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Can an Energy Futures Index Predict US Stock Market Index Movements?

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ABSTRACT

This paper investigates if an energy futures conditions index (EFCI) can predict movements of US major stock market indices. While various financial conditions indices provide information about the financial stress of a country, the existence of an energy conditions index, using futures markets, is scarce. Using weekly data over 1992-2017, this paper proposes an energy futures index using principal component analysis and test its predictability. The EFCI captures 95% of the variability inherent in the crude oil, heating oil and natural gas futures total reportable positions. Stability in forecast errors over different lags suggests 1 week lag is sufficient in forecasting weekly Nasdaq Composite Index, Nasdaq 100 and Russell 3000 values. 95% prediction levels support that the estimated model captures all actual market indices values, except for the 2000 technology bubble. The inability of the energy futures index in predicting stock market indices during the 2000 bubble can be explained by the poor sensitivity of energy futures to this specific event. Distributions were non-normal, not serially correlated and homoscedastic under the whole sample period, with diagnostics on pre and post technology bubble crisis showing mixed results.

Keywords: Energy Futures, Stock Market Index, Reportable Position
JEL Classifications: G15, G18, Q47

1. INTRODUCTION

As China is preparing to wobble the crude oil futures market with its forthcoming Chinese Yuan based crude oil futures contracts, it is critical to understand the role of futures markets and financial stability. In fact, the role of speculators in globalized markets dates back to early studies like Kaldor (1939), Working (1953), Nurske (1944) and Friedman (1953). While the first two authors propelled that speculators act as destabilizers in markets by allowing for speculative decisions based on other players' behavior, the latter two authors support that speculators can help in providing liquidity thereby decreasing volatility in markets. Despite some authors like Meese and Rogoff (1983) find it hard to explain movements in some currency futures markets, Houthakker (1957) and Yoo and Maddala (1991) found speculators in commodities markets to be more profitable. Comparatively, Hartzmark (1987) and Khoury and Perrakis (1998) found hedgers to pick the future direction of prices better than the risk takers. Studies like Figlewski (1981) and Santoni (1987) looked at the effect of futures markets on spot prices, where the former found higher volatility in post futures periods and vice versa with the latter study. More recent studies like Gurrib (2009) found hedgers' and speculators' volatilities in their positions to decay over time, following major events in the 1990s, suggesting that both players react well to news volatility. Gurrib (2018a) looked at the relationship between major currency futures and major financial conditions indexes and found only Chicago's National Financial Condition Index (NFCI) was able to capture 1 week ahead forecast of Japanese Yen speculators and hedgers net positions. More importantly, Aggarwal (1988) found both an increase post futures period volatility, but also an increase in volatility over time, suggesting futures markets is not necessarily linked to volatility in other markets. This suggests other factors like financial conditions can drive volatility as well in markets, including futures markets.

For instance, Dudley (2010) and Koop and Korobilis (2014) found financial conditions information to be helpful for policymakers to assess linkages between reported financial markets, economic activity and policies. Changes in market uncertainty, bailouts or rumors on corporate transactions, and shifts in investor sentiment triggered by eccentric events can all influence financial markets, which in turn affect asset prices, firm's value and ultimately economic performance. IMF (2017) reported that around 20-40% of changes in financial conditions indices (FCIs) can be attributed to global financial conditions, where one factor, which is correlated with the Chicago Board Options Exchange Volatility Index (CBOE VIX), tends to be the main driver. Adrian et al. (2016) found FCIs to be useful in predicting future economic retrenchments. While Aramonte et al. (2017) propel that FCIs generally exhibit a large amount of common variability, they can produce significantly different values on financial conditions at a given point in time. The construction of the FCIs varies considerably, although all of them are largely based on financial market variables, including implied volatilities, Treasury yields, yield spreads and stock market returns. Kliesen et al. (2012) provides a detailed list of variables used in major US FCIs.

Despite studies focusing on the relationship between energy futures conditions and stock market indices markets movements is scarce, some studied looked at the relationships between net positions of hedgers and speculators, futures markets, and the use of financial conditions in foreign currency futures and spot markets. Gurrib (2009) used GARCH/PARCH models to assess the predictability of hedgers' and speculators' positions on 29 futures markets, and found models used to be poor predictors of 1-month return. The same study also found currency futures to be non-normal, more volatile than equity index futures, with volatility decaying over time. Similarly, Gurrib (2008) analyzed the effect of major global events on speculators and hedgers' net positions, and find any significant structural break was short lived. Gurrib (2018b) reported the St Louis Federal Financial Condition Index (STLFSI) to forecast higher than actual values for AUD/USD and CAD/USD in the global financial crisis of 2008-2009, and vice versa during the 2000-2002 technology bubble. Lastly, but not least, Gurrib (2018c) found forecasts in Japanese yen futures net positions were lower (higher) for hedgers (speculators) than actual net positions during the latest financial crisis.

Our paper focuses primarily on the energy futures markets for two main reasons. The first one relates to IBRD (2017) who reported that in 2015-2016, US was the biggest consumer and producer of crude oil and natural gas. While China has surpassed US in terms of crude oil imports, the US crude oil market, natural gas and heating oil markets remain among the most actively futures markets, with the New York Mercantile Exchange (NYMEX) leading other exchanges such as the Intercontinental Exchange (ICE). Second, the focus on the energy futures markets allows for some comparison with earlier studies like Gurrib and Kamalov (2017) who reported a change in the return per unit of risk in crude oil and natural gas markets in the post 2008 crisis, compared to the pre-crisis period. Our study contributes to existing literature on various grounds. Firstly, while there are some studies in the area of equity markets and global financial conditions, the relationship between energy futures markets, financial conditions and stock markets indices movements is scarce. This is the first study to analyze if the largest speculators and hedgers total reportable positions, embedded through a proposed energy futures conditions index can affect major US stock market indices such as Nasdaq 100, Russell 3000, and the Nasdaq Composite Index. The implication of this paper is important in that it reveals whether the biggest players' transactions, through reportable positions in the energy futures markets, can potentially affect stock market index movements. This provides further guidance to regulatory bodies such as the Commodity Futures Trading Commission (CFTC) and the Securities Exchange Commission (SEC) in their mandate of ensuring greater price stability in the futures markets and equity markets. Bearing in mind that the US is among the top two consumers and producers of crude oil and natural gas, this study also shed further light whether cross market transmission is significant between US energy futures markets and the equity market. The rest of the paper provides some literature review, followed by the research methodology and data section. Some descriptive statistics, forecasting results and diagnostics are reported before providing some conclusive remarks.

2. LITERATURE REVIEW

IMF (2017) suggests that global financial integration can complicate the management of domestic financial conditions, especially where countries have integrated more into a global economy, recommending the need for policymakers to consider external factors when pursuing domestic objectives. While IMF and OECD construct and analyze country based FCIs, the global financial conditions are led by the US, which is the key country in the international monetary system. Rey (2013) reported that the average correlation between major US FCIs and two measures of global financial conditions and the VIX is 82%. IMF (2014) supports this conjunction by adding that the US dollar resides as an international currency with important roles in financial assets issuance and commodity trading under the oversight of regulatory bodies such as the CFTC. The importance of a well-functioning financial system to the broad economy is highlighted by the results in many studies. For instance, a contractionary credit supply policy eventually affects investment (Campello et al., 2010) and the broader economy (e.g., Bernanke (1983); Peek and Rosengren, (2000); Calomiris and Mason (2003)). Hakkio and Keeton (2009) provide a good overview of the features encircling financial stress, where it is defined as a disruption to the usual functions of the financial markets. While each period of financial stress is different in nature, they note important common characteristics based on the increase in uncertainty about the fundamental asset values, uncertainty about the behavior of other investors, increased asymmetric information, an increase in the willingness to shift toward less risky assets and an increase in the willingness to hold more liquid assets. While it is accepted that the price of an asset today is based on the present value of all future cash flows, financial stress results in volatility in different asset classes. Uncertainty in these cash flows can arise from uncertainty in future economic conditions or complex products which are difficult to value. For instance, uncertainty in crude oil was found to have significant significant effects on the average growth rate of real economic activity (Rahman and Serletis, 2010).

Similarly, uncertainty about the behavior of other investors can be explained by the fact that investors and lenders rely on their guesses about other investors' decisions instead of relying on fundamentals, which eventually lead to more volatility in prices.

The increase in asymmetric information can be substantiated with lenders having difficulty in determining the true quality of borrowers and also through investors losing confidence on the quality of issuers' credit ratings. Further, a flight to quality during financial stress lead to a move of investors toward safer assets, where safer assets would be expected to yield a lower return than riskier ones. As propelled by Caballero and Kurlat (2008), this is usually accompanied by an increase in borrowing costs for the riskier borrowers, and mostly a manifestation of investors and lenders to overestimate risk during economic bubbles (Guttentag and Herring, 1986). In the same line of thought, issuers of illiquid assets bear the higher cost of borrowing during financial stress periods, in order to compensate investors for the higher risk of not selling their assets. With the importance of financial stability justified, it is vital to understand that FCIs have been constructed using various ways like vector autogressive models (VARs) and impulse functions (Swiston, 2008), large macroeconomic models (Beaton et al., 2009), and principal component analysis (PCA). Since this study makes use of the latter method, an overview of FCI using PCA is necessary. For instance, Montagnoli and Napolitano (2005) used Kalman filtering algorithm for capturing the weight changes of financial variables in the explanation of the output gap, and constructed the FCI of the United States, Canada, Euro zone and the United Kingdom. Swiston (2008) used impulse response functions to build the FCI of the United States, and suggested that FCI could predict the United States' real gross development growth. Hatzius (2010) used the PCA method to select the first principal component as the FCI, and forecast economic growth by using FCI. Gomez (2011) extracted the main ingredient from indicators such as interest rates, exchange rates and asset prices, and constructed an FCI for Colombia using variance probability of the principal components as the weights. Generally, studies have shown that FCI was an effective tool of financial stability. Alternatively stated, the use of PCA in this study is motivated by the capacity of the technique to capture most variability in major energy futures contracts under uncorrelated components dubbed as principal components. The principal component(s) can then be used to test the predictability of major US market indices.

The motivation of this study is also backed by prior studies which looked at spillover effects in energy markets and stock markets. While Lin and Tamvakis (2001) found substantial spillover effects between crude oil markets, King and Wadwani (1990) and Hamao et al. (1990) supported the same but among stock markets. Panagiotidis and Rutledge (2007) found long run relationships between UK natural gas and crude oil prices. Gurrib (2018a) proposed a unified condition index and compared its predictability in the most actively traded USD paired foreign currencies, using root mean squared errors, and found major financial condition indices to be poor predictors of foreign currency spot values. Bessembinder and Chan (1992) tested the use of economic variables like Treasury bill yields and equity dividend yields and rejected the hypothesis that futures and equity markets contain different risk premia. Our study closes the gap in that it is the first to introduce an energy index based on the energy futures markets' largest players and assess if it can be used to predict 1 week ahead stock market indices values.

3. DATA

As stated earlier, the focus of this paper is on the three energy futures markets, namely the #2 Heating Oil, the light sweet crude oil, and natural gas. The latter two markets position US as the one of the biggest consumers and producers globally as per IBRD (2017). The data used is captured by the NYMEX and provided by CFTC. We focus on a weekly data frequency for three main reasons. Firstly, while the Commitment of Traders (COT) data are available from 1962, the weekly data has been available from 2000. Essentially, every Friday, the COT reports provide a breakdown of each Tuesday's open interest (OI) for markets in which 20 or more traders hold positions equal to or above the reporting levels established by CFTC. OI is calculated as follows:

OI = Total reportable positions+Total non-reportable positions

Total reportable positions = Commercial Long (Short) positions+Non-commercial Long (Short) positions+Net non-commercial spread (1)

The CFTC classifies information obtained from Form 40, with traders who manage their business risks by hedging in futures being classified as commercials, and the rest as non-commercials (CFTC, 2018). While the classification is continuously under review by CFTC, our study adopts a similar approach where net positions of hedgers (speculators) are calculated by taking the difference between commercial (non-commercial) long positions and commercial (non-commercial) short positions. Table 1 provides a summary of the Heating Oil, Crude Oil and Natural Gas futures markets, including their contract specifications, the proportion of reportable positions relative to OI, and the correlation coefficients of hedgers and speculators' net positions. As observed, the reportable positions represent a significant portion of the total OI in the most actively traded foreign currency futures, with a range of 0.39-0.96 in the Natural gas market. The largest hedgers and speculators share a strongly negative correlation across all currencies with correlation coefficients nearing-1. This is in line with Gurrib (2009) and Keynes (1930) who support that hedgers are usually net short due to their requirements, to protect their exposures from falling future prices. The Crude Oil hedgers

Table 1: Contract specifications

Futures market	Exchange	Contract size	Long Reportable positions/OI	Short Reportable positions/OI	Hedgers and Speculators'Net positions
#2 Heating oil	NYMEX	42,000 US gallons	0.51-0.91	0.61-0.94	−0.941
Crude oil, light sweet	NYMEX	1000 barrels	0.66-0.96	0.65-0.97	−0.996
Natural gas	NYMEX	10,000 MMBTU	0.39-0.96	0.41-0.98	−0.990

NYMEX is the New York Mercantile Exchange. MMBTU is equal to 1 million British Thermal Units. OI is open interest and speculators share the highest negative correlation of −0.996 suggesting that the largest speculators and hedgers in this markets take opposite positions.

Secondly, previous studies like IMF (2017) used 1-month ahead and one-quarter ahead forecasts to reduce the probability that predictions include business-cycle effects. With many FCIs consisting of the volatility Index measure (VIX), Bollerslev et al. (2009) find that the variance risk premium, which is the difference between the squared value of VIX and a measure of realized variance, can predict stock returns about 3-6 months ahead, with R-squared values slowly declining at longer horizons. Hatzius et al. (2010) find limited value in using FCIs as reliable early warning indicators, similar to Aramonte et al. (2017) who used monthly and quarterly horizons. English et al. (2005), who focus on four- and eight-quarter horizons, however, find aggregated financial variables as a proxy for financial condition to have some predictive power for macroeconomic variables. Thirdly but not least, although Hatzius et al. (2010) and the Federal Reserve Bank of Chicago used more than 45 and 100 variables respectively, Boivin and Ng (2006) argued that including more data does not inevitably yield better results. This is further supported by Lo Duca and Peltonen (2011) who argue that adding more redundant variables may not improve an FCI, and Grimaldi (2011) who find that too many variables can potentially exacerbate to more false periods of high stress in the markets. On these grounds, only the three energy markets under study are used to construct an energy futures conditions index. Although crude oil and heating oil data are available since January 1986, data for the Natural gas was available from April 1990. For consistency, weekly data is gathered across the three markets, over October 02, 1992-December 29, 2017. All markets indices data for the Nasdaq Composite Index, Nasdaq 100 and Russell 3000 are collected from St Louis Federal Reserve database (FRED). Other major market indices such as S and P 500 and the Dow Jones Industrial Average (DJIA) are not used since the data availability dated back to 2008 only and we want to ensure consistency with the energy futures data.

Table 2 reports the correlations among the Nasdaq composite index, the Russell 3000, Nasdaq 100, the net positions of large hedgers and speculators in the heating oil, crude oil and natural gas markets, and the total reportable positions (long and short) under each of the energy markets. While the three market indices share some strongly positive correlations among themselves, the relationship between market indices and net positions of the biggest players in the energy futures markets is different. Only speculators (hedgers) crude oil net positions were found to be strongly positively (negatively) correlated with the three market indices. The net positions held in the three energy markets, for either players, are not strongly correlated with each other, suggesting initially that hedgers and/or speculators within each energy futures market are not affected by other energy market players' net positions. However, on a broader basis, total long and short reportable positions in heating oil, crude oil and natural gas shared strongly correlations with each other across markets, suggesting markets reportable positions (long or short) are related to each other at a broad level, but not net positions of specific players among markets. For instance, the heating oil total

Table 2: Correlations between net positions, total reportable positions and market indices

Variable	Nasdaq composite Index	Russell 3000	Nasdaq 100	HO NP-H	HO NP-S	CROIL NP-H	CROIL NP-S	NGAS NP-H	NGAS NP-S	HO TRP L	HO TRP S	COIL TRP L	COIL TRP S	NGAS TRP L	NGAS TRP S
Nasdaq Composite Index	1.00														
Russell 3000	0.97	1.00													
Nasdaq 100	1.00	0.95	1.00												
HO NP-H	0.11	−0.09	−0.12	1.00											
HO NP-S	0.15	0.15	0.16	−0.94	1.00										
CROIL NP-H	−0.82	−0.86	−0.82	0.28	−0.26	1.00									
CROIL NP-S	0.84	0.88	0.83	−0.24	0.24	−1.00	1.00								
NGAS NP-H	0.41	0.48	0.42	−0.05	0.09	−0.49	0.48	1.00							
NGAS NP-S	−0.45	−0.53	−0.45	0.07	−0.13	0.52	−0.51	−0.99	1.00						
HO TRP L	0.80	0.88	0.80	−0.18	0.27	−0.81	0.82	0.70	−0.74	1.00					
HO TRP S	0.80	0.87	0.80	−0.24	0.31	−0.83	0.84	0.69	−0.74	1.00	1.00				
COIL TRP L	0.81	0.90	0.79	−0.20	0.31	−0.84	0.85	0.62	−0.67	0.94	0.93	1.00			
COIL TRP S	0.81	0.90	0.79	−0.21	0.31	−0.84	0.85	0.62	−0.68	0.94	0.93	1.00	1.00		
NGAS TRP L	0.77	0.86	0.75	−0.13	0.23	−0.80	0.81	0.57	−0.63	0.88	0.87	0.96	0.96	1.00	
NGAS TRP S	0.76	0.86	0.75	−0.13	0.23	−0.79	0.81	0.57	−0.63	0.88	0.87	0.96	0.96	1.00	1.00

HO, CROIL and NGAS represent the #2 Heating Oil futures, Crude Oil futures and Natural Gas. NP-H and NP-S represent the net positions of large hedgers and large speculators respectively, and is calculated by taking the difference between long and short positions. TRP-L and TRP-S represent the total reportable positions which are long and short respectively. Bold figures represents correlations with r-squared values>0.36

reportable long positions are strongly positively correlated with the crude oil and natural gas with 94% and 88% correlation values. This is in line with EIA (2017) who reported correlations between daily futures price changes of crude oil with other commodity markets mostly rose during 2011-2017. Further, correlation values increase significantly when total reporting positions (long or short) are assessed against the market indices, with values ranging from 0.75 to 0.90. This is also in line with EIA (2017) which found stronger positive correlations between crude oil energy futures and financials such as S and P 500. As per Bloomberg (2018), crude oil and natural gas retains a significant 15% and 8% target weight in the Bloomberg Commodity Index. While Panel A of Figure 1 shows the net positions of hedgers and speculators in the heating oil, crude oil and natural gas markets, panel B shows the trend in the total long and short reportable positions in these markets and the performance of the market indices under study. As observed in Panel A, both large speculators and hedgers reduced their net positions during the September 2008 financial crisis and 2000-2002 technology bubble. This was confirmed in the reduction in the total reportable positions during those periods, and the stock market indices which retracted twice during these correction waves. Both total reportable positions and stock markets indices resumed their long run upward following crisis periods. For the later part of this study, only total reportable positions, both long and short, are included, since net positions across futures markets were weakly correlated.

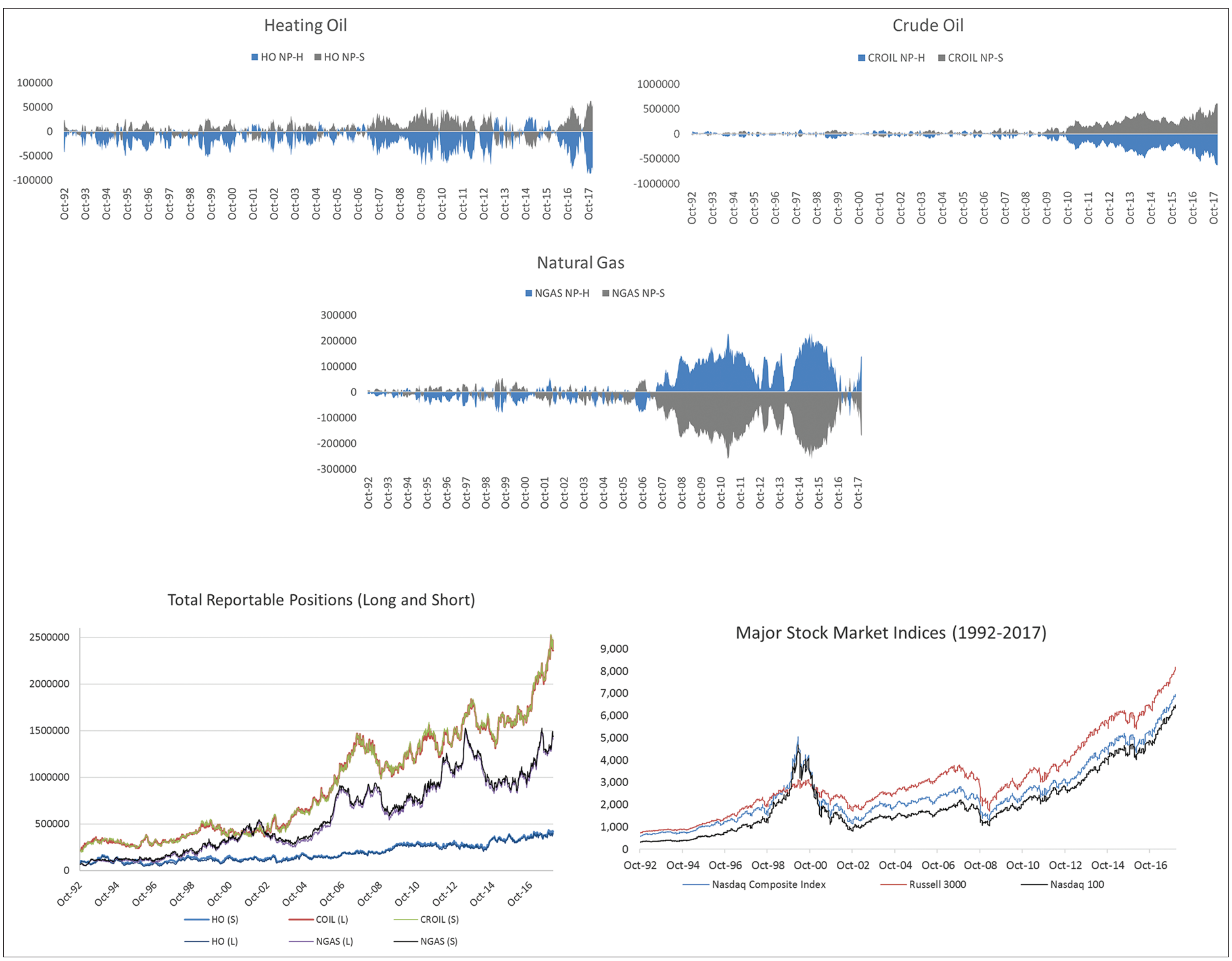
4. RESEARCH METHODOLOGY

The concept of PCA is essentially based on a reduction in the dimensions that connect variables, whilst retaining most of the variability among the variables. Alternatively stated, it is a mathematical procedure which transforms correlated variables into a number of uncorrelated ones called principal components. The first principal component captures the highest variability in the data, followed by the second principal component and so on. The PCA model is centered on eigenvalues and eigenvectors, where the former represents the variance of all variables accounted by a factor and the latter accounts for a scaled direction of a non-zero vector as follows:

$$|A\text{-}\gamma I|=0 \tag{2}$$

$$(A\text{-}\gamma I)\varphi=0 \tag{3}$$

Figure 1: Net positions, total reportable positions and stock market indices performance, Panel A: Net positions of hedgers and speculators, Panel B: Total reportable positions and US stock market indices



Where A is a square matrix in the form of $\begin{bmatrix} cov_{1,1} & cov_{1,2} \\ cov_{1,2} & cov_{2,2} \end{bmatrix}$ φ is a vector, γ is a scalar that satisfy equation (3), and I is an identity matrix The eigenvalues of A are calculated from the determinant of equation (1), followed by eigenvectors is an identity matrixing reduced matrix to row echelon form $\begin{pmatrix} a & \cdots & b \\ 0 & \ddots & \vdots \\ 0 & 0 & c \end{pmatrix}$ and reduced matrix to reduced row echelon form $\begin{pmatrix} 1 & \cdots & b \\ 0 & \ddots & \vdots \\ 0 & 0 & 1 \end{pmatrix}$ $cov_{1,1}$ and $cov_{2,2}$ represents the variance of specific FCIs, while $cov_{2,2}$ represents the covariance between any two FCIs. To identify periods which have witnessed large fluctuations, the FCI are scaled by their respective standard deviations, after having been demeaned. For instance, an index value of −1 is associated with financial conditions that are tighter than on average by one standard deviation, while an index value of 1 indicates that financial conditions are looser than average by one standard deviation. This common approach of standardization can also be found in Nelson and Perli (2007) and Cardarelli et al. (2011). The uncorrelated and linear combinations of standardized variables form the principal components as follows:

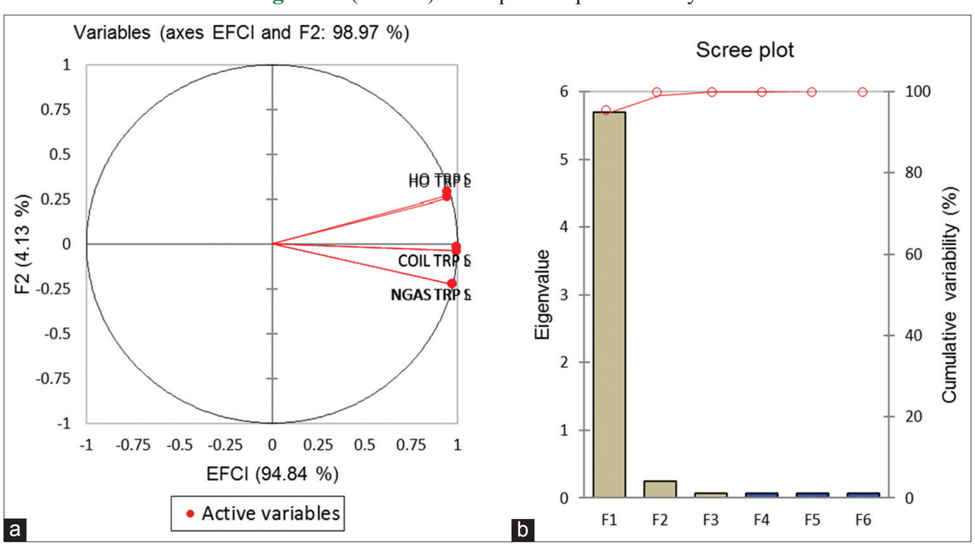
$$\sigma\_PC_1 > \sigma_{PC2} > \sigma_{PC3} > \sigma_{PCN} \quad (4)$$

Where $\sum_{i=1}^{n} \acute{o}_{PC_i} = Number\ of\ FCIs$ and $\sigma PC_{1\ldots n}$ represents the variance of the principal component 1, principal component 2, etc. Alternatively stated, the eigenvalues drop as we move from first principal component to the next one. The first principal component (PC1), which captures most of the variability in the FCIs is essentially the Energy Futures Conditions Index (EFCI) model, where the second and subsequent principal components are uncorrelated with each other.

5. FINDINGS

The results of the PCA is decomposed in Figure 2. As observed in the scree plot, the first principal component (PC1) which has an eigenvalue of 2.535 explains nearly 95% of all variations which exists among all the total reportable positions in the three energy futures markets. The cumulative variability increases only slightly after including the second principal component (PC2), suggesting that the first principal component is sufficient to account for major variations among heating oil, crude oil and natural gas. The correlation circle supports that that the second principal component only contribute to another 4.13% of the total variation in energy markets reportable positions. This is in line with relatively higher squared cosines values of EFCI compared to PC2 and PC3. The length of each of the six vectors shows the representativeness quality in the investigated PC dimension, which in our case is the 1st principal component. Although not reported here, the eigenvalues for the second and third principal components drop significantly to 0.248 and 0.058 respectively. The eigenvectors for the first principal component of heating oil, crude oil and natural gas long (short) reportable positions are

Figure 2: (a and b) Principal component analysis



Squared cosines of the variables

Reportable Positions	EFCI	F2	F3	F4	F5	F6
HO TRP L	0.928	0.068	0.003	0.002	0.000	0.000
HO TRP S	0.921	0.075	0.003	0.002	0.000	0.000
CROIL TRP L	0.979	0.002	0.019	0.000	0.000	0.000
CROIL TRP S	0.980	0.001	0.018	0.000	0.000	0.000
NGAS TRP L	0.941	0.051	0.008	0.000	0.000	0.000
NGAS TRP S	0.942	0.051	0.007	0.000	0.000	0.000

HO, CROIL and NGAS represent the #2 Heating Oil futures, Crude Oil futures and Natural Gas. NP-H and NP-S represent the net positions of large hedgers and large speculators respectively, and is calculated by taking the difference between long and short positions. TRP-L and TRP-S represent the total reportable positions which are long and short respectively. Values in bold correspond for each variable to the factor for which the squared cosine is the largest

0.404 (0.402), 0.415 (0.415), and 0.407 (0.407), with correlations between the EFCI and HO, CROIL and NGAS at 0.963 (0.960), 0.990 (0.990) and 0.970 (0.971) respectively.

Figure 3 displays the EFCI and total reportable long positions over the 1992-2017 period. Although not displayed here, EFCI and total reportable short positions shared similar relationships. As observed in the three graphs, EFCI tracked closely the performance of the three energy markets, including the 2007-2008 global financial crisis and to a less extent the 2000-2001 technology bubble, which also affected the major market indices as seen in Figure 1 Panel B. It is also important to note that the natural gas market experienced more than usual fluctuations in its total reportable long positions during 2012-2014, strong inventories, production growth and warmer than normal winter seasons like the El Nino phenomena (EIA, 2016). The total reportable short positions in the natural gas market also observed similar abrupt volatility change not captured by the EFCI, suggesting specific rather than broad energy market factors affecting markets like natural gas.

Note: The Energy Futures Conditions Index (EFCI) is displayed on the right hand side vertical axis. HO, CROIL and NGAS represent the#2 Heating Oil futures, Crude Oil futures and Natural Gas. NP-H and NP-S represent the net positions of large hedgers and large speculators respectively, and is calculated by taking the difference between long and short positions. TRP-L represent the total reportable positions which are long in their futures positions.

In line with Gurrib (2018a) who looked at the relationship between major currency futures and major financial conditions indexes; IMF (2017) and Stock and Watson (2002) who used PCA to predict excess stocks returns and macroeconomic variables over different time periods; and EIA (2017) who postulated energy markets like crude oil share similar risk and return relationships with stocks in the last decade, this study extends the application of PCA by analyzing the effect of the proposed EFCI onto major US stock market indices. While the root mean squared error (RMSE) is widely used in literature, the normalized root mean squared error values (NRMSE) is also adopted here to allow for the difference in the composition of the market indices and difference in the units. Although not reported here, the average values for the three market indices over the 1992-2017 period ranged from 2093 to 3087, and standard deviations between 1397 and 1688. Skewness and kurtosis values ranged between 0.944-1.005 and 0.327-0.411 respectively. The following model linking market indices with the energy futures conditions index is proposed:

$$M_t^i = \alpha + \beta^i EFCI_{t-n} + \varepsilon_t \tag{5}$$

Where *I* represent the three market indices namely the Nasdaq Composite Index, Nasdaq 100 and Russell 3000. $EFCI_{t-n}$ is the energy futures conditions index where *n* ranges from t, 1, 2, 3, 10, and is used to estimate M_t^i which represents the current market indices values. Current EFCI values are also regressed against current market indices for comparison purposes. The NRMSE is the RMSE adjusted to the difference between the minimum and maximum observed valued of the EFCI. Table 3 reports the forecast errors based on the RMSE and RMSE of the model in equation 5, using current values and lags of 1,2,3 and 10 weeks in the EFCI data. The RMSE for the 3 market indices increased slightly, as the number of lags increased. Normalizing the RMSE suggests that the EFCI based model produced relatively the smallest forecast errors for the Nasdaq Composite Index. Due to the non-sensitivity of forecast errors as number of lags is increased, a 1 week lag in the EFCI is retained as a factor for predicting market indices value.

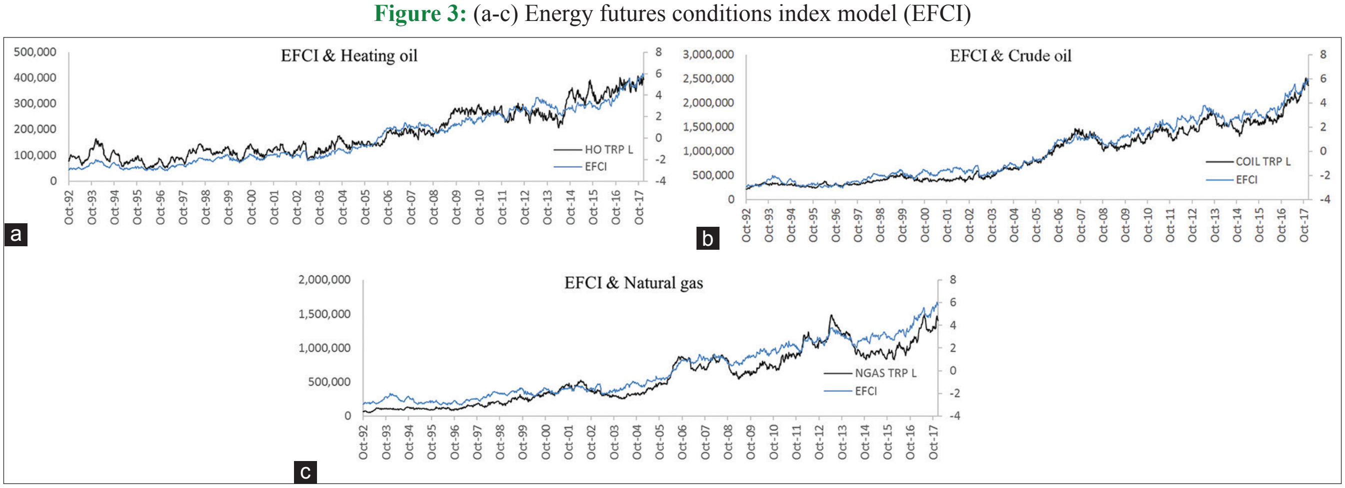
It is also important to capture how the estimated model serve in explaining actual market indices values. Figure 4 displays

Table 3: Forecast errors

Lags	RMSE					NRMSE				
	t	t-1	t-2	t-3	t-10	t	t-1	t-2	t-3	t-10
Nasdaq composite index	820	821	822	823	829	0.16	0.16	0.16	0.162	0.163
Russell 3000	732	733	735	737	748	0.223	0.22	0.213	0.215	0.214
Nasdaq 100	835	836	837	838	843	0.169	0.168	0.165	0.167	0.166

RMSE: Root mean squared error, Normalized RMSE (NRMSE)

Figure 3: (a-c) Energy futures conditions index model (EFCI)



the actual and estimated market indices values over 1992-2017, including a lower and upper boundary level set at 2 standard deviations. As observed, the estimated values of the market indices tracked closely the actual values. The only noticeable exception was the heightened volatility observed in the 2000 period, which was caused by the technology bubble. Our model which is based on the energy futures index failed to capture this event, as observed earlier in Figure 3, where energy futures did not witness similar impacts during the same period as those experienced by equity market indices. Table 4 reports the r-squared values, p-values of the $EFCI_{t-1}$ coefficient and F-statistics. R-squared values ranging from 0.66 to 0.81, and P-values of both the independent variable and F-statistics at zero, suggest that the energy futures conditions index is significant in explaining next week's equity market index value.

Note: Nascompf, Russellf and Nasq100f represent the estimated values of the Nasdaq Composite Index, Russell 3000 and Nasdaq 100 respectively. 2 standard deviations lower and upper bounds are included

5.1. Diagnostic Tests

While the r-squared values and p-values of EFCI coefficients and F-statistics point to a reliable forecast model initially, in order to validate the use of the model based on equation 5, it is important to carry out some diagnostic tests on the model. While not reported here, the model from equation 5 suffers from non-normal distribution, autocorrelation and heteroscedasticity. While non-normal distribution was expected due to positively skewed and kurtosis values reported earlier, autocorrelation and heteroscedasticity needs to be addressed. The non-normality in our model is consistent with Hilliard and Reis (1999) who found non-normality in most futures markets. While we are using total reportable positions, our study is also consistent with Blattberg and Gonedes (1984) who found leptokurtic distributions for hedgers and speculators. To potentially eliminate autocorrelation in the model, a 1 week lag of the market indices is included as an independent variable. To make the model lean more towards homoscedasticity, both market indices and energy futures index

Table 4: Regression statistics

Regression statistics	R-squared	EFCIt-1	F-statistics
Nasdaq composite index	0.660	0.000	0.000
Russell 3000	0.811	0.000	0.000
Nasdaq 100	0.642	0.000	0.000

are transformed in logarithmic variables. A positive constant is imposed on EFCI values to avoid negative logarithmic calculations. The updated model is represented as follows:

$$M_t^i = \alpha + \beta^i EFCI_{t-1} + \alpha^i M_{t-1}^i + \varepsilon_t \qquad (6)$$

where i represents the three market indices namely the Nasdaq Composite Index, Nasdaq 100 and Russell 3000. $EFCI_{t-1}$ is the energy futures conditions index and is used to estimate which represents the current market indices values. M^i_{t-1} is the one-week lag variable of the market indices.

As observed in Table 5, the high r-squared values is attributed to the independent lagged market indices value. Only for the Nasdaq Composite index, was the lagged EFCI coefficient at 10% significance level. Due to the logarithmic transformations, the Jarque-Bera normality test rejected the hypothesis of a normally distributed residual data. More importantly, the Breusch-Godfrey autocorrelation test reported P-values >5% for both the Nasdaq Composite Index and Nasdaq 100, suggesting the removal of autocorrelation in the model. Similarly, the Breusch-Pagan-Godfrey heteroscedasticity test reported P-values >5% for all the market indices, suggesting a homoscedastic model.

Due to the inability of the EFCI model to capture the 2000-2001 technological bubble global event, as observed in Figure 4, it is important to ascertain if indeed there is a break during this time period. The whole sample period is tested for any significant breakpoint in line with Bai and Perron (2003), and findings shows a structural break around April 2000. While not reported here, the residual plot showed a spike around that period. Table 6 reports the pre and post technological bubble crisis robustness test results. While the Jarque-Bera test continues to point towards non-normality, the results are mixed in terms of the removal of autocorrelation and heteroscedasticity in the model. While there was no serial correlation detected by the Breusch Godfrey LM test in the post 2000 bubble crisis, the presence of autocorrelation was noted when predicting Russell 3000 and Nasdaq 100 values in the pre-crisis period. More importantly, the Breusch-Pagan-Godfrey heteroscedasticity test suggest that the error variances are not all equal in both the pre and post financial crisis model. This contradicts earlier findings when the model was found to be homoscedastic when applied over the full sample size. Further, although not reported here, the EFCI lagged coefficient is only

Figure 4: Actual and Estimated Market Indices (1992-2017)

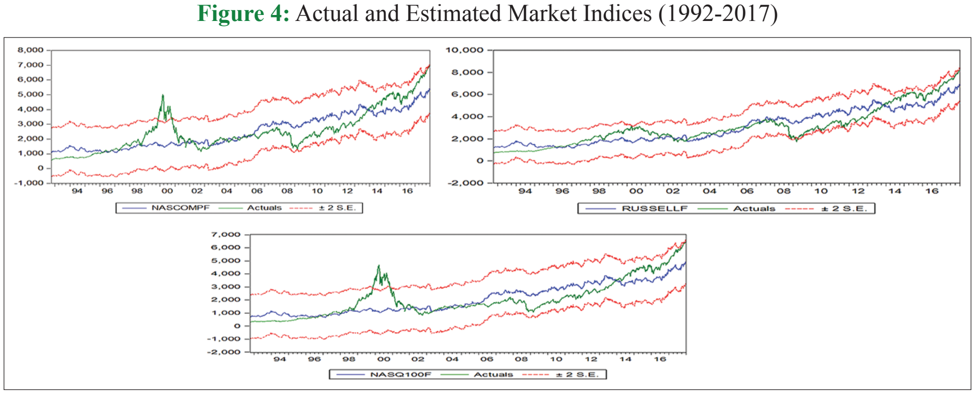


Table 5: Regression statistics and diagnostic tests

Regression statistics		R-squared	Log ($EFCI_{t-1}$)	F-statistics
Nasdaq composite index		0.997	0.081	0.000
Russell 3000		0.998	0.118	0.000
Nasdaq 100		0.998	0.121	0.000
Diagnostic tests		**Jarque Bera normality test**	**Breusch-Godfrey autocorrelation LM test**	**Breusch-Pagan-Godfrey Heteroskedasticity test**
Whole period	10/16/1992-12/29/2017			
Nasdaq composite index		0.000	0.380	0.232
Russell 3000		0.000	0.019	0.716
Nasdaq 100		0.000	0.425	0.232

For the regression statistics, only the *P* values of the log ($EFCI_{t-1}$) and F-statistics are displayed. For the Jarque Bera normality test, only the P value of the Jarque-Bera test statistic is reported. For the Breusch-Godfrey serial correlation LM test, the *P* value of observation*r-squared value is shown. Two residual lags are used. For the heteroskedasticity test, only the *P* value of the observation*r-squared value is displayed. The Breusch-Pagan-Godfrey test is used

Table 6: Pre and post crisis robustness test

Markets		Jarque Bera normality test	Breusch-Godfrey autocorrelation LM test	Breusch-Pagan-Godfrey Heteroskedasticity test
Pre bubble crisis				
Nasdaq composite index	10/16/1992-4/07/2000	0.000	0.528	0.000
Russell 3000		0.000	0.027	0.000
Nasdaq 100		0.000	0.095	0.000
Post bubble crisis				
Nasdaq composite index	4/14/2000-12/29/2017	0.000	0.728	0.009
Russell 3000		0.000	0.162	0.000
Nasdaq 100		0.000	0.509	0.020

For the regression statistics, only the P values of the log ($EFCI_{t-1}$) and F-statistics are displayed. For the Jarque-Bera normality test, only the P value of the Jarque-Bera test statistic is reported. For the Breusch-Godfrey serial correlation LM test, the P value of number of observations*r-squared value is shown. Two lags are used as standard number lags in the residuals. For the heteroskedasticity test, only the P value of the number of observations*r-squared value is displayed. The Breusch-Pagan-Godfrey test is used. The whole sample is tested for any significant breakpoint using the Bai and Perron (2003) breakpoint test

significant in forecasting Nasdaq 100 values in the pre-crisis period, while significant in forecasting the three market indices values post crisis. The p-values of the F statistics remains at zero, with however, heteroskedasticity presence in both pre and post crisis specific periods. Findings suggest that the proposed model in equation 6 is influenced by the sample size, and not consistently reliable. The proposed Energy futures conditions index, despite capturing 95% of variability in the three energy futures under analysis, and despite explaining most of the movements in the equity market indices, failed in the diagnostic parts, where it revealed non homoscedastic presence, when the sample is broken down into pre and post crisis periods. The results are not comparable with Gurrib and Kamalov (2017) who reported a change in the return per unit of risk following the 2008 financial crisis, since the breakpoint test in our study found only the technological bubble in 2000 to have caused some structural breaks in the stock market indices predictive model. This can be explained by the energy futures and subsequently the EFCI which have not been influenced by the 2008 crisis period compared to the 2000 event. This suggests that the presence of cross market information between equity markets and energy markets is weak in our study, and cannot be used to consistent predict the major US equity market indices movements.

6. CONCLUSION

This paper introduces an energy futures index based on the most actively traded energy futures contracts in the US. The use of PCA allows the energy futures index to capture nearly 95% of the variability existing in the crude oil, #2 heating oil and natural gas futures markets, where US and China are leading globally in terms of production and consumption. Initially, the proposed energy futures index model produced stable forecast errors over different lags imposed, and explained most of the actual market indices values of the Nasdaq Composite index, Nasdaq 100 and the Russell 3000. However, diagnostic tests revealed non normal, autocorrelated and heteroskedasticity presence. Logarithmically transformed and calibrated EFCI and stock market indices data, and the inclusion of a 1 week lagged stock market index independent variable, resulted in a non-normal, non-autocorrelated and homoscedastic model, when tested over the full 1992-2017 sample. Based on the structural breakpoint found in the residual plot in early 2000, the sample was broken down into pre and post technology bubble crisis periods. Diagnostic tests showed mixed results with the presence of heteroskedascity in both periods, suggesting the proposed model is sensitive to sample size and hence lacks reliability.

Future research based on autoregressive models is warranted to test further the forecasting ability between the energy futures index and leading US equity markets indices. Further, the link between non-reportable positions in futures markets and equity markets can also be assessed to determine any potential relationship across the two markets.

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