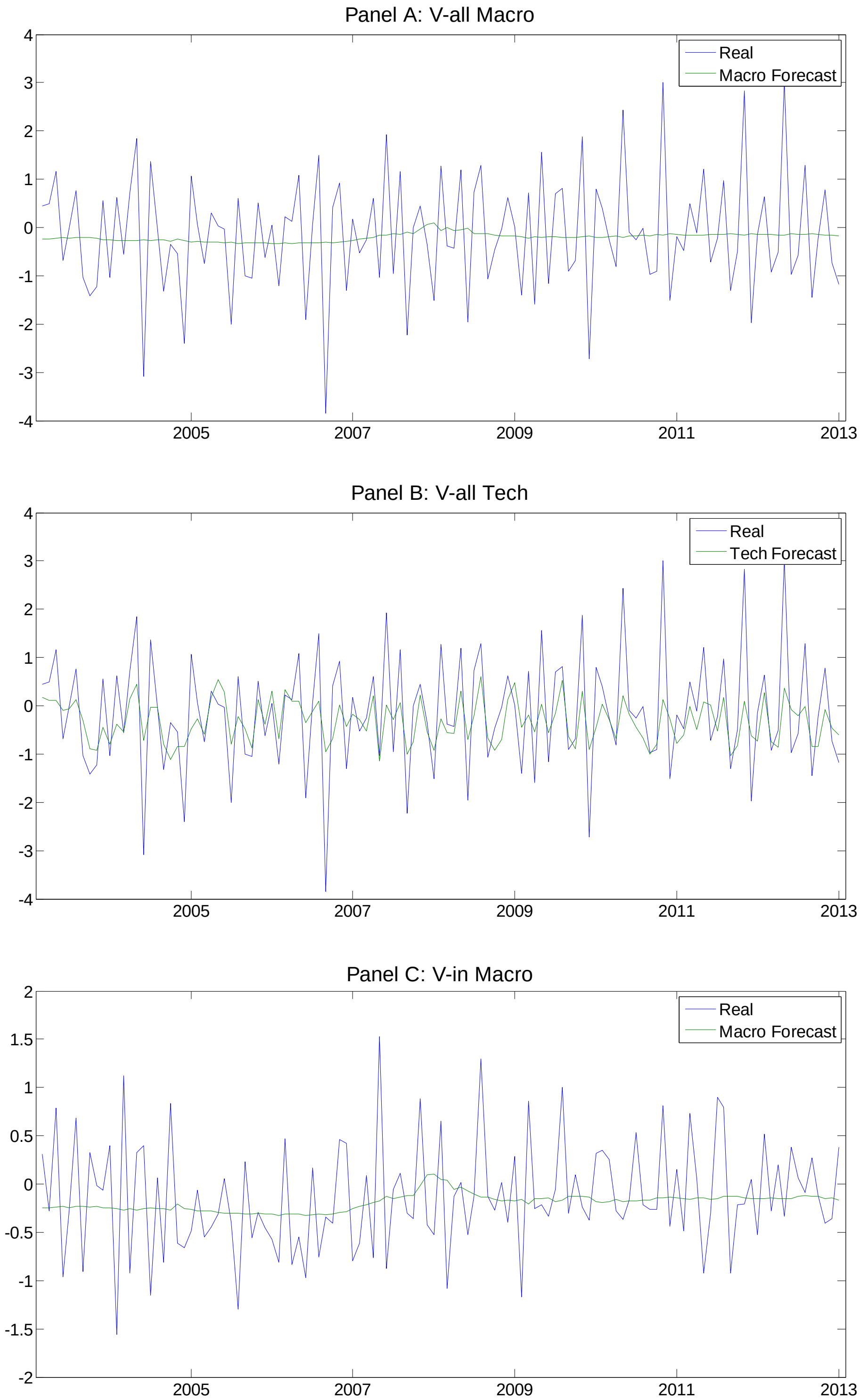


Figure 5 The Mean for the Posterior Distributions for the Global and Sectoral Factors in term of Volatility, 1991-2014.

Notes: This figure describes the means of the posterior distributions for the global, indexed and off-index factors in term of price volatility in Panel A and B for 1991-2014. The estimated factor series is naturally interpreted as a normalized index of corresponding commodity volatility.


Panel A: V-all Macro
Real
Macro Forecast
4
3
2
1
0
-1
-2
-3
-4
2005
2007
2009
2011
2013
Panel B: V-all Tech
Real
Tech Forecast
4
3
2
1
0
-1
-2
-3
-4
2005
2007
2009
2011
2013
Panel C: V-in Macro
Real
Macro Forecast
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2005
2007
2009
2011
2013

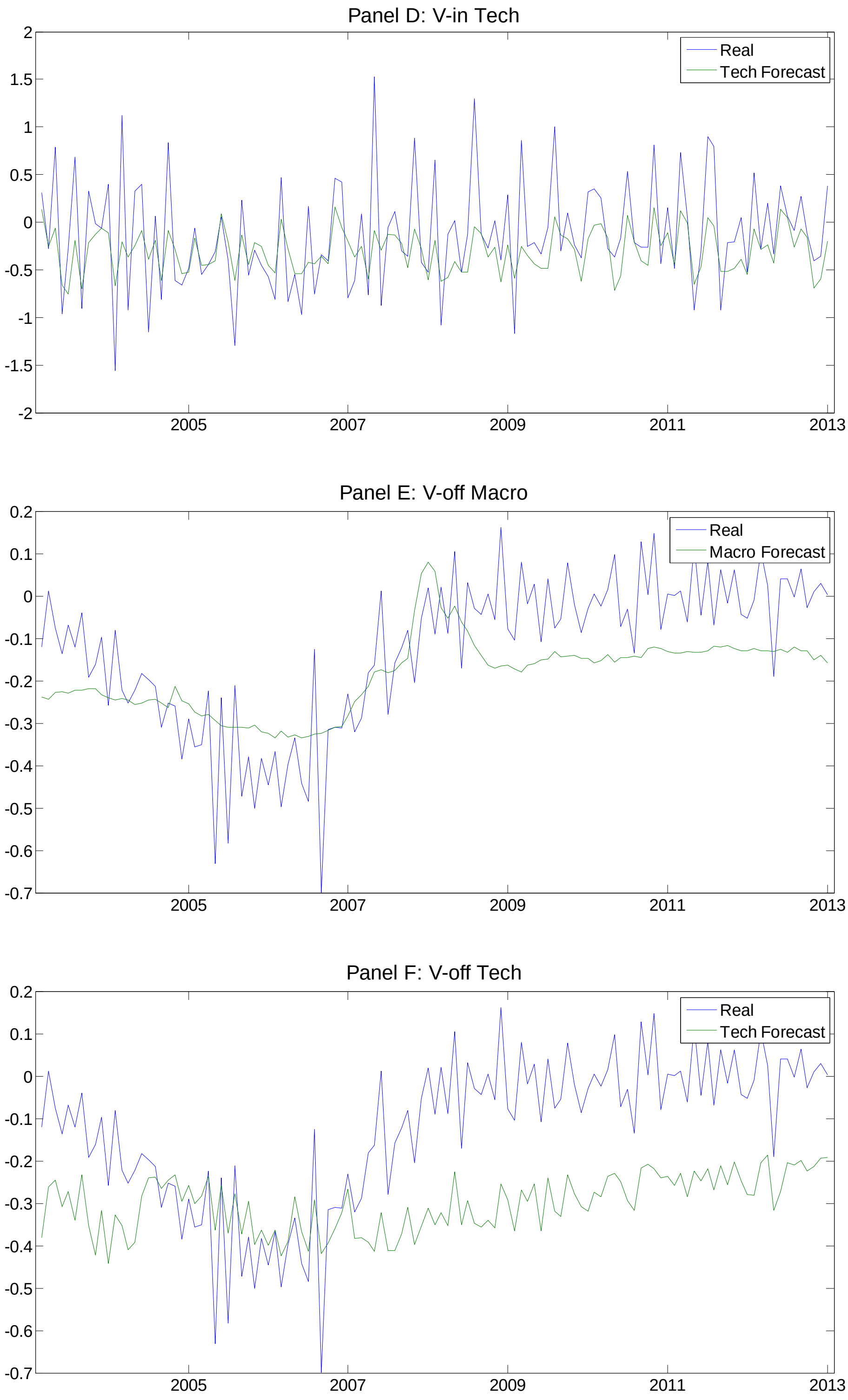


Figure 6 Robust analysis: Out-of-sample return factors forecasts for volatility.

Notes: This figure summarizes the robust analysis for out-of-sample results of principle components, consisting of 6 panels for the technical indicators defined in Section 2.2, the macroeconomic variables descried in Section 2.3 from 1992:01 to 2014:12 with 2004:01 as an interval, respectively. The principal components for the technical indicators ($\hat{F}^{T}_{c,t} = (\hat{F}^{T}_{c,1,t}, ..., \hat{F}^{T}_{c,3,t})'$) and the macroeconomic variables ($\hat{F}^{E}_{c,t} = (\hat{F}^{E}_{c,1,t}, ..., \hat{F}^{E}_{c,3,t})'$) defined in Section 5. Each Panel includes real Volatility factor(Real) and expected Volatility factor for 2004:02-2013:12 estimated by technical or macroeconomics principle components.

Table 1 Summary statistics of returns and volatilities for 26 commodities.

	Mean	Std.dev	Min.	Max.	Skewness	Kurtosis	Jarque-Bera
Panel A: Returns							
Energy							
Brent oil	0.0027	0.0877	-0.4074	0.3370	-0.5923	2.6448	96.4433***
Crude oil	0.0022	0.0892	-0.3948	0.3118	-0.5008	1.6507	42.6868***
Heating oil	0.0028	0.0943	-0.4605	0.3248	-0.3398	2.9225	103.0362***
Natural gas	0.0014	0.1565	-0.5381	0.4862	-0.1783	0.8418	9.3153***
Gasoil	0.0024	0.0890	-0.3624	0.2713	-0.4239	1.4400	31.8633***
Metals							
Gold	0.0038	0.0452	-0.1966	0.1488	-0.0844	1.4978	25.6093***
Silver	0.0046	0.0842	-0.3265	0.2491	-0.2933	1.1485	18.8157***
Palladium	0.0079	0.0933	-0.4012	0.3845	-0.2418	2.8844	97.7878***
Platinum	0.0038	0.0605	-0.3932	0.2565	-1.1933	7.2084	666.2961***
Copper	0.0030	0.0758	-0.4486	0.2931	-0.6434	5.1915	329.4715***
Agriculture							
Corn	0.0019	0.0848	-0.3766	0.2004	-0.6635	1.7799	56.7589***
Oat	0.0035	0.0937	-0.3112	0.2890	0.0556	0.3310	1.2594
Rough rice	0.0017	0.0879	-0.3499	0.3922	0.1028	2.2764	59.4477***
Soybean meal	0.0028	0.0876	-0.4071	0.2446	-0.7218	2.8394	116.7991***
Soybean oil	0.0015	0.0731	-0.2805	0.2379	-0.4118	2.1437	60.2658***
Soybean	0.0021	0.0753	-0.3985	0.1788	-0.9489	3.0775	151.0204***
Wheat	0.0028	0.0860	-0.2910	0.3530	0.1231	0.9808	11.3940***
Industrials							
Lumber	0.0022	0.1009	-0.2723	0.3732	0.0789	0.4517	2.4446

Cotton	-0.0009	0.0921	-0.4481	0.2211	-0.6862	2.5399	95.8870***
Livestocks							
Feeder cattle	0.0031	0.0404	-0.2304	0.1335	-0.5659	3.4725	153.2629***
Lean hogs	0.0018	0.1010	-0.5170	0.3446	-0.3657	2.5983	83.3270***
Live cattle	0.0027	0.0462	-0.2512	0.1497	-0.5595	3.0254	119.4689***
Softs							
Cocoa	0.0033	0.0879	-0.3297	0.2969	0.0768	1.0198	11.8377***
Coffee	0.0023	0.1060	-0.2853	0.4094	0.6050	1.4074	39.6560***
Orange juice	0.0010	0.0921	-0.2501	0.2938	0.2085	0.4173	3.8847
Sugar	0.0016	0.0937	-0.3747	0.2846	0.0217	0.8731	8.4339**
Panel B: Volatilities							
Energy							
Brent oil	0.0143	1.2895	-7.4148	7.0744	0.0530	6.2318	447.1440***
Crude oil	0.0055	0.9903	-2.4945	2.7742	0.0114	-0.0150	0.0213
Heating oil	0.0100	1.0281	-2.7287	4.5082	0.4501	1.4357	32.8131***
Natural gas	0.0183	1.1760	-2.9249	3.7795	0.1183	0.2446	1.2437
Gasoil	0.0057	1.1683	-3.3234	4.3814	0.3101	0.5466	7.7692**
Metals							
Gold	0.0167	1.3219	-4.6421	4.6300	0.0667	0.7358	6.1308**
Silver	0.0120	2.0448	-8.6752	7.9903	-0.0174	3.0758	108.1486***
Palladium	0.0180	1.5377	-5.1737	5.8073	0.2920	1.5629	31.5974***
Platinum	0.0093	1.4439	-7.7436	4.9994	-0.1292	3.5004	141.0844***
Copper	0.0005	1.7963	-6.2387	7.5169	-0.0285	1.6707	31.5736***
Agriculture							
Corn	0.0105	1.2630	-3.8012	3.6239	-0.0920	0.0546	0.4153
Oat	0.0065	1.7414	-6.4874	8.1582	0.2515	3.3662	132.6793***

Rough rice	0.0125	2.0079	-8.4130	6.9463	0.0413	2.6752	81.7151***
Soybean meal	0.0118	1.2355	-3.2089	4.4789	0.2021	0.5320	4.9638*
Soybean oil	0.0085	1.0833	-3.2513	2.7479	-0.0802	-0.1219	0.5430
Soybean	0.0128	1.3548	-3.9805	4.3836	0.2286	0.7251	8.2264**
Wheat	0.0118	1.5283	-7.3089	8.6747	0.2991	6.1692	442.2989***
Industrials							
Lumber	0.0080	1.1035	-3.7956	3.0331	0.0218	0.2869	0.8412
Cotton	0.0027	1.7144	-6.1412	6.0615	0.0340	1.0997	13.5370***
Livestocks							
Feeder cattle	0.0142	1.9822	-5.2336	6.0594	0.1042	0.9806	11.1837***
Lean hogs	0.0130	0.8625	-2.3414	2.9368	0.3001	0.3154	5.2811*
Live cattle	0.0102	1.4799	-3.9749	4.3231	-0.1334	0.0674	0.8697
Softs							
Cocoa	0.0076	1.8544	-6.3175	5.8459	0.1171	0.6925	5.8752*
Coffee	0.0079	1.5071	-6.8286	4.8703	-0.1307	1.0778	13.7506***
Orange juice	-0.0123	1.2142	-2.8786	3.0669	0.0286	-0.3446	1.5891
Sugar	-0.0033	1.7366	-6.4833	5.0945	0.0275	0.3926	1.6354

***Notes*:** This table shows description statistics of returns and volatilities for 26 commodities defined in Section 2.1. The second to eighth columns report the mean, standard deviation (Std. Dev), maximum, minimum, skewness, kurtosis and Jarque-Bera statistic, respectively. Jarque-Bera is the empirical statistics of the Jarque-Bera test for normality. ***and **indicates rejection of the normality at the 1% and 5% level, respectively.

Table 2 Summary statistics of macroeconomic variables.

Abbr.	Mean	Max	Min	Std. Dev	Skewness	Kurtosis	Jarque-Bera	Auto- Correlation
BM	8.6565	9.6863	7.0151	0.7592	-0.5785	1.9535	36.58463***	0.988
TB	0.0398	0.1047	0.0001	0.0265	0.0420	2.1685	18.01215***	0.990
GB	0.0641	0.1381	0.0206	0.0231	0.6082	3.2631	6.533637**	0.979
TS	0.0243	0.0455	0.0000	0.0128	-0.2826	1.9376	21.29396***	0.968
CPI	0.0023	0.0137	-0.0177	0.0026	-1.4782	15.2615	2386.275***	0.425
DP	3.7954	4.5240	3.0226	0.3620	-0.0896	2.0801	14.33433***	0.986
DY	3.7886	4.5313	3.0194	0.3635	-0.0758	2.0985	13.32478***	0.985
EP	3.0143	4.8365	2.2226	0.4115	1.4950	7.3541	540.1958***	0.977
CAY	0.0070	0.0397	-0.0003	0.0218	-0.1536	1.6695	26.76458***	0.980
SVAR	0.0028	0.0709	0.0002	0.0058	8.0692	82.9622	99816.1100***	0.451
NTIS	0.0050	0.0457	-0.0576	0.0210	-0.4341	2.9830	11.3127***	0.974
DFY	0.0102	0.0338	0.0055	0.0040	2.5868	13.4432	2037.3900***	0.961
IK	0.0356	0.0442	0.0280	0.0039	0.3501	2.6734	8.9560**	0.993
UER	0.0619	0.1000	0.0380	0.0150	0.6875	2.7683	34.55863***	0.994
MS2	0.0045	0.0266	0.0000	0.0060	-0.2397	3.8014	12.8592***	0.003
OI	6.0672	7.3586	4.6465	0.7569	0.0444	1.8444	20.70106***	0.989
USDX	4.5589	4.8554	4.3888	0.1018	0.7548	2.9541	35.81191***	0.978
PMI	3.9465	4.1174	3.4995	0.1008	-1.1497	5.2685	157.1617***	0.931
KI	-2.9651	59.2558	-56.8880	23.9283	0.5398	2.8990	17.6363***	0.957
IIP	0.0019	-0.0421	-0.0001	0.0062	-1.5143	11.3421	1156.597***	0.211
CUM	4.3565	4.8554	4.1542	0.0568	-1.0875	4.4492	92.67442***	0.986
FPO	12.1888	12.5541	11.6902	0.1799	0.2359	2.2065	10.37875***	0.941

Notes**:** This table shows description statistics for 22 macroeconomic variables defined in Sections 2.3. The second to ninth columns report the mean, standard deviation (Std. Dev), maximum, minimum, skewness, kurtosis, Jarque-Bera statistic and auto-correlation, respectively. JB is the empirical statistics of the Jarque-Bera test for normality. ***and **indicates rejection of the normality at the 1% and 5% level, respectively.

Table 3 Averages across commodity groups, variance decompositions for commodity returns (%).

	Global factor			Sectoral factor			Commodity-specific factor		
	Mean	0.05	0.95	Mean	0.05	0.95	Mean	0.05	0.95
All	16.68%	14.87%	18.68%	18.53%	16.38%	20.89%	64.79%	61.21%	68.19%
Indexed	22.04%	20.09%	24.21%	22.05%	20.41%	23.89%	55.91%	52.93%	58.67%
Off-index	4.61%	3.11%	6.22%	10.63%	7.31%	14.14%	84.76%	79.84%	89.62%
Brent oil	40.66%	40.07%	41.43%	19.12%	18.85%	19.45%	40.22%	39.48%	40.84%
Crude oil	54.62%	52.04%	56.96%	10.79%	9.48%	12.83%	34.59%	29.79%	39.90%
Heating oil	22.17%	21.08%	23.42%	21.18%	19.42%	23.65%	56.65%	54.03%	58.63%
Natural gas	12.48%	11.27%	13.91%	13.32%	9.96%	17.89%	74.20%	69.66%	77.67%
Gasoil	18.61%	14.73%	23.20%	11.54%	9.50%	14.32%	69.86%	65.24%	73.86%
Gold	19.69%	17.25%	22.42%	20.61%	20.00%	21.34%	59.70%	57.08%	62.04%
Silver	11.77%	9.65%	14.36%	70.52%	66.63%	74.26%	17.71%	14.66%	20.69%
Palladium	3.68%	2.76%	4.79%	40.05%	32.48%	50.64%	56.27%	45.84%	63.79%
Platinum	7.61%	5.99%	9.59%	38.29%	22.35%	51.81%	54.11%	40.35%	70.09%
Copper	23.92%	22.27%	25.93%	10.01%	9.99%	10.09%	66.07%	64.06%	67.72%
Corn	44.80%	39.22%	51.33%	10.05%	9.95%	10.31%	45.15%	38.61%	50.73%
Oat	6.51%	3.53%	8.78%	1.09%	0.91%	1.58%	92.39%	87.89%	98.36%
Rough rice	5.18%	3.07%	7.68%	1.40%	0.83%	2.15%	93.42%	88.53%	97.53%
Soybean meal	0.87%	0.15%	1.75%	0.84%	0.28%	1.47%	98.29%	97.19%	99.27%
Soybean oil	1.05%	0.95%	1.26%	1.40%	0.72%	2.14%	97.55%	96.82%	98.22%
Soybean	20.26%	19.92%	20.69%	10.02%	9.98%	10.12%	69.72%	69.26%	70.08%
Wheat	35.37%	32.89%	38.22%	11.36%	8.88%	13.92%	53.26%	50.76%	55.64%
Lumber	1.60%	0.56%	2.89%	1.71%	0.89%	2.60%	96.68%	95.41%	97.80%
Cotton	4.65%	3.91%	5.57%	11.84%	9.69%	14.04%	83.51%	81.34%	85.55%
Feeder cattle	3.26%	2.30%	4.46%	4.69%	3.95%	5.47%	92.06%	89.82%	93.96%

Lean hogs	3.58%	2.56%	4.86%	4.95%	4.17%	5.75%	91.46%	89.19%	93.43%
Live cattle	1.75%	0.64%	3.13%	3.56%	1.78%	5.12%	94.69%	92.63%	96.92%
Cocoa	1.27%	0.36%	2.44%	92.36%	89.17%	95.23%	6.37%	4.30%	8.48%
Coffee	1.94%	0.88%	3.22%	69.92%	65.65%	74.17%	28.14%	24.53%	31.65%
Orange juice	10.40%	7.90%	13.02%	0.23%	0.00%	0.74%	89.38%	86.67%	91.93%
Sugar	75.86%	70.64%	80.33%	1.05%	0.33%	2.07%	23.09%	18.29%	28.27%

Notes: This table reports averages across various commodities of the means and 0.05and 0.95 quantiles for the posterior distributions. The second (fifth, eighth) to fourth (seventh, tenth) columns report the mean, 0.05 and 0.95 quantiles for global, sectoral and commodity-specific factors, respectively.

Table 4 Bivariate predictive regression estimation results

Predictor	Ret_g			Ret_i			Ret_o		
	Coeff.	t-stat.	R^2	Coeff.	t-stat	R^2	Coeff.	t-stat.	R^2
Panel A: Technical Indicators									
MA(1,9)	0.8164	7.0869***	16.36%	0.7998	7.8792***	19.59%	0.0632	2.5940***	2.51%
MA(1,12)	0.7228	6.2204***	12.87%	0.6642	6.2767***	13.48%	0.0530	2.1727**	1.76%
MA(2,9)	0.5022	4.1385***	6.20%	0.3091	2.7503***	2.92%	0.0239	0.9719	0.36%
MA(2,12)	0.4247	3.4780***	4.44%	0.2828	2.5037***	2.43%	0.0289	1.1827	0.53%
MA(3,9)	0.2447	1.9605**	1.47%	0.2461	2.1836**	1.85%	0.0272	1.1109	0.47%
MA(3,12)	0.2516	2.0368**	1.56%	0.2360	2.0610**	1.68%	0.0056	0.2270	0.02%
MA(6,9)	0.1927	1.5656*	0.91%	0.1111	0.9796	0.38%	-0.0046	-0.1898	0.01%
MA(6,12)	0.1323	1.0707	0.43%	0.1365	1.1861	0.56%	0.0127	0.5212	0.10%
MOM(1)	1.4901	17.6198***	54.64%	1.3874	19.3790***	59.14%	0.1396	6.0966***	12.41%
MOM(2)	1.0568	9.7657***	27.41%	0.8607	8.7294***	22.74%	0.0888	3.6970***	5.01%
MOM(3)	0.8030	6.8183***	15.67%	0.6943	6.6516***	14.75%	0.0738	3.0181***	3.43%
MOM(6)	0.5730	4.7268***	8.02%	0.4720	4.2689***	6.78%	0.0498	2.0414**	1.57%
MOM(9)	0.5991	5.0353***	8.84%	0.4674	4.1436***	6.57%	0.0301	1.2354*	0.57%
MOM(12)	0.4499	3.7133***	4.98%	0.4273	3.8178***	5.52%	0.0369	1.5226*	0.87%
VOL(1,9)	0.6518	5.5993***	10.44%	0.5826	5.3295***	10.30%	0.0441	1.8057**	1.22%
VOL(1,12)	0.6413	5.5292***	10.06%	0.5068	4.6081***	7.82%	0.0161	0.6449	0.16%
VOL (2,9)	0.4246	3.5178***	4.43%	0.3090	2.7536***	2.92%	-0.0163	-0.6618	0.17%
VOL (2,12)	0.3856	3.2104***	3.64%	0.3163	2.8046***	3.05%	-0.0268	-1.0818	0.45%
VOL (3,9)	0.2936	2.4158***	2.10%	0.2329	2.0434**	1.65%	-0.0226	-0.8951	0.31%
VOL (3,12)	0.2345	1.9394**	1.34%	0.2493	2.1910**	1.89%	-0.0402	-1.6254	0.96%
VOL (6,9)	0.0401	0.3284	0.04%	0.1694	1.4935*	0.87%	-0.0425	-1.7183	1.09%

VOL (6,12)	0.0480	0.3911	0.06%	0.2023	1.7534**	1.23%	-0.0569	-2.3418	1.91%
Panel B: Macroeconomic Variables									
TBL	-8.4524	-2.8355	2.93%	-6.9614	-2.7102	2.48%	-8.3434	-28.3137	74.36%
LGB	-11.2569	-2.8039	2.51%	-6.6897	-1.8305	1.11%	-9.2019	-18.3500	43.72%
TermS	6.8022	1.5513*	0.84%	8.4224	2.3628***	1.61%	8.8010	14.2244***	36.61%
DFY	31.0299	1.8119**	1.77%	19.4518	1.3183	0.87%	23.8565	8.1441***	27.24%
DP	-0.1064	-0.5191	0.08%	0.0478	0.2421	0.02%	-0.1915	-4.3197	6.64%
DY	-0.2501	-1.2560	0.44%	-0.0541	-0.2952	0.03%	-0.1787	-4.1682	5.80%
EP	0.0468	0.2702	0.03%	0.2349	1.7864**	1.04%	0.0367	1.2287	0.53%
BM	0.3483	2.0680**	1.14%	0.1809	0.9697	0.39%	0.2817	7.8423***	19.48%
SVAR	-18.1358	-1.2977	0.86%	-27.5611	-1.6035	2.48%	12.3588	8.9618***	10.40%
NTIS	0.0250	0.3482	0.06%	-0.0986	-1.4273	1.10%	0.0110	0.8002	0.28%
CPI	-1.6668	-0.0671	0.00%	37.8922	1.3858	1.26%	-18.6276	-3.9421	6.33%
IK	-42.6430	-3.2578	3.25%	-29.8236	-2.5979	1.99%	-31.8485	-17.0388	47.24%
CAY	-6.3902	-2.5734	1.57%	-6.4437	-2.8826	2.00%	-3.7478	-8.0457	14.09%
UER	0.5971	2.6120***	2.37%	0.5044	2.6090***	2.11%	0.5224	19.2006***	47.21%
MS2	0.3499	0.0365	0.00%	-5.4916	-0.6887	0.15%	2.6471	1.1937	0.72%
IIP	-8.0167	-0.4821	0.27%	18.8150	1.0493	1.86%	-4.7116	-2.6203	2.43%
CUM	-1.4532	-1.0773	0.76%	-0.5549	-0.4039	0.14%	-1.2011	-6.1272	13.44%
PMI	-0.2915	-0.4008	0.08%	1.0928	1.5380*	1.46%	-0.2152	-1.4920	1.18%
OI	0.2014	1.9338**	1.37%	0.0868	0.8179	0.32%	0.1589	8.9760***	22.11%
KI	0.0374	0.6913	0.18%	0.0617	1.4331	0.63%	0.0242	1.9618**	2.00%
USDX	-0.8251	-1.2248	0.51%	-0.0762	-0.1138	0.01%	-0.5288	-3.8478	5.40%
FPO	-0.3499	-0.5919	0.17%	-0.1310	-0.1901	0.03%	-0.1616	-1.6133	0.96%

Notes: This table summarizes the in-sample results, consisting of two panels for the technical indicators defined in Section 2.2, the macroeconomic variables descried in Section 2.3 from 1992:01 to 2014:12. Every three columns list the results of three return factors, respectively. The second (fifth, eighth) and fourth (seventh, tenth) columns show slope coefficient with heteroskedasticity-consistent *t*-statistic. ***, ** and * indicating the rejection of normality at the 1%, 5% and 10% levels, respectively, and the R^2 statistics.

Table 5 Bivariate predictive regression estimation with business cycle

Predictor	Ret_g		Ret_i		Ret_o	
	R^2_{exp}	R^2_{rec}	R^2_{exp}	R^2_{rec}	R^2_{exp}	R^2_{rec}
Panel A: Technical Indicators						
MA(1,9)	17.45%	12.49%	21.25%	16.33%	1.47%	9.75%
MA(1,12)	13.98%	8.96%	14.66%	11.15%	0.89%	7.75%
MA(2,9)	6.31%	5.81%	0.91%	6.88%	-0.14%	3.79%
MA(2,12)	4.45%	4.39%	1.94%	3.41%	0.09%	3.53%
MA(3,9)	1.21%	2.38%	1.03%	3.46%	0.04%	3.39%
MA(3,12)	1.71%	1.02%	0.86%	3.30%	-0.09%	0.77%
MA(6,9)	0.74%	1.52%	-0.42%	1.95%	0.06%	-0.29%
MA(6,12)	0.64%	-0.30%	0.23%	1.20%	0.02%	0.64%
MOM(1)	53.32%	59.28%	65.65%	46.31%	10.80%	23.62%
MOM(2)	26.28%	31.39%	23.08%	22.07%	3.49%	15.52%
MOM(3)	16.91%	11.32%	13.24%	17.72%	2.11%	12.61%
MOM(6)	8.11%	7.70%	4.43%	11.42%	0.85%	6.52%
MOM(9)	10.32%	3.64%	6.23%	7.25%	0.04%	4.29%
MOM(12)	6.81%	-1.45%	5.80%	4.96%	0.13%	5.97%
VOL(1,9)	10.24%	11.16%	6.33%	18.12%	0.13%	8.74%
VOL(1,12)	10.63%	8.06%	5.18%	13.01%	-0.27%	3.15%
VOL (2,9)	3.86%	6.44%	0.53%	7.61%	0.60%	-2.83%
VOL (2,12)	4.18%	1.75%	0.41%	8.23%	1.28%	-5.32%
VOL (3,9)	1.62%	3.77%	-0.55%	5.99%	1.05%	-4.84%
VOL (3,12)	1.92%	-0.71%	-0.01%	5.63%	1.99%	-6.15%

VOL (6,9)	0.16%	-0.39%	-0.13%	2.85%	2.18%	-6.40%
VOL (6,12)	0.26%	-0.65%	0.65%	2.39%	2.96%	-5.35%
Panel B: Macroeconomic Variables						
TBL	3.81%	-0.17%	3.86%	-0.22%	76.47%	59.72%
LGB	2.71%	1.83%	1.43%	0.48%	43.90%	42.49%
TermS	1.37%	-1.01%	2.77%	-0.68%	36.72%	35.85%
DFY	2.37%	-0.35%	1.47%	-0.31%	24.71%	44.79%
DP	0.04%	0.21%	0.24%	-0.42%	2.82%	33.04%
DY	0.23%	1.18%	-0.25%	0.56%	2.87%	26.05%
EP	-0.23%	0.97%	1.72%	-0.30%	-0.82%	9.90%
BM	1.68%	-0.73%	-0.86%	2.85%	21.13%	8.08%
SVAR	-0.52%	5.70%	0.78%	5.83%	1.86%	69.55%
NTIS	0.06%	0.05%	0.89%	1.51%	-0.56%	6.14%
CPI	0.05%	-0.16%	1.91%	-0.03%	2.01%	36.22%
IK	3.74%	1.53%	1.50%	2.94%	50.33%	25.83%
CAY	1.20%	2.91%	2.59%	0.83%	15.66%	3.23%
UER	2.74%	1.08%	1.65%	3.03%	52.16%	12.95%
MS2	0.02%	-0.06%	-0.11%	0.65%	-0.22%	7.20%
IIP	0.84%	-1.72%	-1.44%	8.36%	-0.60%	23.46%
CUM	1.22%	-0.89%	1.19%	-1.95%	11.06%	29.89%
PMI	0.04%	0.23%	1.99%	0.42%	-2.15%	24.27%
OI	1.68%	0.25%	1.01%	-1.05%	19.78%	38.26%
KI	0.23%	0.04%	0.95%	-0.01%	3.02%	-5.03%
USDX	0.45%	0.72%	-0.09%	0.19%	6.42%	-1.60%
FPO	0.45%	-0.80%	0.39%	-0.68%	-0.72%	12.63%

Notes: This table summarizes the in-sample results, consisting of two panels for the technical indicators defined in Section 2.2, the macroeconomic variables descried in Section 2.3 from 1992:01 to 2014:12. Every two columns list the results of three Return factors—Return all, Return_in and Return_off, respectively. The second (fourth, sixth) and third (fifth, seventh) columns report R^2_{exp} and R^2_{rec} during expansion and recession periods, respectively.

Table 6 Bivariate predictive regression estimation: Principle components

Predictor	Coeff.	t-stat.	R^2	R^2_{exp}	R^2_{rec}
Panel A: Ret_g					
$\hat{F}^T_{c,1,t}$	-0.0915	-6.8979***	40.27%	39.88%	41.65%
$\hat{F}^T_{c,2,t}$	-0.0191	-0.6377			
$\hat{F}^T_{c,3,t}$	-0.3792	-10.2508***			
$\hat{F}^E_{c,1,t}$	0.0694	2.5946***	2.81%	4.20%	0.44%
Panel B: Ret_i					
$\hat{F}^T_{c,1,t}$	0.0808	5.3253***	35.87%	37.67%	32.33%
$\hat{F}^T_{c,2,t}$	0.1836	7.7265***			
$\hat{F}^T_{c,3,t}$	-0.2563	-10.8445***			
$\hat{F}^E_{c,1,t}$	0.0392	1.5296***	40.27%	39.88%	41.65%
$\hat{F}^E_{c,2,t}$	0.0046	0.1618			
$\hat{F}^E_{c,3,t}$	-0.0740	-1.7612			
Panel C: Ret_o					
$\hat{F}^T_{c,1,t}$	-0.0036	-1.0464	11.33%	11.04%	13.33%
$\hat{F}^T_{c,2,t}$	0.0267	3.7416***			
$\hat{F}^T_{c,3,t}$	-0.0320	-4.2065			
$\hat{F}^E_{c,1,t}$	0.0624	20.3499***	63.92%	65.36%	53.96%
$\hat{F}^E_{c,2,t}$	0.0186	5.8083***			
$\hat{F}^E_{c,3,t}$	-0.0071	-1.4148			

Notes: This table summarizes the in-sample results of principle components, consisting of 3 panels for the technical indicators defined in Section 2.2, the macroeconomic variables descried in Section 2.3 from 1992:01 to 2014:12, respectively. The principal components for the technical indicators ($\hat{F}^T_{c,t} = (\hat{F}^T_{c,1,t}, ..., \hat{F}^T_{c,3,t})'$) and the macroeconomic variables ($\hat{F}^{E}_{c,t} = (\hat{F}^{E}_{c,1,t},\ldots,\hat{F}^{E}_{c,3,t})'$) defined in Section 4.1.3.The second and third columns show slope coefficient and its heteroskedasticity-consistent t-statistic. ***, ** and * indicate the rejection of normality at the 1%, 5% and 10% levels, respectively. The fourth to sixth columns report R^2, R^2_{exp} and R^2_{rec} overall and during expansion and recession periods, also, respectively.

Table 7 Out-of-Sample Forecasting Results

Predictor	Ret_g			Ret_i			Ret_o		
	MSFE	$R_{c,os}^{2}$	*MSFE-adj*	*MSFE*	$R_{c,os}^{2}$	*MSFE-adj*	*MSFE*	$R_{c,os}^{2}$	*MSFE-adj*
Panel A: Technical Indicators									
HA	1.5342			1.1429			0.0544		
MA(1,9)	1.3174	14.1343	4.4822***	0.9677	15.3290	4.5171***	0.0564	-3.7278	-0.2815
MA(1,12)	1.4063	8.3399	3.2720***	1.0143	11.2490	3.6907***	0.0568	-4.5029	-0.8792
MA(2,9)	1.4725	4.0285	2.2100**	1.1178	2.1937	1.5497*	0.0553	-1.7334	-1.0930
MA(2,12)	1.4827	3.3655	2.0211**	1.1190	2.0952	1.5455*	0.0557	-2.4707	-1.0990
MA(3,9)	1.5238	0.6863	0.9107	1.1254	1.5343	1.3351*	0.0554	-1.9068	-1.0945
MA(3,12)	1.5293	0.3230	0.7619	1.1239	1.6591	1.4161*	0.0551	-1.2436	-1.7310
MA(6,9)	1.5380	-0.2445	0.2927	1.1432	-0.0235	0.1984	0.0550	-1.1687	-1.5686
MA(6,12)	1.5464	-0.7880	-0.3178	1.1417	0.1023	0.4433	0.0555	-1.9715	-1.9019
MOM(1)	0.7287	52.5041	12.8533***	0.5095	55.4189	13.0410***	0.0503	7.4237	3.0262***
MOM(2)	1.1572	24.5783	6.3682***	0.9095	20.4245	5.7210***	0.0539	0.8730	1.2410
MOM(3)	1.2948	15.6103	4.9258***	0.9629	15.7501	4.8841***	0.0544	0.0124	0.8323
MOM(6)	1.4290	6.8610	2.9899***	1.0825	5.2813	2.4556***	0.0558	-2.6699	-0.2894
MOM(9)	1.4639	4.5879	2.3852***	1.0663	6.7056	2.7865***	0.0559	-2.7684	-1.2402
MOM(12)	1.5260	0.5386	1.1817	1.1139	2.5339	1.7275**	0.0565	-3.9710	-0.9291
VOL(1,9)	1.4049	8.4341	3.3096***	1.0213	10.6430	3.7350***	0.0543	0.1535	0.7303
VOL(1,12)	1.4149	7.7799	3.1381***	1.0440	8.6554	3.4324***	0.0549	-0.9234	-0.0670
VOL (2,9)	1.4955	2.5256	1.6757**	1.1061	3.2231	2.0341**	0.0544	-0.1034	-0.0808
VOL (2,12)	1.5130	1.3859	1.2249	1.1069	3.1498	1.9260**	0.0542	0.3357	0.5759
VOL (3,9)	1.5090	1.6494	1.4298*	1.1223	1.8058	1.4988*	0.0543	0.0646	0.2654

VOL (3,12)	1.5411	-0.4430	0.3128	1.1182	2.1599	1.6354*	0.0538	1.0799	1.2188
VOL (6,9)	1.5430	-0.5661	-1.3018	1.1356	0.6376	0.8559	0.0537	1.2107	1.2759
VOL (6,12)	1.5433	-0.5865	-1.2918	1.1298	1.1442	1.1379	0.0529	2.7453	2.4450***
Panel B: Macroeconomic Variables									
TBL	1.5510	-1.0855	0.6483	1.1272	1.3724	1.4057*	0.0100	81.5546	12.8025***
LGB	1.5098	1.5972	1.4520*	1.1396	0.2902	0.8590	0.0224	58.8271	10.2671***
TermS	1.5714	-2.4192	-0.6748	1.1345	0.7358	1.1015	0.0353	35.1465	9.3031***
DFY	1.5761	-2.7230	-0.1392	1.1856	-3.7377	-0.6918	0.0410	24.6879	3.3433***
DP	1.5390	-0.3053	-1.3829	1.1490	-0.5362	-0.5475	0.0492	9.5388	5.4215***
DY	1.5320	0.1507	0.5003	1.1471	-0.3636	-0.5946	0.0498	8.3480	5.6506***
EP	1.5545	-1.3164	-0.3376	1.1420	0.0808	0.8068	0.0577	-6.1056	1.1320
BM	1.5280	0.4087	0.7164	1.1417	0.1025	0.3826	0.0395	27.4413	8.6606***
SVAR	1.5564	-1.4384	0.7346	1.2081	-5.7005	0.9902	0.0461	15.2814	1.8163**
NTIS	1.5439	-0.6262	-1.0548	1.1368	0.5359	0.6319	0.0552	-1.4760	0.0512
CPI	1.5605	-1.7084	-1.0007	1.1630	-1.7574	0.7405	0.0503	7.4516	2.0315**
IK	1.5084	1.6865	1.5308*	1.1152	2.4258	2.1664**	0.0219	59.7841	10.9412***
CAY	1.5125	1.4227	1.6445**	1.1265	1.4377	1.6597**	0.0430	20.8523	7.7109***
UER	1.5202	0.9200	1.2718	1.1170	2.2688	1.9337**	0.0202	62.9414	10.7449***
MS2	1.5457	-0.7457	-1.2060	1.1510	-0.7098	-0.2603	0.0542	0.3494	0.4646
IIP	1.5836	-3.2153	-0.6066	1.1612	-1.6022	0.1104	0.0533	2.0418	1.1679
CUM	1.5443	-0.6515	0.1263	1.1666	-2.0776	-0.6804	0.0447	17.8692	4.5734
PMI	1.5513	-1.1070	-1.4710	1.1622	-1.6867	0.4486	0.0551	-1.3022	0.4501
OI	1.5287	0.3669	0.6223	1.1590	-1.4119	-0.4998	0.0359	34.0428	9.7295***
KI	1.5429	-0.5633	-0.7748	1.1384	0.3936	0.9149	0.0538	1.1074	0.9523
USDX	1.5340	0.0216	0.2900	1.1523	-0.8189	-1.1119	0.0523	3.7592	2.5830***
FPO	1.5559	-1.4050	-0.4901	1.1711	-2.4677	-0.5873	0.0548	-0.7317	1.1704

Notes: This table summarizes the out of-sample results, consisting of 2 panels for the technical indicators defined in Section 2, the macroeconomic variables in Table 1for the 22 years from 1992:01 to 2013:12 with 2004:01 as an interval.E very three columns list the results of three Return factors—Return all, Return_in and Return_off, respectively. The $R_{c,os}{}^{2}$ in the third(sixth, ninth) columnsmeasure the percent reductions in mean squared forecast error (*MSFE*) in the second(fifth, eighth) columns for the predictive regression forecasts based on the predictors relative to the historical average benchmark forecasts. The fourth(seventh, tenth) columns report the *MSFE-adjusted* statistics for testing the null hypothesis that the historical average *MSFE* is less than or equal to the predictive regression *MSFE* against the one-sided (upper-tail) alternative hypothesis that the historical average *MSFE* is greater than the predictive regression *MSFE.*

Table 8 Out-of-Sample Forecasting Results with Business Cycle

Predictor	Ret_g		Ret_i		Ret_o	
	R^2_{exp} (%)	R^2_{rec} (%)	R^2_{exp} (%)	R^2_{rec} (%)	R^2_{exp} (%)	R^2_{rec} (%)
Panel A: Technical Indicators						
MA(1,9)	15.0988	11.9312	17.6624	12.2215	-8.2082	8.9244
MA(1,12)	9.6460	5.3561	14.9387	6.3354	-9.2437	8.8845
MA(2,9)	3.5098	5.2133	0.9769	3.8142	-3.9253	4.4561
MA(2,12)	3.1421	3.8759	2.7722	1.1935	-4.6975	3.8174
MA(3,9)	-0.1331	2.5582	1.5267	1.5443	-3.8089	3.4642
MA(3,12)	0.0222	1.0100	2.2692	0.8467	-2.3461	1.8697
MA(6,9)	-1.2496	2.0516	0.2726	-0.4178	-1.5316	-0.1439
MA(6,12)	-0.6060	-1.2036	0.5290	-0.4660	-2.6660	-0.0104
MOM(1)	51.5198	54.7527	66.1294	41.1556	3.8112	17.6251
MOM(2)	23.5355	26.9606	21.9724	18.3631	-2.1598	9.4372
MOM(3)	18.0281	10.0872	17.1862	13.8376	-2.6465	7.5205
MOM(6)	5.8964	9.0646	2.9242	8.4204	-6.1394	7.1275
MOM(9)	6.0927	1.1503	9.7390	2.6660	-5.0166	3.5804
MOM(12)	2.6219	-4.2204	2.9691	1.9542	-6.8023	4.0244
VOL(1,9)	7.3117	10.9981	8.1212	14.0012	-2.9965	9.0488
VOL(1,12)	7.6381	8.1039	7.7386	9.8764	-3.1594	5.3909
VOL (2,9)	1.0948	5.7942	1.5663	5.4295	-0.5110	1.0476
VOL (2,12)	1.3079	1.5641	0.5935	6.5542	0.4678	-0.0372
VOL (3,9)	0.6181	4.0054	0.2617	3.8620	0.4328	-0.9754
VOL (3,12)	-0.4676	-0.3870	1.4712	3.0770	1.7386	-0.7801
VOL (6,9)	-0.6702	-0.3284	0.3345	1.0412	1.9414	-0.8527

VOL (6,12)	-0.9001	0.1301	1.1860	1.0887	3.8225	-0.2963
Panel B: Macroeconomic Variables						
TBL	-1.1748	-0.8815	4.7331	-3.1032	84.5719	73.0341
LGB	1.4221	1.9973	1.3281	-1.0919	63.1301	46.6760
TermS	-2.9828	-1.1317	2.3154	-1.3679	35.5219	34.0863
DFY	0.7508	-10.6586	1.0743	-10.1459	10.5583	64.5875
DP	-0.2493	-0.4334	-0.2383	-0.9328	6.4766	18.1862
DY	0.0367	0.4111	-0.1069	-0.7054	6.1476	14.5618
EP	-3.4622	3.5857	-1.2929	1.9102	-18.2259	28.1200
BM	0.8150	-0.5195	0.1359	0.0581	30.9602	17.5045
SVAR	-0.2375	-4.1818	2.0537	-16.0270	-4.7899	71.9596
NTIS	-0.5900	-0.7089	0.5961	0.4558	-7.6372	15.9220
CPI	-0.3068	-4.9102	3.3290	-8.5310	2.2471	22.1482
IK	1.7803	1.4720	4.3758	-0.1710	66.1819	41.7178
CAY	1.0967	2.1674	2.1255	0.5218	26.3339	5.3730
UER	0.8805	1.0102	4.2316	-0.3450	72.0787	37.1391
MS2	-0.6489	-0.9668	-0.9773	-0.3535	-0.9217	3.9388
IIP	0.6257	-11.9899	0.4063	-4.2769	-8.5637	31.9901
CUM	0.6583	-3.6437	0.3131	-5.2613	6.8434	49.0044
PMI	-1.1602	-0.9856	4.2006	-9.5270	-13.6372	33.5300
OI	1.0083	-1.0983	-0.3330	-2.8486	40.7066	15.2253
KI	-0.3496	-1.0514	1.0581	-0.4913	2.9845	-4.1931
USDX	0.3700	-0.7744	-1.8012	0.4893	9.9919	-13.8412
FPO	-0.6490	-3.1321	-0.2404	-5.4340	-8.4443	21.0475

Notes: This table summarizes the out-of-sample results, consisting of 2 panels for the technical indicators defined in Section 2, the macroeconomic variables in Table 1 for the 22 years from 1992:01 to 2013:12 with 2004:01 as an interval. Every two columns list the results of three Return factors—Return all, Return_in and Return_off, respectively. The second (fourth, sixth) and third (fifth, seventh) columns report R^2_{exp} and R^2_{rec} during expansion and recession periods, respectively.

Table 9 Out-of-Sample Forecasting Results: Principle Components

Predictor	*MSFE*	$R_{c,os}{}^2$ (%)	*MSFE-adj*	R^2_{exp} (%)	R^2_{rec} (%)
Panel A: Ret_g					
$\hat{F}^T_{c,1,t}$	1.3695	10.7408	5.5015***	11.5666	8.8541
$\hat{F}^T_{c,2,t}$	0.9796	36.1558	6.9438***	33.9942	41.0940
$\hat{F}^E_{c,1,t}$	1.5283	0.3881	0.5746	0.6675	-0.2501
$\hat{F}^E_{c,2,t}$	1.6127	-5.1110	-0.2359	-1.4845	-13.3953
Panel B: Retu_i					
$\hat{F}^T_{c,1,t}$	-0.1564	-0.1564	-0.1564***	13.8749	8.5884
$\hat{F}^T_{c,2,t}$	-17.1335	-17.1335	-17.1335***	38.7499	27.8306
$\hat{F}^E_{c,1,t}$	1.1282	1.2875	1.3070*	2.3717	-0.1564
$\hat{F}^E_{c,2,t}$	1.2125	-6.0880	0.5517	2.2062	-17.1335
Panel C: Ret_o					
$\hat{F}^T_{c,1,t}$	0.0542	0.4175	0.7230	-1.1847	4.9418
$\hat{F}^T_{c,2,t}$	0.0527	3.0948	1.9510**	-2.2573	18.2084
$\hat{F}^E_{c,1,t}$	0.0368	32.3523	8.6952***	29.4831	40.4544
$\hat{F}^E_{c,2,t}$	0.0157	71.1815	6.7743***	75.8826	57.9063

Notes:This table summarizes the out-of-sample results of principle components, consisting of 3 panels for the technical indicators defined in Section 2, the macroeconomic variables in Table 1 for the 22 years from 1992:01 to 2013:12 with 2004:01 as an interval, respectively.The principal components for the technical indicators ($\hat{F}^T_{c,t} = (\hat{F}^T_{c,1,t}, ..., \hat{F}^T_{c,3,t})'$) and the macroeconomic variables ($\hat{F}^E_{c,t} = (\hat{F}^E_{c,1,t}, ..., \hat{F}^E_{c,3,t})'$).The second and third columns show slope coefficient and its heteroskedasticity-consistent *t*-statistic. ***, ** and * indicate the rejection of normality at the 1%, 5% and 10% levels, respectively. The fourth to sixth columns report R^2, R^2_{exp} and R^2_{rec} overall and during expansion and recession periods, also, respectively.

Table 10 Robust Analysis: Out-of-Sample Forecasting Results for Volatility

Predictor	Vola_g			Vola_i			Vola_o		
	MSFE	$R_{c,os}^2$	*MSFE-adj*	*MSFE*	$R_{c,os}^2$	*MSFE-adj*	*MSFE*	$R_{c,os}^2$	*MSFE-adj*
Panel A: Technical Indicators									
HA	1.4582			0.3487			0.0524		
MA(1,9)	1.0575	27.4750	6.5106***	0.2491	28.5603	6.7548***	0.0490	6.5414	3.2203***
MA(1,12)	1.1339	22.2342	5.6684***	0.2595	25.5869	6.3802***	0.0511	2.5411	2.4361***
MA(2,9)	1.4679	-0.6657	-2.5850	0.3507	-0.5801	-1.0792	0.0529	-1.0015	-0.5807
MA(2,12)	1.4629	-0.3283	-1.0302	0.3503	-0.4480	-0.7894	0.0536	-2.2604	-0.6117
MA(3,9)	1.4717	-0.9260	-0.8099	0.3510	-0.6445	-1.0614	0.0536	-2.1923	-0.2778
MA(3,12)	1.4675	-0.6380	-1.3872	0.3509	-0.6189	-1.6573	0.0538	-2.6581	-0.1116
MA(6,9)	1.4638	-0.3896	-0.3620	0.3508	-0.5884	-1.1935	0.0544	-3.7091	-0.7488
MA(6,12)	1.4664	-0.5632	-0.6006	0.3538	-1.4686	-0.8593	0.0541	-3.1634	0.2742
MOM(1)	0.6173	57.6649	12.8153***	0.1651	52.6630	10.9203***	0.0498	4.9357	2.8261***
MOM(2)	1.2133	16.7933	4.8589***	0.3081	11.6568	3.9398***	0.0494	5.7170	2.9988***
MOM(3)	1.3083	10.2769	3.6549***	0.3059	12.2643	3.9310***	0.0518	1.1829	1.3301*
MOM(6)	1.3217	9.3599	3.4954***	0.3002	13.9178	4.5171***	0.0516	1.6587	1.8189**
MOM(9)	1.3674	6.2247	2.8330***	0.3272	6.1696	2.8770***	0.0524	-0.0223	1.5818*
MOM(12)	1.3261	9.0535	3.4689***	0.3367	3.4518	2.2040**	0.0518	1.1911	1.6583**
VOL(1,9)	1.4630	-0.3308	1.4029*	0.3385	2.9209	2.0851**	0.0550	-4.8899	-0.2590
VOL(1,12)	1.4422	1.0950	1.6026*	0.3449	1.0831	1.5000*	0.0558	-6.4386	-0.8113
VOL (2,9)	1.4811	-1.5720	-0.8651	0.3500	-0.3558	0.1435	0.0534	-1.7836	-1.0584
VOL (2,12)	1.4799	-1.4931	-1.0907	0.3507	-0.5816	-0.4621	0.0542	-3.3916	-1.5655
VOL (3,9)	1.4631	-0.3371	-0.7134	0.3514	-0.7842	-0.2684	0.0544	-3.7702	-1.5599
VOL (3,12)	1.4785	-1.3960	-1.4717	0.3506	-0.5472	-0.5074	0.0556	-6.0157	-1.8385

VOL (6,9)	1.4663	-0.5613	-1.6450	0.3508	-0.6017	-0.5601	0.0538	-2.5800	-1.3213
VOL (6,12)	1.4678	-0.6629	-1.6963	0.3494	-0.1991	-0.3338	0.0545	-3.8751	-1.1245
Panel B: Macroeconomic Variables									
TBL	1.4329	1.7289	1.5504*	0.3103	11.0030	3.8198***	0.0071	86.5104	14.6201***
LGB	1.4459	0.8426	1.0237	0.3199	8.2689	3.2324***	0.0210	60.0259	10.6493***
TermS	1.4535	0.3216	0.8084	0.3352	3.8802	2.4619***	0.0317	39.4328	9.5962***
DFY	1.4796	-1.4688	-0.2292	0.3566	-2.2584	0.8301	0.0468	10.7651	4.1930***
DP	1.4603	-0.1447	-1.1309	0.3470	0.4948	1.7345**	0.0492	6.1462	5.9654***
DY	1.4608	-0.1812	-1.3561	0.3474	0.3658	1.4796*	0.0494	5.7098	6.1810***
EP	1.4799	-1.4911	-0.6471	0.3570	-2.3714	-0.3923	0.0566	-7.9056	0.9353
BM	1.4495	0.5953	0.9380	0.3367	3.4525	2.9184***	0.0387	26.2403	8.8098***
SVAR	1.4711	-0.8890	-2.3870	0.3672	-5.3088	0.3105	0.0505	3.5966	1.8125**
NTIS	1.4651	-0.4782	-3.8170	0.3506	-0.5410	-0.9827	0.0528	-0.8039	-0.2190
CPI	1.4773	-1.3129	-0.9530	0.3521	-0.9744	-0.0751	0.0522	0.4702	0.8498
IK	1.4389	1.3213	1.3055*	0.3247	6.8769	3.4414***	0.0196	62.6181	10.9626***
CAY	1.4545	0.2521	0.5706	0.3357	3.7450	2.6968***	0.0392	25.2451	7.8608***
UER	1.4479	0.7008	0.9407	0.3239	7.1114	3.3991***	0.0178	66.0757	10.3950***
MS2	1.4718	-0.9360	-1.0674	0.3510	-0.6448	-0.1793	0.0525	-0.0583	0.0298
IIP	1.4661	-0.5473	-0.2605	0.3406	2.3205	1.2622	0.0522	0.4404	0.7747
CUM	1.4609	-0.1884	0.0495	0.3419	1.9649	1.5645*	0.0445	15.0361	5.2140***
PMI	1.4695	-0.7804	-1.9601	0.3521	-0.9597	-2.0119	0.0530	-1.1505	-0.3619
OI	1.4656	-0.5129	-0.2203	0.3373	3.2707	2.4475***	0.0349	33.3533	9.4163***
KI	1.4583	-0.0088	0.1030	0.3494	-0.2009	-0.3161	0.0509	2.8855	2.1762***
USDX	1.4652	-0.4839	-0.9814	0.3504	-0.4829	-0.2426	0.0514	2.0265	1.6275***
FPO	1.4736	-1.0571	-0.4223	0.3520	-0.9325	-0.0379	0.0536	-2.3174	1.4197***

Notes:This table summarizes the robust analysis for out of-sample results, consisting of 2 panels for the technical indicators defined in Section 2, the macroeconomic variables in Table 1for the 22 years from 1992:01 to 2013:12 with 2004:01 as an interval.Every three columns list the results of three volatility factors—Volatility_all, Volatility_in and Volatility_off, respectively. The

$R_{c,os}^{2}$ in the third(sixth, ninth) columnsmeasure the percent reductions in mean squared forecast error (*MSFE*) in the second(fifth, eighth) columns for the predictive regression forecasts based on the predictors relative to the historical average benchmark forecasts. The fourth(seventh, tenth) columns report the *MSFE-adjusted* statistics for testing the null hypothesis that the historical average *MSFE* is less than or equal to the predictive regression *MSFE* against the one-sided (upper-tail) alternative hypothesis that the historical average *MSFE* is greater than the predictive regression *MSFE.*

Table 11Robust Analysis: Out-of-Sample Forecasting Resultsfor Volatility with Business Cycle

Predictor	Vola_g		Vola_i		Vola_o	
	R^2_{exp} (%)	R^2_{rec} (%)	R^2_{exp} (%)	R^2_{rec} (%)	R^2_{exp} (%)	R^2_{rec} (%)
Panel A: Technical Indicators						
MA(1,9)	29.0472	17.4918	32.3495	12.3380	14.9157	-40.0072
MA(1,12)	22.2233	22.3029	28.7763	11.9326	13.8994	-60.5938
MA(2,9)	-0.6825	-0.5586	-1.0727	1.5287	-0.0908	-6.0642
MA(2,12)	-0.2521	-0.8117	-0.4817	-0.3037	1.0560	-20.6947
MA(3,9)	-1.0780	0.0390	-1.0537	1.1072	2.4567	-28.0337
MA(3,12)	-0.6475	-0.5775	-0.9115	0.6338	3.4153	-36.4170
MA(6,9)	-0.2689	-1.1558	-0.7610	0.1501	0.9978	-29.8720
MA(6,12)	-0.5714	-0.5108	-2.0856	1.1728	4.2630	-44.4436
MOM(1)	57.0502	61.5683	53.9820	47.0163	5.0718	4.1793
MOM(2)	17.1315	14.6453	12.0523	9.9639	8.1203	-7.6417
MOM(3)	8.8015	19.6459	16.0346	-3.8767	3.5467	-11.9566
MOM(6)	10.6256	1.3222	13.9982	13.5736	7.1577	-28.9079
MOM(9)	5.8882	8.3613	8.5300	-3.9357	7.4371	-41.4855
MOM(12)	7.9795	15.8733	1.5458	11.6118	8.2868	-38.2504
VOL(1,9)	-0.8456	2.9380	2.5132	4.6664	-5.0606	-3.9410
VOL(1,12)	-0.2472	9.6179	1.1286	0.8885	-7.6447	0.2656
VOL (2,9)	-1.3682	-2.8662	0.0425	-2.0613	-2.4592	1.9722
VOL (2,12)	-1.2923	-2.7679	-0.8078	0.3871	-3.7851	-1.2046
VOL (3,9)	-0.3161	-0.4709	-0.4652	-2.1502	-4.7344	1.5891
VOL (3,12)	-1.1827	-2.7508	-0.8066	0.5632	-6.0725	-5.6994
VOL (6,9)	-0.4711	-1.1343	-0.8480	0.4527	-3.8892	4.6969

VOL (6,12)	-0.6309	-0.8661	-0.1762	-0.2968	-4.5280	-0.2460
Panel B: Macroeconomic Variables						
TBL	1.9106	0.5755	12.9564	2.6402	86.3931	87.1624
LGB	0.6959	1.7739	9.2058	4.2576	60.1686	59.2332
TermS	0.4187	-0.2949	4.1583	2.6895	37.3945	50.7630
DFY	0.1929	-12.0205	1.1915	-17.0282	7.8879	26.7578
DP	-0.0331	-0.8531	0.6493	-0.1664	4.6430	14.5018
DY	-0.0654	-0.9163	0.4665	-0.0652	4.6432	11.6385
EP	-1.2756	-2.8589	-2.4163	-2.1793	-18.9559	53.5179
BM	0.7015	-0.0794	4.1210	0.5906	27.2930	20.3893
SVAR	-0.2951	-4.6603	-0.5972	-25.4798	-2.8254	39.2935
NTIS	-0.4352	-0.7510	-0.8545	0.8012	-3.2800	12.9595
CPI	-0.2999	-7.7456	-0.5475	-2.8022	-0.7094	7.0270
IK	1.6138	-0.5360	8.5883	-0.4497	63.2731	58.9775
CAY	0.1604	0.8340	4.4051	0.9188	27.8511	10.7600
UER	0.9854	-1.1062	8.6479	0.5335	68.3711	53.3162
MS2	-0.6656	-2.6535	0.9310	-7.3912	-0.3426	1.5223
IIP	-1.1870	3.5149	0.2441	11.2102	-4.7116	29.0778
CUM	0.0605	-1.7690	2.1099	1.3440	6.9887	59.7674
PMI	-0.3993	-3.2003	-0.4231	-3.2571	-4.0848	15.1600
OI	-0.4374	-0.9925	3.8878	0.6289	35.7273	20.1573
KI	-0.2104	1.2712	-0.2998	0.2224	3.3242	0.4472
USDX	-0.2292	-2.1010	0.3955	-4.2434	7.0553	-25.9258
FPO	-1.4929	1.7102	-1.5063	1.5242	-7.9193	28.8208

Notes: This table summarizes the robust analysis for out-of-sample results, consisting of 2 panels for the technical indicators defined in Section 2, the macroeconomic variables in Table 1 for the 22 years from 1992:01 to 2013:12 with 2004:01 as an interval. Every two columns list the results of three volatility factors—Volatility all, Volatility _in and Volatility_off, respectively. The second (fourth, sixth) and third (fifth, seventh) columns report R^2_{exp} and R^2_{rec} during expansion and recession periods, respectively.

Table 12 Robust Analysis:Out-of-Sample Forecasting Results for Volatility with Principle Components

Predictor	*MSFE*	$R_{c,os}^{2}$ (%)	*MSFE-adj*	R^2_{exp} (%)	R^2_{rec} (%)
Panel A: Vola_g					
$\hat{F}^{T}_{c,1,t}$	1.2749	12.5666	7.8946***	12.3137	14.1725
$\hat{F}^{T}_{c,2,t}$	0.7905	45.7897	8.3977***	44.6083	53.2918
$\hat{F}^{E}_{c,1,t}$	1.4549	0.2230	0.5641	0.3699	-0.7095
$\hat{F}^{E}_{c,2,t}$	1.4511	0.4840	1.0798	1.6917	-7.1853
Panel B: Vola_i					
$\hat{F}^{T}_{c,1,t}$	0.3029	13.1267	6.8868***	13.8425	10.0624
$\hat{F}^{T}_{c,2,t}$	0.1924	44.8241	7.8626***	48.4079	29.4812
$\hat{F}^{E}_{c,1,t}$	0.3355	3.8025	3.1806***	4.1832	2.1725
$\hat{F}^{E}_{c,2,t}$	0.3280	5.9315	2.8218***	10.4794	-13.5390
Panel C: Vola_o					
$\hat{F}^{T}_{c,1,t}$	0.0518	1.2506	1.4861*	4.1630	-14.9379
$\hat{F}^{T}_{c,2,t}$	0.0502	4.1470	2.9442***	11.5092	-36.7757
$\hat{F}^{E}_{c,1,t}$	0.0363	30.8030	12.0162***	27.9975	46.3973
$\hat{F}^{E}_{c,2,t}$	0.0171	67.3254	11.2243***	76.6816	15.3185

Notes: This table summarizes the robust analysis out-of-sample results for volatility of principle components, consisting of 3 panels for the technical indicators defined in Section 2, the macroeconomic variables in Table 1 for the 22 years from 1992:01 to 2013:12 with 2004:01 as an interval, respectively. The principal components for the technical indicators ($\hat{F}^{T}_{c,t}=(\hat{F}^{T}_{c,1,t},...,\hat{F}^{T}_{c,3,t})'$) and the macroeconomic variables ($\hat{F}^{E}_{c,t}=(\hat{F}^{E}_{c,1,t},...,\hat{F}^{E}_{c,3,t})'$).The second and third columns show slope coefficient and its heteroskedasticity-consistent *t*-statistic. ***, ** and * indicate the rejection of normality at the 1%, 5% and 10% levels, respectively. The fourth to sixth columns report R^2, R^2_{exp} and R^2_{rec} overall and during expansion and recession periods, also, respectively.