The Low Energy Investor: Energy Risks and the Cross Section of Stock Returns*

Virgilio Zurita†

May 24, 2019

Abstract

Energy risks carry systematic effects in the cross-section of equity portfolios and individual stocks. Using a recursive framework, we endogenously derive expected returns from investors' preferences for uncertainty and expectations about distress states of the economy, which we estimate from the crude oil options market. Increasing distress risks decrease firms' energy usage, triggering an amplification mechanism that impact expected returns. We empirically confirm this channel, stocks with lower exposure to energy risks exhibit higher returns months ahead, indicating that investors demand extra compensation to hold these assets. Energy risk exposure remains significant after controlling for stock market, commodity-specific and global risk factors, as well as abnormal media coverage. With the financialization of commodities stock return predictability increases, strengthening the commodity-equity markets link.

JEL Classification: G12, G13

Keywords: energy risks; cross-section of stock returns; options market

*For valuable comments I thank Ethan Chiang, Zhi Da, Bob Dittmar, Hitesh Doshi, Andrea Gamba, Cam Harvey, Kewei Hou, Jianfeng Hu, Kris Jacobs, Haibo Jiang, Tim Loughran, Neil Pearson, Geert Rouwenhorst, Ivan Shaliastovich, Marta Szymanowska, Bohui Zhang and seminar participants at the University of Connecticut, Houston, LSU, Nanyang Tech, SMU, UNSW, and Warwick.

†Hankamer School of Business, Baylor University. Email: virgilio_zurita@baylor.edu, Ph: (254) 710-4650.

1 Introduction

Crude oil is widely considered an important driver of economic activity. Through its use in the production chain, the evolution of the commodity greatly influences business conditions in industrialized economies. Hamilton (2013) finds that spikes in crude oil prices preceded nine out of the ten postwar U.S. recessions, and Chiang, Hughen, and Sagi (2015) document the negative effects of oil risks on the economy and in particular, energy-related stocks.[1] Earlier studies (e.g., Harvey and Siddique (2000), Gomes, Kogan and Zhang (2003)) show that state variables affecting changes in investment opportunities in turn affect a security' covariance with these state variables, and therefore its expected return. A natural question is to what extent the pricing energy risks matter for the predictability of stock returns, and do they capture information beyond common risks factors and characteristics?

In this paper, we develop a dynamic framework where expected returns of a representative oil-intensive firm are derived from investors' optimal decisions and have economic foundations. Expected returns depend on investors' preferences for uncertainty and expectations about bad states of the economy. The first feature uses a combination between investors' risk aversion and willingness to delay investments. The second feature uses the crude oil options market to estimate distress risks, the likelihood of entering a bad state of the economy.[2] We show that the pricing of energy risks do matter for explaining the return of assets. Not all energy risks are alike, the risks of spikes prove economically significant, beyond volatility and skewness risk, a finding in line with the empirical work of Hamilton (2009). Stocks with relatively low energy risk beta exhibit higher subsequent returns, and the exposure to these risks becomes more relevant with the financialization of commodity markets (e.g., Cheng and Xiong (2014), Henderson, Pearson and Wang (2015)).

[1] Table A.1 reports the top net users and providers of crude oil, with the U.S. economy leading the first group, and countries with a history of geo-political instability leading the second group. Bailey and Chan (1993) and Hamilton (1983, 2003) document the interaction between commodity risks and the economy.

[2] We use interchangeable the terms energy risk, distress risk and distress state probability to define the likelihood of entering a distress state of the economy.

The low energy investor, who is long a portfolio of stocks with low energy beta and short a portfolio of stocks with high energy beta, generates an annualized return of 16.9% and its statistical significance exceeds the Harvey, Liu, and Zhu (2016) threshold. We compute the sensitivity of individual stock returns to energy risks (ER) and find strong economic and statistical significance in the cross-section. We sort energy related stocks into decile portfolios, and compute the out of sample portfolio returns, conditioning on past ER beta information. We find that the cross sectional significance of ER beta is not affected after controlling for well-established risk factors and characteristics.

ER beta seems to capture additional information on top of stock market and commodity-specific factors such as the factors in Fama and French (1993) and Carhart (1997) as well as the commodity futures variance, skewness, basis, and open interest (see for example Chabi-Yo, Doshi and Zurita (2018), Kang, Rouwenhorst and Tang (2017), Hong and Yogo (2012), and Szymanowska, de Roon, Nijman and van den Goorbergh (2014)). Moreover, we cannot attribute the performance of the strategy to the limited attention of investors to media coverage about energy risks. We compute several textual analytics to identify and isolate information specific to energy risks. We find that the results of the strategy in times of media coverage above and below trend remain largely unchanged.

Investors care about the uncertainty of events over which the future return distribution occurs. Since the future return distribution is influenced by the state of the economy, distress risks endogenously affect an investor's utility function, the pricing kernel, and expected returns. Harvey (2017) notes the importance of risk factors derived from first principles. Our findings are consistent with Bloom (2009) and Drechsler (2013), who show that economic uncertainty is a relevant state variable proxing for investment opportunities.

Our empirical results confirm the preference-based explanation for energy risks. Due to their negative ER beta, individual stocks in decile 1 correlate negatively with increasing energy risks, the risk of entering into a bad economic state. Hence, investors demand extra compensation in the form of higher expected return to hold these stocks with lower energy risk exposure. On the other hand, with their positive ER beta, the returns of individual stocks in decile 10 correlate positively with increases in energy risks. Since stocks with positive ER beta would be viewed as relatively safer assets at times of increased economic uncertainty, investors are willing to pay higher prices for these stocks and accept lower returns.

We study the performance of the long-short strategy over time and find that it increases with the financialization of commodities in the early 2000s, marked by the increase in investment inflows to the sector (Tang and Xiong (2012) and Singleton (2014)), which suggests a link between trading in the energy derivatives market and the pricing of energy related stocks. Several authors link this increased correlation to the trading of hedge funds holding position in both markets (see for instance Buyuksahin and Robe (2014) and Cheng and Xiong (2014)). Our results complement Basak and Pavlova (2016) and Goldstein and Yang (2018), who show that financialization strengthens the commodity-equity market co-movement.

Our stylized economy features a production technology that is oil intensive, and the usage of oil for production purposes is affected by the likelihood of entering a distress state. As the risk of a distress scenario increases, the total usage of oil decreases, triggering an amplification mechanism across the economy, which ultimately impacts on expected returns. Intuitively, as the distress state probability increases, returns on investments become riskier, and therefore investors demand a higher compensation for risk. We show that this compensation for risk is positive when investors exhibit preferences for an early resolution of uncertainty.

Our paper contributes to the literature on the links between energy markets, the economy, and stock returns. Earlier studies (e.g., Chen, Rolls and Ross (1986), Driesprong, Jacobsen, and Maat (2008), Ferson and Harvey (1993), Jones and Kaul (1996)) document the effects of oil price changes on the economy and stock markets. Sockin and Xiong (2015) show that prices of key industrial commodities can serve as signals for the strength of the economy. Gao, Hitzemann, Shaliastovich, and Xu (2017) and Ready (2018) model the effects of oil volatility risks on stocks. Using crude oil option prices, Christoffersen and Pan (2017) empirically confirm the importance of oil risks in the cross section of stock returns. Chiang, Hughen, and Sagi (2015) find that a latent oil volatility factor negatively loads on the return of energy related stocks, indicating the systematic nature of energy risks. Hamilton (2003, 2009) finds that asymmetric oil shocks help explain economic activity.[3] Motivated by these findings, we develop a stylized model where the expected return of a representative oil intensive firm is endogenously affected by distress risks, proxied by the probability of drastic increases in crude oil prices. We empirically find that the sensitivity of stocks to energy risks is significant in the cross section of energy related stocks, and is robust to stock market exposure and additional risk factors and characteristics.

The structure of the paper is as follows. Section 2 introduces the model. Section 3 describes the data and methodologies. Section 4 provides an analysis of distress risks and the pricing kernel. Section 5 investigates the relation between ER beta and the cross section of stock returns. Section 6 concludes.

2 The Model

To build intuition for the empirical analysis, we first describe the stylized economic framework and the modeling of the distress state probability.

We consider a representative agent with Epstein-Zin (1989) recursive preferences, with utility V_t over consumption C_t

$$V_t = \left[(1-\delta)\, C_t^{1-\frac{1}{\psi}} + \delta \left[E_t \left(V_{t+1}^{1-\gamma} \right) \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}} \tag{2.1}$$

where δ is the time discount factor, γ is the relative risk aversion, and ψ is the intertemporal

[3] Consistent with this argument, Baumeister and Kilian (2016) find no effects of sharp declines in crude oil prices for the U.S. economy.

elasticity of substitution (IES).

In this economy the production technology is oil intensive

$$Y_t = A_t^{1-\eta} O_t^{\eta} \tag{2.2}$$

where A_t embeds the normal shock, and O_t embeds the recessive shock.

This technology is similar to Sockin and Xiong (2015) where the dynamics of the model are driven by A, the productivity factor. In our model, the key implications come from the dynamics of O, the energy usage from production purposes.

Let $A_t = \exp(a_t)$. Changes in the log of productivity are normally distributed with mean μ and standard deviation σ

$$\Delta a_t = \mu + \sigma \epsilon_t \tag{2.3}$$

This specification is assumed for analytical tractability, since homogeneity of degree 1 in the factors allows the value function to be normalized by the productivity process (see for example Bloom (2009)).

The total usage of oil for production evolves according to

$$\Delta O_{t+1} = \begin{cases} (\phi + I_t) \text{ with probability } (1 - \pi_t) \\ (\phi + I_t)(1 - b) \text{ with probability } \pi_t \end{cases} \tag{2.4}$$

where ϕ is a positive parameter and π_t is the probability of entering a distress state in the next period. If a distress state materializes, then the total usage of oil for production decreases by a factor b. Otherwise, the economy is only affected by normal, symmetric, shocks. Ex-ante, the risk of a distress scenario adds uncertainty to the investment process and is measured by the distress state probability.[4]

[4] Harvey and Siddique (2000) and Lettau, Maggiori and Weber (2014) discuss the importance of investors'

The stochastic discount factor is given by

$$M_{t+1} = \delta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left[\frac{V_{t+1}}{E_t \left(V_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}}} \right]^{\frac{1}{\psi}-\gamma} \tag{2.5}$$

Distress risks affect expected returns through the continuation utility component (in brackets) when investors exhibit preferences for the resolution of uncertainty $\left(\gamma \neq \psi^{-1}\right)$.

Recursive preferences and the homogeneity property allow us to express optimal investments in terms of distress risk

$$i_t = \frac{e^{\mu+\sigma\varepsilon_{t+1}} \left[(1-\pi_t) + \pi_t (1-b)^{1-\gamma} \right]^{\frac{\psi-1}{1-\gamma}} \delta^{\psi} \left[E_t f\left(\theta_{t+1}\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{\psi-1}{1-\gamma}} - \phi}{1 + \left[(1-\pi_t) + \pi_t (1-b)^{1-\gamma} \right]^{\frac{\psi-1}{1-\gamma}} \delta^{\psi} \left[E_t f\left(\theta_{t+1}\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{\psi-1}{1-\gamma}}} \tag{2.6}$$

where i_t denotes investments normalized by a_t and $f\left(\theta_{t+1}\right)$ includes state variables beyond the current period. See Appendix A for details on the solution of the model.

Note the relation (2.6) between investments and distress risks is negative when investors have preferences for the early resolution of uncertainty. The dynamics of the model also depend on the evolution of the market's perception of distress states. The probability of entering a distress state of the economy in next period π_t follows the process

$$\ln \pi_t = (1-\rho) \ln \pi + \rho \ln \pi_{t-1} + \varepsilon_t \tag{2.7}$$

We follow the vast empirical evidence surveyed in Hamilton (2013) and use market expectations of large crude oil price increases to proxy for the probability of a distress state of the economy. Using crude oil options on futures prices we estimate a forward looking measure of distress risk.

concerns about bad economic times and asymmetric risks for explaining the return of assets.

Let $F(x) = \int_{-\infty}^{x} f(x)\,dz$ denote the cumulative distribution function. Following Breeden and Litzenberger (1978), we twice differentiate the value of the option B with maturity T and interest rate r with respect to the strike price K to obtain the risk neutral distribution to the option prices $\frac{\partial F}{\partial K} = e^{rT}\frac{\partial^2 B(K,T)}{\partial K^2}$. Given that we are interested in accurately estimating large oscillations, we estimate the tails of the distribution and complete the entire density function using a generalized extreme value distribution (Figlewski (2008) and Linn, Shive and Shumway (2018)). See Appendix B for derivation details.

3 Data and Methodologies

In this section we describe the data sources, parameter calibration, and empirical methodologies.

We use the empirical evidence relating oil spikes and bad economic times and estimate the likelihood of entering a bad economic state in next period using the entire cross section of crude oil option prices. Singleton (2014) emphasizes the importance of accounting for agents' expectations in explaining movements in commodity prices. Moreover, Sockin and Xiong (2015) note that investors observe crude oil prices in a timely fashion but observe quantity variables such as global oil production with delay.

We obtain data on crude oil futures and options from the Chicago Mercantile Exchange (CME group, formerly NYMEX). The sample period is from October 1, 1990 to May 30, 2014. Market liquidity determines the start of the sample. Futures contracts expire on the third business day prior to the 25th calendar day (or the previous business day before if the 25th is not a business day) of the month that precedes the delivery month. Options on futures contracts expire three business days prior to the expiration date of futures.

We convert American option prices into European option prices following Trolle and

Schwartz (2009), who use the methodology of Barone-Adesi and Whaley (1987). We discard observations with Black (1976) implied volatility less than 1% or greater than 200%. In addition, we discard observations with prices less than $0.01 and contracts violating standard no-arbitrage constraints. We fit a spline function of 4th order to the implied volatilities to compute a dense set of interpolated volatilities. We then convert them to call prices.

We use data on aggregate economic indicators from the Federal Reserve Bank of St. Louis (FRED). We obtain open interest data on crude oil futures from the U.S. Commodity Futures Trading Commission (CFTC). We download the data on market wide factors from Kenneth French's website. The data on energy usage is from the Energy Information Administration (EIA). Figure 1 shows the usage of oil for the U.S. economy in thousand barrels per day. We adjust for seasonalities using the U.S. Census Bureau's X-12-ARIMA methodology. The figure indicates that energy usage is highly sensitive to economic downturns.

[Insert Figure 1 Here]

We obtain energy related stocks from CRSP using the four-digit SIC code classifications 1311, 1381, 1389, 2911, and 5172. We compute the sensitivities of stocks to stock market factors and commodity specific characteristics. We use the Fama and French (1993) and Carhart (1997) for stock related factors. For commodity specific variables, we compute the crude oil basis, open interest, variance risk premium, and skewness risk premium. Commodity Basis (BAS) is the log difference between the two-month maturity futures contract and the one-month maturity futures contract and adjusted by days between contracts. Commodity Open Interest Growth (OPI) is the monthly growth rate of open interest. Open interest is the total of all futures contracts entered into and not yet offset as reported by the CFTC. We follow Bakshi, Kapadia, and Madan (2003) and compute the commodity variance and skewness under the risk neutral measure. In line with the literature, we proxy for the physical risk measure using the lagged realized variance and skewness using a 60-day rolling window. We define variance risk premia (VRP) as the difference between the commodity variance under the physical measure and variance under the risk neutral measure. Similarly, we define skewness risk premia (SRP) as the difference between the commodity skewness under the physical measure and skewness under the risk neutral measure. Appendix D provides further details.

We focus the empirical analysis on energy related U.S. stocks and therefore calibrate the model to the U.S. economy Our goal is to reproduce the aggregate moments of the U.S. economy along with the observed dynamics between distress risks and business conditions. Table 1 reports the parameters of the benchmark model. These are broadly in line with the literature reviewed in Section 1.

[Insert Table 1 Here]

In the household sector, the time discount factor δ is set to 0.99. Reasonable parameterizations for risk aversion (γ) are between 1 and 10. Campanale, Castro, and Clementi (2010) argue that risk aversion values above this range are economically implausible. Consistent with the literature, we set the baseline value of γ to 8.

There is a large literature on the magnitude of the intertemporal elasticity of substitution parameter (IES) ψ. Vissing-Jorgensen and Attanasio (2003) and Guvenen (2006) estimate the IES to be in excess of 1, while Campbell (1999) estimates the IES to be below 1. Bansal and Yaron (2004) argue that low estimates of IES are based on a model without time-varying volatility. The implications of our model with time-varying distress risks are in line with the long-run risk literature, where IES larger than 1 is necessary to explain key features of asset markets (see for instance Bansal, Kiku, Shaliastovich, and Yaron (2013)).

We solve the model for different values of IES to match the relation between investments and distress risks observed in the data. Note that when risk aversion exceeds the reciprocal of IES, investors prefer early resolution of uncertainty of consumption. The level parameter

ϕ is to 0.01. We set the share of oil usage in total production η is set to 0.6, in line with Baker (2014). We set the parameter b to 0.084, the average decrease in oil usage during U.S. recessions reported by the Energy Information Administration. Distress risks correspond to the probability of large crude oil prices increases (more than 50%). We estimate the risk neutral density and compute π_t for each month using the right tail of the distribution. In (2.7) we set to $\rho = 0.97$ and $\pi = 0.048$, the corresponding autocorrelation and historical average for π_t.

Despite the simplicity of the model, this setup allows us to generate plausible moments for consumption, investment, and income, along with the observed dynamics between investments and distress risks. See Appendix C for details.

In the next two sections we present the main empirical results from the model.

4 The Distress Risk – Pricing Kernel Link

In this section we study the relation between distress risk, energy risks estimated from the cross section of crude oil options prices, and the stochastic discount factor. Figure 2 shows the time series for the distress state probability from October 1990 to May 2014. This measure determines the likelihood of entering a distress scenario in the following period as reflected by the crude oil options market. The time series exhibit a mean of 0.0484 and standard deviation of 0.0109. Its autocorrelation coefficient is 0.97.[5] The figure shows that distress risks are time-varying, increasing before or at the onset of periods of economic or geo-political distress. Once the market recovers from these periods of turmoil, the distress state probability recedes.

[5] Using a different approach, Kelly and Jiang (2014) estimate a tail risk measure from the cross-section of equity prices and find that persistence for this measure of risk is a necessary condition for generating significant predictability of returns.

[Insert Figure 2 Here]

Note that in our model, distress risks affect expected returns endogenously, and value-maximizing behavior of investors leads to an impact of distress risks on investment decisions. To highlight the main intuition for our results, we next analyze the relation between distress risks, investments, and the pricing kernel.

How do distress risks relate to investments? Intuitively, an increase in the distress state probability implies higher uncertainty about future returns on investments and therefore requires for a higher compensation for risk. We thus expect that, as the likelihood of entering a distress state of the world increases, total investments will consequentially decrease.[6]

In the model, the relation between distress risks and investments is determined by the agent's preferences for the timing of the resolution of uncertainty. In turn, the timing preference is determined by the relation between the relative risk aversion parameter (γ) and the intertemporal elasticity of substitution parameter (ψ). Investors have a preference for an early resolution of uncertainty when the relative risk aversion is higher than the reciprocal of the IES $\left(\gamma > \psi^{-1}\right)$. We show in Appendix A that in this case, as the distress state probability increases, investment decreases. While there is no clear consensus about the exact value for the relative risk aversion, conventional values in the asset pricing literature set this parameter above 1.[7] Regarding the intertemporal elasticity of substitution parameter, several authors argue for a parameter value larger than 1.[8] Finally, note that in the power utility case, a relative risk aversion parameter above 1 implies an IES parameter below 1.

In order to compare our results to the data, we solve the model for different values for the timing preference of the resolution of uncertainty. We set the benchmark specification for the relative risk aversion at 8, in line with the asset pricing literature, and then solve the model for

[6] This mechanism is also consistent with the empirical findings of Da, Huang, and Yun (2017), who document a negative relation between industrial electricity usage and future stock returns.

[7] See Campanale, Castro, and Clementi (2010) and references therein.

[8] See for instance Bansal, Kiku, Shaliastovich, and Yaron (2013).

different values of the IES. Figure 3 shows the unconditional correlation between the distress state probability and investments as a function of the data and the model. Consistent with the intuition of the model, we observe that in the data this relation is negative and around -20 percent. Figure 3 also shows the correlation between the distress state probability and investments for the model under different preferences for the resolution of uncertainty. The figure shows that, as the IES increases, the correlation between the distress state probability and investment decreases. Starting from a low value for an IES of 0.25, which implies a positive correlation of 0.61, correlation decreases in magnitude and change signs reaching its minimum value of -0.38 for an IES value of 3. Note that our benchmark calibration sets the IES at 2 and generates a correlation of -0.26, in line with the data.

It is important to note that investments increase with distress risks when the IES is below unity, a counterintuitive results. The lack of economic intuition is consistent with consumption-based models using power utility preferences. In these models, a decrease in expected growth generates an increase in asset prices, at odds with the data. The inclusion of recursive preferences resolves this problem (see for example Bansal and Yaron (2004) and Hasseltoft (2012)).

[Insert Figure 3 Here]

These results imply that agents care not only about the riskiness of the environment, but also about the timing for the resolution of uncertainty. For the model to reproduce the sign and level of the relation between distress risks and investments in the data, a preference for an early resolution of uncertainty is required.

We next study another important implication of time-varying distress risks. Since these risks reflect the likelihood of entering into bad periods of the economy, it is natural to think about their relation with the stochastic discount factor. Intuitively, as the probability of entering a bad state of the economy in the next period increases, the marginal utility of consumption increases as well. This interpretation is consistent with the relation between wealth and marginal utility of endowment based models. In these models, low levels of wealth (bad states of the economy) carry high levels of marginal utility of consumption.

In Figure 4, we plot the pricing kernel as a function of increasing probabilities of being in a distress state in the following period. The figure shows that when the likelihood of entering a distressed state is low, the pricing kernel is consequently low. As this likelihood increases, so does the pricing kernel, reflecting worse states of the economy and lower real rates. The seven probabilities imply stochastic discount factors of 0.9896, 0.9898, 0.9902, 0.9911, 0.9937, 0.9979 and 1.0048, which in turn imply real interest rates of 1.05, 1.03, 0.99, 0.90, 0.64, 0.21 and -0.48 percent respectively. These real rate values are economically plausible and intuitive. Note that the average three-month real interest rate (the three-month U.S. Treasury Bill deflated by the Consumption Price Index) during last three recessions in our sample is -0.42 percent. In addition, the results from our model are in line with the empirical findings of Linn, Shive and Shumway (2018), who obtain a monotone relation between the pricing kernel and economic states.

[Insert Figure 4 Here]

Overall, these empirical findings highlight the interesting features of the model. A preference for the early resolution of uncertainty generates the correlation between investments and distress risks observed in the data. Moreover, these time-varying risks are positively related with the pricing kernel.

5 Energy Risks Sensitivities and Stock Returns

In this section we discuss the main empirical results of the paper. We first analyze the importance of ER beta in the cross sectional pricing of energy related stocks. We then investigate on the time series of the long-short strategy and its relation to commodity financialization, as well as investors attention to crude oil news coverage.

5.1 The Cross Section of Stock Returns

We compute the exposure of individual stocks to energy risks using monthly rolling regressions of excess stock returns on the one-month-ahead ER

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{ER} ER_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{MOM} MOM_t + \varepsilon_{i,t}$$

We use a 60-month fixed window estimation. The first set of ER betas are obtained using the sample from September 1990 to September 1995. We then use these monthly ER betas to predict the cross-sectional stock returns in the following month (October 1995). We repeat this approach until April 2014. Each month, we form decile portfolios by sorting individual stocks based on their ER betas (β^{ER}). Decile 10 contains stocks with the highest β^{ER} during the previous month, while decile 1 contains stocks with the lowest β^{ER} during the previous month. The difference portfolio (High minus Low) results from holding a long position in the high beta ER portfolio P10 and a short position in the low beta ER portfolio P1. Table 2 reports the average monthly returns for portfolios sorted by ER betas. Column 2 reports the average ER betas for the decile portfolios, and columns 3 to 7 present the average excess returns and the alphas on the equal-weighted portfolios.

[Insert Table 2 Here]

Moving from decile 1 to decile 10, there is significant cross-sectional variation in the average values of β^{ER}. The average ER beta increases from -1.18 to 1.01. The average return difference between decile 10 (high- β^{ER}) and decile 1 (low- β^{ER}) is -1.53% per month with a six-lags Newey and West (1987) $t-$statistic of -3.50. This result indicates that stocks in the lowest β^{ER} decile generate 18.36% higher annual returns compared to stocks in the highest β^{ER} decile. In addition to the average raw returns, Table 2 presents the magnitude and statistical significance of the risk- adjusted returns (alphas) from four different factor models. In column 4, α is the intercept from the regression of the excess portfolio returns on a constant and the excess market return (MKT). Column 5 to 7 incrementally augment the model factors with a size factor (SMB), a book-to-market factor (HML), and a momentum factor (MOM). In all cases, the risk adjusted returns remain significant.

In column 4, the alpha from the long-short strategy α_{MKT} decreases from 2.66% to 1.25% per month, when moving from the lowest to the highest β^{ER} decile. The difference in alphas between the high- β^{ER} and low- β^{ER} portfolios is -1.41% per month (or -16.92% per annum) with a Newey-West $t-$statistic of -2.86. Next, we investigate the source of the 16.92% annualized risk-adjusted return difference between the high- β^{ER} and low- β^{ER} portfolios. Is it due to outperformance by low- β^{ER} stocks, underperformance by high- β^{ER} stocks, or both? For this, we focus on the economic and statistical significance of the risk-adjusted returns of decile 1 versus decile 10. As reported in Table 2, the risk adjusted returns α of decile 1 (low- β^{ER} stocks) and decile 10 (high- β^{ER} stocks) are significantly positive. Hence, we conclude that the significantly negative alpha spread between high- β^{ER} and low- β^{ER} stocks is due to both the outperformance by low- β^{ER} stocks and the underperformance by high- β^{ER} stocks.

The next three columns in Table 2 present similar alpha results from alternative factor models. The alphas α_2, α_3, and α_4 decrease almost monotonically when moving from the lowest to the highest β^{ER} decile. The difference in alphas between the high- β^{ER} and low- β^{ER} portfolios is α_2= -1.45% per month ($t = -2.96$), α_3 = -1.38% per month ($t = -2.78$), and α_4 = -1.38% per month ($t = -2.72$) for the combined four-factor model. This indicates that after controlling for the well-known market, size, book-to-market, and momentum factors, the return difference be tween the high- β^{ER} and low- β^{ER} stocks remains negative and statistically significant.

These results are consistent with a well-established literature that distinguishes risk and uncertainty. Due to their negative ER betas, the returns of individual stocks in decile 1 correlate negatively with increases in economic uncertainty, hence uncertainty-averse investors would demand extra compensation in the form of higher expected return to hold these stocks with negative β^{ER} . On the other hand, with their positive ER betas, the returns of individual stocks in decile 10 correlate positively with increases in economic uncertainty. Since stocks with positive β^{ER} would be viewed as relatively safer assets at times of increased economic uncertainty, investors are willing to pay higher prices for these stocks and accept lower returns. Note that in our model, expected returns depend on investors expectations of bad economic times, as well as their preferences for the resolution of uncertainty.

The ER betas in Table 2 are for the portfolio formation month and, not for the subsequent month over which we measure average returns. Investors may pay high prices for stocks that have exhibited high ER beta in the past in the expectation that this behavior will be repeated in the future. These expectations are natural derivations from the model in Section 2, but we now test them empirically. To this end, we examine the persistence of β^{ER} by running firm-level cross-sectional regressions of β^{ER} on lagged β^{ER} and lagged cross-sectional predictors. Specifically, for each month in the sample we run a regression across firms of 6-month to 60-month-ahead β^{ER} ($\beta^{ER}_{i,t}$) on the lagged β^{ER} ($\beta^{ER}_{i,t}$) and 8 lagged control variables defined in Section 3.

In Table 3, the second row reports the average cross-sectional coefficients on $\beta^{ER}_{i,t}$ from the multivariate cross-sectional regressions. In the regression of 6-month-ahead β^{ER} on lagged β^{ER} , the coefficient is positive, quite large, and extremely statistically significant. In other words, stocks with high β^{ER} also tend to exhibit similar features in the following 6 months. We also investigate the persistence of β^{ER} for one to five years ahead. The last five rows in Table 3 show that β^{ER} remains highly persistent up to four years into the future. These results indicate that the estimated historical ER betas successfully predict future ER betas and hence are good proxies for the true conditional betas. These results show that the ER betas are not simply characteristics of firms that result in differences in expected returns, but proxies for a source of economic uncertainty.

[Insert Table 3 Here]

So far we have tested the significance of the ER beta as a determinant of the cross-section of future returns at the portfolio level. This portfolio-level analysis does not account for information in the cross-section due to aggregation, and does not allow to control for multiple effects or factors simultaneously. Consequently, we now examine the cross-sectional relation between the ER beta and expected returns at the stock level using the Fama and MacBeth (1973) regressions. We present the time-series averages of the slope coefficients from the regressions of one-month-ahead stock returns on the ER beta with and without control variables. The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables on average have nonzero premiums. We implement monthly cross-sectional regressions for the following econometric specification and incremental versions

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{ER} + \lambda_{X,t}\beta_{i,t}^{X} + \varepsilon_{i,t+1}$$

where $R_{i,t+1}$ is the realized excess return on stock i in month $t+1$, $\beta_{i,t}^{ER}$ is the ER beta of stock i in month t, and $\beta_{i,t}^{X}$ is a collection of stock sensitivities observable at time t for stock i.

Table 4 reports the time-series averages of the slope coefficients and the Newey-West $t-$statistics in parentheses. The univariate regression results reported in the first column indicate a negative and statistically significant relation between the ER beta and the cross-section of future stock returns. The average slope from the monthly regressions of realized returns on $\beta_{i,t}^{ER}$ alone is -0.51 with a Newey-West $t-$statistic of -2.01, and it is -0.62 ($t =$

-2.56) after controlling for stock and commodity characteristics. Its statistical significance is consistent with Harvey (2017) and Harvey, Liu, and Zhu (2016), who argue for a lower threshold for a risk factor developed from first principles, as is in the case of ER beta. The second column in Table 4 controls for the market beta ($\beta_{i,t}^{MKT}$) and the average slope on $\beta_{i,t}^{ER}$ remains negative and highly significant, whereas the average slope on $\beta_{i,t}^{MKT}$ is statistically insignificant.

[Insert Table 4 Here]

Columns 3 to 9 incrementally include additional sensitivities. Column 9 includes the full set of sensitivities. The beta with respect commodity open interest remains significant but economically small. Hong and Yogo (2012) document that the open interest of a broad set of commodities helps explain economic variables, while Boons, de Roon, and Szymanowska (2014) find similar result for stocks. Note that in all 9 cases beta ER remains economically and statistically significant.

To determine the economic significance of this average slope coefficient, we use the average values of the ER betas in the decile portfolios. Table 2 shows that the difference in $\beta_{i,t}^{ER}$ values between average stocks in the first and tenth deciles (β_{High}^{ER} - β_{Low}^{ER}) is 2.19. If a stock were to move from the first to the tenth decile of $\beta_{i,t}^{ER}$, what would be the change in that stock's expected return? The average slope coefficient of -0 .62 on $\beta_{i,t}^{ER}$ in Table 3 represents an economically significant decrease of 1.35% per month (-0.62×2.19) in the average stock's expected return for moving from the first to the tenth decile of $\beta_{i,t}^{ER}$.

We next assess the cross sectional relations between ER beta and stock returns after controlling for alternative sorting sensitivities. We use sensitivities to stock market factors (Fama and French (1993) and Carhart (1997)), as well as commodity specific variables including variance risk premium, skewness risk premium, basis, and open interest. To study these interaction we implement a bi-variate independent sort analysis.

We divide the sample into three groups based on ER beta (percentiles 25 and 75), and two groups based on the alternative beta (percentile 50). We thus generate six portfolios each time-period and compute the average for each group as well as the difference group (top minus bottom).

Table 5 reports the results from the double sorts using ER beta. The top panels (Panels A to E) report the double sorts using ER beta and stocks exposure to stock markets factors MKT, SMH, HML and MOM. The bottom panels (Panels F to H) report the double sorts using ER beta and stocks exposure to commodity specific characteristics VRP, SRP, BAS, and OPI. For ease of exposition, we focus on the top and bottom groups for each of the two measures as well as the difference between the top and bottom groups ($ER_{Diff.}$). We also report the risk adjusted return α_4 from the regression of the difference group on to the four factor model of Fama and French (1993) and Carhart (1997). In all panels, rows correspond to different groups of ER beta, given a group of the alternative beta. Columns correspond to different groups of the alternative beta, given a group of ER beta.

[Insert Table 5 Here]

The economic and statistical significance of ER beta is present in sub-groups. Panel A shows that returns from the ER beta strategy remain positive and statistically significant in the high MKT beta group with an ER beta difference portfolio monthly return of -1.21% and $t-$statistic of -3.1. The risk adjusted return shows an alpha of -1.21% monthly ($t = 2.79$). The significance of the difference group for ER beta decreases in the low MKT beta group, suggesting the performance of the beta ER strategy is relatively stronger in good economic times. Stronger results for the ER beta strategy are obtained when double sorting by sensitivities to SMB, HML, and MOM in Panels B to D. These results suggest that the long-short beta ER strategy is significant regardless of the size, value, and momentum of stocks. Panels E to H of Table 5 double sort by commodity specific variables estimated from the crude oil options and futures markets. In panel E, the risk adjusted return of the beta ER difference portfolio is -1.08% monthly ($t = -3.05$), suggesting the performance of the β^{ER} strategy increases in times of high uncertainty in the crude oil market. Similar results are obtained in Panels F to H, with the strategy losing significance when double sorting by crude oil futures basis. Yang (2013) finds that commodity basis helps explain the cross section of commodities and is related to investment shocks.

Overall these findings indicate that the well-known cross-sectional effects cannot explain the significant performance of the β^{ER} strategy. Note that when controlling for different groups of beta, most alternative sorting measures lose significance. Interestingly, the difference group (top minus bottom) of the β^{ER} strategy remains economically and statistically significant after controlling for the different groups of the alternative sorting measure.

5.2 Stock Returns, Energy Risks, and Commodity Financialization

We investigate the time series behavior the trading strategy and compute the cumulative returns of the long-short strategy. In Figure 5, we plot the cumulative returns and as well as the commodity open interest, the number of crude oil contracts outstanding at each point in time.

[Insert Figure 5 Here]

A recent literature studies the large inflow of investment capital to commodity derivatives since the early 2000s (see for instance Tang and Xiong (2012) and Henderson, Pearson and Wang (2015)). Buyuksahin and Harris (2011) document a change in two key market indicators since 2002. Total open interest in crude oil futures contracts and the ratio of positions between commercial and non-commercial investors drastically increased since 2002.

Figure 6 shows the time series for the total open interests in crude oil futures reported by the CFTC. The figure confirms the findings of previous studies. Between 1990 and 2001, the figure displays a stable pattern with an average open interest of 399,039 contracts. Between 2002 and 2012, it shows an increasing trend, with an average open interest of 1,068,368 contracts. This represents an increase of 168 percent between both periods.

Several interest results emerge. First, despite mostly positive throughout the entire sample, the performance increases since the early 2000s. This period corresponds to drastic increases in trading in the commodity derivatives markets, which is confirmed by the increase in open interest as shown in Figure 5, suggesting there is a stronger interlink between the crude oil derivatives market and the oil related companies since the financialization of commodity markets (Basak and Pavlova (2016)). The results are also consistent with a time-varying market segmentation between equity and commodity markets (Acharya, Lochstoer and Ramadorai (2013) and Bessembinder (1992)).

Second, given the strong economic and statistically significance of the long-short strategy, it is natural to ask what can empirically explain it. Do stock market, commodity specific, or global risk factors explain the returns of the ER beta strategy? If these factors can explain the spikes' risks embedded in the commodity market, standard asset pricing tests imply that the intercept equals zero. We thus regress the long-short portfolio returns on different risk factors. These include the stock market factors MKT, SMB, HML, and MOM, along with the commodity specific factors VRP, SRP, BAS, and OPI. We also include factors related to the overall economy proxied by changes in the VIX index, U.S. Treasury-Eurodollar spread (TED), and economic policy uncertainty index (EPU) of Baker, Bloom, and Davis (2016).

Table 6 reports the results for the univariate and multivariate time-series regressions. The results in Table 6 are consistent with the findings from the cross-sectional analysis in Section 5.1. Columns 1 to 11 report the univariate regressions. In all cases, the intercept of the ER beta long-short portfolio is negative and significant even after controlling for the 11 covariates individually. The intercept remains negative and significant, with an average coefficient of -0.149 and average $t-$statistic of -2.9. The univariate time series regressions suggest the ER beta strategy is marginally statistically related to the market factor and economic policy uncertainty, confirming the systematic nature of energy risks. Column 12 reports the multivariate regression. Only the commodity variance risk premium shows an economically and statistically significant slope. This result is in line with the literature studying the importance of commodity volatility for explaining economic activity and the return of assets (see for example Chiang, Hughen, Sagi (2015) and Gao, Hitzemann, Shaliastovich, and Xu (2017)). Note that including all covariates only explain 1.73% of the total variation in the strategy.

[Insert Table 6 Here]

These results are consistent with the literature on financialization of commodities, and confirm our findings in the cross-sectional analysis of Section 5.1. Tang and Xiong (2012) find an increase in the volatility of commodity futures prices as well as the correlation with equities since the early 2000s.[9] This is in line with the pattern observed in Figure 5. Moreover, results from the double sort analysis confirm these findings. In table 5, the long-short strategy seems to perform particularly well in times of high trading volume in the commodity market (high OPI group in Panel H). In addition, the strategy performs particularly well in periods of high volatility risk in the energy markets as shown in panel E.

5.3 Energy Risk Exposure and Investors Attention

A final concern about the performance of the ER relates to the attention of investors to the arrival of news about crude oil prices. Perhaps the strategy is driven not by a risk based

[9] Christoffersen, Lunde and Olesen (2018) document the empirical non-linear dependencies between commodity and equity markets.

explanation but by the limited attention of investors.[10] Recent studies investigate the effect of media coverage on crude oil prices (see for example Brandt and Gao (2017) and Loughran, McDonald, and Pragidis (2018)). Our goal is different, we ask what are the effects of crude oil news on the performance of the energy risk strategy. If our ER measure, computed using crude oil option prices and energy usage, shows different performance when news coverage is above or below trend, then ER may be just capturing the limited attention of investors to media coverage.

To this end, we search for monthly news covering crude oil prices in the Wall Street Journal, the New York Times, Dow Jones News Wires, and Reuters News Wires. We classify our search into news on crude oil price spikes, and the broader term crude oil price uncertainty. Appendix F describes the methodology. We then compute the spread of monthly news from the 12-month average news count. We examine the performance of the strategy when news coverage is above its annual trend and when it is below its annual trend.

In Table 7, Panel A reports the summary statistics. On average, the number of news referring to crude oil prices spikes or crude oil price uncertainty are 148 and 240 respectively. Between September 1995 and April 2014, the total number of news referring to crude oil spikes is 33,215, and the total number news referring to the broader search, crude oil uncertainty, is 53,794.

[Insert Table 7 Here]

In Panel B, the left column reports the results for the news search about crude oil price spikes, and the right column reports the results for a broader search, namely crude oil price uncertainty. For the case of crude oil price spikes, in times of higher media coverage when the monthly number of news exceeds the historical annual average, the monthly return is 1.57% ($t = -2.04$). Note the return of the strategy when the media coverage is below

[10] Andrei and Hasler (2015) show that investors attention can affect asset pricing.

average is similar (1.50%), which suggest that limited investors attention to crude oil news is not driving the performance of the ER strategy. We obtain similar results when using media coverage about crude oil uncertainty, but the significance of the below average group decreases.

These empirical findings are a by product of our recursive preference framework, where investors prefer to resolve uncertainty earlier rather than later. Our results are consistent with Sicherman, Loewenstein, Seppi and Utkus (2016), who find that investor attention is important in financial markets because attention affects trading, and empirically document the importance of investors preferences for the timing of information revelation.

Overall, using textual analysis to examine the effects of abnormal media coverage of crude oil prices, we find that the performance of the ER strategy remains largely unchanged under different media coverage environments, which provides further support to the risk based explanation for energy risk exposure.

6 Conclusion

To the best of our knowledge, we are the first to provide a channel through which energy risks can have systematic effects in the economy, including energy related stocks. We provide evidence that the pricing of energy risks capture additional and unaccounted information in the cross-section of portfolios and individual stocks. Investors' willingness to delay investments over time and expectations about a distress scenario drive expected returns. We estimate distress risks using crude oil options prices, and show that the negative relation between investments and distress risks observed in the data can be achieved in the model when investors exhibit preferences for the early resolution of uncertainty.

Our goal is not to implement a horse race in search for a risk factor but rather to provide an economic rationale using a dynamic model to answer why disruptions from the energy sector can have pervasive effects in the economy and individual stocks (Chiang, Hughen, and Sagi (2015)). In his American Finance Association presidential address Harvey (2017) highlights the importance of economically motivated risk factors over alternatives discovered from a purely empirical exercise.

The exposure of stocks to energy risks seems to explain the cross section of returns. We show that stocks in the lowest energy risk beta decile generate 16.9% more annualized risk-adjusted return compared to stocks in the highest risk beta decile. We find that the energy risk strategy is driven by the outperformance of stocks with negative ER betas as well as the underperformance of stocks with positive ER betas. Stocks exposure to energy risks remains strong after controlling for stock market, commodity-specific, and global risk factors. Moreover, the results from the strategy do not change under different media coverage environments. We find that with the financialization of commodity markets, the performance of the long-short strategy increases, suggesting a link between trading in the energy derivatives market and the pricing of energy-related stocks.

Appendix

A Model Solution

We numerically solve the model by value function iteration. The optimization procedure discretizes the dynamics for π using a Markov chain.[11] We maximize the value function (A.1) subject to the resource constraint (A.2), the process for oil usage (A.3), and the technology process (A.4)

$$
\begin{aligned}
V\left(O_t, \pi_t, a_t\right) &= \max_{C_t, I_t} \left\{ \left[(1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left[E_t \left(V_{t+1}^{1-\gamma} \right) \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}} \right\} && \text{(A.1)} \\
C_t + I_t &= A_t^{1-\eta} O_t^{\eta} && \text{(A.2)} \\
\Delta O_{t+1} &= \left(\phi + I_t\right) \text{ w.p. } \left(1 - \pi_t\right) && \text{(A.3)} \\
&= \left(\phi + I_t\right)(1-b) \text{ w.p. } \pi_t \\
a_{t+1} &= a_t + \mu + \sigma \epsilon_{t+1} && \text{(A.4)}
\end{aligned}
$$

We normalize the problem by the technology process and write the value function in terms of the state variables $(o,\, \pi)$ and subject to the oil usage process

$$
v\left(o_t, \pi_t\right) = \left\{ \begin{array}{c} \left(e^{(\mu+\sigma)} - i_t\right)^{1-\frac{1}{\psi}} + \delta \left[\left(\phi + i_t\right)^{1-\gamma} \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \times \\ \left[\left(1-\pi_t\right) + \pi_t (1-b)^{1-\gamma} \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \left[E_t v\left(o_{t+1}, \pi_{t+1}\right) \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \end{array} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \qquad \text{(A.5)}
$$

When investors are indifferent about the timing for the resolution of uncertainty $\left(\gamma = \frac{1}{\psi}\right)$,

[11] See Judd (1991) and Richter, Throckmorton, Walker (2013) for an analysis on the numerical solution method. See Kopecky and Suen (2010) and Tauchen and Hussey (1991) for a treatment of markov chains for persistent processes.

optimality conditions indicate that increments in π lead to increments in i

$$i_t = \frac{e^{\mu+\sigma\varepsilon_{t+1}}\left[(1-\pi_t)+\pi_t(1-b)^{1-\gamma}\right]\delta^{\psi}E_t f(\theta_{t+1}) - \phi}{1+\left[(1-\pi_t)+\pi_t(1-b)^{1-\gamma}\right]\delta^{\psi}E_t f(\theta_{t+1})} \tag{A.6}$$

Conversely, when $\left(\gamma > \frac{1}{\psi}\right)$, an increment in π leads to a reduction in the optimal i, which corresponds with (2.8) in Section 2.

B Estimation Procedure for Distress State Probabilities

The value of a call option B with underlying asset value S, strike price K, maturity T, and risk-free rate r is given by

$$\begin{aligned} B(S,K,T) &= e^{-rT}\int_0^{\infty}(S-K)^+ Q(S,S_T,T)\,dS && \text{(B.1)} \\ &= e^{-rT}\int_K^{\infty}(S-K)\,Q(S,S_T,T)\,dS && \text{(B.2)} \end{aligned}$$

We relate option prices B to state price densities Q by taking first derivatives in (B.2) with respect to the strike price

$$\begin{aligned} \frac{\partial B(K,T)}{\partial K} &= e^{-rT}\left[-(K-K)\,Q(K,T)+\int_K^{\infty}-Q(S,S_T,T)\,dS_T\right] && \text{(B.3)} \\ &= -e^{-rT}\left[1-\widetilde{Q}(K,T)\right] && \text{(B.4)} \end{aligned}$$

where the second derivative corresponds to the state price density $e^{rT}\frac{\partial^2 B(K,T)}{\partial K^2}$ in Section 2.

We extend the left and right tails of the empirical density using a Generalized Extreme Value (GEV) distribution (Figlewski, 2008). The GEV density is governed by the shape (ξ), location (μ) and scale (σ) parameters

$$f(\xi,\mu,\sigma) = \frac{1}{\sigma}\left[1+\xi\left(\frac{S_T-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}-1} e^{-\left[1+\xi\left(\frac{S_T-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}} \tag{B.5}$$

Given the strike price K corresponding to the quantile α of the density, we select an inner (α_0) and outer (α_1) value for the right tail.[12] We require that the cumulative probability in the tail for the empirical and GEV densities must equal. In addition, we require for the empirical and GEV densities to have the same curvature in the overlapping area

$$\begin{aligned} F\left(K\left(\alpha_0\right)\right) &= \alpha_0 && \text{(B.6)} \\ f\left(K\left(\alpha_0\right)\right) &= \widetilde{f}\left(K\left(\alpha_0\right)\right) && \text{(B.7)} \\ f\left(K\left(\alpha_1\right)\right) &= \widetilde{f}\left(K\left(\alpha_1\right)\right) && \text{(B.8)} \end{aligned}$$

where f denotes the GEV density, and $\widetilde{f}$ denotes the estimated density.

C Economic Implication of the Model

We calibrate the model parameters to the first moments of aggregate economic indicators and report the results for the second moments. Table A.2 reports the unconditional moments for income, consumption, and investments. Our sample period is from October 1990 to May 2014.

[Insert Table A.2 Here]

The table reports that the annualized volatility of income is 2.4 percent in the model and 2.3 percent in the data. Similarly, the volatility of consumption is 2.4 percent in the model and 2.2 in the data, while the volatility of investments is 7.4 percent in the model and 8.1 in the data. The correlations with income are also in line with the data. Namely, consumption correlates with income at 0.75 both in the model and the data, and investments correlates with income at 0.66 in the model and 0.86 in the data.

[12] A similar procedure is implemented for the fitting of the left tail.

D Risk Neutral Variance and Skewness

We follow Bakshi, Kapadia, and Madan (2003) to estimate the variance and skewness of the risk-neutral density function of individual securities. The risk neutral variance ($VAR_t^{\mathbb{Q}}$) and skewness ($SKE_t^{\mathbb{Q}}$) at time t for a τ-maturity contract are given by

$$VAR_t^{\mathbb{Q}} = e^{r\tau}V_t(\tau) - \mu_t(\tau)^2 \tag{D.1}$$

$$SKE_t^{\mathbb{Q}} = \frac{e^{r\tau}W_t(\tau) - 3\mu_t(\tau)^2 e^{r\tau}V_t(\tau) + 2\mu_t(\tau)^3}{\left[e^{r\tau}V_t(\tau) - \mu_t(\tau)^2\right]^{\frac{3}{2}}} \tag{D.2}$$

where $\mu_t(\tau) = e^{r\tau} - 1 - e^{r\tau}V_t(\tau)/2 - e^{r\tau}W_t(\tau)/6 - e^{r\tau}X_t(\tau)/24$ and r is the risk free rate. Bakshi, Kapadia, and Madan (2003) show that one can express the τ-maturity price of a security that pays the quadratic, cubic, and quartic return on the base security as

$$V_t(\tau) = \int_{F_t}^{\infty} \frac{2\left(1-\ln\left(\frac{K}{F_t}\right)\right)}{K^2} C_t(\tau;K)\,dK + \int_0^{F_t} \frac{2\left(1-\ln\left(\frac{K}{F_t}\right)\right)}{K^2} P_t(\tau;K)\,dK \tag{D.3}$$

$$W_t(\tau) = \int_{F_t}^{\infty} \frac{6\ln\left(\frac{K}{F_t}\right) - 3\ln\left(\frac{K}{F_t}\right)^2}{K^2} C_t(\tau;K)\,dK + \int_0^{F_t} \frac{6\ln\left(\frac{K}{F_t}\right) - 3\ln\left(\frac{K}{F_t}\right)^2}{K^2} P_t(\tau;K)\,dK \tag{D.4}$$

$$X_t(\tau) = \int_{F_t}^{\infty} \frac{12\ln\left(\frac{K}{F_t}\right)^2 - 4\ln\left(\frac{K}{F_t}\right)^3}{K^2} C_t(\tau;K)\,dK + \int_0^{F_t} \frac{12\ln\left(\frac{K}{F_t}\right)^2 - 4\ln\left(\frac{K}{F_t}\right)^3}{K^2} P_t(\tau;K)\,dK \tag{D.5}$$

where (D.3)-(D.5) are the time t prices of $\tau-$maturity quadratic, cubic, and quartic contracts, respectively. $C_t(\tau;K)$ and $P_t(\tau;K)$ are the time t prices of European calls and puts written on the underlying asset with strike price K and expiration τ periods from time t.

E Media Coverage

We search for financial news pertaining to crude oil risks. Importantly, we restrict our search to articles where words referring to crude oil risks are within 5 words of distance. A preliminary inspection suggest that the location of the three arguments within the news article matters, and that without a nearest neighbor algorithm restriction the results bring news that are not specifically related to our target.[13] We drop news when this restriction is violated. Because of this restriction, manual validation reveals that our success rate upwards 90% in selecting specialized news. Given the importance of crude oil in the general news media, we find that using an unrestricted location algorithm yields results that are unrelated to crude oil prices.

We use Factiva to search for two groups of news: Crude oil price spikes, and crude oil price uncertainty. Our source includes the Wall Street Journal, the New York Times, Dow Jones News Wires, and Reuters News Wires. Based on our initial manual search, the following set of words encompass most of the financial news articles, and adding additional words does not change our overall results.

We define the spike set of related words: spike*, large increase, shoot up, much higher, climb*, drastic increase, massive increase.

We define the uncertainty set of related words: risk*, volatil*, fear*, uncertain*.

Terms that end with * search for words sharing the first characters (e.g.: spike* searches for spike, spikes, spiked).

[13] Manual inspection reveals that using simpler word connectors such as AND, OR, or using longer word window yields results that are not specifically related to crude oil risks.

References

[1] Acharya, Viral, Lochstoer, Lars, and Tarun Ramadorai. 2013. "Limits to arbitrage and hedging: Evidence from commodity markets", *Journal of Financial Economics*, 109, 441-465.

[2] Andrei, Daniel and Michael Hasler. 2015. "Investor Attention and Stock Market Volatility", *Review of Financial Studies*, 28, 1, 33-72.

[3] Bailey, Warren, and K. C. Chan. 1993. "Macroeconomic Influences and the Variability of the Commodity Futures Basis", *Journal of Finance,* 48, 2, 555–573.

[4] Bakshi, Gurdip, Kapadia, Nikunj, and Dilip Madan. 2003. "Stock return characteristics, skew laws, and the differential pricing of individual equity options", *Review of Financial Studies,* 16, 101–143.

[5] Bansal, Ravi, and Amir Yaron. 2004. "Risks for the Long Run: A Potential Explanation of Asset Pricing Puzzles", *Journal of Finance,* 59, 1481–1509.

[6] Bansal, Ravi, Kiku, Dana, Shaliastovich, Ivan, and Amir Yaron. 2014. "Volatility, the Macroeconomy and Asset Prices", *Journal of Finance,* 69, 6, 2471–2511.

[7] Barone-Adesi, Giovanni, and Robert Whaley. 1987. "Efficient Analytic Approximation of American Option Values", *Journal of Finance,* 42, 301-320.

[8] Baumeister, Christiane, and Lutz Kilian. 2016. "Lower Oil Prices and the U.S. Economy: Is This Time Different?", Brookings Papers on Economic Activity, 287-336.

[9] Basak, Suleyman and Ana Pavlova. 2016. "A Model of Financialization of Commodities", *Journal of Finance*, 71, 4, 1511—1556.

[10] Bessembinder, Hendrik. 1992. "Systematic risk, hedging pressure, and risk premiums in futures markets", *Review of Financial Studies*, 5, 637-667.

[11] Bessembinder, Hendrik, and Kalok Chan. 1992. "Time Varying Risk Premia and Forecastable Returns in Futures Markets", *Journal of Financial Economics*, 32, 169-193.

[12] Black, Fischer. 1976. "The Pricing of Commodity Contracts", *Journal of Financial Economics,* 3, 167-179.

[13] Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks", *Econometrica*, 77, 3, 623–685.

[14] Boons, Martijn, de Roon, Frans, and Marta Szymanowska. 2014. "The Price of Commodity Risk in Stock and Futures Markets", Working Paper.

[15] Brandt, Michael, and Lin Gao. 2017. "Macro Fundamentals or Geopolitical Events? A Textual Analysis of News Events for Crude Oil", Working Paper.

[16] Breeden, Douglas, and Robert Litzenberger. 1978. “Prices of State Contingent Claims Implicit in Options Prices”, *Journal of Business*, 51, 621–651.

[17] Büyükşahin, Bahattin, and Jeffrey Harris. 2011. “Do Speculators Drive Crude Oil Futures Prices?”, *Energy Journal*, 32, 167-202.

[18] Büyükşahin, Bahattin, and Michel Robe. 2014. “Speculators, commodities and cross-market linkages”, *Journal of International Money and Finance*, 42, 38-70.

[19] Carr, Peter, and Jiming Yu. 2012. “Risk, Return, and Ross Recovery”, *Journal of Derivatives,* 20.

[20] Carhart, Mark. 1997. “On Persistence in Mutual Fund Performance”, *Journal of Finance,* 52, 1, 57–82.

[21] Chabi-Yo, Fousseni, Doshi, Hitesh, and Virgilio Zurita. 2018. “Never a Dull Moment: Entropy Risk in Commodity Marketss”, Working Paper.

[22] Chen, Nai-Fu, Rolls, Richard, and Stephen Ross. 1986. "Economic Forces and the Stock Market", *Journal of Business*, 59, 3, 383-403.

[23] Cheng, Ing-Haw, and Wei Xiong. 2014. “The Financialization of Commodity Markets”, *Annual Review of Financial Economics*, 6, 419-441.

[24] Chiang, I-Hsuan Ethan, Hughen, Keener, and Jacob Sagi. 2015. “Estimating Oil Risk Factors Using Information from Equity and Derivatives Markets”, *Journal of Finance*, 70, 2, 769–804.

[25] Christoffersen, Peter, Lunde, Asde, and Kasper Olesen. 2018. "Factor Structure in Commodity Futures Return and Volatility", *Journal of Financial and Quantitative Analysis*, forthcoming.

[26] Christoffersen, Peter, and Xuhui Pan. 2017. “Oil volatility risk and expected stock returns”, *Journal of Banking and Finance*, 1-22.

[27] Da, Zhi, Huang, Dayong, and Hayoung Yun. 2017. “Industrial Electricity Usage and Stock Returns”, *Journal of Financial and Quantitative Analysis*, 52, 1, 37-69.

[28] Drechsler, Itamar. 2013. “Uncertainty, time-varying fear, and asset prices”, *Journal of Finance,* 68, 1843–1889

[29] Driesprong, Gerben, Jacobsen, Ben, and Benjamin Maat. 2008. “Striking oil: Another puzzle?”, *Journal of Financial Economics*, 89, 307-327.

[30] Edwards, Franklin, and Michael Canter. 1995. “The Collapse of Metallgesellschaft: Unhedgeable Risks, Poor Hedging Strategy or Just Bad Luck?”, *Journal of Futures Markets*, 15.

[31] Epstein, Larry, and Stanley Zin. 1989. "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework", *Econometrica*, 57, 4, 937-969.

[32] Fama, Eugene, and Kenneth French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics,* 33, 1,3–56.

[33] Ferson, Wayne, and Campbell Harvey. 1993. "The Risk and Predictability of International Equity Returns", *Review of Financial Studies,* 6, 3, 527–566.

[34] Figlewski, Stephen. 2008. "Estimating the Implied Risk Neutral Density for the U.S. Market Portfolio", Volatility and Time Series Econometrics: Essays in Honor of Robert Engle. Oxford University Press.

[35] Gao, Lin, Hitzemann, Steffen, Shaliastovich, Ivan, and Lai Xu. 2017. "Oil Volatility Risk", Working Paper.

[36] Goldstein, Itay and Liyan Yang. 2018. "Commodity Financialization and Information Transmission", Working Paper.

[37] Gomes, Joao, Kogan, Leonid, and Lu Zhang. 2003. "Equilibrium Cross Section of Returns", *Journal of Political Economy*, 111, 4, 693-732.

[38] Hamilton, James. 1983. "Oil and the Macroeconomy Since World War II", *Journal of Political Economy,* 91, 228-48.

[39] ———. 2003. "What Is an Oil Shock?", *Journal of Econometrics*, 113, 2, 363-98.

[40] ———. 2009. "Causes and Consequences of the Oil Shock of 2007-2008", Brookings Papers on Economic Activity, 215-261.

[41] ———. 2013. "Historical Oil Shocks", Handbook of Major Events in Economic History, Routledge International Handbooks, Part III-21.

[42] Harvey, Campbell. 2017. "Presidential Address: The Scientific Outlook in Financial Economics", *Journal of Finance*, 77, 4, 1399-1440.

[43] Harvey, Campbell, Liu, Yan, and Heqing Zhu. 2016. " ...and the cross-section of expected returns", *Review of Financial Studies*, 29, 5-68.

[44] Harvey, Campbell and Akhtar Siddique. 2000. "Conditional skewness in asset pricing tests", *Journal of Finance*, 55,1263-1295.

[45] Hasseltoft, Henrik. 2012. "Stocks, Bonds, and Long-Run Consumption Risks", *Journal of Financial and Quantitative Analysis*, 47, 309-332.

[46] Henderson, Brian, Pearson, Neil, and Li Wang. 2015. "New Evidence on the Financialization of Commodity Markets", *Review of Financial Studies*, 28, 5, 1285-1311.

[47] Hong, Harrison, and Jeremy Stein. 2007. “Disagreement and the Stock Market”, *Journal of Economic Perspectives,* 21, 2, 109–128.

[48] Hong, Harrison, and Motohiro Yogo. 2012. “What Does Futures Market Interest Tell Us about the Macro-economy and Asset Prices?”, *Journal of Financial Economics*, 105, 3, 473-490.

[49] Jones, Charles , Gautam Kaul. 1996. “Oil and the stock markets”, *Journal of Finance*, 51, 2, 463–491 .

[50] Judd, Kenneth. 1998. “Numerical Methods in Economics”, MIT Press, Cambridge.

[51] Kelly, Bryan, and Hao Jiang. 2014. “Tail Risk and Asset Prices”, *Review of Financial Studies,* 27, 10, 2841-2871.

[52] Kilian, Lutz. 2008. “Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy?”, *Review of Economics and Statistics*, 90, 216-240.

[53] Kopecky, Karen, and Richard Suen. 2010. “Finite State Markov-chain Approximations to Highly Persistent Processes”, *Review of Economic Dynamics,* 13, 701-714.

[54] Lettau, Martin, Maggiori, Matteo, and Michael Weber. 2014. "Conditional risk premia in currency markets and other asset classes", *Journal of Financial Economics*, 114, 197-225.

[55] Linn Matthew, Shive, Sophie and Tyler Shumway. 2018. "Pricing kernel monotonicity and conditional information", *Review of Financial Studies*, 31, 2, 493-531.

[56] Loughran, Tim, McDonald, Bill, and Ioannis Pragidis. 2018. "Assimilation of Oil News into Prices", Working Paper.

[57] Ready, Robert. 2017. “Oil prices and the stock market”, *Review of Finance* (forthcoming).

[58] Richter, Alexander, Throckmorton, Nathaniel, and Todd Walker. 2013. “Accuracy, Speed and Robustness of Policy Function Iteration”, *Computational Economics*, 1-32.

[59] Sicherman, Nachum, Loewenstein, George, Seppi, Duane, and Stephen Utkus. 2016. “Financial Attention”, *Review of Financial Studies*, 29, 4, 863-897.

[60] Singleton, Kenneth. 2014. “Investor Flows and the 2008 Boom/Bust in Oil Prices”, *Management Science,* 60, 2, 300–318.

[61] Sockin, Michael, and Wei Xiong. 2015. "Informational Frictions and Commodity Markets", *Journal of Finance*, 70, 5, 2063-2098.

[62] Szymanowska, Marta, de Roon, Frans, Nijman, Theo, and Rob van den Goorbergh. 2014. “An Anatomy of Commodity Futures Risk Premia”, *Journal of Finance*, 69, 1, 453–482.

[63] Tang, Ke, and Wei Xiong. 2012. "Index Investment and the Financialization of Commodities", *Financial Analysts Journal,* 68, 54-74.

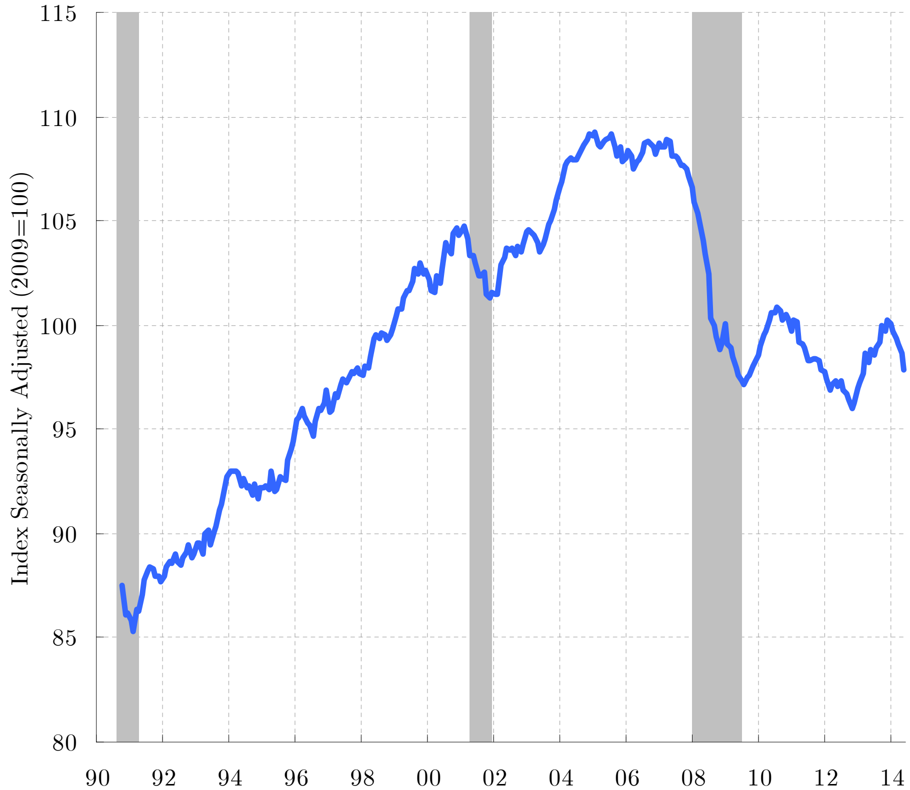
[64] Tauchen, George, and Robert Hussey. 1991. "Quadrature-based Methods for Obtaining Approximate Solutions to Nonlinear Asset Pricing Models", *Econometrica*, 59, 317–396.

[65] Trolle, Anders, and Eduardo Schwartz. 2009. "Unspanned Stochastic Volatility and the Pricing of Commodity Derivatives", *Review of Financial Studies*, 22, 4423-4461.

[66] Vissing-Jørgensen, Annette, and Orazio Attanasio. 2003 "Stock-Market Participation, Intertemporal Substitution, and Risk-Aversion", *American Economic Review*, 93, 2, 383-391.

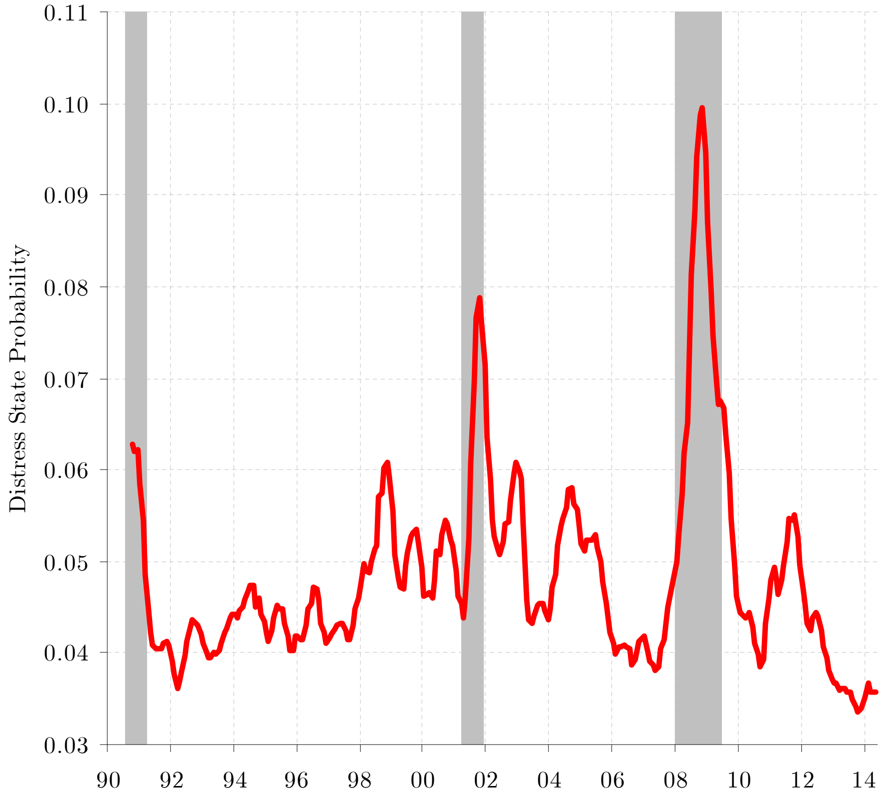
[67] Yang, Fan. 2013. "Investment Shocks and the Commodity Basis Spread", *Journal of Financial Economics*, 110, 164-184.

Figure 1: Energy Usage



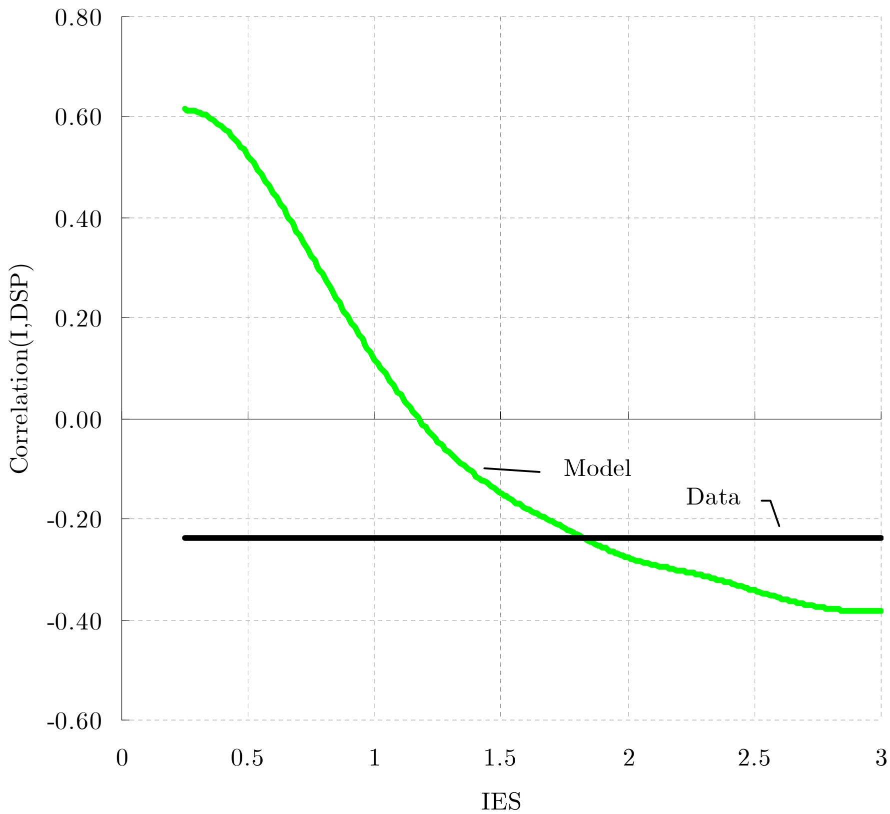
Notes to Figure: We plot the total usage of oil, in thousand barrels per day, from the Energy Information Administration (EIA). The time series is seasonally adjusted and indexed to 2009 (2009=100). The vertical axis displays the index values. U.S. recessions in gray bars from the National Bureau of Economic Research (NBER). The sample period is from October 1990 to May 2014.

Figure 2: Distress State Probabilities



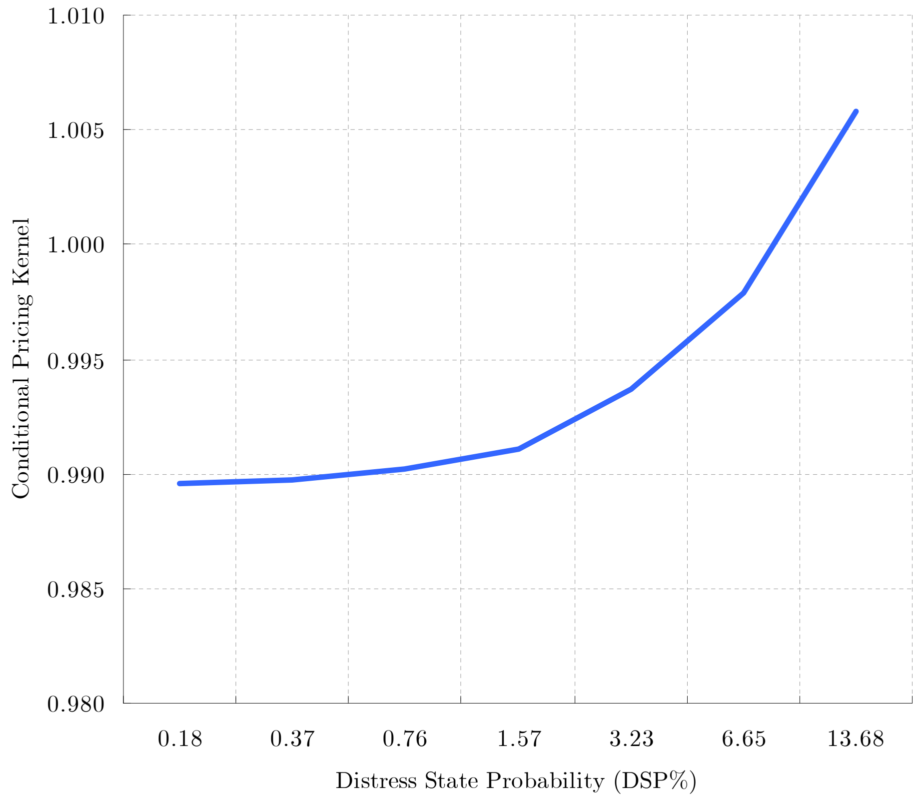
Notes to Figure: We plot the time series for the conditional probability of entering a distress state in the next period. U.S. recessions in gray bars from the National Bureau of Economic Research (NBER). The sample period is from October 1990 to May 2014.

Figure 3: Distress State Probability and Investment Correlation



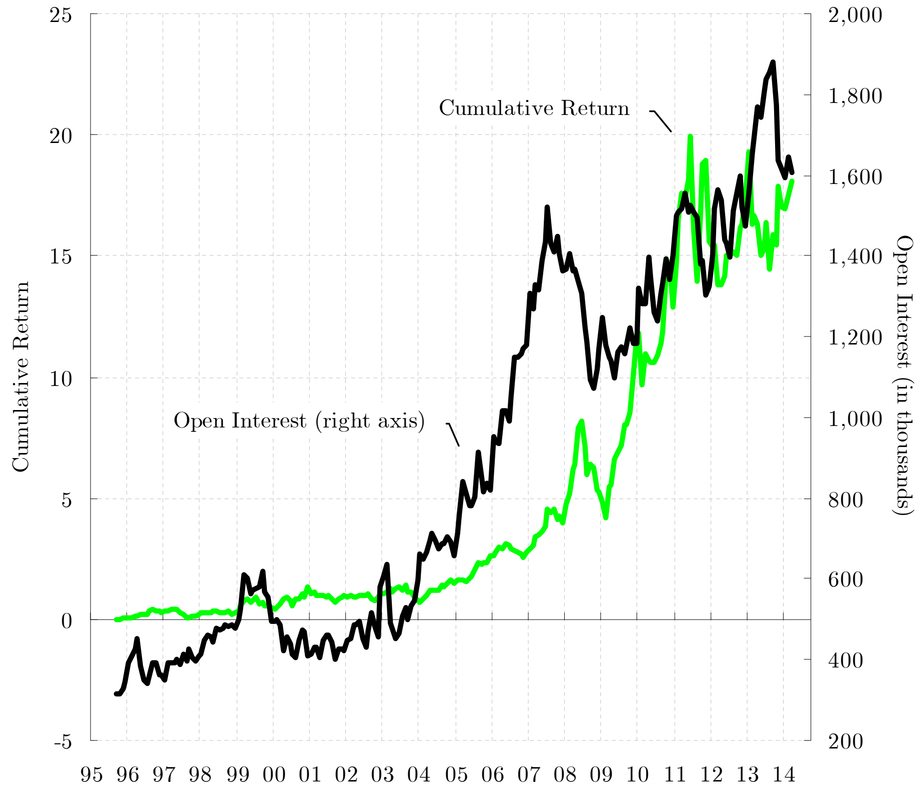
Notes to Figure: We plot the correlation between the distress state probability (DSP) and investments (I) as a function of the intertemporal elasticity of substitution (IES), given a relative risk aversion parameter of 8 (benchmark specification). The vertical axis measures correlation. The horizontal axis displays the intertemporal elasticity of substitution parameter.

Figure 4: Conditional Pricing Kernel



Notes to Figure: We plot the conditional pricing kernel for different likelihoods of entering a recessive state in the next period. The vertical axis measures the conditional pricing kernel. The horizontal axis displays the distress state probability (DSP). Distress state probability $\times 100$.

Figure 5: ER Beta Strategy and Open Interest



Notes to Figure: We plot the cumulative returns of the long-short ER beta strategy and the crude oil open interest of futures contracts (right axis) from September 1995 to April 2014.

Table 1: Model Parameter Calibration

Parameter	Value
δ	0.99
γ	8
ψ	2
ϕ	0.01
η	0.6
b	0.084

Notes to Table: We report the parameters for the benchmark calibration of the model. The second row reports the time discount factor parameter (δ). The third row reports the relative risk aversion parameter (γ). The fourth row reports the intertemporal elasticity of substitution parameter (IES). The fifth row reports the level parameter (ϕ). The sixth row reports the share of oil usage in total production (η). The seventh row reports oil usage reduction factor (b).

Table 2: Portfolio Returns

Decile	β^{ER}	Return	α_{MKT}	α_2	α_3	α_4
High	1.01	0.0133	0.0125	0.0121	0.0109	0.0130
		(2.55)	(2.21)	(2.17)	(2.00)	(2.49)
9	0.42	0.0176	0.0170	0.0170	0.0160	0.0174
		(3.69)	(2.81)	(2.82)	(2.79)	(3.02)
8	0.24	0.0139	0.0133	0.0133	0.0125	0.0136
		(3.09)	(2.19)	(2.19)	(2.11)	(2.27)
7	0.13	0.0165	0.0157	0.0157	0.0146	0.0166
		(3.65)	(2.77)	(2.78)	(2.77)	(3.09)
6	0.03	0.0147	0.0141	0.0141	0.0132	0.0151
		(3.37)	(2.50)	(2.53)	(2.47)	(2.74)
5	-0.07	0.0179	0.0172	0.0173	0.0165	0.0184
		(4.02)	(3.13)	(3.13)	(3.02)	(3.35)
4	-0.18	0.0173	0.0168	0.0167	0.0153	0.0172
		(3.53)	(2.88)	(2.86)	(2.68)	(2.90)
3	-0.31	0.0196	0.0183	0.0182	0.0170	0.0193
		(3.60)	(2.65)	(2.66)	(2.59)	(2.90)
2	-0.53	0.0226	0.0216	0.0215	0.0206	0.0225
		(3.97)	(2.87)	(2.87)	(2.80)	(2.97)
Low	-1.18	0.0286	0.0266	0.0266	0.0247	0.0268
		(4.77)	(3.70)	(3.67)	(3.53)	(3.78)
High-Low		-0.0153	-0.0141	-0.0145	-0.0138	-0.0138
		(-3.50)	(-2.86)	(-2.96)	(-2.78)	(-2.72)

Notes to Table: We report the monthly excess returns by portfolio deciles. We report the risk adjusted returns (alphas) from the regression onto the incremental risk factors. We report in parentheses the Newey-West corrected $t-$statistics.

Table 3: Persistence of Energy Risk Beta

	Months Ahead					
	6	12	24	36	48	60
Intercept	-0.0204	-0.0106	-0.0228	-0.0717	-0.1161	-0.1221
	(-1.31)	(-0.54)	(-0.77)	(-2.05)	(-2.67)	(-2.56)
β^{ER}	0.8529	0.7223	0.4817	0.2501	0.1151	0.0465
	(39.03)	(22.68)	(10.94)	(5.79)	(3.10)	(1.69)
β^{MKT}	2.696	2.918	3.937	8.679	12.674	12.762
	(1.65)	(1.31)	(1.42)	(2.94)	(3.05)	(2.25)
β^{SMB}	-0.9414	-2.4700	-3.3874	-2.3614	1.7958	4.1322
	(-0.90)	(-1.67)	(-1.54)	(-1.14)	(0.76)	(1.57)
β^{HML}	-0.5315	-3.1330	-5.6746	-5.2804	-1.3567	1.7546
	(-0.57)	(-2.03)	(-2.12)	(-2.06)	(-0.63)	(0.55)
β^{MOM}	0.4958	0.6658	-1.2707	-5.3394	-8.8983	-5.1913
	(0.30)	(0.35)	(-0.40)	(-1.79)	(-2.45)	(-1.37)
β^{VRP}	0.0027	0.0291	0.0764	0.1340	0.1352	0.1288
	(0.07)	(0.86)	(1.65)	(1.62)	(1.89)	(2.47)
β^{SRP}	0.5044	1.3046	1.8460	0.9361	-0.2077	-0.5017
	(0.88)	(1.95)	(2.56)	(1.24)	(-0.22)	(-0.61)
β^{BAS}	-0.0002	-0.0002	0.0003	0.0007	0.0003	0.0000
	(-0.65)	(-0.40)	(0.65)	(1.41)	(0.59)	(0.03)
β^{OPI}	0.0167	0.0232	-0.0238	-0.0810	-0.1062	-0.1227
	(0.97)	(0.89)	(-0.80)	(-2.47)	(-3.20)	(-2.55)

Notes to Table: We report the persistence of ER beta onto lagged cross sectional predictors for 6 to 60 months. We report in parentheses the Newey-West corrected t-statistics.

Table 4: Cross Sectional Firm Level Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.018	0.014	0.014	0.014	0.014	0.014	0.014	0.013	0.011
	(3.31)	(2.90)	(3.22)	(2.93)	(3.13)	(3.23)	(3.37)	(3.10)	(2.71)
β^{ER}	-0.510	-0.512	-0.478	-0.486	-0.671	-0.565	-0.614	-0.578	-0.624
	(-2.01)	(-2.02)	(-2.01)	(-2.16)	(-2.81)	(-2.46)	(-2.42)	(-2.44)	(-2.56)
β^{MKT}		0.484	0.151	0.225	0.015	-0.163	-0.096	-0.015	-0.008
		(1.87)	(0.51)	(0.64)	(0.04)	(-0.45)	(-0.27)	(-0.04)	(-0.02)
β^{SMB}			0.418	0.414	0.339	0.330	0.307	0.181	0.119
			(2.26)	(2.09)	(1.71)	(1.57)	(1.48)	(0.81)	(0.53)
β^{HML}				0.069	-0.246	-0.196	-0.159	0.007	0.030
				(0.33)	(-0.95)	(-0.78)	(-0.64)	(0.03)	(0.12)
β^{MOM}					-0.803	-0.514	-0.426	-0.327	-0.344
					(-2.15)	(-1.45)	(-1.16)	(-0.84)	(-0.83)
β^{VRP}						0.013	0.015	0.012	0.009
						(2.69)	(2.64)	(2.09)	(1.35)
β^{SRP}							0.040	0.019	-0.014
							(0.62)	(0.25)	(-0.17)
β^{BAS}								0.000	0.000
								(-0.81)	(-0.97)
β^{OPI}									0.009
									(2.37)
$R^2_{Adj.}$	1.94%	4.22%	5.34%	6.37%	7.24%	8.10%	9.13%	10.12%	11.00%

Notes to Table: We report the incremental Fama-MacBeth cross sectional regressions for individual stocks. The bottom row reports the adjusted $R-$squared. We report in parentheses the Newey-West corrected $t-$statistics.

Table 5: Double Sorts

	Panel A. β^{MKT}		Panel B. β^{SMB}		Panel C. β^{HML}		Panel D. β^{MOM}	
	High	Low	High	Low	High	Low	High	Low
High	0.0150	0.0196	0.0168	0.0149	0.0198	0.0144	0.0130	0.0190
	(2.60)	(4.00)	(2.93)	(3.22)	(3.68)	(2.68)	(2.50)	(3.48)
Low	0.0277	0.0210	0.0246	0.0242	0.0257	0.0218	0.0235	0.0265
	(3.90)	(3.61)	(3.50)	(4.26)	(3.84)	(3.53)	(3.85)	(3.85)
$ER_{Diff.}$	-0.0127	-0.0014	-0.0078	-0.0092	-0.0056	-0.0082	-0.0105	-0.0075
	(-3.10)	(-0.33)	(-2.10)	(-2.30)	(-1.27)	(-2.12)	(-2.89)	(-1.75)
α_4	-0.0121	-0.0009	-0.0076	-0.0084	-0.0082	-0.0092	-0.0118	-0.0062
	(-2.79)	(-0.20)	(-1.95)	(-2.11)	(-1.96)	(-2.15)	(-3.16)	(-1.28)

	Panel E. β^{VRP}		Panel F. β^{SRP}		Panel G. β^{BAS}		Panel H. β^{OPI}	
	High	Low	High	Low	High	Low	High	Low
High	0.0165	0.0169	0.0193	0.0156	0.0190	0.0172	0.0179	0.0158
	(3.03)	(3.23)	(3.44)	(2.95)	(3.81)	(2.45)	(3.34)	(2.90)
Low	0.0248	0.0221	0.0263	0.0211	0.0225	0.0235	0.0281	0.0199
	(3.61)	(3.64)	(3.91)	(3.29)	(3.77)	(3.42)	(4.04)	(3.22)
$ER_{Diff.}$	-0.0086	-0.0049	-0.0091	-0.0064	-0.0035	-0.0059	-0.0102	-0.0041
	(-2.14)	(-1.23)	(-2.14)	(-1.46)	(-0.82)	(-1.36)	(-2.42)	(-1.04)
α_4	-0.0108	-0.0061	-0.0109	-0.0083	-0.0023	-0.0042	-0.0096	-0.0040
	(-3.05)	(-1.61)	(-2.54)	(-2.37)	(-0.38)	(-1.11)	(-2.14)	(-0.97)

Notes to Table: We report the independent double sorts of ER beta and alternative variables. Panels A to D report the double sorts for ER beta along with stock sensitivities to MKT, SMB, HML, and MOM factors. Panels E to H report the double sorts for ER beta along with stock sensitivities to VRP, SRP, BAS, and OPI characteristics. We report the intercept α_4 from the difference group onto the Fama and French (1992) and Carhart (1997) factors. Newey-West corrected t-statistics in parentheses.

Table 6: Energy Risks and Equity, Commodity, and Global Risk Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.0141	-0.0158	-0.0148	-0.0157	-0.0125	-0.0139	-0.0152	-0.0153	-0.0153	-0.0153	-0.0154	-0.0103
	(-2.84)	(-3.13)	(-2.93)	(-3.14)	(-2.21)	(-2.30)	(-2.91)	(-2.98)	(-3.10)	(-3.05)	(-3.07)	(-1.68)
b_{MKT}	-0.0021											-0.0026
	(-1.88)											(-1.24)
b_{SMB}		0.0020										0.0030
		(1.57)										(2.12)
b_{HML}			-0.0018									-0.0022
			(-1.12)									(-1.32)
b_{MOM}				0.0009								0.0001
				(0.79)								(0.05)
b_{VRP}					0.0510							0.0723
					(1.65)							(2.11)
b_{SRP}						-0.0026						0.0010
						(-0.77)						(0.24)
b_{BAS}							1.9806					7.2142
							(0.21)					(0.84)
b_{OPI}								-0.0032				0.0221
								(-0.04)				(0.28)
b_{VIX}									0.1330			-0.0603
									(1.62)			(-0.34)
b_{TED}										-0.0798		-0.7681
										(-0.04)		(-0.41)
b_{EPU}											0.0003	0.0003
											(1.95)	(1.88)
$R^2_{Adj.}$	1.25%	0.32%	0.21%	0.01%	-0.11%	-0.35%	-0.44%	-0.45%	0.21%	-0.45%	1.64%	1.73%

Notes to Table: We report the time series regressions of the long short energy risk strategy onto alternative covariates. Columns 1 to 11 report the univariate regressions. Column 12 reports the multivariate regression. The bottom row reports the adjusted R^2. We report in parentheses the Newey-West corrected t-statistics

Table 7: Energy Risks and Media Coverage

Panel A. Crude Oil Media Coverage		
	Crude Oil Spikes	Crude Oil Uncertainty
Avg.	148	240
Std. Dev.	162	248
Min.	8	8
Max.	1,345	2,062
Total	33,215	53,794

Panel B. ER Beta Strategy		
	Coverage Above Trend	
	Crude Oil Spikes	Crude Oil Uncertainty
Return	-0.0157	-0.0208
t-Stat.	-2.04	-2.85
Sharpe	-0.22	-0.29
	Coverage Below Trend	
	Crude Oil Spikes	Crude Oil Uncertainty
Return	-0.0150	-0.0112
t-Stat.	-2.33	-1.68
Sharpe	-0.20	-0.15

Notes to Table: Panel A reports the summary statistics for the number of news referring to crude oil spikes and crude oil uncertainty. Panel B reports the results of the ER beta long-short strategy in times of above average and below average media coverage on crude oil spikes and crude oil uncertainty. The sample period is from September 1995 to April 2014.

Table A.1: Top Oil Consumers and Net Exporters

Panel A. Top World Oil Consumers				Panel B. Top World Oil Net Exporters		
	(Thousand Barrels per Day)				(Thousand Barrels per Day)	
Country	2012	2013		Country	2012	2013
United States	18,490	18,961		Saudi Arabia	8,865	8,733
China	9,875	10,303		Russia	7,201	7,249
Japan	4,726	4,531		United Arab Emirates	2,544	2,743
India	3,450	3,509		Kuwait	2,347	2,345
Russia	3,195	3,515		Iraq	2,247	2,289
Brazil	2,997	2,998		Nigeria	2,224	2,070
Saudi Arabia	2,861	2,968		Qatar	1,829	1,847
Germany	2,388	2,403		Iran	1,728	1,322
Korea	2,301	2,324		Angola	1,713	1,756
Canada	2,281	2,431		Venezuela	1,712	1,905

Notes to Table: We report the top ten oil consumers and net exporters from the Energy Information Administration (EIA). Panel A reports the top ten world oil consumers for the years 2012 in the second column and 2013 in the third column (latest available year). Panel B reports the top ten world oil net exporters for the years 2012 in the second column and 2013 in the third column. The units are in thousand barrels per day for both panels.

Table A.2: Economic Moments

	σ_Y	σ_C	σ_I	$\rho_{Y,C}$	$\rho_{Y,I}$
Model	0.024	0.024	0.074	0.748	0.656
Data	0.023	0.022	0.081	0.748	0.863

Notes to Table: We report unconditional aggregate economic moments for the model and the data. The second row reports results from the model. The third row reports results from the data. The second column reports the standard deviation of income, the third column reports the standard deviation of consumption, the fourth column reports the standard deviation of investments, the fifth column reports the correlation between income and consumption, and the sixth column reports the correlation between income and investments. The sample period is from October 1990 to May 2014. All values are annualized.