Can energy prices predict stock returns? An extreme bounds analysis

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Abstract

We assess the predictive abilities of energy prices for future US stock market returns using Sala-i-Martin's (1997) extreme bounds analysis (EBA). The EBA results reveal that predictive power of energy prices substantially vary across the regression models with different combinations of conditioning variables. Energy prices are not robust predictors for the stock return in the whole sample period from June 1987 to April 2015. However, before the 2008 global financial crisis, energy prices exerted a moderate negative effect on future stock returns and their effects have become strongly positive afterwards. In general, the predictive power declines with forecast horizon and varies considerably over time.

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1. Introduction

Whether stock returns can be predicted by changes in energy prices has been a topic of interest in the literature on stock return predictability (see, for example, Driesprong et al., 2008; Narayan and Gupta, 2015; Liu, Ma and Wang, 2015). Although a number of studies have been conducted, no clear consensus has been reached on the existence of economically meaningful relationship between stock returns and energy price changes.[1] Contrary to the conventional wisdom of a negative predictive relationship between the two variables (Driesprong et al., 2008), Kilian and Park (2009) have established that the relationship is unstable over time and depends on whether oil price changes are driven by demand or supply shocks. In this paper, we argue that the empirical results reported in the prior studies were affected by a range of factors such as model uncertainty, model instability, and multiple testing. As a result, individual studies on this issue may have been subject to the biases from data-snooping, data-mining, and *p*-hacking. In order to address these issues and obtain the empirical results free from these biases, we examine the relationship between energy price changes and future stock returns by adopting the extreme bounds analysis (EBA) (Leamer, 1983, 1985; Sala-i-Martin, 1997). It is a global sensitivity analysis where the predictive ability of a variable of interest is assessed by considering a large number of combinations of other control variables.

It should be noted that past studies adopt predictive models largely different in their model specifications. Some adopt a bivariate model between stock returns and oil price change, excluding other possibly relevant predictors (see, for example, Fan and Jahan-Parvar, 2012; Narayan and Gupta, 2015; Phan et al., 2015). In contrast, other studies augment the bivariate

[1] See Section 2 for a brief literature review.

model with a range of fundamental valuation ratios and other control variables. For example, Driesprong et al. (2008) use a model augmented with the interest rate; Casassus and Higuera (2012) include the interest rate, dividend-price ratio, consumption-wealth ratio and output gap in their predictive model; and Liu et al. (2015) and Chiang and Hughen (2017) include the dividend yield, dividend-payout ratio, earnings to price ratio, Treasury bill rate and long-term yield, among others. This type of model modification process can add to model uncertainty because predictor variables may not be orthogonal to each other. On the other hand, the bivariate model with no other control variables included may suffer from model mis-specification bias, due to omission of relevant variables. Unfortunately, economic theories provide little specific guidance about the choice of predictor variables in this case. The problem is exacerbated when a researcher favors a model that provides a statistically significant result for the predictor variable of interest, which may lead to problems such as multiple testing (Harvey et al. 2016), *p*-hacking (Harvey, 2017), data-snooping (Hsu and Kuan, 2005), and data-mining (Häring and Storbeck, 2009).

Another source of model uncertainty is the instability of the underlying relationship, where the impact of energy price change on stock returns is context-dependent. This phenomenon has largely been overlooked in the literature. A decline in energy price is usually considered good news for a net energy importing economy like the United States, which leads to an expectation that energy prices have a negative impact on stock prices. This conventional wisdom comes from the evidence of a strong negative relationship between oil price and future economic growth (Hamilton, 1983).[2] However, in recent years, stock prices and oil prices have moved together (Kilian and Park, 2009; Bernanke, 2016). It has been pointed out that the effect of oil price changes on stock return

[2] Subsequent studies, however, show that this relationship is unstable and model-dependent (Hamilton, 2003; Kilian and Vigfusson (2017). See Section 2 for a detailed discussion.

may be different depending on whether the energy price changes are driven by demand or supply factors (see Kilian, 2008; Kilian and Park, 2009; Ready, 2016). An increase in energy price caused by a positive demand shock may serve as an indicator of strong aggregate demand for goods and services, which in turn may increase stock prices. Conversely, an increase in energy price driven by a supply shock is likely to be a bad news because of its adverse implications for the cost of producing goods and services, which may reduce stock prices. That is, the direction of the effects of energy price changes on stock returns depends on whether energy price changes are caused by demand shocks or supply shocks.[3] In general, a change in the nature of shocks in energy market over time can lead to time variation in the predictive relationship between energy price changes and stock returns. An additional source of time-variation in return predictability is the fact that the share of fossil fuels in US energy consumption evolves over time with the change in oil prices (see Baumeister and Kilian, 2016.). Thus, fossil fuel prices' relevance to stock prices may have changed over time. Finally, investors' speed of response to energy price change may vary over time; this is due to the difficulty they face in fully appreciating its impact on firms' future cash flows and discount rates. This difficulty may be further worsened by energy policy uncertainty, which is a recurring feature of the US policy landscape.

In this paper, we examine the impact of changes in energy prices on future stock returns, by addressing the issue of model uncertainty, paying attention to time-variation in the underlying relationship. The EBA developed by Leamer (1983, 1985) and Sala-i-Martin (1997) provides a

[3] Previous studies such as Kilian and Park (2009) show that oil price increases caused by positive demand shocks raise stock returns while oil price decreases caused by negative demand shocks reduce stock returns (see also Filis et al., 2011; Degiannakis et al., 2013; Bernanke, 2016). In most European markets, Cunado and de Gracia (2014) find an inverse relationship between oil price changes and stock returns, specifically when oil price changes are triggered by supply shocks. Previous US studies typically find an inverse relationship between oil price changes and future stock returns, but most of these findings are obtained from the samples that cover periods before the global financial crisis (GFC). See the next section for a review of the relevant literature.

useful and natural tool for this purpose, allowing for model estimation and statistical inference under a wide range of different alternative model specifications. The resulting bounds or distributions of the predictive coefficient estimates can provide a useful indication for the robustness of the predictive ability of the variable of interest. To capture the time variations of the predictive relationship, we conduct the EBA by applying rolling sub-sample windows of fixed length to the entire data set. To the best of our knowledge, the EBA method has not been previously used in studies on return predictability.[4] Moreover, while past studies focus only on the predictive ability of crude oil price, we consider both crude oil price and an energy price index, which is a weighted average of crude oil, natural gas and coal prices. This is on the basis that, in the US, the three major fossil fuels—crude oil, natural gas, and coal—account for 36%, 29% and 16%, respectively, of all energy consumed in 2015 (EIA, 2016). Thus, we provide comprehensive evidence for the predictive power of energy prices compared to that of past studies.

Our main finding is that the predictive ability of energy price changes for US stock returns varies across the regression models with different combinations of conditioning variables. A considerable variation in the sign and magnitude of the predictive coefficient of energy price change is observed across models and also over time. For 1-month forecast horizon, before the GFC, the sign of the coefficient is mostly negative and small (in absolute value), but it becomes positive and large after the crisis. This result, firstly, indicates that the strength and direction of the relationship between energy price changes and future stock returns have substantially changed after the GFC. This finding is in line with the Kilian and Park's (2009) evidence of unstable

[4] A number of approaches have been proposed in the literature for addressing model uncertainty and selecting robust regressors. These include, for example, Bayesian model averaging (Clyde and George, 2004) and Bayesian averaging of classical estimates (Doppelhofer and Miller, 2004), among others. However, relative to the competing methods, the EBA method is intuitively easy to comprehend and simple to estimate, and its results are easy to interpret (Hlavac, 2016).

relationship between stock returns and energy price changes. The predictive ability of energy prices for stock returns declines dramatically with the increase in forecast horizon. The rest of this paper is organized as follows. Section 2 presents a select review of the literature. Section 3 presents the EBA method in the context of this study. Section 4 provides data description. Section 5 presents empirical results, and Section 6 concludes the paper.

2. A select review of the literature

This section provides a selected review of the literature on the static and dynamic relationship of energy prices and US stock returns. Table 1 provides a concise summary of the key papers, outlining the relevant context, key variables used, and major findings.

In spite of the evidence of a strong negative relationship between oil prices and future economic growth (Hamilton, 1983)[5], empirical studies provide mixed findings on the contemporaneous effect of oil price change on stock returns. For instance, Jones and Kaul (1996) report a negative relationship between oil price changes and stock returns. Decomposing oil price changes into negative and positive shocks, Sadorsky (1999) show that positive shocks have greater impact on real stock returns compared to that of negative shocks. More specifically, positive shocks reduce real stock returns while negative shocks do not. Chiang et al. (2015) extract oil risk factors

[5] Hamilton (2003) however shows that the relationship between oil price and economic growth is non-linear. He reports that an increase in oil price has an impact on the economy whereas a decrease does not. The author further shows that an oil price increase followed by a stable price has a greater impact on the economy than that of an oil price increase which corrects a previous decrease in oil price. More recently, Kilian and Vigfusson (2017) argue that the effect of oil price shocks on real GDP growth depends on how their relationship is modelled. They compare the linear vector autoregressive model (VAR) model with the non-linear net oil price increase model of Hamilton (2003). The authors show that the effect of oil price shocks on the economy in the net oil price increase model dissipates when the model is augmented with other determinants of economic cycles (such as credit supply condition, monetary policy stance, and consumer confidence). On an average the linear model better fits the data compared to the non-linear net oil price increase model particularly after net oil price increases. In contrast to Hamilton (2003), this result implies that unexpected oil price decline would at least have a modest stimulating impact on the economy. The conventional evidence of negative relationship between oil prices and future economic growth is also refuted by Kilian and Vigfusson (2011).

and establish that they have significant ability to explain stock returns. In contrast, Huang et al. (1996) show that although oil futures returns can predict stock returns of some individual oil producing companies, they do not have ability to predict aggregate stock returns. Kilian (2008; 2009) explains this puzzle by identifying oil price changes originating from two different sources—demand shocks and supply shocks. The authors show that demand and supply shocks in the crude oil market have qualitatively and quantitatively different effect on stock returns and aggregate economy. Several papers subsequently show an asymmetric impact of demand and supply shocks on aggregate stock returns. For instance, Kilian and Park (2009) show that (i) an increase in oil price resulting from an oil-market related demand shock reduces stock returns, (ii) an oil price rise linked to an unexpected global economic expansion increases stock returns, and (iii) cumulative stock return is not significantly affected by a supply shock associated with crude oil production disruption. Ready (2016) reports that demand shocks (supply shocks) have a strong positive (negative) correlation with US stock returns. A complementary explanation to the mixed findings may be market participants' sluggish response to oil price changes in line with the gradual-information-diffusion model of Hong and Stein (1999).

Although a large body of literature examines the contemporaneous relationship between stock market returns and energy prices, predictive power of energy prices for stock returns has received far less attention. Driesprong et al. (2008) find that oil price changes are contrarian predictors of future aggregate stock returns in 12 out of 18 developed countries they considered. They attribute this finding to investors' under-reaction to oil price changes since they do not find evidence of higher discount rates following a positive oil price shock. The under-reaction phenomenon is explained by Hong and Stein (1999) and Hong et al. (2007) in terms of the gradual information diffusion hypothesis, who argue that investors may fail to utilize price-sensitive information in a timely manner due to either limited information processing capacity (bounded rationality) or market segmentation.

Fan and Jahan-Parvar (2012), Xu (2015) and Narayan and Sharma (2011) concentrate on energy prices' ability to predict stock returns at the industry and firm levels. These papers, in general, support the under-reaction argument of Driesprong et al. (2008). Fan and Jahan-Parvar (2012) show that oil spot prices can negatively predict stock returns of only a small number of industries (about 20% of 49 industries) where the impact of oil price change is difficult to assess, providing support for the gradual information diffusion hypothesis. Xu (2015), however, finds that there is an asymmetric effect of oil price changes across industries. Specifically, oil price has a positive effect on future returns of oil and gas industry stocks but a negative effect on returns of other industry stocks such as consumer goods, health care, consumer services, utilities, and financials. Narayan and Sharma (2011) also find that the effect of oil price change on stock return is asymmetric and depends on firms' industry affiliation. They report that oil price change is negatively related to future returns for around 20% – 30% of firms.[6]

Casassus and Higuera (2012) use unexpected rather than actual oil price change (proxied by short-term crude oil futures returns) to predict aggregate stock returns. They reveal that unexpected oil price change is a contrarian predictor of stock returns, and its predictive ability is stronger compared to that of commonly used predictor variables such as consumption-wealth ratio,

[6] Baumeister and Kilian (2016) also show that the recent oil price decline exerted an asymmetric effect on excess industry stock returns (over aggregate market returns) across the US industries. The petroleum and natural gas, chemicals, agriculture, and mining were among the worst hit industries with annualized excess stock returns of -28%, -6%, -12%, and -31%, respectively. On the other hand, tobacco (16%), airlines (15%), retail sales (14%), apparel (11%), tourism (11%), and food products (7%) did particularly well. Nonetheless, sectors such as recreation, entertainment, and publishing were not influenced by the oil price decline.

price-dividend ratio, output gap, and interest rate. This result holds for one to three quarter horizons. Liu et al. (2015) and Naser and Alaali (2017) report significant predictive ability of oil price change, which is further strengthened when the predictive model is augmented with the commonly used valuation ratios and interest rate variables. On the other hand, Sørensen (2009) shows that stock returns can be predicted using oil price changes only when the latter is triggered by extreme exogenous events (such as military conflicts or OPEC crises), and predictability disappears in non-crisis periods. The author concludes that the oil price change's predictive power arises from a few extreme events rather than time-varying risk premia or investor under-reaction. Narayan and Gupta (2015) detect a positive effect of oil price change on future stock returns with the effect of a negative oil price change dominating that of a positive oil price change.

In general, previous studies arbitrarily choose the conditioning variable to evaluate predictive power of energy prices using samples that are overrepresented by pre-GFC data. More importantly, addressing model uncertainty using the EBA method with time-varying model parameters was beyond the scope of previous studies.

[Insert Table 1]

3. Extreme bounds analysis of return predictability

The EBA is a large-scale and automatic sensitivity analysis, which examines how robustly the dependent variable of a model is associated with the key explanatory variable(s) of interest, when the relationship is controlled for various combinations of other possible explanatory variables. Through the EBA, a researcher can identify the explanatory variable that is most robustly associated with the dependent variable. This approach can address the issue of model uncertainty as it tests robustness of the claimed model or relationship within a large number of alternative model specifications that include different combinations of other potentially important variables. Let y be the dependent variable and X be the set of all possible explanatory variables. The purpose of the EBA is to examine whether a particular variable, called the focus variable, $Z \in X$ is robustly related to y. A subset F (not including Z) of X is called the free variables, which are included in every regression model along with Z. The rest of the variables in X are called the doubtful variables, and a set of k variables are drawn from the entire set of doubtful variables in each regression of the EBA. The j^{th} regression model in the EBA is written as:

$$y = \alpha_j + \beta_j Z + \gamma_j F + \delta_j D_j + u, \tag{1}$$

where α, β, γ, and δ denote the coefficients and u represents the error term. In each j^{th} regression, different k combinations from the entire set of doubtful variables (denoted D_j) are included. The value of k is usually set at three but the choice is up to the researcher.

To assess the robustness of the focus variable Z in explaining the variation of y, we pay attention to the distribution $\{\hat{\beta}_j\}_{j=1}^{M}$, where $\hat{\beta}_j$ is the estimates for β_j, while M is the total number of regression models in the EBA. A $\{\hat{\beta}_j\}_{j=1}^{M}$ distribution with positive and large values indicates that a positive effect of the focus variable on y is robust and strongly positive. While the total number of regression models (M) is determined by the number of combinations from the entire set of doubtful variables, there are exclusions. That is, in choosing k variables out of the entire set of doubtful variables, we may pre-exclude a set of variables which economically carry the same information. We also exclude a set of variables which shows a high degree of multicollinearity. More details of these exclusions are provided in the next section.

In this paper, the dependent variable is h-month average stock return (h = 1, 3, or 6). That is, $y_t = h^{-1}\sum_{i=1}^{h} r_{t+i-1}$, where r_t is excess return over risk-free rate in month t. By using 3-month and 6-month future returns, we are able to examine whether predictive power of energy prices persists over longer horizons. We note that these multi-period returns are auto-correlated by construction due to overlapping observations; and, to remove this autocorrelation, we apply an autoregressive (AR) filter to these returns (AR order chosen by AIC). The explanatory variables are the one-month lagged values of the predictor variables. Our focus variable is the one-month lagged change of an energy variable. For the free variables F, we use one-month lagged dividend yield and interest rate, on the basis that these two predictor variables are commonly used in the return predictability literature (see, for example, Ang and Bekaert, 2007; Rapach et al., 2016). We also consider a large number of doubtful variables, setting k = 3.[7] Further details about the data and variable descriptions are given in the next section.

In estimating the parameters of a predictive regression, the ordinary least squares (OLS) method is widely used assuming that explanatory variables are non-random and uncorrelated with the error term of the predictive model. However, this assumption is unrealistic since the predictor variables are often highly correlated with the shocks to stock return. In this case, the OLS estimators for predictive coefficients can be severely biased in small samples, over-estimating the predictive ability of the model (Stambaugh, 1999). In response to this, Amihud and Hurvich (2004), Amihud et al. (2009, 2010) and Kim (2014) propose the bias-corrected estimators for the predictive coefficients. The method takes explicit account of the endogeneity of predictor variables by incorporating separate equations for them whose error terms are allowed to be

[7] We also use up to five variables from the set of doubtful variables; however, the findings on the predictive ability of energy prices remain robust.

correlated with that of the predictive regression. These authors report that their bias-corrected estimators substantially improve parameter estimation and statistical inference in small samples. In this paper, to estimate equation (1), we employ Kim's (2014) augmented regression method (ARM) which is an improved version of its precursors.[8] We note that, although the changes of energy prices do not exhibit a high degree of persistence (see Driesprong et al., 2008), <u>it is a fact</u> that the commonly used valuation ratios such as the dividend-yield are typically highly persistent (see, for example, Ferson et al., 2003).

Leamer's (1985) EBA concentrates on the extreme bounds of the regression coefficients to determine the robustness or fragility of an explanatory variable. For a particular focus variable, lower and higher extreme bounds are defined as the minimum of $\hat{\beta}_i - \tau\hat{\sigma}_i$ and the maximum of $\hat{\beta}_i + \tau\hat{\sigma}_i$ respectively, from $\left\{\hat{\beta}_j\right\}_{j=1}^{M}$ where τ represents standard normal critical value for the confidence level (e.g., 1.96 for the 95% level) and $\hat{\sigma}_i$ is the standard error estimator for $\hat{\beta}_i$. A focus variable Z is judged to be robust (fragile) if the lower and upper extreme bounds have the same (opposite) sign. This criterion is very stringent because if the sign of a focus variable's coefficient changes or if the coefficient becomes statistically insignificant in a single regression model among the M number of estimated regressions, the variable will be deemed fragile.

In this paper, we use a more lenient version of the EBA proposed by Sala-i-Martin (1997), which focuses on a regression coefficient's entire distribution rather than only its extreme bounds. More specifically, we consider the value of cumulative distribution function of a regression coefficient at zero, denoted *CDF*(0), which is calculated as the proportion of $\left\{\hat{\beta}_j\right\}_{j=1}^{M}$ less than 0.

[8] The main improvements include using the bias-correction method with a higher order accuracy, and stationarity correction which ensures the stationarity of bias-corrected parameter estimators.

A low (high) value of *CDF*(0) indicates that most of the values of regression coefficients are positive (negative). In addition, a graphical presentation of the CDF can provide a visual impression about the magnitude and dispersion of the regression coefficients. Statistical significance of the coefficients can also be checked by evaluating CDF of the t-statistics. Thus, this version of the EBA allows the researcher to examine the degree of robustness, instead of forcing a dichotomous outcome of being robust or fragile.

In calculating the CDF, we follow Sala-i-Martin's (1997) method which can be conducted based on two alternative assumptions The first assumes that the estimated regression coefficients across all models follow a normal distribution, while the second assumes a generic distribution not based on any particular distribution. For the former, the weighted mean ($\overline{\beta}$) and variance ($\overline{\sigma}^2$) of the regression coefficients (of the focus variable) are calculated in the following manner:

$$\overline{\beta} = \sum_{j=1}^{M} w_j \hat{\beta}_j \text{ ; and} \tag{2}$$

$$\overline{\sigma}^2 = \sum_{j=1}^{M} w_j \hat{\sigma}_j^2 \tag{3}$$

where w_j denotes weight assigned to the j^{th} regression on the basis of the results obtained from all estimated regression. After calculating the weighted mean and variance, the value of *CDF*(0) is computed from $N(\overline{\beta}, \overline{\sigma}^2)$. The generic method calculates an aggregate CDF from individual CDF of each regression model. More specifically, from $\left\{\hat{\beta}_j\right\}_{j=1}^{M}$, an individual *CD*F(0), denoted as $\pi_j(0 | \hat{\beta}_j, \hat{\sigma}_j^2)$, is obtained. Then the aggregate CDF is calculated as the weighted average of all individual CDFs:

$$\Phi(0) = \sum_{i=1}^{M} w_i \pi_i (0 \mid \hat{\beta}_i, \hat{\sigma}^2) \tag{4}$$

For both cases, the weights (w_i's) are determined as a function of R^2, so that a better-fit regression model is assigned greater weight. That is,

$$w_j = \frac{R_j^2}{\sum_{i=1}^{M} R_j^2}, \tag{5}$$

where R_j^2 is the coefficient of determination from the j^{th} regression model of the EBA.

4. Data and summary statistics

We use monthly data from June 1987 to September 2015: the choice of sample period is based on the availability of energy price data. Table 2 provides the description of the variables used in the EBA. The dependent variable is continuously compounded returns on the S&P 500 index minus three-month Treasury bill rate (see Panel A of Table 2). We consider two free variables which are the aggregate dividend-yield and short-term interest rate, as listed in Panel B. As for the focus variables, we consider the logarithmic changes in the crude oil (Brent) price[9] and an energy price index (weighted average of oil, natural gas and coal price series), as listed in Panel C. Panel D of Table 2 provides brief descriptions of the eleven doubtful variables, including the log dividend-to-price ratio, log earnings-to-price ratio, log book-to-market ratio, default yield spread, long-term yield, net equity issuance, inflation rate, long-term returns, default returns spread, stock

[9] There are three primary crude oil price benchmarks—Brent, West Texas Intermediate (WTI) and Dubai. We use Brent oil price since it is considered as a benchmark for pricing two-thirds of the world's traded crude oil. It is also included to construct the aggregate energy price index used in this paper. Since some previous studies employ WTI as the crude oil price, we check the robustness of our results using the WTI series. The results remain robust when WTI is used instead of Brent.

variance, and investor sentiment (Baker and Wurgler, 2006). Our choice of doubtful variables is guided by the empirical studies in return predictability published in the top-tier business, finance and economics journals since the seminal work of Campbell and Shiller (1988) and Fama and French (1988). The data sources are given in the notes to Table 2.

[Insert Table 2]

The time-plots of energy prices are presented in Figure 1 along with NBER-dated business cycle peaks and troughs indicated by the vertical shaded areas. In our sample period, three business cycle peaks (troughs) are identified, which are July 1990 (March 1991), March 2001 (November 2001), and December 2007 (June 2009). We observe that energy prices do not exhibit much variation until the late 1990s. For example, the crude oil price was at its lowest ($9.82 per barrel) in December 1998 and this continued to increase until November 2000 ($32.55 per barrel). Since December 2001, this price showed a steady increase until July 2008 when the price reached its all-time high ($132.72 per barrel). These oil price shocks may have contributed to a mild recession in 2001 and the GFC in 2008. In both instances the subsequent period of economic recession was accompanied by a decline in crude oil price. The energy price index closely follows the crude oil price series.

[Insert Figure 1]

Although the details are not reported, many variables listed in Table 2 appear highly persistent. For example, for most of the valuation ratios the estimated AR(1) coefficient is close to 1, as widely documented in previous studies such as Amihud et al. (2009, 2010). Kim (2014) shows that the ARM adopted in this paper provides a highly effective bias-corrected estimation and inference method in small samples, especially when the predictors are persistent and its error term is contemporaneously correlated with that of predictive regression.

A further examination of data (results not reported) suggests the presence of significant correlations among some of the predictor variables. This may lead to the multicollinearity problem in the EBA. We address this issue by excluding a class of regression models from the EBA based on the following criteria. First, we specify a set of mutually exclusive variables that should never be included in the same regression model because they represent the same fundamental information: they are the dividend-price ratio, earning-price ratio, and book-to-market ratio. Second, we exclude the regression models from the EBA that show the variance inflation factor (*VIF*) above 10, which is widely regarded as a threshold for a high degree of multicollinearity. Note that $VIF \equiv 1/(1-R_x^2)$ where R_x^2 denotes the coefficient of determination of the regression of one explanatory variable to the others.

5. Empirical results

In this section, we present the empirical results from our EBA of the predictive ability of energy price changes for stock returns. First, we present the analysis based on the whole sample and sub-samples, and then we examine the time-variation of the predictive ability by adopting the rolling sub-sample windows. In analyzing the EBA results, we present the histograms of the predictive coefficients obtained from all possible model specifications and pay attention to their sign and magnitude (effect size estimates). For example, if the histogram shows that most of the estimated coefficients are positive (negative) and large in absolute value, then this is an indication for robust positive (negative) predictability. We also discuss the proportion of the statistically significant coefficients from our EBA. One may consider the critical value of ±1.96 for the t-test, associated with the 5% level of significance, adopted by the past studies. However, we note that extreme care should be taken in interpreting this result, since this is a case of multiple testing where the actual level of significance (probability of Type I error) can be much higher than nominal level of 5%, which may lead to a false discovery rate much higher than 0.05. Following Harvey et al. (2016), we also use a much higher critical value of ± 3 for the t-test, associated with the level of significance of around 0.1%. The use of a tighter criterion for statistical significance is also consistent with the "revised standard of statistical evidence", which was recently advocated by a number of authors in many fields of science (see Johnson, 2013; Benjamin et al., 2017).

5.1 The distribution of the estimated coefficients of energy prices across models

Figure 2 presents the histograms of the predictive coefficients $\{\hat{\beta}_j\}_{j=1}^{M}$ based on Sala-i-Martin's (1997) EBA for the whole sample period. For 1-month future return, the distributions do not indicate a strong pattern of being positive or negative coefficients over the whole sample period. However, for 3-month and 6-month prediction horizons, energy prices are clearly positive predictors of returns in most of the models. The summary statistics of the distributions of predictive coefficients are presented in Panel A of Table 3. According to CDF(0) for the 1-month prediction horizon, 67.97% of the predictive coefficients of oil price change lies below zero. This proportion is 17.74% for 3-month return and 34.86% for 6-month return. We find a similar result for the energy price index with 58.86%, 29.56% and 40.82% of the coefficients are negative for the 1-month, 3-month, and 6-month prediction horizons, respectively. At the 5% significance level, the proportion of statistically significant coefficients is 2.33% for the crude oil and 8.17% for the energy price index for 1-month forecast horizon. Over the longer forecast horizons, the predictive coefficients are statistically insignificant at the 5% significance level. At the higher threshold of ± 3 for statistical significance, all predictive coefficients of oil price and energy price index are statistically insignificant. These results indicate that energy variables do not have robust predictive ability in the whole sample period because the predictive coefficients are highly sensitive to model specifications.

Figure 3 plots the histogram of $\left\{\hat{\beta}_j\right\}_{j=1}^{M}$ for the last 10 years of data, from May 2005 to April 2015. The coefficients of crude oil and energy price index are mostly positive for all forecast horizons. The estimated coefficients can be as large as 0.4 for 1-month return, 0.03 for 3-month return and 0.02 for 6-month return. From Panel B of Table 3, for 1-month forecast horizon, we find CDF(0) value of 6.94% and 7.18%, respectively for the oil price and energy price index, implying dominance of positive coefficients. At a threshold of ±1.96, 62.76% (63.18%) of the coefficients of oil price (energy price index) are significant, while at a threshold of ±3, 30.96% (33.47%) of the coefficients of crude oil (energy price index) are significant. For the longer forecast horizons, the CDF(0) value lies between 32% and 43%, indicating that coefficients are distributed with a tilt toward positive values across the regression models. We further find that in the case of longer horizon returns, none of the coefficients are statistically significant irrespective of the different threshold t-statistics. Thus the crude oil price and energy price index are strong positive predictors of future one-month return, yet their predictive ability declines sharply with the forecast horizon.

Figure 4 plots the histograms for the first 10 years of data, covering the period June 1987 to May 1997, with the corresponding summary statistics displayed in Panel C of Table 3. From Figure 4, it is observed that in the case of 1-month return horizon, the predictive coefficients of crude oil and energy price index are mostly negative, however, this dominance declines in the 3-month horizon and reverses in the 6-month horizon. The negative effect can be as large as -0.1 for the 1-month horizon. In Panel C of Table 3, CDF(0) value indicates that 82.35% and 76.72% of the predictive coefficients of crude oil and energy price index are negative for 1-month horizon, respectively. However, these proportions decline to 50.81% (58.74%) in the 3-month horizon and 15.55% (23.32%) in the 6-month horizon for the crude oil (the energy price index). Although 19.88% and 16.87% of the predictive coefficients of crude oil and the energy price index, respectively, are statistically significant at the 5% level in 1-month horizon, no regression model generates a statistically significant coefficient for either 3-month or 6-month forecast horizons. At the higher threshold of ±3, none of the estimated coefficients are found to be statistically significant.

From the sub-sample analysis, it is evident that the crude oil and energy price index are important predictors of stock return from May 2005 to April 2015. As shown in Figure 3, the effect size estimates of these variables are large, especially for 1-month forecast horizon. The majority of the estimated coefficients of crude oil are between 0.1 and 0.3 at the 1-month horizon, which indicates a strong effect. The effect size appears to decrease with the increase in forecast horizon. In the sub-sample from June 1987 to May 1997 (Figure 4), most of the estimated coefficients of the crude oil and the energy price index are between -0.1 and 0 at the 1-month horizon. This means that the elasticity of stock return with respect to energy price changes is at most -0.1.

[Insert Figure 2], [Insert Figure 3], [Insert Figure 4], [Insert Table 3]

5.2 Time-varying predictive ability of energy prices

Given the strong evidence of structural change in the relationship between energy variables and stock returns, it will be interesting to examine this relationship over the rolling sub-sample window. We take the sub-sample windows that have a length of 60 months. More specifically, the first sub-sample window covers the period from June 1987 to May 1992. Then, moving one month forward, the second window covers the period from July 1987 to June 1992. This process continues until the end of the data set is reached over a total of 281 sub-sample windows. The EBA based on the predictive model (1) is conducted for each window and the CDF(0) values for the predictive coefficients are reported over time. We plot CDF(0) values in Figure 5 for the models that include the crude oil price or the energy price index as a predictor variable at a time. Panel A, Panel B, and Panel C of this figure, respectively, report the results derived from 1-month, 3-month and 6-month return horizons. Panel A shows that for both the crude oil and energy price index, the predictive coefficients have been predominantly negative until around 1997 with the values of CDF(0) close to 100%. However, at the height of the Asian financial crisis during the period 1997–1999, predictive coefficients of the two variables are found to be mostly positive. Conversely, from 2005 until the outbreak of the GFC in 2008, the CDF(0) values are almost 100%, thus indicating the dominance of negative coefficients. Finally, after 2008, the predictive coefficients of the crude oil and energy price index change their pattern dramatically by showing an increasingly higher proportion of positive values.[10] In particular, during the period from 2010 – 2015, the estimated coefficients are mostly positive with the CDF(0) values falling to less than 10%.

Panel B of Figure 5 shows that the predictive coefficients for the 3-month return horizon also vary over time in terms of their both signs and magnitudes. The CDF(0) value fluctuates around 30% from the start of the sample period until the late 1990s, providing some evidence of the positive predictive relationship. However, from 1999 to early 2000, predictive coefficients are typically negative with a CDF(0) value of more than 80%. Nonetheless, this pattern reverses over time with CDF(0) reaching close to 0 during 2010-2015. Panel C of Figure 5 presents that CDF(0) for the 6-

[10] Our finding for the pre-GFC period is qualitatively similar to that of studies using predominantly pre-GFC data. For example, the coefficient of the one-month lagged oil price change is -0.086 in Driesprong et al. (2008) and between -0.10 to -0.08 in Sørensen (2009). However, Narayan and Gupta (2015, Table 4) find a 95% confidence interval of 0.028 to 0.016 for the coefficient of the one-month lagged oil price change. This result is obtained from a bivariate regression model using a long pre-GFC sample.

month prediction horizon fluctuates over time without showing any strong positive or negative predictive power of energy prices.

Overall, the evidence indicates that the crude oil and energy price index have been strong predictors of stock returns in shorter prediction horizons, but their effect on stock return has changed considerably over time, and shown high sensitivity to model specifications. In the 1-month forecast horizon, both the variables are strong contrarian predictors of stock return during the mid-1990s, and for the 2005 – 2008 period. However, they appear to be strong positive predictors of stock return in the post-GFC period. Overall, these findings allude to the dominance of supply shocks in driving energy prices during the mid-1990s and pre-GFC period, and demand shocks after the GFC. The post-GFC period has also been accompanied by high uncertainty, which may have induced risk-averse investors to retreat from both commodities and stocks, giving rise to a co-movement in stock prices and oil prices (Bernanke, 2016).

[Insert Figure 5]

5.3 Predictive abilities of natural gas and coal prices

We also examine the predictive ability of the price changes of two other fossil fuels – natural gas and coal – for US excess stock returns. While crude oil's role in predicting stock returns has been examined previously (see Table 1), natural gas and coal prices as predictor variables have not been considered. We use the US natural gas prices for commercial consumers and the producer price index of coal mining industry as the separate predictor variables in equation 1.[11] The EBA results for 1-month return horizon are summarized in Table 4. Neither natural gas nor coal exhibit significant

[11] Natural gas prices are obtained from US Energy Information Administration (https://www.eia.gov/) while coal prices are taken from Economic Data of Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/search?st=coal+price).

predictive power. In the whole sample, CDF(0) is 55.26% for the natural gas price change and 43.51% for the coal price change. Similar results are also found over the last 10 years of our sample. This outcome implies that the sign of the predictive coefficients of natural gas and coal prices are not robust across regression models. In the first 10 years, coefficients are mostly positive with the CDF(0) values of 36.26% and 16.44% for natural gas and coal prices, respectively. Nonetheless, the proportion of statistically significant coefficient is close to zero for both the predictor variables regardless of which sample period is considered.[12] Our overall finding indicates that natural gas and coal prices lack robust predictive ability for US excess returns.

[Insert Table 4]

6. Conclusion

We provide a comprehensive analysis of the predictive ability of the prices of three major fossil fuels (crude oil, natural gas, and coal) for US stock returns. We focus on two important sources of model uncertainty surrounding the predictive abilities of energy prices for US stock market returns. First, we use the extreme bounds analysis to address the model uncertainty arising from arbitrary selection of predictor variables. Second, we examine the predictive power of energy prices over the rolling sub-sample windows to address the model uncertainty due to parameter instability.

The cumulative distribution of the predictive coefficients obtained from the EBA method provides three key results. First, the predictive power of energy prices is sensitive to model specification. This result is in line with the Kilian and Vigfusson's (2017) finding that energy prices' impact on US economy depends on the way the relationship is modeled. Second, although

[12] The EBA results for the 3-month and 6-month horizons also provide statistically insignificant predictive coefficients for natural gas and coal prices. These results are not reported in Table 6 but they can be obtained from the corresponding author on request.

energy prices are not robust predictor of US excess returns in the whole sample period, the predictive coefficients vary over time in terms of their signs and magnitudes, supporting evidence of an unstable relationship between stock returns and energy price changes reported in the literature (see Kilian and Park, 2009). Third, statistically significant predictive ability of the crude oil and energy price index is found in the 1-month prediction horizon. However, we find little evidence of predictive ability over the 3-month and 6-month horizons.

Interestingly, both the oil price and energy price index served as a strong contrarian predictor of future 1-month stock market returns during most of the pre-GFC period. This finding is aligned with the evidence of an inverse relationship between oil price change and future stock returns reported in previous studies (e.g., see Driesprong et al., 2008; Casassus and Higuera, 2012; Chiang and Hughen, 2017). In contrast, in the post-GFC period, the oil price and energy price index served as a positive predictor of 1-month ahead stock returns. This finding is at odds with the conventional view that a decline (increase) in energy price is good (bad) news for a net energy importing economy like the US, but is consistent with Bernanke's observation (2016) that the relationship between oil prices and stock prices depends on the nature of the signal investors extract from oil price changes. For example, if a decline in energy price is triggered by a demand shock, investors will interpret it as an indicator for a softening of aggregate demand for goods and services, which will reduce future stock returns. This relationship can be further strengthened by increased economic uncertainty, which has been a constant feature of the US and its major trading partners following the GFC.

References

Amihud, Y., and Hurvich, C. M. 2004. Predictive regressions: A reduced-bias estimation method. *Journal of Financial and Quantitative Analysis*, 39, 813-841.

Amihud, Y., Hurvich, C. M., and Wang, Y. 2009. Multiple-predictor regressions: Hypothesis testing. *Review of Financial Studies*, 22, 413-434.

Amihud, Y., Hurvich, C. M., and Wang, Y. 2010. Predictive regression with order-p autoregressive predictors. *Journal of Empirical Finance*, 17, 513-525.

Ang, A., and Bekaert, G. 2007. Stock return predictability: Is it there? *Review of Financial Studies*, 20, 651-707.

Baker, M., and Wurgler, J. 2006. Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61, 1645-1680.

Baumeister, C., and Kilian, L. 2016. Lower oil prices and the US economy: Is this time different? *Brookings Papers on Economic Activity*, 2016(2), 287-357.

Benjamin, D. J., J. O. Berger, M. Johannesson, et al. 2017. Redefine Statistical Significance. *Nature Human Behaviour*, forthcoming.

Bernanke, B. 2016. The relationship between stocks and oil prices, February 19, 2016, The Brookings Institution; accessed from www.brookings.edu/blog/ben-bernanke.

Campbell, J. Y., and Shiller, R. J. 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies*, 1, 195-228.

Casassus, J., and Higuera, F. 2012. Short-horizon return predictability and oil prices. *Quantitative Finance*, 12, 1909-1934.

Chiang, I. H. E., and Hughen, W. K. 2017. Do oil futures prices predict stock returns? *Journal of Banking & Finance*, 79, 129-141

Chiang, I., Ethan, H., Hughen, W. K., and Sagi, J. S. 2015. Estimating oil risk factors using information from equity and derivatives markets. *The Journal of Finance*, 70, 769-804.

Clyde, M., and George, E. I. 2004. Model uncertainty. *Statistical Science*, 19, 81-94.

Cunado, J., and de Gracia, F. P. 2014. Oil price shocks and stock market returns: Evidence for some European countries. *Energy Economics*, 42, 365-377.

Degiannakis, S., Filis, G., and Floros, C. 2013. Oil and stock returns: Evidence from European industrial sector indices in a time-varying environment. *Journal of International Financial Markets, Institutions and Money*, 26, 175-191.

Doppelhofer, G., and Miller, R. I. 2004. Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach. *The American Economic Review*, 94, 813-835.

Driesprong, G., Jacobsen, B., and Maat, B. 2008. Striking oil: Another puzzle? *Journal of Financial Economics*, 89, 307-327.

EIA 2016. Monthly Energy Review, Table 1.3 and 10.1 (April 2016), preliminary data. US Energy Information Administration.

Fama, E. F., and French, K. R. 1988. Dividend yields and expected stock returns. *Journal of Financial Economics*, 22, 3-25.

Fan, Q., and Jahan-Parvar, M. R. 2012. US industry-level returns and oil prices. *International Review of Economics & Finance*, 22, 112-128.

Ferson, W. E., Sarkissian, S. and Simin, T. T. 2003. Spurious regressions in financial economics? *The Journal of Finance*, 58, 1393-1414.

Filis, G., Degiannakis, S., and Floros, C. 2011. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, 20, 152-164.

Hamilton, J. D. 1983. Oil and the macroeconomy since World War II. *Journal of Political Economy*, 91, 228-248.

Hamilton, J. D. 2003. What is an oil shock? *Journal of Econometrics*, 113, 363-398.

Häring, N. and Storbeck, O. 2009. *Economics 2.0: What the Best Minds in Economics Can Teach You about Business and Life*, Palgrave Macmillan, New York.

Harvey, C. R. 2017. Presidential Address: The Scientific Outlook in Financial Economics, *Journal of Finance*, 72, 1399-1440.

Harvey, C. R., Lin, Y., and Zhu, H. 2016. . . . and the Cross-Section of Expected Returns. *The Review of Financial Studies*, 29, 5-68.

Hlavac, M. 2016. ExtremeBounds: Extreme Bounds Analysis in R. *Journal of Statistical Software*, 72, 1-22.

Hong, H., and Stein, J. C. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54, 2143-2184.

Hong, H., Torous, W., and Valkanov, R. 2007. Do industries lead stock markets? *Journal of Financial Economics*, 83, 367-396.

Hsu, P. H., and Kuan, C. M. 2005. Reexamining the profitability of technical analysis with data snooping checks. *Journal of Financial Econometrics*, *3*, 606-628.

Huang, R. D., Masulis, R. W., and Stoll, H. R. 1996. Energy shocks and financial markets. *Journal of Futures Markets*, 16, 1–27.

Johnson, V. E. 2013. Revised standards for statistical evidence. *Proceedings of the National Academy of Sciences*, 110, 19313-19317.

Jones, C. M., and Kaul, G. 1996. Oil and the stock markets. *The Journal of Finance*, 51, 463- 491.

Kilian, L . 2008. The economic effects of energy price shocks. *Journal of Economic Literature*, 46, 871-909.

Kilian, L. 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99, 1053-69.

Kilian, L., and Park, C. 2009. The impact of oil price shocks on the US stock market. *International Economic Review*, 50, 1267-1287.

Kilian, L., & Vigfusson, R. J. 2011. Are the responses of the US economy asymmetric in energy price increases and decreases? *Quantitative Economics*, 2, 419-453.

Kilian, L., and Vigfusson, R. J. 2017. The role of oil price shocks in causing US recessions. *Journal of Money, Credit and Banking*, 49, 1747-1776.

Kim, J. H. 2014. Predictive regression: An improved augmented regression method. *Journal of Empirical Finance*, 26, 13-25.

Leamer, E. E. 1983. Let's take the con out of econometrics. *The American Economic Review*, 73, 31-43.

Leamer, E. E. 1985. Sensitivity analyses would help. *The American Economic Review*, 75, 308-313.

Liu, L., Ma, F., and Wang, Y. 2015. Forecasting excess stock returns with crude oil market data. *Energy Economics*, 48, 316-324.

Narayan, P. K., and Gupta, R. 2015. Has oil price predicted stock returns for over a century? *Energy Economics*, 48, 18-23.

Narayan, P. K., and Sharma, S. S. 2011. New evidence on oil price and firm returns. *Journal of Banking & Finance*, 35, 3253-3262.

Naser, H., and Alaali, F. 2017. Can oil prices help predict US stock market returns? Evidence using a dynamic model averaging (DMA) approach. *Empirical Economics*, 1-21.

Phan, D. H. B., Sharma, S. S., and Narayan, P. K. 2015. Stock return forecasting: some new evidence. *International Review of Financial Analysis*, 40, 38-51.

Rapach, D. E., Ringgenberg, M. C., and Zhou, G. 2016. Short interest and aggregate stock returns. *Journal of Financial Economics*, 121, 46-65.

Ready, R. C. 2016. Oil prices and the stock market. *Review of Finance*, 2016, 1-22.

Sadorsky, P. 1999. Oil price shocks and stock market activity. *Energy Economics*, 21, 449-469.

Sala-i-Martin, X. X. 1997. I just ran two million regressions. *The American Economic Review*, 87, 178-183.

Sørensen, L. Q. 2009. Oil Price Shocks and Stock Return Predictability, EFA 2009 Bergen Meetings Paper. Available at SRN: https://ssrn.com/abstract=1341013.

Stambaugh, R. F. 1999. Predictive regressions. *Journal of Financial Economics*, 54, 375-421.

Xu, B. 2015. Oil prices and UK industry-level stock returns. *Applied Economics*, 47(25), 2608-2627.

Table 1. Major studies on the relationship between oil price change and stock returns

Studies	Sample period	Key predictor	Control variable*	Predictive ability of oil price change
Jones and Kaul (1996)	1970 – 1991	Producer price index	IP, DY, DS, TS	Negative effect
Huang et al. (1996)	1979:10 – 1990:03	NYMEX futures	N/A	Insignificant relationship
Sadorsky (1999)	1947:01 – 1996:04	Producer price index	N/A	Positive oil price shocks reduce real stock returns.
Driesprong et al. (2008)	1973:10 – 2003:04	Brent, WTI and Dubai	SR	Negative in 12 out of 18 developed markets.
Sørensen (2009)	1973:01- 2007	WTI	DP, SR, TS, INF	Negative in 6 markets including the US.
Kilian and Park (2009)	1973:01 – 2006:12	Refiner's acquisition cost of imported crude oil	N/A	Asymmetric effect of demand and supply shocks
Narayan and Sharma (2011)	2000:01 – 2008:12	Crude oil price	SR, ER	Negative impact on 20% – 30% firms.
Casassus and Higuera (2012)	1983:Q2–2009: Q4	Futures prices of crude oil	SR, DP, CAY, OG	Negative and significant.
Fan and Jahan-Parvar (2012)	1979:01 – 2009:01	WTI and Oklahoma light sweet	N/A	Negative and significant in 9 out of 49 industries.
Narayan and Gupta (2015)	1859:10 – 2013:12	WTI	N/A	Positive and significant
Liu et al. (2015)	1975:01 –2012:12	Refiner's acquisition cost of imported crude oil	DY, EP, DP, SR, LTY, GOP, GOD, COI, PC	Significant forecasting ability in the out-of-sample.
Phan et al. (2015)	1988:01 – 2012:12	WTI	N/A	Predictive ability is significant in the out-of-sample.
Chiang et al. (2015)	1983:03 – 2012:12	WTI futures	NA	Oil risk factors explain oil related stock returns
Xu (2015)	1988:01 – 2013:02	Brent	N/A	Asymmetric impact across industry returns.
Ready (2016)	1986:01 – 2011:11	NYMEX futures	N/A	Demand shocks (supply shocks) have a positive (negative) effect on stock returns
Chiang and Hughen (2017)	1983:03 – 2014:12	Curvature factor of WTI futures prices	DY, DP, EP, LTR, BM	Negative and significant.
Naser and Alaali (2017)	1959:01 – 2013:12	WTI	DY, EP, BM, SR, INF, TS, MS, UR, IP	Significant predictive ability

*Notes: BM = Book-to-market ratio; CAY = Consumption-wealth ratio; COI = Crude oil inventory; DP = Dividend-to-price ratio; DS = Default spread; DY = Dividend yield; EP = Earnings-to-price ratio; ER = Exchange rate, GOD = Global oil demand; GOP = Global oil production; INF = Inflation rate, LTY = Long-term yield; LTR = Long-term treasury returns; OG = Output gap; PC = Petroleum consumption; SR = Short-term interest rate; TS = Term spread, MS = Money supply, UR = unemployment rate, IP = industrial production growth, WTI = West Texas Intermediate.

Table 2. Variable definitions

Variables	Definition
Panel A: Excess returns	
Excess returns	The continuously compounded returns on the S&P 500 index minus three-month Treasury bill rate.
Panel B: Free variables	
Log dividend yield	Difference between the log of dividends and the log of lagged prices
Treasury bill rate	Interest rate on a three-month Treasury bill.
Panel C: Focus variables	
Crude oil	Logarithmic changes in Brent spot prices (FOB, US dollars per barrel).
Energy price index	Logarithmic changes in energy price index which is a weighted average of crude oil, natural gas and coal prices. This index is based on current US dollars, 2010=100.
Panel D: Doubtful variables	
Log dividend-to-price ratio	Difference between the log of dividends and the log of stock prices (S&P 500 index). Dividends are computed as 12-month moving sum of dividends paid on the S&P 500 index.
Log earning-to-price ratio	Difference between the log of earnings and the log of prices. Earnings are measured as the 12-month moving sum of earnings on the S&P 500 index.
Log book-to-market ratio	The log of ratio of book value to market value for the Dow Jones Industrial index.
Default returns spread	Difference between long-term corporate bond and long-term government bond
Default yield spread	Difference between BAA and AAA-rated corporate bond yields.
Long-term returns	Return on long-term government bonds.
Long-term yield	Yield on long-term US government bonds.
Inflation rate	Inflation is calculated from the Consumer Price Index (All Urban Consumers). Since inflation data is released in the following month we use second lag of the variable in the predictive equation.
Stock variance	Monthly sum of squared daily returns on the S&P 500 index.
Investor sentiment	Baker and Wurgler's (2006) sentiment index which is constructed as the first principal component of six sentiment proxies, namely closed-end fund discount, dividend premium, equity issuance as a proportion of total issuance, number of IPOs, first-day IPO returns and volume.
Net equity expansion	The ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks.

Note: Data for excess returns, the free variables and the doubtful variables (except investor sentiment) are collected from Amit Goyal's data library (http://www.hec.unil.ch/agoyal/). The investor sentiment series is obtained from Jeffrey Wurgler's data library (http://people.stern.nyu.edu/jwurgler/). Crude oil prices data are obtained from US Energy Information Administration (https://www.eia.gov/). The energy price index is obtained from YCharts (https://ycharts.com/indicators/energy_index_world_bank).

Table 3. Extreme bounds analysis: Crude oil and the energy price index

	% |t| > 1.96	**%|t| > 3**	**CDF(0)**
Panel A: Whole sample period (1987:06 to 2015:04)			
1-month return			
Crude oil	2.33	0.00	67.97
Energy price index	8.17	0.00	58.86
3-month return			
Crude oil	0.00	0.00	17.74
Energy price index	0.00	0.00	29.56
6-month return			
Crude oil	0.00	0.00	34.86
Energy price index	0.00	0.00	40.82
Panel B: Last 10 years (2005:05 to 2015:04)			
1-month return			
Crude oil	62.76	30.96	6.94
Energy price index	63.18	33.47	7.18
3-month return			
Crude oil	0.00	0.00	32.14
Energy price index	0.00	0.00	32.84
6-month return			
Crude oil	0.00	0.00	43.29
Energy price index	0.00	0.00	34.80
Panel C: First 10 years (1987:06 to 1997:05)			
1-month return			
Crude oil	19.88	0.00	82.35
Energy price index	16.87	0.00	76.72
3-month return			
Crude oil	0.00	0.00	50.81
Energy price index	0.00	0.00	58.74
6-month return			
Crude oil	0.00	0.00	15.55
Energy price index	0.00	0.00	23.32

Notes: % |t| > 1.96: Percentage of the beta coefficients whose t-statistics are greater than 1.96 in absolute value;

% |t| > 3: Percentage of the beta coefficients whose t-statistics are greater than 3 in absolute value;

CDF(0): Percentage of the beta coefficients (weighted by R^2) less than 0, with CDF based on the generic distribution.

Table 4. Extreme bounds analysis: Natural gas and coal (1-month return)

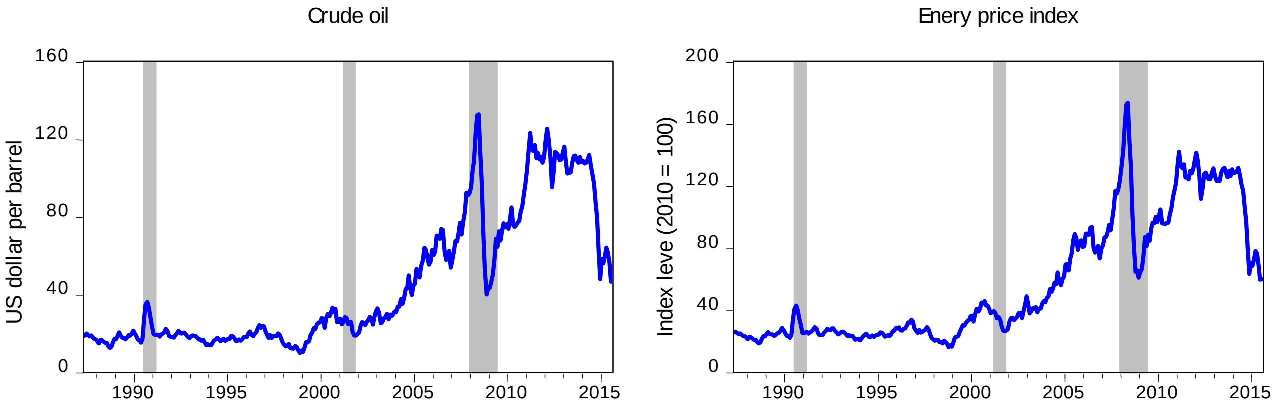
	% |t| > 1.96	%|t| > 3	CDF(0)
Panel A: Whole sample period (1987:06 to 2015:04)			
Natural gas	0.00	0.00	55.26
Coal	0.00	0.00	43.51
Panel B: Last 10 years (2005:05 to 2015:04)			
Natural gas	0.00	0.83	59.66
Coal	0.00	0.00	47.41
Panel C: First 10 years (1987:06 to 1997:05)			
Natural gas	0.61	0.00	36.26
Coal	0.00	0.00	16.44

Notes: % |t| > 1.96: Percentage of the beta coefficients whose t-statistics are greater than 1.96 in absolute value;

% |t| > 3: Percentage of the beta coefficients whose t-statistics are greater than 3 in absolute value;

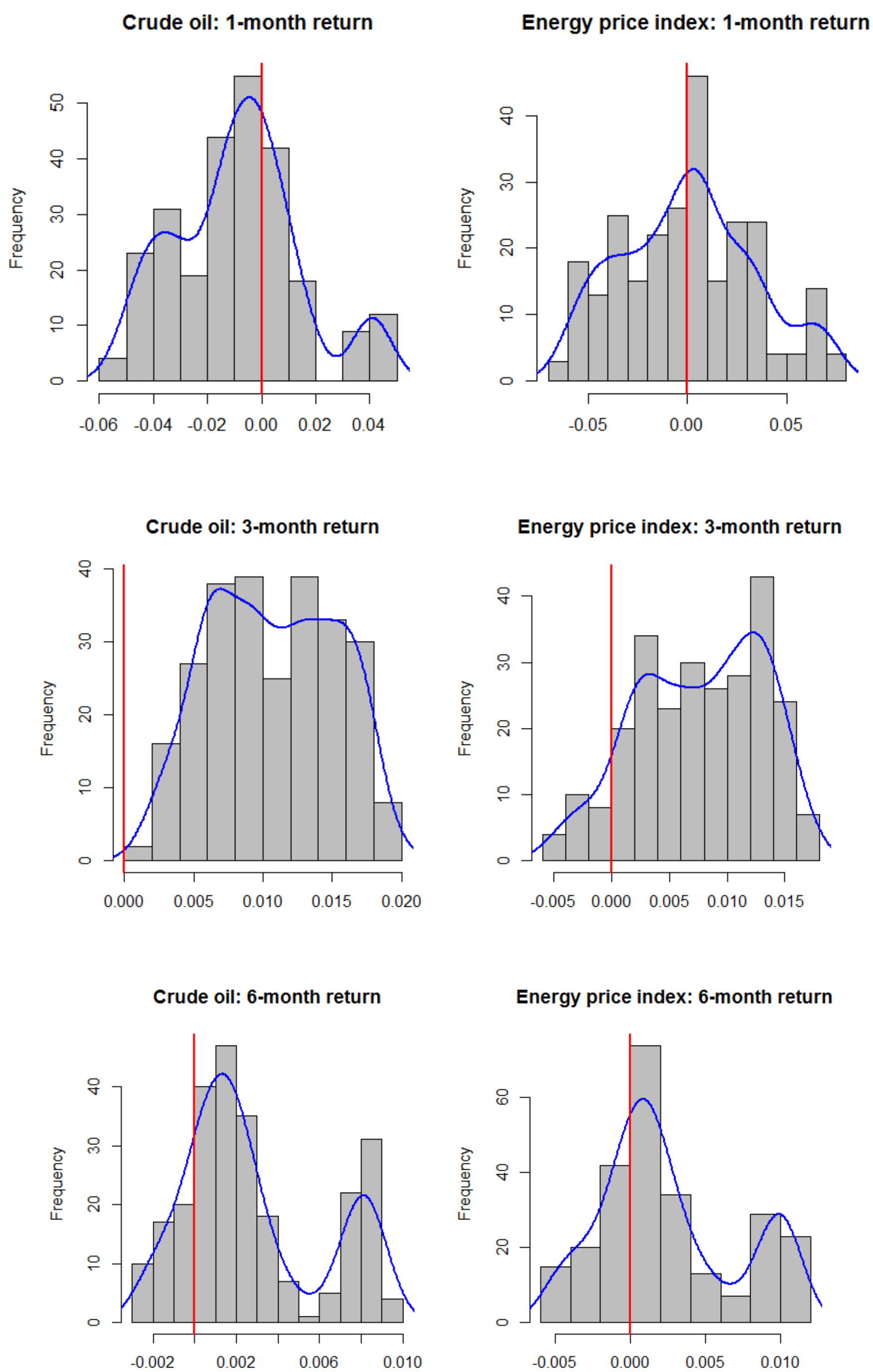
CDF(0): Percentage of the beta coefficients (weighted by R^2) less than 0, with CDF based on the generic distribution.

Figure 1. Time-plots of energy prices



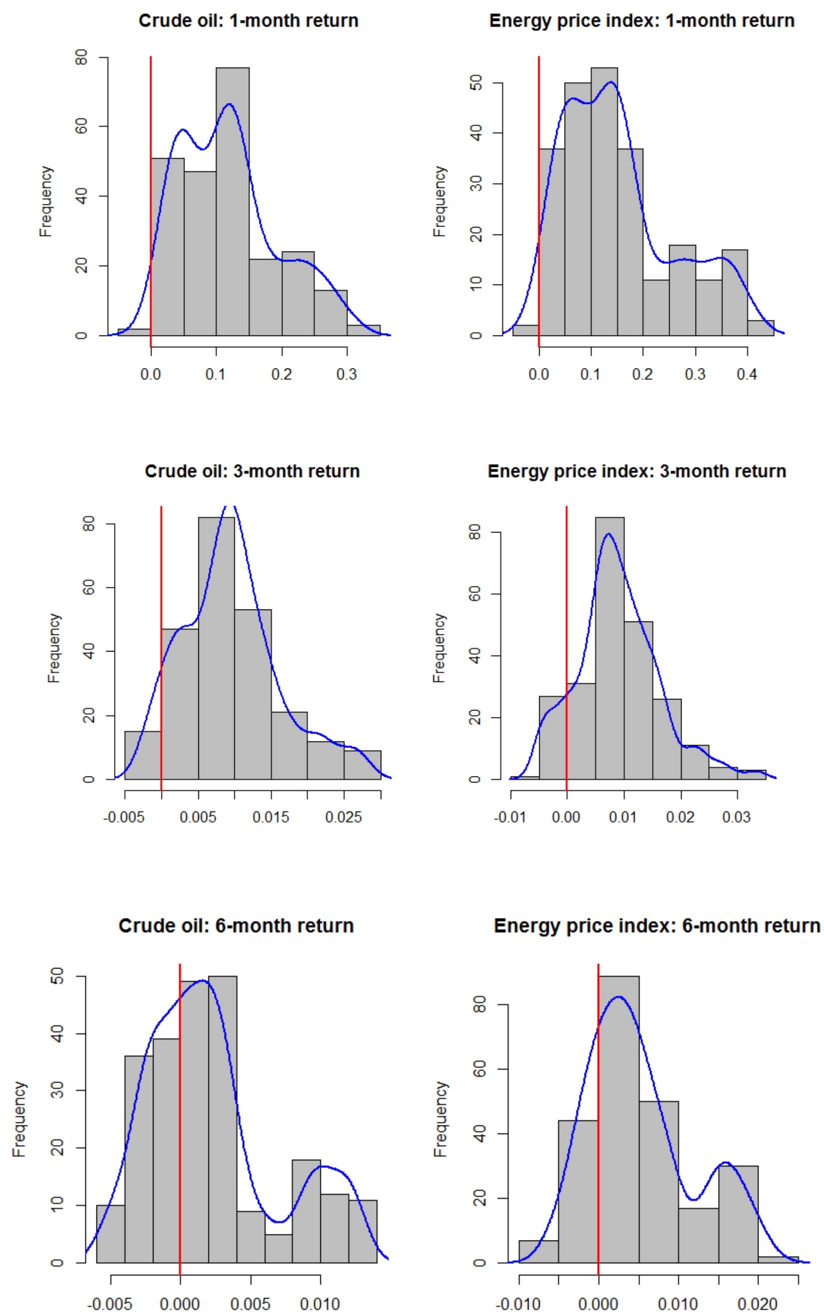
Notes: This figure illustrates the time-plots of energy prices. Crude oil represents Brent spot prices, and the energy price index is the weighted average of crude oil, natural gas and coal prices. Vertical shaded areas represent US recessions (recession dates are obtained from economic data of Federal Reserve Bank of St. Louis: https://fredhelp.stlouisfed.org/fred/data/understanding-the-data/recession-bars/).

Figure 2. Distribution of the predictive coefficients of the energy variables across models, whole sample period from 1987:06 to 2015:04



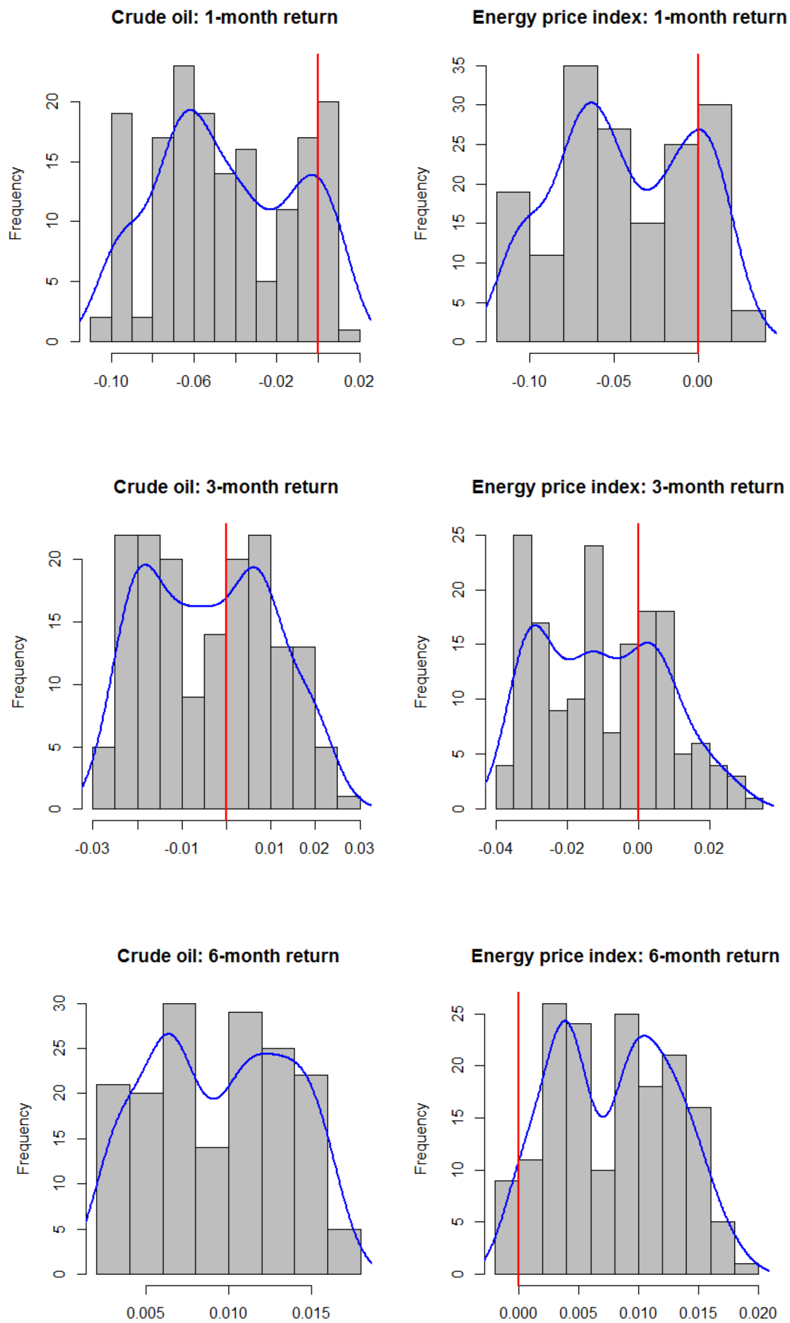
Notes: This figure presents the histograms of the predictive coefficients of the energy price variables derived from the extreme bounds analysis. The horizontal axis represents the values of the coefficients and the vertical axis displays corresponding frequencies. The blue line represents the probability density estimates and the red vertical line is at 0.

Figure 3. Distribution of the predictive coefficients of the energy variables across models, subsample from 2005:05 to 2015:04 (last 120 observations)



Notes: This figure presents the histograms of the predictive coefficients of the energy price variables derived from the extreme bounds analysis. The horizontal axis represents the values of the coefficients and the vertical axis shows corresponding frequencies. The blue line represents the probability density estimates and the red vertical line is at 0.

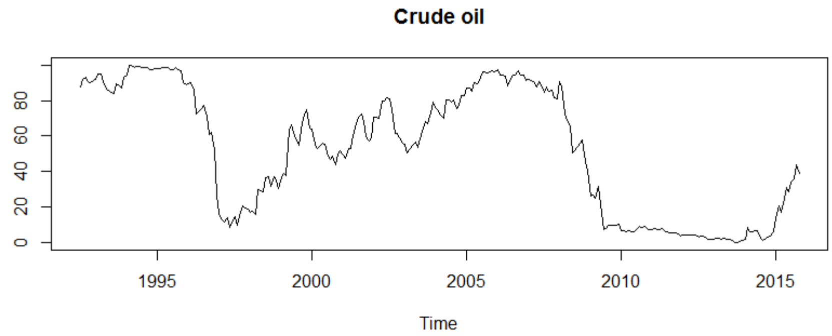
Figure 4. Distribution of the predictive coefficients of the energy variables across models, subsample from 1987:06 to 1997:05 (first 120 observations)

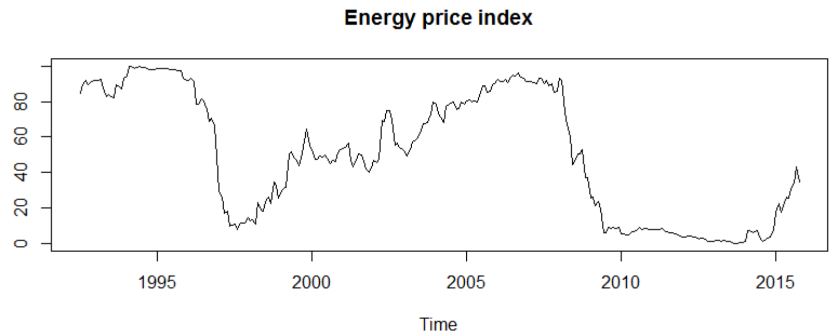


Notes: This figure presents the histograms of the predictive coefficients of the energy price variables derived from the extreme bounds analysis. The horizontal axis represents the values of the coefficients and the vertical axis displays corresponding frequencies. The blue line represents the probability density estimates and the red vertical line is at 0.

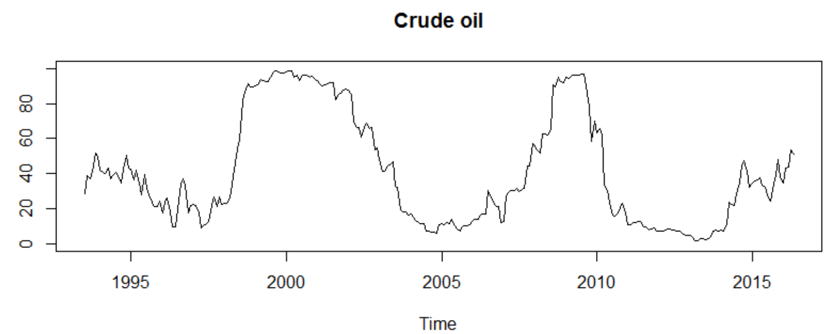
Figure 5. CDF(0) based on generic distribution weighted by R^2, rolling subsample window of 5 years

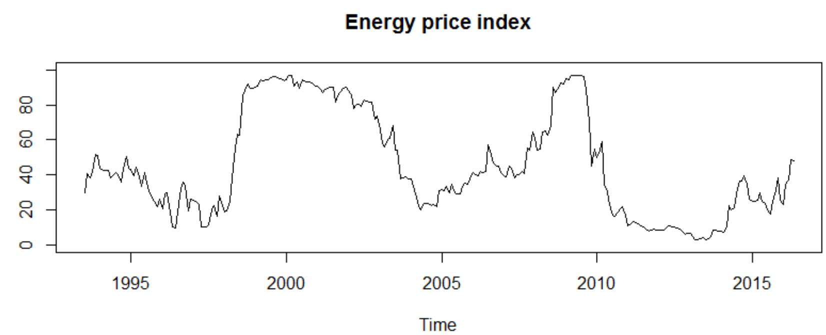
Panel A: 1-month prediction horizon



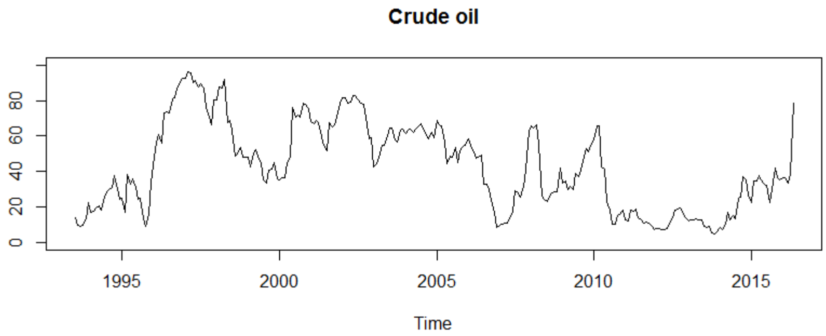


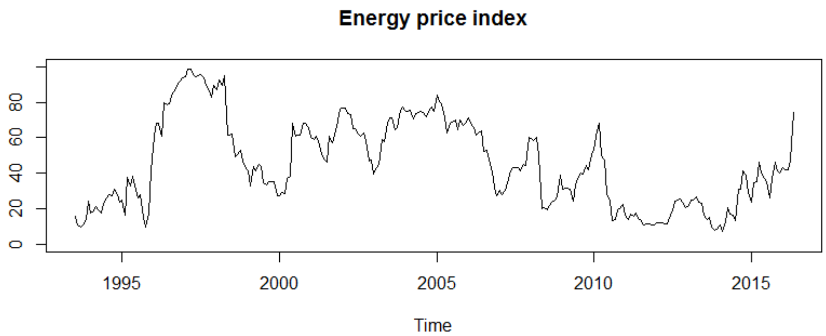
Panel B: 3-month prediction horizon





Panel C: 6-month prediction horizon





Notes: CDF(0) refers to the percentage of the regression coefficients less than 0, which is calculated as the weighted average of all individual CDFs using equations (4) and (5).