Stroke of a Pen: Investment and Stock Returns under Energy Policy Uncertainty

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Abstract

Energy policy uncertainty - as measured by uncertainty about a U.S. President signing an energy related executive order in the future - covaries positively with corporate investment, positively with aggregate consumption growth, and its innovations carry a negative price of risk. I propose and test a q-theory explanation in which firms invest in energy-efficient capital when facing energy policy uncertainty. This uncertainty amplifies cross-sectional differences in investment, as the benefits of substituting energy for capital increase with growth opportunities. When investment becomes more profitable, aggregate current consumption decreases relative to future consumption, creating expected return variation in market returns and consumption growth. Without an investment factor, innovations to uncertainty explain cross-sectional variation in stock returns across portfolios that differ in their growth opportunities. However, since investment endogenously reacts to uncertainty, an asset pricing model that accounts for an investment factor absorbs the cross-sectional differences in expected returns explained by this policy uncertainty. I show that the impact of policy uncertainty on investment and asset prices depends on the endogenous reaction of firms' corporate policies to this uncertainty. Moreover, uncertainty about future energy policies in the last 40 years might have contributed to firms' adoption of energy-efficient capital.

Keywords: energy, policy uncertainty, executive orders, cross-section of expected returns, investment, Q theory

JEL Classification: G10, G11, G12, G18

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1 Introduction

Proxies of policy uncertainty, the uncertainty about future policy decisions, quintupled in April 2020 their level from 20 years ago, triggered by a global pandemic, U.S. political and demographic tensions, and a global trade war.[1] In recent decades, policy uncertainty has been documented to impact financial markets and the real economy, dampening investment and requiring higher risk compensation for investors (Bloom 2009; Kelly et al. 2016; Gulen and Ion 2015). While there is a growing literature that considers policy uncertainty as a shock to the Total Factor Productivity (TFP) of firms (Pástor and Veronesi 2012, 2013), less is known about the impact of policy uncertainty on the demand of non-capital factors of production such as energy.[2] How do firms' investment policies change in the presence of uncertainty about future energy regulations? Do investors require a compensation for holding equity from firms exposed to this uncertainty? Do changes in aggregate investment captured by uncertainty translate into return and consumption predictability? To the best of my knowledge, my paper is the first to study how uncertainty regarding energy policies impacts corporate investment, risk premia, and return predictability.[4]

My contribution is to show empirically that uncertainty regarding future energy policies (energy policy uncertainty), covaries positively with firm investment, and amplifies the spread return between value and growth companies. This uncertainty predicts lower future returns, and higher future aggregate consumption. Further, I show that these findings are consistent with a q-theory mechanism in which investment and expected returns are determined by a firm's growth opportunities and the level of uncertainty. As energy policy uncertainty increases, firms invest in energy-efficient capital to hedge against higher energy costs in bad times. Since substitution is more profitable for firms with more growth potential, growth opportunities appreciate relative to assets in place, increasing investment and valuation spreads between (growth) companies rich in

[1] The Economic Policy Uncertainty index of Baker et al. (2016), a standard measure of policy uncertainty shows that in April 2020 its level more than quadrupled from 80 to 423 over two decades. `https://www.policyuncertainty.com/`

[2] See, for example, Riem (2016); Snowberg et al. (2007); Colak et al. (2017); Mattozzi (2008); Brogaard and Detzel (2015). The impact of factor-uncertainty on investment and stock returns is ex-ante ambiguous, as it depends theoretically on the level of risk sharing and risk aversion in the economy (Stewart 1978; Dou 2017). How and to what extent policy uncertainty about future energy policies impact investment and financial markets is ultimately an empirical question.[3]

[4] The idea that factor uncertainty can trigger capital investment goes back to Stewart (1978). Risk averse managers exploit the substitution between capital and non-capital factors, to dial up investment when the price of a non-capital factor is uncertain. My paper is the first to empirically study policy uncertainty regarding future energy policies, and its impact on investment and stock returns.

investment opportunities, and mature (value) companies that yield valuations out of their assets in place (Papanikolaou 2011; Kogan and Papanikolaou 2013, 2014). As investment increases, a predictable pattern in consumption arises, which translates into market return predictability.

I study the questions above by analyzing energy-related U.S. executive orders. This instrument provides a unique opportunity to study policy uncertainty. On one hand energy is crucial for the functioning of any modern economy. In recent decades we have experienced an increase in the supply of brown energy sources, due to technological changes and OPEC countries failing to control an increasing supply of oil (Gilje et al. 2016; Dou et al. 2020), while simultaneously experiencing worldwide environmental concerns that have increased the demand for cleaner energy sources and environmentally friendly companies (Pástor et al. 2019).

Given the importance that energy has in our daily life, it is not uncommon for governments to intervene in moments when energy related events jeopardize the economy.[5] Moreover, energy has become such an important bullet in the political agenda, that energy and environmental policies are as cyclical as the economic policies between political parties.[6] On the other hand, U.S. executive orders are difficult to anticipate, making them a suitable tool to study the impact of policy uncertainty on firms' behavior and financial markets. This contrasts with public laws for example, which can be highly anticipated given the long process required for their approval and media coverage. Moreover, executive orders capture the way that the incumbent U.S. President manages the country on a daily basis. Executive orders provide the U.S. President with a tool to make unilateral policy decisions with minimal interference from either Congress or the courts just with the "stroke of a pen" (Palmer 2002).[7]

[5] In 2017 U.S. President Donald J. Trump signed an Executive Order to increase Arctic drilling by 2022. Despite a judge in Alaska ruling that the Executive Order was unconstitutional, by August 2020 Trump's administration finalized the plan to open oil drilling in the Arctic `https://www.nytimes.com/2020/08/17/climate/alaska-oil-drilling-anwr.html`

[6] As an example, in 2010 U.S. President Barack Obama signed Executive Order 13543 creating the National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling suggesting new regulations to mitigate the impact of offshore drilling. On the other hand, U.S. President Donald Trump signed in 2019 Executive Order 13868 promoting the Energy Infrastructure and Economic Growth by facilitating Oil and Gas pipelines. Time varying energy and/or environmental policies can be the result of a political cycle induced by time-varying risk aversion (Pástor and Veronesi 2017) as well as an environmental concern in the spirit of Pástor et al. (2019) similar to the inequality aversion modelled in Pástor and Veronesi (2018).

[7] Palmer (2002) states that the phrase stroke of a pen is defined by Safire's Political Dictionary as "by executive order; action that can be taken by a Chief Executive without legislative action.". Its use has been traced to a nineteenth-century poem *Wanted - A Man* by the American poet Edmund Clarence. "Give us a man of God's own mold, Born to marshal his fellow-men; One whose fame is not bought and sold At the stroke of a politician's pen; Give us the man of thousands ten, Fit to do as well as to plan; Give us a rallying-cry, and then, Abraham Lincoln, give us a Man!"

To measure energy policy uncertainty I use data on U.S. Executive Orders from the Comparative Agendas Project, a political science database that provides information on a large sample of U.S. executive orders manually classified into different policy topics. I fit a rolling probability model on the existence of an energy related executive order next month, and define energy policy uncertainty as its conditional volatility. This measure of uncertainty allows me to capture the blurriness in forecasting future energy decisions, from the point of view of an economic agent. My measure of energy policy uncertainty sets out to define the representative agent's information set. I start by assuming a small and conservative information set which consists of oil, business cycle, and political information. Variables are suggested by a topic analysis of the text in energy related executive orders. For robustness, I show that the main results of the paper survive a data-rich uncertainty estimation in the spirit of Jurado et al. (2015), in which the information set contains an approximation of all available public information, and the forecastable variation in uncertainty is removed from the estimation.

To develop the hypotheses tested in the paper, I extend a production based asset pricing model to consider firms that require energy and capital to produce an output. To avoid higher energy costs in bad times, managers substitute energy for energy-efficient capital. This behaviour is more prominent within firms with higher marginal q, and therefore amplifies cross-sectional differences in investment. Since investment correlates negatively with expected returns in the cross-section, uncertainty amplifies valuations between growth and value companies. In the model, given that incentives to invest increase with uncertainty, under reasonable preference assumptions, households substitute current for future consumption. This forecastable variation in marginal utility leads to predictability in aggregate market returns.

The first verifiable hypothesis, states that cross-sectional differences in investment explained by firms' growth opportunities are amplified when uncertainty is high. To test this hypothesis, I run cross-sectional investment-Q regressions (Gala et al. 2019) in which I interact energy policy uncertainty with variables proxing for growth opportunities. Consistent with the hypothesis, across U.S. public firms, differences in investment between small and large companies, and companies with high and low average Q are amplified when uncertainty increases. The same specification including industry fixed effects shows that these cross-sectional differences are amplified both across all firms in the sample, as well as for firms operating in the same industry, since energy dynamics impact most of them.

The second testable hypothesis, relates energy policy uncertainty with expected returns and expected consumption growth. If firms invest more when uncertainty is high, all things equal, current consumption is substituted with current investment as households smooth consumption. If firms' growth opportunities decrease over time, expected consumption would increase in the future. This predictable pattern in marginal utility can be tested by forecasting aggregate returns and consumption (Papanikolaou 2011; Kogan and Papanikolaou 2014). I proceed to study if energy policy uncertainty predicts aggregate market returns. Predictability regressions of the U.S. monthly compounded value weighted CRSP return (VWCRSP) on energy policy uncertainty, and control variables documented to capture expected return variation yield negative and significant estimates for horizons of up to one year. This result is robust to time-varying risk aversion between political cycles (Pástor and Veronesi 2017), as well as oil prices (Jones and Kaul 1996).

Similarly, I also study if energy policy uncertainty predicts consumption growth. Given the endogeneity between aggregate market returns and consumption growth in a consumption based asset pricing model (Lucas 1978; Rubinstein 1976), I follow a similar methodology to Harvey (1988) and simultaneously predict the U.S. aggregate market return as well as U.S. consumption growth. GMM estimations suggest that for horizons up to six years, energy policy uncertainty positively predicts consumption growth, a finding that is consistent with the substitution hypothesis between consumption and investment. As in Zhang (2017), investment covaries negatively with expected returns. Since investment differences are amplified with energy policy uncertainty, expected returns should vary across firms with different uncertainty betas. However, controlling for investment, differences in uncertainty exposure should not help explain differences in expected returns since other things equal, investment negatively correlates with returns in the cross-section.

To test this hypothesis, I run cross-sectional linear asset pricing regressions in which one of the factors consists of the innovations to energy policy uncertainty. Following Maio and Santa-Clara (2012) in an ICAPM (Merton 1973) framework, I extend common asset pricing models with innovations to energy policy uncertainty in an expected return - covariance formulation. Since the cross-sectional differences in investment are captured across firms' growth opportunities, I use the 25 Size and Book-to-Market testing portfolios in Fama and French (1992, 1993). I extend asset pricing models that do not consider an investment factor which yield negative and significant prices of risk. However, in the presence of an investment factor the magnitude of the price of risk decreases and even becomes insignificant. The five factor model of Fama and French (2015) extended with the innovations to energy policy uncertainty reduces the magnitude of the price of risk, while using the q^4 and q^5 model of Hou et al. (2014) and Hou et al. (2020) completely absorbs the uncertainty price of risk.

I perform an extensive robustness analysis in the paper to ensure that the methodology used to estimate energy policy uncertainty does not drive the main results. Robustness analysis is done with two ideas in mind. First, I ensure that the measure is in fact capturing states of nature valuable for energy-sensitive companies. I check that changes in energy policy uncertainty explain changes in market valuations for companies that are ex-ante more likely to be exposed to the uncertainty. In particular, energy-sensitive companies whose returns covary with oil and gas prices. In fact, since 1970, oil, and gas have been the main commodities discussed in the body of U.S. executive orders as presented in Figure (2).[8] I find that energy-sensitive companies, companies with higher oil and gas betas (Jones and Kaul 1996), tend to be companies with higher energy policy uncertainty betas.

Secondly, I use a quasi-natural experiment to study how energy policy uncertainty betas change between energy and non-energy sensitive companies: the OPEC announcement in November 2014 to not cut oil supply despite the increasing supply of oil from non-OPEC countries as studied in Dou et al. (2020). The difference in difference estimator of the uncertainty beta between oil and non-oil related companies, as defined in Chiang et al. (2015), shows that after the announcement, the energy policy uncertainty beta of oil related companies increased by 200%. Finally, using lobbying data available since the 1990s, I show that firms in energy related sectors with higher lobby expenditures have lower energy policy uncertainty betas. This provides indirect evidence about the risk management benefits of lobbying by energy-policy sensitive companies.

My paper provides an investment-based explanation for a series of recent studied empirical patterns regarding climate risk and financial markets. Bolton and Kacperczyk (2020) find that stocks from companies with higher CO2 emissions earn higher expected returns that are not explained by their exposure to common factors, suggesting that investors are already considering compensation

[8]Examples include the executive attempts to minimize the impact of the deregulation of oil prices and the geopolitical conflicts in the 1970s and beginning of 1980s, to the deregulation of energy consumption and loosen environmental control in the beginning of the 1990s, and the environmental concerns to green the energy consumption since the end of the 1990s.

for Carbon Emission risk. In my framework, companies exposed to CO2 risk are companies with a lower degree of substitution between energy and capital. As these companies invest less to hedge against future volatility on energy costs, all things equal, they generate higher expected returns. Pástor et al. (2019) develop a demand-side model in which environmentally friendly stocks underperform brown stocks. Equivalently, since in my framework these companies invest more relative to brown companies in order to hedge energy risks in the future, they earn lower expected returns.

The remaining of the paper is organized as follows: Section (2) reviews the literature. Section (3) presents an stylised model of corporate investment used to develop the main testable hypotheses. Section (4) describes all the data sources and variable construction used in the paper and through the robustness tests. Section (5) builds the main measure of energy policy uncertainty used in the main paper. Section (6) studies how energy policy uncertainty amplifies cross-sectional differences in investment. Section (7) studies the predictability power of energy policy uncertainty into aggregate market returns and consumption growth. Section (8) studies the market reaction to energy policy uncertainty. Section (9) presents all robustness tests. Section (10) concludes. The appendix presents tables and calculations omitted from the main paper.

2 Literature Review

My paper contributes to different branches of the literature. First, I contribute to the literature studying the relation between political uncertainty and asset prices (Pástor and Veronesi 2012, 2013; Kelly et al. 2016; Füss and Bechtel 2008; Mattozzi 2008; Bialkowski et al. 2008; Brogaard and Detzel 2015; Döpke and Pierdzioch 2006).[9] My paper is closest to Brogaard and Detzel (2015). The authors compute innovations to the News Based Economic Policy Uncertainty index of Baker et al. (2016) and show that these innovations earn a negative price of risk. Different to theirs, I study the mechanism driving these results by studying the behaviour of firms' corporate policies, as well as the predictability power. Moreover, the negative price of risk found in the cross-section of expected stock returns is not consistent with the negative impact that policy uncertainty has on corporate investment (e.g. Gulen and Ion 2015).

I also contribute to the literature by proposing a new proxy for policy uncertainty. There is a

[9]Other studies have focused on the reaction of firms to political (policy) uncertainty in the form of lobbying (Grotteria 2019)

growing literature studying the relation among policy uncertainty, financial markets, and investment. However, policy uncertainty is unobservable to the researcher. Because of this, it has been studied indirectly by either looking at periods that are known to have high policy uncertainty (Kelly et al. 2016), or by using more general measures of uncertainty that indirectly capture policy uncertainty (Baker et al. 2016). To the best of my knowledge extant measures of policy uncertainty do not directly exploit political data which is nowadays widely available. Studies exploiting events such as elections to study how political uncertainty affect financial markets and corporate decisions include Kelly et al. (2016), Bialkowski et al. (2008), Colak et al. (2017), Füss and Bechtel (2008), Goodell and Vahamaa (2013), and Li and Born (2006). These studies have documented the pervasive effect that this uncertainty has on investment as well on making financial markets more volatile. However, the low frequency of these events only captures a small source of policy uncertainty, focusing exclusively on the uncertainty regarding structural changes that come after a change in the political party in power.[10]

Other studies rely on proxies available at higher frequencies allowing the study of financial markets and firms' behaviour as policy uncertainty evolves. The News-Based Economic Policy Uncertainty Index (EPU) of Baker et al. (2016) is an example, spanning several years and countries, being highly used in financial studies during recent years. The energy policy uncertainty index developed in this paper complements the EPU index of Baker et al. (2016) as it focus only on energy related matters, and its shown that impacts firms in a different way. In fact, from Figure (3) we see that both measures complement each other given a correlation between of 0.18. Given that the information set used to compute the uncertainty depends on oil and political variables, my measure of uncertainty covariates with EPU only in moments of time in which these two variables are relevant, the golf war, the financial crisis, and the recent increase in the supply of oil by non OPEC members.

I also contribute to the literature studying the relation between uncertainty and investment. Among the most important studies are (Pástor and Veronesi 2006, 2009; Bloom 2009; Bai et al. 2011; Bloom et al. 2018; Bachmann and Bayer 2014; Dou 2017).[11] Among these 7papers, Dou

[10] Other authors such as Mattozzi (2008) study the performance of portfolios expected to perform different depending on the result of the Bush vs Gore election in 2000 showing that a fraction of the political uncertainty during that period could have been hedged.

[11] Other studies include Bai et al. (2011); Christiano et al. (2010, 2014); Basu and Bundick (2012)

(2017) studies the impact of two types of idiosyncratic uncertainties that affects assets in place and growth opportunities separately. He develops a general equilibrium model in which under poor risk sharing conditions that avoid the idiosyncratic volatility of the quality of growth options to be diversified, higher uncertainty increases the valuation of growth companies and increases investment in equilibrium. The mechanism studied in this paper is similar, with the only difference being that energy policy uncertainty is not diversifiable given its price of risk, which is similar to having idiosyncratic volatility on the quality of growth options under poor risk sharing conditions.

Since my paper studies how corporate investment and market valuations react to energy policy uncertainty, I also contribute to the literature in energy economics that studies the relation between the energy sector and energy-efficient investment in firms. A non exhaustive list of papers in this literature include Reuter et al. (2012); Hassett and Metcalf (1993); Barradale (2010); Chassot et al. (2014); Margolis and Kammen (1999). This literature studies regulation that encourages firms to invest in energy-efficient capital either by imposing carbon taxes, feed-in-tarifs, or tax incentives for energy related R&D. My main finding suggests that uncertainty regarding future energy policies has a similar impact on investment for firms, regardless the industry where they operate. Contrary to most studies in this literature who focus on firms in the utilities sector.

I also contribute to the literature that relates policy uncertainty with the macro-economy. Some of the most relevant studies include Karnizova and Li (2014); Demir et al. (2018); Li and Zhong (2020); Klößner and Sekkel (2014); Gulen and Ion (2015); Liu and Zhang (2015). Finally I contribute to the literature studying energy and environmental concerns such as climate risk into financial markets and firm's decisions. Papers in this branch include Gilje et al. (2016); Jin and Jorion (2006); Chiang et al. (2015); Pástor et al. (2019); Dou et al. (2020); Hong et al. (2019); Bolton and Kacperczyk (2020). Bolton and Kacperczyk (2020) show that companies with higher CO2 emissions earn higher expected returns, which they interpret as investors requiring a compensation for holding Climate Risk. Pástor et al. (2019) develop a general equilibrium model in which green companies, companies with a higher ESG score, earn lower returns in equilibrium. My framework provides an alternative supply-side interpretation of these results. Companies with higher CO2 emissions, or lower ESG scores, are companies that do not invest in energy-efficient capital. As this companies invest less in equilibrium, they earn higher expected returns.

3 A Stylised Model of Investment and Stock Returns under Factor Uncertainty

In this section I present a stylised dynamic corporate model to study how investment and expected returns vary in the presence of uncertainty about energy prices (factor uncertainty) that arises from the blurriness in anticipating government decisions. The model builds on the Investment CAPM presented in Zhang (2017) extended to consider two inputs to firms' production technology: capital and energy. The model preserves the classical characteristics of the neoclassical paradigm as it contains rational expectations, absence of market frictions, and firms maximize their equity value. The model is in partial equilibrium, firms take the pricing kernel as given, and the government acts exogenously by randomly setting energy prices. As a result, uncertainty regarding future energy prices, amplifies cross-sectional differences in investment and expected returns captured by the q theory of investment (Kaldor 1966; Tobin 1969; Hayashi 1982; Cochrane 1991; Liu et al. 2009; Zhang 2017).[12] The appendix provides all mathematical details.

Consider a two dates economy, t and $t+1$ with a continuum of heterogeneous firms indexed by $i \in [0,1]$. Firms produce an homogeneous good that requires capital K (e.g. Property, Plant and Equipment - PPE) and energy E (e.g. electricity) using a Cobb-Douglas technology $Y = K^{\alpha}E^{\beta}$ where $\alpha > 0, \beta > 0$, and $\alpha + \beta < 1$, after deciding optimally all other required inputs such as labor, intangible capital, or raw materials. This technology implies an inverse relation between capital and energy given output $E = (YK^{-\alpha})^{(1/\beta)}$, and equivalently a substitution between energy and capital $\partial E/\partial K < 0$.

This assumption is consistent with the evidence reported in the literature on energy economics. For instance, Tovar and Iglesias (2013), find that elasticity regressions between production costs and factors such as capital, energy, labor, and intermediate materials in the US yield negative estimates of cross-price elasticities between energy an capital, which suggests a systematic adoption of energy efficient technology in recent decades for U.S. firms.[13]

[12] This is contrary to models that explicitly model the government's optimization problem as in Pástor and Veronesi (2012, 2013)

[13] As agents dislike uncertainty regarding energy prices, induced innovation towards energy-efficient technology is more likely to occur (See Popp 2002). The discussion of whether capital and energy are substitutes or complements in firms' production functions is extensive with the literature on energy economics presenting mixed evidence. A common approach is to assume complementarity in the short run and substitution in the long run. See Haller and Hyland (2014) for a detailed discussion.

The price of energy w_t, one of the inputs in firms' production functions, is randomly drawn from a stationary distribution with constant mean $\mathbb{E}[w_{t+1}] = \mu$ and variance $Var(w_{t+1}) = \sigma_e^2$. The volatility of energy price σ_e captures energy policy uncertainty in the model. Firm i starts period t with an amount of capital K_{it} and energy demand E_{it} to produce output Y_{it}. I assume that the firm's PPE configuration is not instantaneously adjustable, and since there are no shocks to the TFP of firms, capital and output are determined in advance. Firms face convex investment adjustment costs $a(I/K)K^2$ (e.g. Zhang 2005; Kogan and Papanikolaou 2012). where $a > 0$. All firms operate in both dates with a liquidation value of zero, and a depreciation rate of 100 %.

Firms take as given the Stochastic Discount Factor (SDF) in the economy $M_{t,t+1}$. I assume that the stochastic price of energy w_{t+1} covariates positively with the SDF with a constant correlation such that $cov(M_{t,t+1}, w_{t+1}) = \rho\sigma_m\sigma_e > 0$, where $\sigma_m = \sqrt{Var(M_{t,t+1})}$This assumption although restrictive, is consistent with empirical evidence: Edelstein and Kilian (2009) show that energy-price shocks have a negative impact on real consumption of unanticipated changes in discretionary income, shifts in precautionary savings, and changes in the operating cost of energy durables.[14]

Given current output Y_{it}, capital K_{it}, energy demand E_{it}, energy price per unit w_t, and the stochastic discount factor $M_{t,t+1}$, firm i chooses investment and future output to maximize shareholder's value which equals current market price plus dividends

$$P_{it}+D_{it} = \max_{I_{it},Y_{i,t+1}} \Big\{Y_{it}-w_t(Y_{it}K_{it}^{-\alpha})^{(1/\beta)}-I_{it}-\frac{a}{2}\Big(\frac{I_{it}}{K_{it}}\Big)^2 K_{it}+\mathbb{E}\Big[M_{t+1}\Big(Y_{t+1}-w_{t+1}(Y_{t+1}K_{t+1}^{-\alpha})^{(1/\beta)}\Big)\Big]\Big\} \tag{1}$$

The first order condition with respect to future output $Y_{i,t+1}$ is

$$I_{i,t} = Y_{i,t+1}^{\frac{1-\beta}{\alpha}}\Big(\frac{r_{ft}}{\beta}\mathbb{E}\Big[M_{t+1}w_{t+1}\Big]\Big)^{\frac{\beta}{\alpha}} \tag{2}$$

where $r_{ft} = \mathbb{E}[M_{t+1}]^{-1}$ is the gross risk free rate in the economy. Equivalently, the first order condition with respect to future capital $K_{i,t+1}$ is

$$1 + a\Big(\frac{I_{it}}{K_{it}}\Big) = \frac{\alpha}{\beta}I_{i,t}^{-\frac{\alpha+\beta}{\beta}} Y_{i,t+1}^{\frac{1}{\beta}}\mathbb{E}\Big[M_{t+1}w_{t+1}\Big] = q(Y_{i,t+1}, I_{it}) \tag{3}$$

[14] Unreported monthly regressions of the natural logarithm of oil prices (1980m1-2019m12) and gas prices (1997m1-2019m12), report a positive correlation with the monthly NBER recession dummies, and the probability of recession and the Sahm Rule estimated by the FRED at St Louis. This confirms the empirical evidence that energy prices increase in bad times.

Equation (2) shows that given optimal future output $Y_{i,t+1}$, investment increases with the present market value of the cost per energy $\mathbb{E}[M_{t,t+1}w_{t+1}]$, while Equation (3) states that in the optimum, firms invest up to the point in which the marginal investment cost equals marginal q.[15] Following Cochrane (1991) I can express the firm's first order conditions without the SDF, given the ex-dividend equity value $P_{it} = \mathbb{E}\Big[M_{t+1}\Big(Y_{t+1} - w_{t+1}(Y_{t+1}I_{i,t}^{-\alpha})^{\frac{1}{\beta}}\Big)\Big]$, and the gross return definition $R_{i,t+1} = \Big(P_{i,t+1} + D_{i,t+1})\Big)/P_{it}$ as follows

$$\mathbb{E}\Big[R_{i,t+1}\Big] = \frac{\alpha}{\beta}\frac{Y_{i,t+1}^{\frac{1-\beta}{\beta}} I_{i,t}^{-\frac{\alpha}{\beta}}\mu - 1}{\frac{I_{it}}{Y_{i,t+1}}\Big(1 + a\frac{I_{it}}{K_{it}}\Big) - \frac{\alpha}{\beta r_{ft}}} \tag{4}$$

Given equations (2), (3), and (4) I derive testable predictions to study how investment and stock returns relate with energy policy uncertainty. I start by deriving the standard results in any q theory model with a pricing kernel regarding investment and expected returns, and then show how these relations are amplified in the presence of factor uncertainty. The following proposition relates uncertainty with investment

Proposition 1. *Investment increases with uncertainty, and it increases more across firms with larger growth opportunities (firms with larger investment)*

$$\frac{\partial I_{it}}{\partial \sigma_e} > 0 \ and \ \frac{\partial^2 I_{it}}{\partial \sigma_e^2} > 0 \tag{5}$$

The predicted relation between investment and uncertainty can be observed in Figure (1). This relation is due to the fact that firms' marginal q is increasing with uncertainty, as the present value of energy costs $\mathbb{E}[M_{t,t+1}w_{t+1}]$ increases with σ_e since $\rho > 0$. Since the benefits of investment increase with energy price uncertainty, but marginal investment costs remain fixed, in equilibrium investment increases with uncertainty. The second testable prediction states that the relation between investment and uncertainty is convex. This means that in the cross-section, growth firms, firms which invest to exploit growth opportunities, invest even more relative to value companies when uncertainty is high. This mechanism amplifies the cross-sectional differences explained by the q-theory components of the model. The third hypothesis relates aggregate consumption and

[15] The assumption of a stochastic discount factor is required to study the asset pricing implications of uncertainty, but is not required to study investment. For instance Stewart (1978) shows that if risk averse managers receive utility for consuming a fraction of dividends, non-capital factor uncertainty increases investment when capital can substitute other factors in the production function.

energy policy uncertainty. Even though my model is in partial equilibrium, and firms take the SDF as exogenous, I can derive predictions with respect to aggregate consumption in a setup in which a representative household owns the firms, and derives consumption out of the output of all firms. As in Papanikolaou (2011), I assume that households have preferences for later resolution of uncertainty.[16]

Proposition 2. *If the level of uncertainty in the economy is sufficiently high $\sigma_e > \bar{\sigma}$, an increase in uncertainty predicts aggregate consumption growth*

$$\frac{\partial g_{t+1}}{\partial \sigma_e} > 0 \text{ where } g_{t+1} = \mathbb{E}[\frac{C_{t+1}}{C_t}] = \mathbb{E}[\frac{Y_{t+1}}{Y_t - I_t}] \tag{6}$$

where C represents aggregate consumption, and Y, and I are aggregate output and investment equivalently.

This proposition states that all things equal, an increase in uncertainty covaries with aggregate consumption growth. Moreover, this predictability on consumption growth gets translated into SDF predictability (Harvey 1988), and therefore firm returns are negatively predicted in the time-series.

Proposition 3. *Uncertainty negatively predicts returns in the time series*

$$\frac{d\mathbb{E}[R_{i,t+1}]}{d\sigma^e} = \frac{\partial \mathbb{E}[R_{i,t+1}]}{\partial I_{it}} \frac{dI_{it}}{d\sigma^e} < 0 \tag{7}$$

given the standard inverse relation between investment and expected returns in the q-theory of investment $\frac{\partial \mathbb{E}[R_{i,t+1}]}{\partial I_{it}} < 0$

Finally, I derive a prediction regarding the cross-section of expected returns by using the CCAPM beta representation which relates firm characteristics to firm's consumption beta

[16] Although not explicitly modeled, preference for early resolution of uncertainty is required in a general equilibrium set-up to relate an increase in investment with states of higher marginal utility. More specifically, in a continuous time economy with consumption and leisure in which households have Duffie and Epstein (1992) utility (or Epstein and Zin 1989 in discrete time). In this set-up households have preferences of the form $J_0 = \mathbb{E}_0 \int_0^\infty h(C_t, N_t, J_t)dt$ where $h(C, N, J) = \frac{\rho}{1-\theta^{-1}} \left\{ \frac{(C, N^\psi)^{1-\theta^{-1}}}{[(1-\psi)J]^{(\gamma-\theta^{-1})/(1-\gamma)}} - (1-\gamma)J \right\}$, ρ is a time preference parameter, γ is the coefficient of risk aversion, and θ is the elasticity of intertemporal substitution, and ψ balances the relative shares of consumption and leisure. Under this parametrization, early resolution of uncertainty $\psi\theta < 1$ implies that leisure is a good $\psi(1-\theta^{-1}) < 0$. (Papanikolaou 2011)

Proposition 4. *Uncertainty amplifies cross-sectional differences in expected returns captured by investment*

$$\mathbb{E}[R_{i,t}] - r_{ft} = \beta^S_{it}\lambda_t \tag{8}$$

where the firm's consumption beta is defined as

$$\beta^S_{it} = -\frac{\alpha}{\beta}\frac{(\frac{Y_{i,t+1}}{A})^{\frac{1-\beta}{\beta}} I_{i,t}^{-\frac{\alpha}{\beta}}}{\frac{AI_{it}}{Y_{i,t+1}}\Big(1 + a\frac{I_{it}}{K_{it}}\Big) - \frac{\alpha}{\beta r_{ft}}}\rho\frac{\sigma^e}{\sigma^M} \tag{9}$$

and λ is the price of consumption risk $\lambda_t = r_{ft}(\sigma^M)^2$

This proposition shows that differences in expected returns captured by the firm's consumption beta are amplified when energy policy uncertainty increases. Firms that invest more in equilibrium have a more negative beta, and earn lower expected returns. These differences in expected returns between companies with low and high investment, or equivalent growth and value companies, is amplified when energy policy uncertainty is higher.

4 Data

4.1 Firm Accounting and Financial Data

Accounting and Financial data comes from CRSP and the Compustat Quarterly Database. From the quarterly Compustat database I download all firm-quarter observations up to 2019q4 (1,789,987). I keep only observations with ISO currency code in US dollars (curcdq), drop observations with missing assets (atq) or stockholders' equity (seqq) for a total of (1,235,343 observations). Accounting variables are defined as follows: Market equity is defined as the number of common shares outstanding (cshoq) times the calendar close price in the quarter (prccq). Size is the natural logarithm of market equity, book-to-market is the ratio of Stockholder's equity (seqq) to market equity. Book debt is defined as the sum of debt in current liabilities (dlcq) and long-term debt (dlttq). Profitability is the quarterly operating income after depreciation (oiadpq) over the sum of book debt and market equity. Leverage is defined as the book value of debt over the book value of debt plus market equity.

From the monthly CRSP database I download all observations from December 1961 up to

December 2019 (4,230,439). I keep only companies trading in the NYSE AMEX or Nasdaq universe (exchcd 1, 2, and 3) with sharecodes (shrcd) equal to 10 or 11 for a total of 3,223,430 observations. I use the WRDS linking table between gvkey and permno identifiers to match the Compustat database with CRSP. I lag accounting variables by 2 months following Campbell et al. (2008) to correct for look-ahead bias. The merged database contains 2,355,017 firm-month observations. To compute market betas I download the Daily CRSP database between January 1965 and December 2019 (86,115,478 observations) and define market beta following Dimson (1979) computing intra-monthly regressions with respect to current, lagged, and led market returns as in Bali et al. (2019). Daily market excess return and daily risk free rate obtained from Prof. Kenneth French's website.[17]

4.2 Financial and Macroeconomic Data

To construct the macro-finance data needed as a robustness test to model the investors' information set I rely on the methodology presented in Jurado et al. (2015) which I update until 2019. Jurado et al. (2015) present a Big Data methodology for uncertainty estimation using 147 macroeconomic and financial variables. Macroeconomic variables come from the FRED-MD database (McCracken and Ng 2015), financial variables are constructed following Jurado et al. (2015), and Ludvigson and Ng (2007, 2009). For details on the construction of the financial variables see the Appendix for Updates of Uncertainty Data available from Prof. Sydney Ludvigson website.[18] I replicate the construction of all the 147 time series except from the VXO index which is available from the FRED-MD database, and the Cochrane-Piazzesi factor (Cochrane and Piazzesi 2005) which I exclude given that it does not cover the same sample as the rest of the variables. Portfolio data for the construction of the variables comes from Prof. Kenneth French's website, dividend data comes from the monthly index CRSP database, and aggregate earnings data comes from Prof. Robert Shiller website.

The analysis in this paper relies heavily on oil and gas price data, as well as macroeconomic data commonly used in the predictability literature (Fama and French 1989a, 1988; Stambaugh 1999; Campbell and Yogo 2006) such as the term and default spread, the aggregate dividend yield and the aggregate payout ratio. Oil prices correspond to the West Texas Intermediate standard

[17] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[18] `https://www.sydneyludvigson.com/data-and-appendixes`

price per barrel, gas prices correspond to the Henry Hub Natural Gas Spot price. Oil and gas information are obtained from the FRED at St. Louis.

The term spread is defined as the difference between the monthly average of the 10 year and 1 year risk free rate (DGS10-DGS1) and the default spread as the difference between the monthly average of the rate on BAA and AAA bonds obtained as well from the FRED at St. Louis. The dividend price ratio is the natural logarithm of the fraction of aggregate dividends inferred using the CRSP value weighted return with and without dividends (vwretd, vwretx) which is averaged across the last 12 months over an aggregate price index (See the Appendix of Jurado et al. 2015 for a detailed explanation). The aggregate dividend to earnings ratio is obtained from Prof. Robert Shiller's website.[19]

4.3 Political Data

The main political data used in this paper contains U.S. executive orders classified into 20 topics from the Comparative Agendas Project.[20] To ensure the consistency of the data I double check all executive orders in the database from public sources to ensure the database has no timing mistakes. First I check that the total number of executive orders available in the dataset from the Comparative Agendas project correspond to the total number of executive orders reported by official sources. To determine the true number of executive orders that were issued in a particular month I recollect data from the national archives and check for consistency.[21] Although prior to the first half of the 20th century presidents used executive orders in their mandates, these executive orders were not documented and archived until the 1940s. I am able to obtain 974 executive orders from 1937 to 2019, and count the number of executive orders issued each month which corresponds almost entirely with the dataset provided by the comparative agendas project.

The Comparative Agendas Project also contains data on public laws passed by the Senate and the House of Representatives which are used as control variables in the robustness test. The database contains a random subsample of all public laws starting in 1948. These public laws and executive orders are classified into 20 different policy topics based on the variable (pap_majortopic).

The dataset containing the subsample of public laws does not contain information about the

[19] http://www.econ.yale.edu/~shiller/
[20] https://www.comparativeagendas.net/
[21] https://www.archives.gov/federal-register/executive-orders/disposition

month within each year in which the public law was issued before 1973. In order to determine the month in which the public law was issued I use two methodologies. First, I use the id of the public law provided in the database and web-scrape the information about the month from one of three sources. The library of congress contains information on all public laws issued since the period of George Washington, up to 1951.[22] Public laws from 1952 to 1973 are available from the Legis Work website.[23] Finally public laws from 1974 to nowadays are available from the US congress website.[24]

To determine the exact month in which the public law was issued the id of each law contains the number of the congress. Congresses have a number assigned since the first congress in 1789. Congresses from 1948 to 1951 correspond to numbers 80 to 81, congresses from 1952 to 1973 correspond to congresses 82 to 92 and congresses from 1974 to 2019 correspond to congresses 93 to 115. The Legis Work website organizes public laws into Volumes and not congress numbers. Congresses have mostly 2 volumes of laws which are normally split into half during the legislative mandate. Congresses from 1952 to 1973 correspond to volumes 65 to 86.

Once all public laws are downloaded from these websites the second step consists of assigning the law to the month and year when it was signed. From the library of congress this can be done by searching for the name of the month, year and date within the description of each law. For public laws from 1952 to 1973 obtained from Legis Work this is done by searching for sentences with words containing month names and obtain the year by looking at all words inside each sentence. Finally the congress website provides a more friendly format to obtain the date of each law.

The information of some of the public laws is not digitalized in these three sources. For these laws, I download the original text in image format. Using Optical Character Recognition (OCR) algorithms, I isolate the text of each law and using textual analysis isolate the part of the Public Law containing the year and month. I check that the year inferred from the OCR algorithm corresponds to the year provided by the original dataset for robustness of the OCR algorithm. I also collect information regarding the political party in power from the data-planet website. I collect data on the party of the president of the United States, as well as the political party holding majority in the Senate and the House of Representatives.[25]

[22] `https://www.loc.gov/law/help/statutes-at-large`
[23] `http://legisworks.org/sal/`
[24] `https://www.congress.gov/public-laws/`
[25] `https://data-planet.libguides.com/politicalpartycontrol`

5 Measuring Energy Political Uncertainty

In this section I construct a measure of energy policy uncertainty by fitting a probability model to estimate how likely it is to have an energy related executive order signed by a U.S. President in the future. Define by N_t the number of energy related executive orders (pap_majortopic = 8) signed in month t. The random variable defined as

$$Y_t = \begin{cases} 1 & \text{if } N_t > 0 \\ 0 & \text{if } N_t = 0 \end{cases} \tag{10}$$

has a conditional Bernoulli distribution with probability $Pr(Y_t = 1) = p_t$. The estimation of probability p_t is performed as follows: Given an information set I_{t-1} available for an economic agent at time $t-1$, and assuming the process Y_t is stationary, she estimates a probability model based on the history of realizations of $\{Y_s\}_{s=0}^{t-1}$.

$$\hat{p}_t = Prob(Y_t = 1|I_{t-1}) = f(I_{t-1}, \theta) \tag{11}$$

before observing the true realization of the variable Y_t at time t. Where f is the functional form of a Probit model.[26] The uncertainty about the value of variable Y_t before its realization can be seen as its conditional standard deviation

$$\mathcal{U}_t = \sqrt{Var(Y_t|I_{t-1})} = \sqrt{\hat{p}_t(1-\hat{p}_t)}. \tag{12}$$

This measure provides time varying uncertainty on Y_t due to changes in the information set as well as new realizations of Y_{t-1} which updates the parameters in the underlying probability model $f(I_{t-1}, \theta)$. To model the information set required to fit the probability model I start with a base specification that includes the level and return of the West Texas Intermediate price per barrel, the aggregate dividend price ratio, and the Presidential Dummy of Santa-Clara and Valkanov (2003).

I show in robustness tests that the choice of the agents' information set does not qualitatively change the main results in the paper. However, there is evidence that the environmental and energy

[26] Here I assume variable Y_t occurs before or simultaneously as any other variable in the information set I_t which avoids the economic agent to update its probability based on current information set I_t. In the appendix I relax this assumption by considering a more general information set I_t as well as fitting the probability model over variable N_t.

agenda of politicians differ between Republican and Democratic mandates (Gustafson et al. 2020), governments are more likely to change existing policies in bad times (Pástor and Veronesi 2012, 2013), oil and financial markets are strongly interdependent (Jin and Jorion 2006), and textual analysis of the text in executive orders suggest oil behaviour triggers energy policy. As seen in Figure (2) during the 1970s and 1980s Oil is one of the topics most discussed within the text of executive orders given its importance and the consequences of the oil crisis.

Table (3) provides estimations of the probability model in which the left hand side variables is the probability of having at least one energy related executive order in the following 1, 3, 6, and 12 months. The return on oil, more than the level of the WTI predicts the occurrence of energy related executive orders for horizons of more than 3 months (Columns 2-4). The business cycle captured by the dividend price ratio predicts the occurrence for energy related executive orders for all specifications in an inverse u-shape depending on the horizon considered. Energy policies are more likely to occur after low market valuations, and finally they are more likely to occur under Democrat mandates.

The uncertainty used in the rest of the paper assumes a forecasting horizon of one month. In particular I fit a probit model as follows:

$$\hat{p_t} = \Phi(\hat{\beta}_0 + \hat{\beta}_1 \text{wti}_{t-1} + \hat{\beta}_2 R^{oil}_{t-1} + \hat{\beta}_3 (d-p)_{t-1} + \hat{\beta}_4 \text{Republican}_{t-1}) \tag{13}$$

where $\{\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4\}$ are computed recursively using Maximum Likelihood Estimation based on information $\{Y_s, \text{wti}_s, R^{oil}_s, (d-p)_s, \text{Republican }_s\}_{s=0}^{t-1}$, wti is the West Texas Intermediate oil price per barrel relative to the price in 1970, R^{oil}_t is the return on wti_t between month $t-1$ and t, $(d-p)$ is the CRSP Value Weighted log dividend price ratio, and Republican is a dummy variable that takes the value of one if the U.S. President in power at month t has a Republican affiliation, and $\Phi(.)$ is the standard normal cdf.

The first estimation corresponds to January 1980 using information available since January 1970.[27] Each estimation is done recursively using all information available until month $t-1$. Figure (3) plots the evolution of energy political uncertainty starting from January 1985 to December 2018

[27] Oil prices before 1973 were highly regulated and do not exhibit significant time-series variation. I only use information since 1970 despite having executive orders starting in 1950 since most likely energy related decisions in the 50s and 60s were related to Nuclear Energy and Coal which probably not as relevant as they used to be.

plotted against the EPU index of Baker et al. (2016). My index complements the aggregate EPU index by isolating uncertainty variation in energy related conjunctures. As a result my measure has a transitory spike during the Iraqi invasion of Kuwait in august 1990, then it increased in 1993 when the OPEC failed to agree to cut production decreasing consistently during the 2000s. During the financial crisis the energy policy uncertainty increased with aggregate uncertainty, and declining in 2017 following a regularization in the Supply of oil by the OPEC. My measure of energy policy uncertainty strongly rejects the null of unit root with a t-statistic of -3.78 (p=0.003), which decreases the likelihood of biasing the its coefficient in predictability and cross-sectional regressions due to correlation between regression residuals and innovations to energy political uncertainty (Stambaugh 1999).

So far I have only described the time-series behaviour of energy policy uncertainty and its ability to capture underlying changes in the world energy supply. However, if this uncertainty is anticipated by the market, it should be incorporated into asset prices. In order to study the asset pricing consequences of this uncertainty I use the unexpected component of the uncertainty estimation in cross-sectional asset pricing regressions later on. I fit an AR(1) process into the conditional variance of random variable Y_t as follows

$$p_t(1 - p_t) = \phi_0 + \phi_1 p_{t-1}(1 - p_{t-1}) + u_t \tag{14}$$

after estimating ϕ_0 and ϕ_1 via OLS, and define $\hat{u}_t$ is the unexpected component of uncertainty. As in Dou et al. (2020) and Bansal and Yaron (2004) I assume that the variances follow an AR(1) process. The OLS estimator of ϕ_1 is 0.96 significant at the 1 percent level, and rejects the null of unit root under a standard Dickey and Fuller (1979) test with a z-statistic of -22.8. The first sub-table in Table (1) presents summary statistics of the number of energy related executive orders per month N_t, the indicator variable Y_t, as well as summary statistics of the energy political uncertainty index $\mathcal{U}_t$ and its innovations $\Delta\mathcal{U}_t$. In average, between January 1980 and December 2018 there were 0.1 executive orders signed per month, with executive orders occurring in average in 7 percent of the months in the sample.

The robustness section of the paper contains analysis of performing the estimation of energy political uncertainty modelling the information set I_t in a data rich environment. I follow Jurado et al. (2015) and define energy policy uncertainty as the volatility of the unforecastable component of Y_t by fitting a stochastic volatility model in the residuals. All details are presented in the Robustness section and in the appendix.

6 Cross-sectional differences in investment under uncertainty

In this section I study how cross-sectional differences in investment across firms are amplified when energy policy uncertainty is high. The main result in the q-theory of investment states that marginal q is a sufficient statistic of firms' asset growth, as it captures firms' investment opportunities. The first hypothesis developed in Section (3) shows that energy policy uncertainty should amplify differences in investment explained by firms' marginal q. Substitution between energy and capital, or equivalently investment in energy-efficient technology should be profitable for all firms when energy policy uncertainty is high, but more profitable for firms with higher investment opportunities.

I begin by extending an otherwise standard investment-Q regression in which growth opportunities are proxied by size (Gala et al. 2019) and Tobin's average Q (Tobin 1969; Hayashi 1982; Cochrane 1991), and growth opportunities and profitability are sufficient statistics for investment.[28] In particular I estimate the following panel regression for public U.S. firms

$$\text{Inv}_{it} = a + b \times \text{Size}_{it} + c \times \log(\text{q})_{it} + d \times \text{Profitability}_{it} + \gamma \times \mathcal{U}_t + \epsilon_{it} \tag{15}$$

where investment (Inv) is defined as capital expenditures over total assets (the quarterly change of reported annual compustat item capxy for quarters 2, 3, and 4 divided by atq). I also estimate the above specification interacting growth opportunities (Size and Average Q) with my measure of energy policy uncertainty. If energy policy uncertainty triggers investment in capital, and this behaviour is more prominent for growth firms we should expect $b < 0$, $c > 0$, and the interaction with uncertainty amplifying the impact in the same direction.

Table (6) presents the results of estimating the above equation with and without industry fixed effects at the four SIC digits level to account for the fact that the impact that energy policy

[28] Extending Q regressions with ad-hoc variables has been widely used in the literature mainly to study the role of financial frictions in driving differences between marginal and average Q (Gomes 2001; Cooper and Ejarque 2003; Abel and Eberly 1994; Barnett and Sakellaris 1998; Bolton et al. 2011)

uncertainty can have on the growth opportunities of a firm depends on the industry it operates. Columns 1 and 2 present the baseline results with and without industry fixed effects in which differences in investment are captured by profitability and growth opportunities and the level of energy political uncertainty. The baseline specification is consistent with Gala et al. (2019). Larger firms and firms with higher average Q invest more. Both significant at the 1% level. Other things equal, a one standard deviation increase in firm's size translates into a decrease in monthly average investment from 0.3 to 0.26 percent of total assets, for the average firm, or a 15% reduction in investment. Equivalently, a one standard deviation increase in the natural logarithm of average Q, translates into an increase in monthly investment for the average firm between 0.3 to 0.24 percent of total assets.

Columns 3 and 4 present the estimation results of interacting energy policy uncertainty with the first measure of firms' growth opportunities, the natural logarithm of average Q. A one standard deviation increase in energy policy uncertainty from its unconditional mean between March 1980 and October 2018, increases the marginal relation between average Q and investment across all firms by 12.5 % (from 0.08 to 0.09) a magnitude that is significant at the 1% percent level. This amplification in the relation between average Q and investment also occurs across firms within the same industry at the 10 % level, for which the marginal relation increases by 4% (from 0.09 to 0.094).

In columns 5 and 6, I interact the second measure of firm's growth opportunities, firm size, with energy policy uncertainty in the monthly investment regressions. Across all firms in the sample, an increase of one standard deviation of energy policy uncertainty above its unconditional mean between March 1980 and October 2018, amplifies the marginal relation between size and investment by 11 % (from -0.27 to -0.3) and by 13% (from 0.029 to 0.34). The result for all U.S. public firms is significant at the 5% level while the result for all firms within the same industry is significant at the 1% level. These results confirm the hypothesis that an increase in the level of energy policy uncertainty, increases the incentives to invest by those firms with larger growth-opportunities - firms with larger average Q and smaller firms. Moreover, as shown in the robustness section, this finding survives a more robust specification of the agent's information set when computing energy policy uncertainty.

7 Energy Policy Uncertainty, Consumption, and Aggregate Returns

In this section I study the relation between the level of energy policy uncertainty, aggregate market returns and household consumption. If the incentives of growth firms to invest in capital are sufficiently high when energy policy uncertainty increases, one can expect an overall increase in aggregate investment if investment across value companies remains stable. This increase in aggregate investment decreases overall consumption in the current period as more output is used for investment rather than consumption. If this impact is transitory, and consumption and investment patters are expected to reverse in the future, this creates a forecastable pattern in consumption, which can be translated into a predictable patter in expected returns following the Consumption CAPM paradigm (Lucas 1978; Rubinstein 1976).

The idea that incentives to growth firms to invest in capital creates forecastable patterns in expected returns and consumption has been explored extensively in a recent literature (e.g. Papanikolaou 2011; Kogan and Papanikolaou 2013, 2014; Dou 2017). These papers suggest that these patterns in investment are caused by investment-specific shocks that decrease the per-unit cost of capital investment, as well as improving the quality of growth opportunities. Although, the mechanism that I test has a similar impact on aggregate investment, in my setup, firms invest more in capital when energy policy uncertainty is high, not because capital goods are cheaper, nor because they expect higher profits from the investment, but rather because the market value of the cost of not investing and relying more on energy consumption is higher.[29]

In a partial equilibrium setup, in which firms' decisions are exogenous, and households invest their income between investment and consumption goods, a transitory incentive to invest, causes households to substitute consumption for investment goods. Under reasonable assumptions on the households' preferences, firms substitute present consumption for future consumption (Papanikolaou 2011), yielding in a predictable pattern in households' marginal utility and therefore in aggregate returns.

To test this hypothesis I follow the literature on return predictability (e.g. Campbell and

[29]In unreported tests I find that energy policy uncertainty does not help explain cross-sectional differences in expected investment growth, which shades light on the transitory impact of the uncertainty on investment. Interacting energy policy uncertainty with average Q, operating cash flows, and changes in return on equity in similar investment growth regressions of Hou et al. (2020) yield no significant results.

Yogo 2006; Stambaugh 1999; Fama and French 1988, 1989b; Cochrane 2008) and fit the following time-series model

$$R_{t\to t+k} = a + \delta\mathcal{U}_t + \gamma X_t + \epsilon_{t\to t+k} \tag{16}$$

where $R_{t\to t+k}$ is the log cumulative return between month t and $t+k$ of the CRSP Value Weighted return including dividends, $\mathcal{U}_t$ is the energy policy uncertainty at time t regarding the possibility of an energy executive order at time $t+1$, and X_t is a vector of variables documented to capture expected return variation such as the log dividend yield (Cochrane 2008; Fama and French 1988), the term and default spreads (Fama and French 1988), and the return on oil prices (Jones and Kaul 1996; Ready 2017). I also control for time varying risk aversion proxied by the political party in power (Pástor and Veronesi 2017, 2018) by including a dummy variable for those months in which the U.S. president is a republican (Santa-Clara and Valkanov 2003).

According to one of the hypotheses presented in Section (3), if households have a preference for late resolution of uncertainty, current aggregate consumption decreases at time t as investment becomes more atractive. Since investment translates into future output, agents expect consumption to grow and therefore lower marginal utility in the future, which captures lower expected returns ($\delta < 0$) as in the Consumption CAPM.

Table (2) presents OLS estimates with Newey and West (1987) standard errors with k lags to account for residual autocorrelation due to overlapping returns. For horizons of one month, one quarter, and one year, energy policy uncertainty negatively predicts market expected returns, above and beyond the variability captured by the dividend yield, the term and default spreads, the presidential dummy and oil returns.

As a common finding in predictability regressions, the magnitude of the coefficient of most variables and R^2s in the regression increases with the horizon (Cochrane 2008). However the coefficient of energy policy uncertainty has a different behaviour and becomes not significant for horizons larger than one year. For horizons of up to one year, energy policy uncertainty negatively captures expected return variation with a significance of 1% accounting for residual autocorrelation. The magnitude of this predictability is also economically significant. A one standard deviation increase in the level of energy policy uncertainty translates into a decrease in expected returns of 1.3 % in one month, 0.9 % monthly within one quarter and 1% per month within one year.

The dividend price ratio remains a significant predictor of expected returns for all horizons consistent with Cochrane (2008). My results are also robust to the party in power. Results for the regressions with horizons up to one year, show that the coefficient of the dummy capturing a Republican mandate, are negative and significant at the 1% level, which replicates the finding of Santa-Clara and Valkanov (2003) in our sample, democrat presidencies tend to have higher expected returns.[30]

Next I test if energy policy uncertainty captures changes in expected consumption growth. This is a more direct way to test the hypothesis that when energy policy uncertainty is high, aggregate investment increases at the expense of consumption. However, testing for predictability on consumption growth is not trivial. In the consumption CAPM (Rubinstein 1976; Breeden and Litzenberger 1978; Lucas 1978; Breeden 1979), expected consumption growth is a function of expected aggregate returns, which are simultaneously a function of the model primitives. To overcome this problem I estimate simultaneously the following two equations via GMM as in Harvey 1988

$$\begin{aligned} \ln\left(\frac{c_{t+k}}{c_t}\right) &= \gamma_0 + \gamma_1 \mathcal{U}_t + \gamma_2 R_{t\to t+k} + \gamma_3 \text{term}_t + \upsilon_{t\to t+k} \\ R_{t\to t+k} &= \delta_0 + \delta_1 (d-p)_t + \delta_2 \text{term}_t + \delta_3 \text{def}_t + \epsilon_{t\to t+k} \end{aligned} \tag{17}$$

where c_t are the US monthly personal consumption expenses. I estimate the system of equations with similar moment conditions as for an OLS estimation, for parameters $\theta = \{\gamma_0, \gamma_1, \gamma_2, \delta_0, \delta_1, \delta_2, \delta_3, \delta_4\}$

$$g(\theta) = \frac{1}{T}\sum_t \begin{Bmatrix} \ln\left(\frac{c_{t+k}}{c_t}\right) - \gamma_0 - \gamma_1 \mathcal{U}_t - \gamma_2 R_{t\to t+k} - \gamma_3 \text{term}_t \\ R_{t\to t+k} - \delta_0 - \delta_1 (d-p)_t - \delta_2 \text{term}_t - \delta_3 \text{def}_t \end{Bmatrix} \times Z_t = 0 \tag{18}$$

with instruments $Z_t = \{\text{Constant}, \mathcal{U}_t, R_{t\to t+k}, \text{term}_t, \text{def}_t, (d-p)_t\}$, and an initial identity matrix in the first stage of the GMM estimation.[31]

Table (4) presents the results of the two step GMM estimation using as initial weighting matrix

[30] Pástor and Veronesi (2017) propose a rational explanation for the presidential puzzle (Santa-Clara and Valkanov 2003). The fact that under democrat U.S. presidential mandates stock returns are higher than under republican mandates, is a consequence that democrats are more likely to be elected when risk aversion is higher. In particular, if high energy uncertainty coincides with republican mandates where risk aversion is lower, and as a consequence expected returns.

[31] When using returns in GMM regressions it is common to obtain numerically singular covariance matrices in the first step of the GMM estimation, which can be solved by giving equal importance to every single moment condition (Cochrane 2009).

an identity matrix, for horizons of one, three, five and six years. My reasons to choose year horizons for the consumption growth regressions are twofold. First it eliminates the seasonality in consumption within a year, and second it allows the regressions to have higher volatility in the left hand side to be explained by our regressions since it is known that consumption patterns are smooth and consumption growth is not volatile enough to meet the Hansen and Jagannathan (1991) bound.[32]

As observed in columns 1 to 4, the coefficient γ_1 capturing the predictability power of energy political uncertainty on expected consumption growth is positive and significant for all horizons. Point estimates increase with the prediction horizon and is significant at the 1% level except for the one year horizon for which is significant at the 5% level. The magnitude of this finding is also economically significant. A one standard deviation increase in the level of energy policy uncertainty translates into an expected increases in yearly consumption growth of 17, 43, 23 and 36 percent for horizons of 1, 3, 5, and 6 years.

All together the predictability pattern in consumption and aggregate market returns supports the hypothesis that in periods of time with high energy policy uncertainty, aggregate consumption decreases relative to future consumption which gives room for a forecastable pattern in expected marginal utility that translates into return and consumption growth predictability. As shown in robustness tests, this finding survives a more complete specification of the information set when computing energy policy uncertainty. Moreover, as shown in next section, innovations to energy policy uncertainty are priced across portfolios of firms with differences in their growth opportunities, which sheds light of this uncertainty being a relevant state-variable for investors (Merton 1973).

8 Energy Policy Uncertainty and the Cross-section of expected stock returns

In this section I show that innovations to energy policy uncertainty are priced in the cross-section of portfolio returns sorted on growth opportunities (e.g. Size and Book-to-Market), and moreover since investment reacts to the level of energy policy uncertainty, differences in investment capture the cross-sectional variation explained by energy policy uncertainty.

[32]See Bulusu and Gómez Biscarri (2012) and references inside for a discussion on the difficulty of using consumption data in testing the CCAPM.

If energy policy uncertainty anticipates future states of low marginal utility, assets that appreciate in relative terms following the shock should earn lower expected returns, which according to the model presented in Section (2) corresponds to companies investing more (growth companies). Given that market valuations of growth companies appreciate with unexpected news about energy policy uncertainty (positive betas), the price of risk of this innovations should be negative. To test this hypothesis I follow a standard asset pricing approach in which I extend a linear asset pricing model with the innovations to energy policy uncertainty.

Given that my interest is to relate expected returns among firms with different investment opportunities across Size (Gala et al. 2019) and average Q (Hou et al. 2014). I use as testing portfolios the 25 portfolios sorted on Size and Book-to-market (Fama and French 1992, 1993, 1995) which proxy for differences in investment opportunities. I follow the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973) to relate energy policy uncertainty with state variables capturing changes in the investment opportunity set and perform GMM estimations of the price of risk following Maio and Santa-Clara (2012).[33]

In particular, given a linear asset pricing model with factors f_{it}, I estimate the price of risk of energy policy uncertainty from the following expected return-covariance formulation

$$\mathbb{E}[R_j^e] = \gamma Cov(R_i, R_m) + \sum_i \gamma_i^f Cov(R_i, f_i) + \gamma_u Cov(R_i, u) \tag{19}$$

where R_j^e correspond to the expected excess return of testing portfolio j, R_m corresponds to the market factor, u corresponds to the innovations on energy policy uncertainty, and γ_i^f is the covariance price of risk of factor i. As a robustness test to check if my results are consistent with an ICAPM explanation, I study if my results satisfy the restrictions in Maio and Santa-Clara (2012): The ICAPM predicts that the covariance price of market risk γ should be a feasible estimate of

[33] To avoid a fishing-license (Fama 1991) arising from using a data rich environment in asset pricing regressions, I follow Maio and Santa-Clara (2012) and test if energy political uncertainty satisfies 3 restrictions. First, for energy political uncertainty to capture changes in the investment opportunity set, it should predict the distribution of aggregate returns. In particular, the first or second moment of the return distribution. Second, innovations to energy political uncertainty must earn a significant price of risk in the cross-section of expected returns with the sign of the price of risk equal to the sign obtained in the predictability regressions. Third, the market price of covariance risk obtained from the cross-sectional regressions should be a reasonable estimate of the Relative Risk Aversion (RRA) of the representative agent in the economy. Finally, I check that the absolute value of the z-statistic in a GMM regression of the price of risk overcomes the threshold of 3 as in Harvey et al. (2016) in at least one of the specifications studied. Since the predictability power of energy political uncertainty was assured in the last section I focus on the estimation of the covariance price of risk as well as the estimates for the relative risk aversion coefficient.

the representative agent's risk aversion, and since energy policy uncertainty negatively predicts expected returns it must follow that $\gamma_u < 0$.[34]

In the empirical analysis I extend some standard asset pricing models with innovations to energy policy uncertainty. I use the CAPM model of Sharpe (1964), Lintner (1965), and Mossin (1966), the 3 factor model (FF3F) of Fama and French (Fama and French 1992, 1993, 1996), the 5 factor model (FF5F) of Fama and French (2015) which includes both an investment and profitability factor, the q^4 model of Hou et al. (2014) which also relate expected returns with profitability and investment as FF5F but the factors construction differs, and finally, the q^5 model in Hou et al. (2014) and Hou et al. (2020).

I use the above mentioned factors to achieve two goals. Standard asset pricing models such as the CAPM, FF3F, allow me to test if investors care about unexpected innovations to energy policy uncertainty and how they adjust their market valuations. A result that is derived directly from energy policy uncertainty being relevant a state variable as in the ICAPM. The second set of asset pricing models (FF5F, q^4, and q^5), which include factors related to investment and profitability, have a different use. They test if the way in which they adjust their investment policy after changes in energy policy uncertainty, is enough to explain cross-sectional differences across firms with lower and higher exposures to u. They allow me to test if differences in expected returns across companies with different u betas, can be explained because systematically some of these companies invest relatively more or less intensively. Naturally, if firms adjust their investment policy in the presence of uncertainty, magnitudes and z-statistics of the price of risk in u should be higher across the simpler set of asset pricing models.

Across the CAPM, FF3F, FF5F asset pricing models, factors mktrf_t smb_t, hml_t, cma_t, rmw_t and mom_t which are factors related to the market, size, book-to-market, investment, and profitability, are obtained from Prof. Kenneth French website. On the other hand, across the q^4 and q^5 models, the $R_{me}, R_{I/A}, R_{roe}, R_{eg}$, factors related to market equity, investment-over-assets, return on equity and expected growth are obtained from Prof. Lu Zhang's website.

The above models can be estimated with the following $N + K$ moment conditions following

[34] Maio and Santa-Clara (2012) point that in equilibrium the covariance price of market risk equals the Relative Risk Aversion coefficient of the representative agent $\gamma = -W\frac{V_{WW}}{V_W}$, where W is aggregate wealth, and V is the Value Function result of the representative investor's optimization problem.

Maio and Santa-Clara (2012)

$$g_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\left\{\begin{matrix}(R_{it} - R_{ft}) - \sum_{k=1}^{K}\gamma_k(R_{it} - R_{ft})(f_{kt} - \mu_k) \\ (f_{kt} - \mu_k)\end{matrix}\right\} = 0$$

Where N is the number of testing portfolios, K is the number of factors in the model, f_k corresponds to a factor in each specification, and μ_k is the unconditional average of the factor. The vector of parameters $\theta = (\{\gamma_k\}_{k=1}^{K}, \{\mu_k\}_{k=1}^{K})$ is then estimated using a one step GMM procedure (Hansen 1982) using an identity matrix as optimal weighting matrix. Following the original methodology by Maio and Santa-Clara, I add to the 25 testing portfolios the market return to merge the cross-sectional component of the ICAPM with the time-series aggregate risk-return trade-off.

Using equally weighted moments is equivalent to running an ordinary least squares (OLS) cross-sectional regression of average excess returns on factor covariances (right-hand side variables), however the GMM estimator accounts for residual correlation among testing assets. Moreover, this methodology allows me to account for estimation error in the factor means as in Cochrane (2009)[Chapter 13] and Yogo (2006).[35] [36]

Table (5) provides estimates of GMM cross-sectional regressions. Column 1 to 5 present the expected value and price of risk of energy policy uncertainty together with the factor means after the GMM estimation. Columns 1 to 2 present the base specifications extending the CAPM and FF3F models. The covariance price of risk of energy policy uncertainty is significant and negative across all five specifications, which suggest that portfolio with assets that perform better when energy policy uncertainty is unexpectedly high, are preferred by investors, and therefore earn lower expected returns. Finally, as shown in Columns 4 and 5, the price of risk earned by innovations to energy policy uncertainty is completely captured by the portfolio exposure to the q factors, as studied in Section (3) of the paper. The investment policy of firms reacts to energy policy uncertainty, and its a sufficient measure to explain the cross-sectional differences in expected returns. Finally, I report the Mean Absolute Error (MAE) in the cross-sectional regressions which equals the average of the absolute value of pricing errors. The q^4 and q^5 models yield the lowest MAE of all five

[35] As pointed by Maio and Santa-Clara (2012) this procedure is more convenient when estimating an asset pricing in expected return-covariance form instead of expected return-beta form Brennan et al. (2004)

[36] Recall that factor premia must be estimated jointly when the factor considered is not a portfolio, since the factor does not price itself in the cross-section, see (Cochrane 2009[Chapter 13])

specifications, with MAEs of 0.11 and 0.09 percent respectively. [37]

A potential concern that can arise is that z statistics in the cross-section analysis are not high enough to overcome potential biases caused by data-snooping and publication biases (Harvey et al. 2016, 2019). I tackle this potential concern in two ways. First I show in the robustness test, that this is caused by the conservative selection of variables in the information set used to estimate energy policy uncertainty. By considering a large battery of variables into this information set, some z statistics in the first set of asset pricing models overcome the threshold of 3 in Harvey et al. (2016) or remain slightly below while remaining significant. Second, the objective of the paper is to understand how energy policy uncertainty shapes firms' investment decisions, and how these decisions can be translated into differences in expected returns. It is not to propose a new asset pricing factor, that explains cross-sectional differences not explained before.

To ensure that portfolios of firms with larger growth opportunities are in fact earning higher expected returns when energy policy uncertainty is un expectedly large, I compute the portfolio betas using the model in column 1 of Table (5) but presented in a expected return beta form $R^e_{it} = a + b\text{mktrf}_t + \beta\Delta\mathcal{U}_t + \epsilon_{it}$, and report them in Figure (4).[38] As expected, portfolios of companies with more growth opportunities, small companies and companies with lower book-to-market ratios, tend to have a larger beta than value companies. Portfolios mainly of small companies, and companies with low book to market ratios have larger and positive $\Delta\mathcal{U}$ betas.

9 Robustness Analysis

In this section I provide robustness analysis supporting the main findings in the paper. First, I provide more evidence that the measure of energy policy uncertainty developed, is in fact capturing uncertainty about future energy policies. Second, I show that qualitatively the main results of the paper, are robust to a more complete modelling of the investors' information set to compute energy policy uncertainty.

[37]In unreported tests I extend the model of Stambaugh and Yuan (2016), which contains two anomaly factors, and find that the factor also digests the price of risk of energy political uncertainty. Given the fact that the object of interest in the paper are the investment opportunities of firms, I exclude it from the analysis.

[38]Results are similar when computing the betas based on any specification in which the price of risk of innovations to energy policy uncertainty are significant.

9.1 Robustness on the measure of Energy Policy Uncertainty

I study if companies that operate in businesses that are more sensitive to energy policies, such as companies whose cash-flows are energy-price sensitive, are also exposed to my measure of energy policy uncertainty. I define energy exposure following Jin and Jorion (2006) as the sensitivity of stock returns with respect to oil and gas returns controlling for aggregate market returns. In particular I use a 60 month rolling window for each company to fit regressions

$$R_{it} = a + bR_{mt} + \beta^{oil} R_t^{oil} + \epsilon_{it} \tag{20}$$

and

$$R_{it} = a + bR_{mt} + \beta^{gas} R_t^{gas} + \epsilon_{it} \tag{21}$$

together with an energy policy uncertainty beta.

$$R_{it} = a + bR_{mt} + \beta^{energy} u_t + \epsilon_{it} \tag{22}$$

and study if energy sensitive companies coincide with companies whose stocks are sensitive to uncertainty regarding energy policies. I run cross sectional regressions between oil and gas betas on β^{energy} and market leverage to account for equity risk as follows

$$\beta_{it}^{oil,gas} = \delta_0 + \delta_1 \beta_{it}^{energy} + \delta_2 \text{Leverage} + \delta_3 \beta_{it} + \epsilon_{it} \tag{23}$$

Where $\beta_{it}^{oil,gas}$ represents either the oil or gas beta, leverage is the market debt ratio of the firm, and β_{it} is the company equity's market beta. Table (7) presents results of estimating the above regression allowing for fixed variation at the time, industry, and firm level. Clustered standard errors at the month level are presented in parenthesis. Consistent with the nature of the uncertainty, companies sensitive to energy policy uncertainty coincide mostly with oil-sensitive companies while the relation to gas sensitive companies is weak, although coefficients in columns 4 and 5 are significant, they are economically insignificant. As seen in columns 2, and 3, this is not due to these companies operating in energy sensitive sectors. Results including the industry fixed effect suggest that within industry, companies more exposed to oil fluctuations are in fact companies more exposed to innovations on energy policy uncertainty. Additionally, the fact that the coefficient δ_1 survives the inclusion of firm fixed effects suggest that this relation is not firm specific.

9.2 A quasi-natural experiment, The 2014 OPEC Announcement

Oil and gas betas are noisy estimates of the reaction of firms' valuations to oil and gas prices. To better study the energy policy uncertainty betas of oil-sensitive companies I use a quasi-natural experiment recently used by (Dou et al. 2020): the 2014 OPEC announcement to not cut the supply of oil. In November 2014 in the 166 OPEC Meeting leaded by Saudi-Arabia, the OPEC decided to not cut oil production despite the increasing supply from non-OPEC countries, which lead to a decrease of 10 percent in oil prices in one day, and persistent high volatility for the next years.[39] Given the persistent increase in the volatility of oil prices, energy-sensitive companies should experience an increase in their energy policy uncertainty beta. To estimate this impact, I run the following difference in differences regression

$$\begin{aligned}\beta_{it}^{energy} &= a + b \times \text{Oil related dummy}_{it} + c \times \text{After OPEC announcement dummy}_t \\ &\quad + d \times \text{Oil related dummy}_{it} \times \text{After OPEC announcement dummy}_t + \epsilon_{it}\end{aligned} \tag{24}$$

where Oil related dummy$_{it}$ is equal to one if the SIC code provided by Compustat equals to 1311, 1381, 1389, 2911, or 5172 as in (Chiang et al. 2015). After OPEC announcement dummy$_t$ equals one if the current month $t \geq 2014m11$. The diff-diff estimator d captures how the energy policy uncertainty beta of oil-related companies changed after the announcement. Table (8) provides OLS estimates with double clustered standard errors at the year-month and firm (gvkey) level. I keep a symmetric estimation sample of 4 years before and after the announcement, and provide in column 1 the standard specification while in column 2 I include time fixed effects and remove the after OPEC announcement dummy. The difference in difference estimator d is economically and statistically significant with a value of 0.84. Figure (6) plots the average β_{it}^{energy} for oil related companies in solid black line, and for non oil related companies in dashed line. The average EnPU or oil related betas before the announcement is 0.66 and becomes 1.32 for the four years after the announcement. As expected, non oil related companies did not suffer a change in their energy

[39] I thank Winston Dou for referring me to his work with Leonid Kogan and Wei Wu, which allowed me to implement the quasi-natural experiment in my analysis.

policy uncertainty betas after their announcement.

9.3 Does lobbying decrease the exposure to energy policy uncertainty?

If firms have the ability to create political connections and lobby, energy-sensitive betas of companies that actively incur in lobbying should experience a systematic reduction in their exposure to energy policy uncertainty. In order to test this hypothesis. I use a conditional beta model similar to Jin and Jorion (2006), and model political uncertainty betas as a function of lobby expenditures as follows.

$$R_{it} = a_i + b_i R_{mt} + \left(\beta_i^{energy} + \gamma_i \frac{L_{it}}{A_{i,t-1}}\right) u_t + \epsilon_{it} \tag{25}$$

where L_{it} corresponds to lobby expenditures, and $A_{i,t-1}$ corresponds to firm's total assets in the period before. Lobby expenditures are queried via the LobbyView API using the Compustat gvkey of the firms in my sample, firms with missing lobby expenditures are treated as zero. Lobbying expenses are winsorized at the one percent level.[40] If lobby expenditures of ex-ante exposed companies reduce the exposure to political uncertainty we would expect $\gamma_i < 0$ for energy sensitive companies. I estimate the above equation using the entire sample for which lobby expenditures are available between 1997 and 2018. I aggregate coefficients γ_i using a simple average scaling for the fraction of lobby expenditures per total assets within companies in the same industry

$$\gamma_j \bar{l}_j = \frac{1}{|\mathcal{I}_j|} \sum_{i \in \mathcal{I}_j} \gamma_i \bar{l}_i \tag{26}$$

where $\bar{l}_i$ corresponds to the average lobby expenditures over assets of firm i, and $\mathcal{I}_j$ is the set containing all firms in industry j. I aggregate using the 12 industries definitions in Prof. Kenneth French's website. Results of the impact of lobbying into systematic exposure to energy policy uncertainty as well as the zero lobby betas, the betas for companies with no lobby expenses, are presented in Figure (5). As expected, firms in sectors such as energy, durables, manufacture and health benefit from lobbying to decrease their exposure to energy policy uncertainty, with energy being the sector with the largest reduction in exposure to uncertainty given their lobby expenditures. Not surprisingly, the exposure of zero lobbying energy firms to uncertainty is the largest across these

[40] I thank Marco Grotteria for sharing his code to perform the API requests from the LobyView website using the Compustat gvkeys.

sectors. This does not only contribute to ensure my measure of energy policy uncertainty is in fact robust, but it also provides evidence that lobby is an effective risk management tool in the presence of policy uncertainty.

9.4 Robustness tests on the Information Set

I perform robustness analysis to ensure that the main results in the paper are not driven by the specification of the information set presented in Section (5). I model the information set following Jurado et al. (2015) and perform a data-rich forecasting exercise in which I forecast the existence of at least one energy related executive order in the future. The details of the forecasting procedure are presented in the appendix. I refer to this measure of energy policy uncertainty as the "complete measure".

I repeat the main three econometric specifications with this measure to test the hypotheses developed in Section (3). First I repeat aggregate return and consumption growth predictability regressions. Table (9) presents results over forecasting horizons of one month, one quarter, one year, and three years. For this specification I modify the control variables in two ways. First, I exclude the level of the West Texas Intermediate oil price, given that the construction of the complete measure uses data available since the 1950s, and oil prices were strongly regulated until de mid 1970s. Second, following Maio and Santa-Clara (2012) I include two more control variables, corresponding to the state variables whose innovations correspond to the factors smb and hml of Fama and French (1993) (see Maio and Santa-Clara 2012 for variable construction), since they have been documented to capture expected return variation, and finally Republican dummies over the majority in the Senate and the House of Representatives to account for differences in the political agenda in the legislative branch of power not considered before. The complete measure of energy policy uncertainty negatively captures expected return variation for horizons between one quarter and three years. This result is stronger than the one presented in the main paper where predictability was only documented for horizons of up to one year.

Second, I study if this measure of uncertainty captures variation in expected consumption growth. Repeating GMM regressions presented in Section (7) we can see in Table (10) that the complete measure of energy policy uncertainty positively predicts expected consumption growth for horizons between one and six years. Thirdly, I study if its innovations are priced in the cross-section of expected returns following Section (8). Extending the five asset pricing models considered with innovations to the complete measure of energy policy uncertainty yield negative and significant prices of risk. Moreover, the price of risk for the first set of asset pricing models that exclude the investment factor, yield z statistics larger than 3 which decrease the likelihood of any data-snooping concerns in my analysis (Harvey et al. 2016). Finally, I study if differences in investment captured by a firm's growth opportunities are amplified when using this measure of uncertainty. Table (12) presents results of interacting an investment-Q regressions with the firms average Q. I show that within each industry, the cross-sectional differences in investment are amplified when the complete measure of energy policy uncertainty is higher. These robustness tests ensure that my measure of energy policy uncertainty is capturing relevant state variables for energy-sensitive companies, and that results do not depend on the specification of the informationo set used to construct the uncertainty.

10 Conclusion

In this paper I show that energy policy uncertainty measured as the blurriness in anticipating a U.S. President signing an energy-related executive order covaries positively with corporate investment, aggregate consumption growth, and carries a negative price of risk. I develop and test a q-theory explanation in which firm's invest in energy-efficient capital in anticipation of larger energy costs in bad times. This uncertainty amplifies cross-sectional differences in investment as the benefits of substituting energy for capital increase with growth opportunities. My results suggest that contrary to the pervasive consequences of policy uncertainty as a shock to the TFP of firms, energy policy uncertainty as it impacts the demand of a non-capital factor, has a positive relation with investment and asset prices as firms dial-up investment to hedge against future energy policies.

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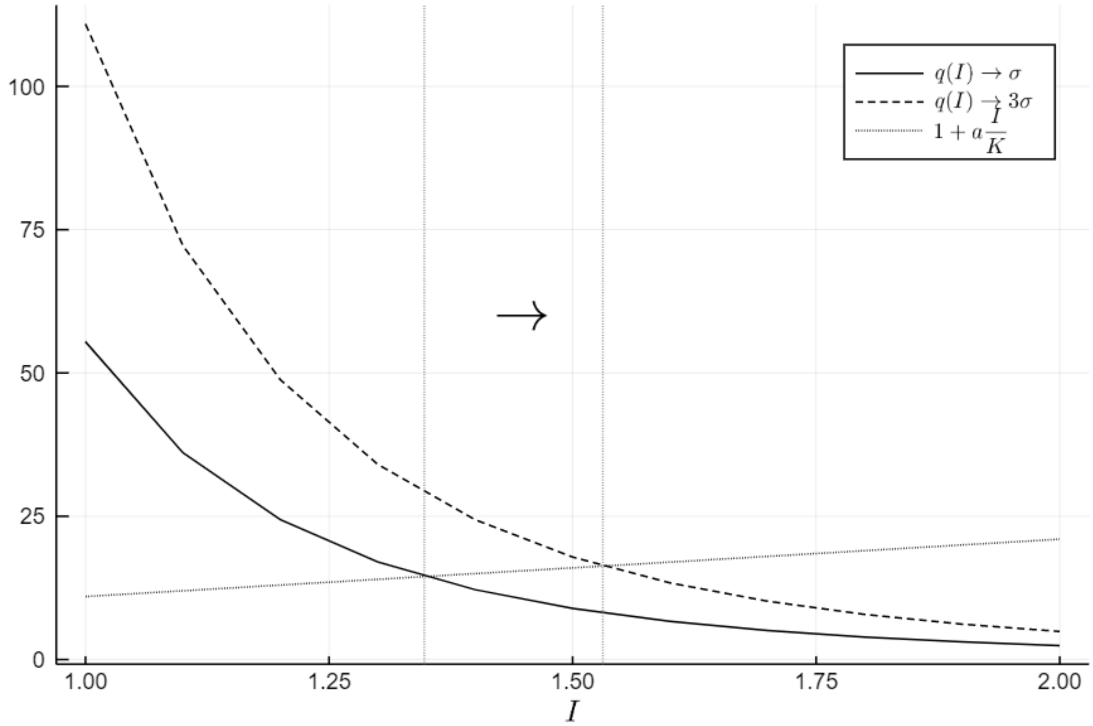
Figure 1: Theoretical relation between Energy Policy Uncertainty and Investment



Note: This graph shows how ceteris paribus investment increases when Energy Policy Uncertainty increases. The model is solved assuming parameter values $R_f = 1.01$, $a = 10$, $K_{i,t} = 1$, $A = 2$, $Y_{i,t+1} = 2$, $\alpha = 0.7$, $\beta = 0.2$, $\mathbb{E}[w_{t+1}] = 0.5$, $\mathbb{E}[M_{t,t+1}] = 1/R_f$, $Var(M_{t,t+1}) = \mathbb{E}[M_{t,t+1}]$, $\sigma^2 = Var(w_{t+1}) = \mathbb{E}[M_{t,t+1}]$. Optimal investment corresponds to 1.35 and 1.53 respectively for σ and 3σ.

Figure 2: Number of Energy related U.S. Executive Order signed per year together with the most common topic inferred from its text

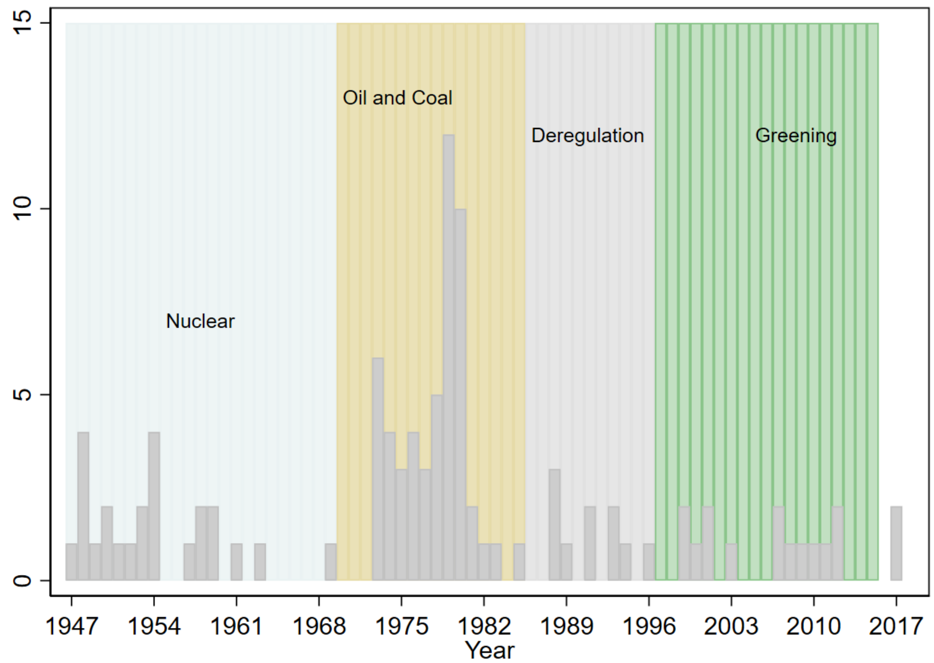


Figure 3: Energy policy uncertainty between 1985m1-2018m12, compared with the EPU index of Baker et al. (2016)

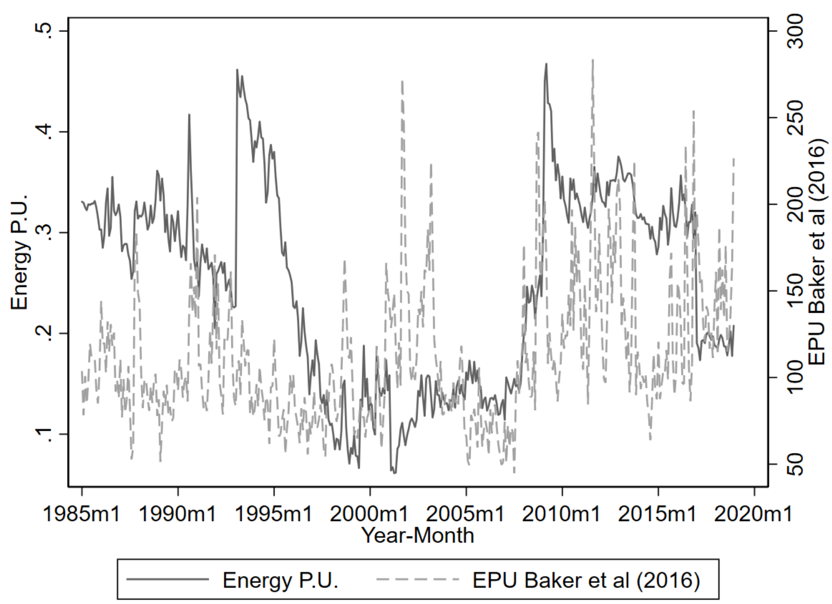


Table 1: Descriptive Statistics Energy Political Uncertainty

	(1)				
	mean	sd	p1	p50	p99
N_t	0.1	0.3	0.0	0.0	2.0
Y_t	0.07	0.26	0.00	0.00	1.00
$\mathcal{U}_t$	0.36	0.05	0.26	0.35	0.50
$\Delta\mathcal{U}_t$	0.00	0.02	-0.05	0.00	0.05
Observations	468				

	(1)				
	mean	sd	p1	p50	p99
$\beta^{energy} \times 100$	-8.2	162.2	-479.5	-5.5	523.4
$\beta^{Y_t} \times 100$	0.15	4.68	-11.42	-0.12	13.79
$\beta^{gas} \times 100$	0.36	8.49	-20.79	0.08	27.38
$\beta^{oil} \times 100$	-2.21	18.85	-47.65	-3.11	54.56
Observations	452,251				

Note: This table presents summary statistics regarding the total number of energy related executive orders signed by a US president N_t (pap_majortopic 8 in the Comparative Agendas database), dummy variable Y_t that takes the value of 1 if $N_t > 0$ and 0 otherwise. The conditional volatility of variable Y_t captured by variable $\mathcal{U}_t$, and its innovations $\Delta\mathcal{U}_t$ defined as the residual of AR1 process $\mathcal{U}_{t+1}^2 = \phi_0 + \phi_1\mathcal{U}_t^2 + \nu_t$. The beta from energy is computed using a 60 month rolling window of running firm's returns on the market return and innovations on the energy political uncertainty measure. $R_{it} = a + bR_{mt} + \beta^{energy}\Delta\mathcal{U}_t + \epsilon_{it}$ where R_{mt} is the return on the CRSP Value Weighted Market Portfolio. Oil beta β^{oil} is defined as the slope of regressing firm returns on the market return and the West Texas Intermediary monthly return using a 60 month rolling window. $R_{it} = a + bR_{mt} + \beta^{oil}R_t^{oil} + \epsilon_t$. Gas betas are computed using the return on the monthly Henry Hub Natural Gas Spot price $R_{it} = a + bR_{mt} + \beta^{oil}R_t^{gas} + \epsilon_t$, β^{Y_t} is computed equivalently as the slope in rolling regression $R_{it} = a + bR_{mt} + \beta_i^{Y_t}Y_t + \epsilon_{it}$. Descriptive statistics of $N_t, Y_t, \mathcal{U}_t$, and $\Delta\mathcal{U}_t$ are computed from January 1980 to December 2018.

Table 2: Return predictability regressions

	(1) $R_{t\to t+1}$	(2) $R_{t\to t+3}$	(3) $R_{t\to t+12}$	(4) $R_{t\to t+36}$
$\mathcal{U}_t$	-0.12***	-0.27***	-1.09***	-0.69
	(0.04)	(0.06)	(0.32)	(0.62)
$d-p$	0.05***	0.11***	0.45***	0.68***
	(0.01)	(0.02)	(0.11)	(0.20)
term	0.00	0.00	0.03***	0.09***
	(0.00)	(0.00)	(0.01)	(0.03)
def	-0.00	-0.01	-0.01	-0.06
	(0.01)	(0.01)	(0.04)	(0.06)
Republican President	-0.02***	-0.05***	-0.18***	-0.23**
	(0.01)	(0.01)	(0.06)	(0.11)
R^{oil}	0.02	0.09**	0.06	0.05
	(0.03)	(0.05)	(0.11)	(0.15)
Constant	0.25***	0.53***	2.14***	3.10***
	(0.06)	(0.10)	(0.52)	(0.97)
Observations	468	468	468	444
Adjusted R^2 (%)	1.37	3.12	16.02	44.96

Note: This table presents results from the return predictability regressions using energy related U.S. executive orders. The econometric model is: $R_{t\to t+k} = a + b \times \mathcal{U}_t + \gamma X_t + \epsilon_{t\to t+k}$ where $R_{t\to t+k}$ is the cumulative log return between month t and $t+k$. $\mathcal{U}_t = \sqrt{\hat{p}_t(1-\hat{p}_t)}$ is the conditional volatility of random variable Y_t conditional on information set $I_{t-1} = \{R_{m,t-1}, wti_{t-1}, R^{oil}_{t-1}\}$, X_t is a vector of controls including the log dividend to price ration $d-p$, the dividend to earnings ration $d-e$, the term structure (term), the default spread (def), the consumption over wealth ration (cay), the monthly return of the West Texas Intermediate price per barrel R^{oil}_t, dummy variables that take the value of 1 is the President is Republican, or if the Senate or The House of Representatives has a Republican Majority transformed to first differences, as well as the first difference of the level of oil prices wti. The probit model is specified as $p_t = \Phi(\beta_0 + \beta_1 \text{wti}_{t-1} + \beta_2 R_{m,t-1} + \beta_3 R^{oil}_{t-1} + \upsilon_t)$ where parameters β_0 and β_1 are estimated on a recursive basis starting with an initial time window from 1970m1 to 1979m12 up to 1970m1 to 2018m12, and oil is the price per barrel of the West Texas Intermediate reference normalised to be one at the beginning of the sample. Newey West standard errors for k lags reported in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Estimation sample of the predictability regression is 1980m1 to 2018m12.

Table 3: Probability Model regressions

	(1) $\sum_{s=t}^{t+1} Y_s > 0$	(2) $\sum_{s=t}^{t+3} Y_s > 0$	(3) $\sum_{s=t}^{t+6} Y_s > 0$	(4) $\sum_{s=t}^{t+12} Y_s > 0$
WTI	-0.00	-0.01	-0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
R^{oil}	0.53	1.39*	1.27*	1.59**
	(0.87)	(0.72)	(0.67)	(0.69)
$d - p$	0.98***	1.00***	0.90***	0.66***
	(0.19)	(0.16)	(0.15)	(0.15)
President	-0.39***	-0.40***	-0.42***	-0.34***
	(0.15)	(0.12)	(0.11)	(0.11)
Constant	2.53***	3.25***	3.32***	2.86***
	(0.77)	(0.63)	(0.60)	(0.60)
Observations	588	588	588	588
Pseudo R^2 (%)	8.08	7.63	6.11	3.96
Sample	1970m1-2018m12	1970m1-2018m12	1970m1-2018m12	1970m1-2018m12

Note: This table presents results from fitting probability models on the existence of one energy related executive order in the next month, quarter, semester and year. Probability estimation is performed using maximum-likelihood on a Probit model. WTI and R^{oil} correspond to the level and return of oil. $d - p$ is the log dividend price yield, and President is a dummy variables that takes the value of one if the U.S. President at month t has a Republican affiliation, and zero otherwise. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Estimation sample of the predictability regression is 1980m1 to 2018m12.

Table 4: Consumption growth regressions

$$g(\theta) = \frac{1}{T}\sum_t \begin{Bmatrix} \ln\left(\frac{c_{t+k}}{c_t}\right) - \gamma_0 - \gamma_1 \mathcal{U}_{t\to t+1} - \gamma_2 R_{t\to t+k} - \gamma_3 \text{term}_t \\ R_{t\to t+k} - \delta_0 - \delta_1 (d-p)_t - \delta_2 \text{term}_t - \delta_3 \text{def}_t \end{Bmatrix} \times \text{Instruments}_t = 0$$

	(1) $\ln\left(\frac{c_{t\to t+12}}{c_t}\right), R_{t\to t+12}$	(2) $\ln\left(\frac{c_{t\to t+36}}{c_t}\right), R_{t\to t+36}$	(3) $\ln\left(\frac{c_{t\to t+60}}{c_t}\right), R_{t\to t+60}$	(4) $\ln\left(\frac{c_{t\to t+72}}{c_t}\right), R_{t\to t+72}$
γ_0	4.73***	12.17***	20.86***	22.96***
	(0.21)	(0.60)	(0.99)	(1.14)
γ_1	1.78**	12.91***	11.95***	21.68***
	(0.79)	(2.16)	(4.56)	(5.87)
γ_2	-0.42***	-1.66***	-2.48***	-2.47***
	(0.07)	(0.16)	(0.23)	(0.26)
γ_3	0.07***	0.08***	0.11***	0.10***
	(0.01)	(0.01)	(0.01)	(0.02)
δ_0	229.14***	371.79***	423.46***	441.67***
	(17.62)	(18.95)	(20.33)	(16.19)
δ_1	47.18***	84.94***	95.50***	97.42***
	(3.58)	(4.11)	(4.52)	(3.66)
δ_2	-0.85	10.30***	10.03***	8.34***
	(0.82)	(0.91)	(0.85)	(0.84)
δ_3	-37.07***	-33.83***	-25.64***	-26.08***
	(5.37)	(4.09)	(3.63)	(2.93)
Observations	456	432	408	396
Sample	1980m1-2017m12	1980m1-2015m12	1980m1-2013m12	1980m1-2012m12
Hansen's J	87.98	186.48	178.57	179.26
p-value	0	0	0	0

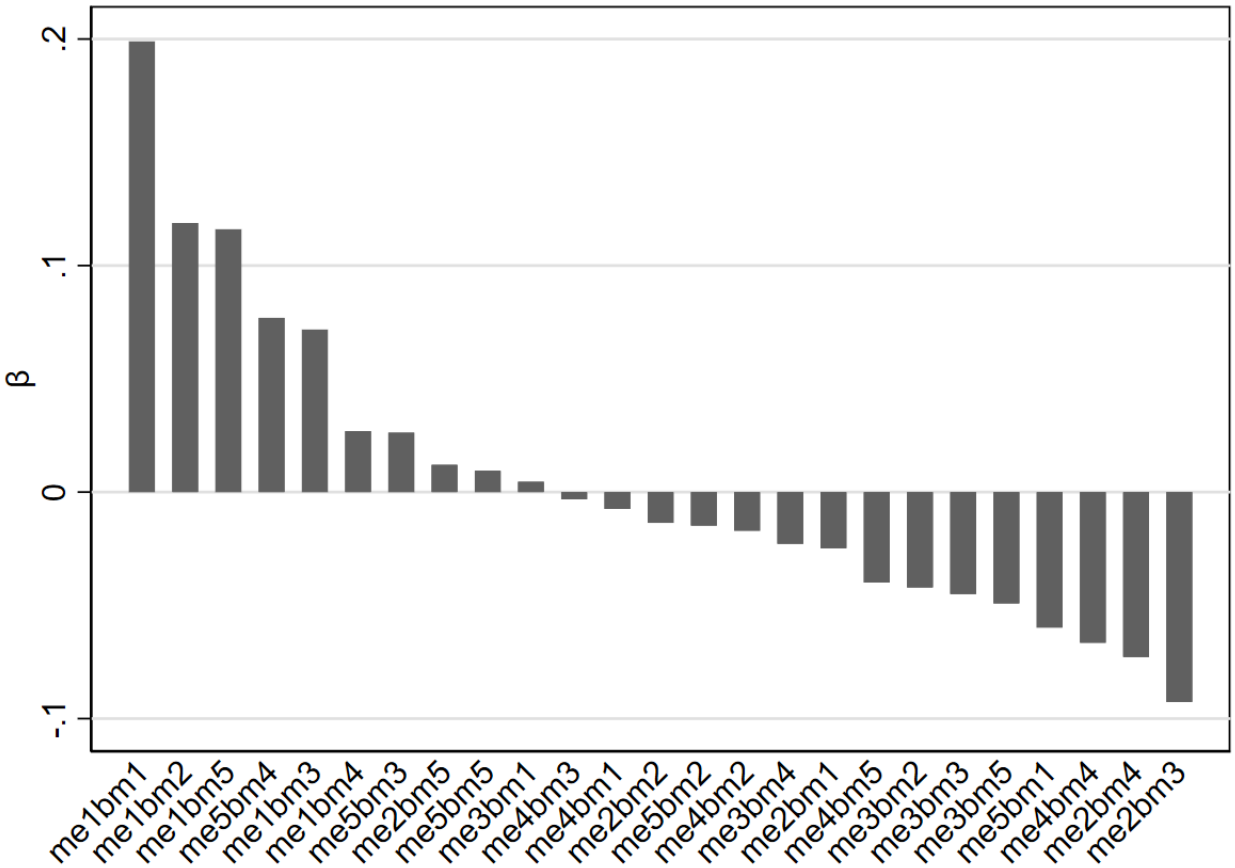
Note: This table presents results from the return and consumption growth predictability regressions using energy related U.S. executive orders. The econometric model estimates via GMM the following equations: $R_{t\to t+k} = \delta_0 + \delta_1 X_t + \epsilon_{t\to t+k}$ and $\ln(c_{t+k}/c_t) = \gamma_0 + \gamma_1 \mathcal{U}_t + \gamma_2 R_{t\to t+k} + \gamma_3 X_t + \upsilon_{t\to t+k}$ where $R_{t\to t+k}$ is the cumulative log return between month t and $t+k$. $\mathcal{U}_t = \sqrt{\hat{p}_t(1-\hat{p}_t)}$ is the conditional volatility of random variable Y_t conditional on information set $I_{t-1} = \{(d-p)_t, wti_{t-1}, R^{oil}_{t-1}, \text{President}\}$, X_t is a vector of controls including the log dividend to price ration $d-p$, the term structure (term), the default spread (def). $\ln(c_{t+k}/c_t)$ is the growth on consumption between month t and $t+k$ measured as the personal consumption expenses. The probit model is specified as $p_t = \Phi(\beta_0 + \beta_1 \text{wti}_{t-1} + \beta_2 (d-p)_t + \beta_3 R^{oil}_{t-1} + \beta_4 \text{President} + \upsilon_t)$ where parameters are estimated on a recursive basis starting with an initial time window from 1970m1 to 1979m12 up to 1970m1 to 2018m12, and oil is the price per barrel of the West Texas Intermediate reference normalised to be one at the beginning of the sample. Newey West standard errors for k lags reported in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Estimation sample of the predictability regression is 1980m1 to 2018m12.

Table 5: Cross-sectional return regressions

	Size and Book-to-Market				
	(1)	(2)	(3)	(4)	(5)
μ_{mktrf}	0.004*	0.005**	0.006***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
γ_{mktrf}	-0.070	2.495	5.559**	5.903***	9.944***
	(2.267)	(2.056)	(2.216)	(2.046)	(2.737)
μ_{smb}		0.000	0.001		
		(0.001)	(0.001)		
γ_{smb}		1.211	2.149		
		(1.707)	(2.455)		
μ_{hml}		0.003**	0.002*		
		(0.001)	(0.001)		
γ_{hml}		5.589**	-4.225		
		(2.259)	(5.076)		
μ_{cma}			0.249***		
			(0.089)		
γ_{cma}			0.212**		
			(0.099)		
μ_{rmw}			0.353***		
			(0.103)		
γ_{rmw}			0.089**		
			(0.042)		
μ_{me}				0.002	0.002
				(0.001)	(0.001)
γ_{me}				5.805***	11.044***
				(2.202)	(2.854)
μ_{ia}				0.003***	0.003***
				(0.001)	(0.001)
γ_{ia}				17.788***	10.998*
				(4.669)	(5.843)
μ_{roe}				0.005***	0.005***
				(0.001)	(0.001)
γ_{roe}				13.657***	-4.229
				(3.883)	(6.520)
μ_{eg}					0.008***
					(0.001)
γ_{eg}					48.353***
					(14.931)
μ_{pol}	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
γ_{pol}	-57.653***	-34.558**	-27.699*	-17.717	-19.528
	(21.357)	(16.859)	(16.295)	(12.821)	(15.393)
Observations	468	468	468	468	468
MAE %	.24	.29	.17	.17	.18

Note: This table presents results from estimating the price of risk in expected return - covariance form by extending the CAPM model, Fama and French three and five factor models, and the q^4 and q^5 models. Estimations are performed via GMM in which factor loadings (covariances) and covariance prices of risk are estimated jointly. Factors smb, hml, cma, rmw, correspond to the Fama and French factors related to size, book-to-market, investment and profitability. Factors, me, ia, roe, and eg, correspond to factors related to size, investment, profitability, and expected investment growth. Factor pol corresponds to the innovations to energy policy uncertainty. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Estimation sample of the cross-sectional regression is 1980m1 to 2018m12.

Figure 4: Differences in EnPU betas across portfolios on Size and Book-to-Market



Note: This figure provides estimates for each portfolio sorted on size and book-to-market of running the following time series regression $R_{it} = a + b \times (R_{mt} - r_{ft}) + \beta \Delta \mathcal{U}_t + \epsilon_t$, where $R_{mt} - r_{ft})$ is the excess return of the CRSP value weighted portfolio over the one month risk free rate. Portfolio returns R_{it} for each quintile in the double sorting of size and book to market firms are obtained from Prof. Kenneth French's website, me1 to me5 correspond to quintiles 1 to 5 on size, and bm1 to bm5 correspond to quintiles on book to market, $\mathcal{U}_t = \sqrt{\hat{p}_t(1 - \hat{p}_t)}$ is the conditional volatility of random variable Y_t conditional on information set $I_{t-1} = \{(d-p)_t, wti_{t-1}, R^{oil}_{t-1}, \text{President}_t\}$. The probit model is specified as $p_t = \Phi(\beta_0 + \beta_1 \text{wti}_{t-1} + \beta_2 (d-p)_t + \beta_3 R^{oil}_{t-1} + \beta_4 \text{President}_t + \upsilon_t)$ where parameters are estimated on a recursive basis starting with an initial time window from 1970m1 to 1979m12 up to 1970m1 to 2018m12, and oil is the price per barrel of the West Texas Intermediate reference normalised to be one at the beginning of the sample. Estimation sample is 1980m1 to 2018m12.

Table 6: Investment Cross-sectional Regressions

	(1) Inv	(2) Inv	(3) Inv	(4) Inv	(5) Inv	(6) Inv
Profitability	5.76***	6.68***	5.84***	6.76***	5.62***	6.55***
	(0.48)	(0.38)	(0.48)	(0.38)	(0.47)	(0.38)
Q	0.18***	0.22***	0.12***	0.16***	0.18***	0.22***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.23***	-0.23***	-0.23***	-0.23***	-0.11***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
$\mathcal{U}_t$	0.19	0.23	-0.36*	-0.34*	3.66***	3.98***
	(0.24)	(0.22)	(0.21)	(0.19)	(0.75)	(0.71)
$\mathcal{U}_t \times Q$			0.29***	0.29***		
			(0.06)	(0.06)		
$\mathcal{U}_t \times$ Size					-0.48***	-0.52***
					(0.08)	(0.08)
Constant	3.09***	3.04***	3.21***	3.17***	2.22***	2.11***
	(0.09)	(0.08)	(0.09)	(0.08)	(0.18)	(0.17)
Observations	570746	570746	570746	570746	570746	570746
Adjusted R^2 (%)	3.71	15.79	3.76	15.84	3.78	15.88
Industry F.E.	No	Yes	No	Yes	No	Yes
From	1981m1	1981m1	1981m1	1981m1	1981m1	1981m1
To	2018m10	2018m10	2018m10	2018m10	2018m10	2018m10

Note: This table presents results from regressing investment (the percentage of capital expenditures over assets) on profitability, average Q, size, and Energy Policy Uncertainty $\mathcal{U}_t$ for U.S. public firms. Standard errors clustered by month reported in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 5: Average impact of lobby on political uncertainty exposure by industry

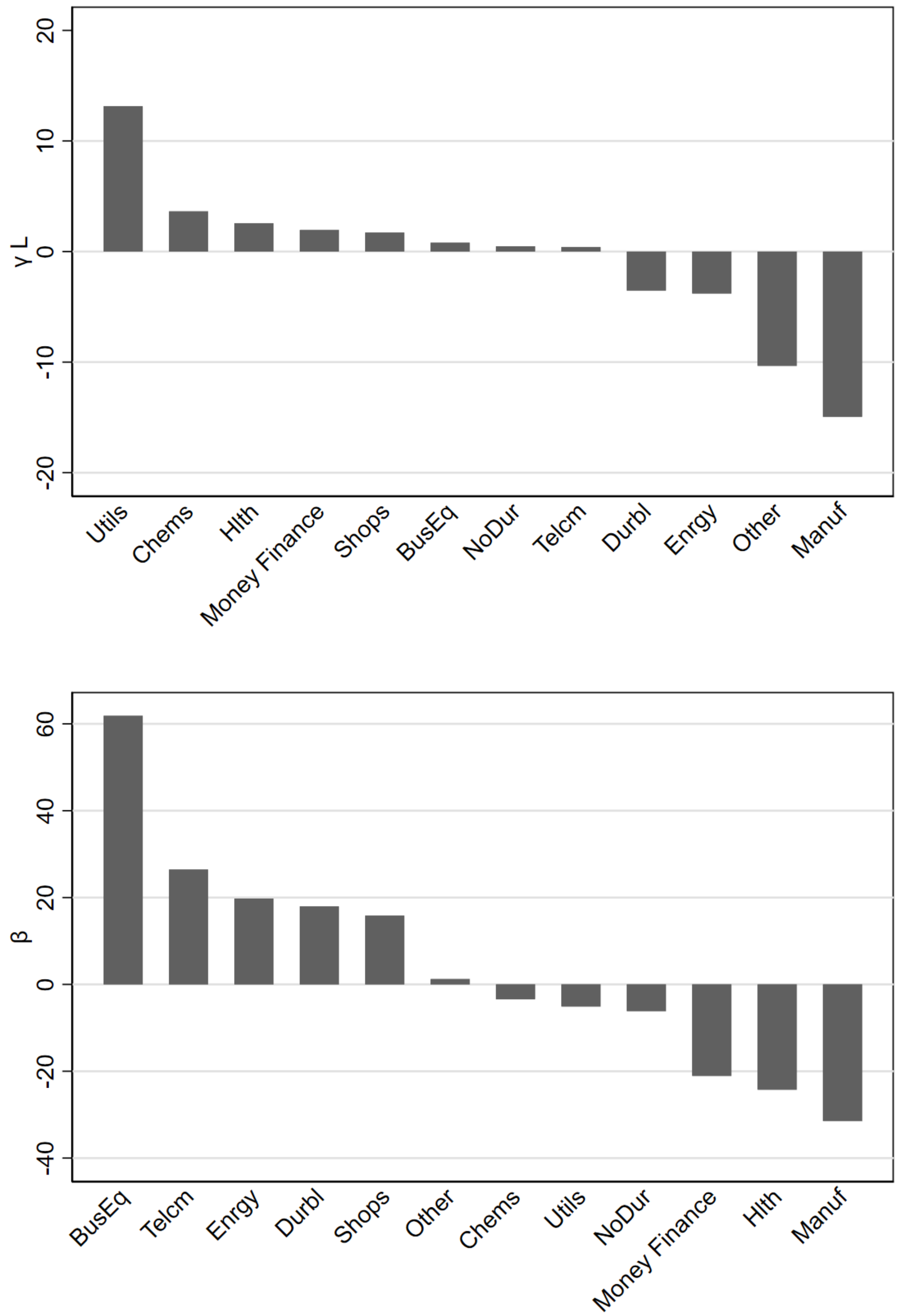


Table 7: Regressions of oil and gas betas on energy political betas

	(1) β^{oil}	(2) β^{oil}	(3) β^{oil}	(4) β^{gas}	(5) β^{gas}	(6) β^{gas}
β^{energy}	4.74***	4.42***	3.87***	0.08*	-0.04	-0.04**
	(0.12)	(0.11)	(0.08)	(0.05)	(0.03)	(0.02)
$\beta/100$	7.81	11.16*	-2.50	-3.10	-1.13	-3.54
	(8.04)	(5.79)	(4.22)	(6.33)	(3.61)	(2.76)
Leverage	1.22**	0.17	1.62***	0.70***	-2.04***	-4.43***
	(0.49)	(0.39)	(0.58)	(0.26)	(0.19)	(0.38)
Constant	-2.08***	-1.84***	-2.16***	0.29***	0.90***	1.48***
	(0.15)	(0.11)	(0.16)	(0.09)	(0.06)	(0.09)
Observations	421193	421193	421141	190649	190649	190629
Adjusted R^2 (%)	18.17	27.48	54.94	1.45	22.02	56.74
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	Yes	No	Yes	Yes
Firm F.E.	No	No	Yes	No	No	Yes
From	1974m6	1974m6	1974m6	2002m1	2002m1	2002m1
To	2018m10	2018m10	2018m10	2018m10	2018m10	2018m10

Note: This table presents results from regressing firm level gas and oil betas on market beta, beta from energy related executive orders and leverage. The beta from energy is computed using a 60 month rolling window of running firm's returns on the market return and innovations on the energy political uncertainty measure. $R_{it} = a+bR_{mt}+\beta^{energy}\Delta\mathcal{U}_t+\epsilon_{it}$ where R_{mt} is the return on the CRSP Value Weighted Market Portfolio, and $\Delta\mathcal{U}_t^{energy}$ is the innovation on the conditional variance of the stochastic process defined as 1 if there is at least one executive order in a month and zero otherwise. The innovation is computed as the residual of regression $(p_{t+1} - p_{t+1}^2) = \phi_0 + \phi_1(p_t - p_t^2) + \nu_t$. Oil beta β^{oil} is defined as the slope of regressing firm returns on the market return and the West Texas Intermediary monthly return using a 60 month rolling window. $R_{it} = a + bR_{mt} + \beta^{oil}R_t^{oil} + \epsilon_t$. Gas betas are computed using the return on the monthly Henry Hub Natural Gas Spot price $R_{it} = a + bR_{mt} + \beta^{oil}R_t^{gas} + \epsilon_t$, β is computed using daily returns within each month and is defined as the sum of coefficients $\beta = b_1 + b_2 + b_3$ from estimating the following regression month by month: $R_{is}^e = a + b_1Rm_{i,s+1}^e + b_2Rm_{is}^e + b_3Rm_{i,s-1}^e + \epsilon_{is}$ for all days s within month t and R_m^e is the daily market excess return over the daily risk free rate. Leverage is computed as total debt = Compustat Quarterly items (dlcq+dlttq) over total debt plus market equity (prccq $\times$ cshoq). Oil and gas prices come from the Federal Reserve Economic Data at St. Louis. Clustered standard errors at the month level reported in parenthesis. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 6: Differences in the average EnPU beta between oil and non oil related firms

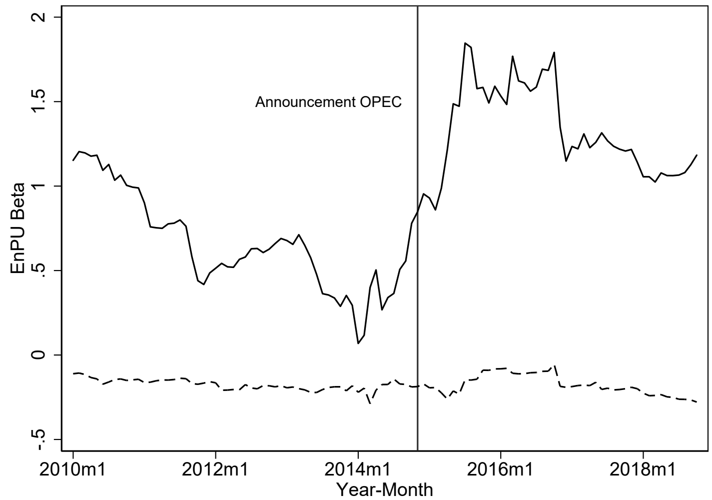


Table 8: Differences in Differences regressions of EnPU betas on the 2014 OPEC announcement

	(1) β^{energy}	(2) β^{energy}
Oil related dummy$_{it}$	0.21***	0.21***
	(0.02)	(0.02)
After OPEC announcement dummy$_t$	0.07***	
	(0.01)	
After OPEC announcement dummy$_t$ $\times$ Oil related dummy$_{it}$	0.84***	0.84***
	(0.04)	(0.04)
Constant	-0.14***	-0.11***
	(0.00)	(0.00)
Observations	103021	103021
Adjusted R^2 (%)	2.18	2.75
Time F.E.	No	Yes
From	2010m1	2010m1
To	2018m10	2018m10

Note: This table presents Clustered standard errors at the month, firm, and month-firm level reported in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A Details of the Stylised Model and Hypotheses Formulation

Proof. of the positive relation between investment and uncertainty. Equation (2) can be written as

$$I_{it} = Y_{i,t+1}^{\frac{1-\beta}{\alpha}}\Big(\frac{r_{ft}}{\beta}(\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e)\Big)^{\frac{\beta}{\alpha}}$$

the derivative of investment with respect to energy price uncertainty is

$$\frac{\partial I_{it}}{\partial\sigma^e} = \frac{\beta}{\alpha}Y_{i,t+1}^{\frac{1-\beta}{\alpha}}\Big(\frac{r_{ft}}{\beta}(\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e)\Big)^{\frac{\beta-\alpha}{\alpha}}\rho\sigma^M\sigma^e$$

given that $M_{t+1} > 0, w_{t+1} > 0$, $\mathbb{E}[M_{t+1}w_{t+1}] = \mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e > 0$ so the sign of the partial derivative depends directly on the sign of ρ. □

Proof. of the convex relation investment and uncertainty. To compute the second derivative we forget about the term $\frac{\beta}{\alpha}Y_{i,t+1}^{\frac{1-\beta}{\alpha}}\rho\sigma^M$ which for the partial derivative is assumed constant and positive. The derivative of the remaining term $\Big(\frac{r_{ft}}{\beta}(\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e)\Big)^{\frac{\beta-\alpha}{\alpha}}\sigma^e$ is

$$\Big(\frac{r_{ft}}{\beta}(\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e)\Big)^{\frac{\beta-\alpha}{\alpha}} + \frac{\beta-\alpha}{\alpha}\Big(\frac{r_{ft}}{\beta}(\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e)\Big)^{\frac{\beta-2\alpha}{\alpha}}\rho\sigma^M\sigma^e \quad (27)$$

whose sign is ambiguous given that the term $\beta - \alpha$ can be either positive or negative. If $\beta - \alpha > 0$ the second derivative is always positive, however if $\alpha > \beta$ the second derivative is positive if

$$\begin{aligned}\Big(\frac{r_{ft}}{\beta}(\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e)\Big)^{\frac{\beta-\alpha}{\alpha}} + \frac{\beta-\alpha}{\alpha}\Big(\frac{r_{ft}}{\beta}(\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}] + \rho\sigma^M\sigma^e)\Big)^{\frac{\beta-2\alpha}{\alpha}}\rho\sigma^M\sigma^e &> 0\\ \frac{\alpha-\beta}{\alpha}\rho\sigma^M &< \frac{r_{ft}}{\beta}(\frac{\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}]}{\sigma_e} + \rho\sigma^M)\\ \rho\sigma^M(\frac{\beta}{r_{ft}}\frac{\alpha-\beta}{\alpha} - 1) &< \frac{\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}]}{\sigma_e}\\ \sigma_e &> \frac{\mathbb{E}[M_{t+1}]\mathbb{E}[w_{t+1}]}{\rho\sigma^M(\frac{\beta}{r_{ft}}\frac{\alpha-\beta}{\alpha} - 1)} = \bar{\sigma}\end{aligned} \quad (28)$$

where the last change in the inequality sign comes from the fact that $\frac{\beta}{r_{ft}}\frac{\alpha-\beta}{\alpha} < 1$. Since $\bar{\sigma} < 0$ the second derivative is positive for every value of σ_e. □

Proof. of the substitution hypothesis. If households consume the difference $Y - I$, and there is a representative firm, expected consumption growth is given by

$$g_{t,t+1} = \mathbb{E}\Big[\frac{Y_{t+1}}{Y_t - I_t}\Big] \tag{29}$$

its derivative with respect to σ_e is positive if and only if

$$\sigma_e > \frac{I^{\frac{\beta}{\alpha}}\rho\sigma_m - \mathbb{E}[M_{t,t+1}]\mu}{\rho\sigma_m} = \bar{\sigma} \tag{30}$$

$\square$

Proof. that expected returns decrease with investment. The proof proceeds by inspection of the term I_{it} inside the expression, it can be observed that increasing investment decreases the numerator given the term $I_{it}^{-\frac{\alpha}{\beta}}$ for $\alpha > 0, \beta > 0$, and equivalently investment increases the term in the denominator $\frac{I_{it}}{Y_{i,t+1}}\Big(1 + a\frac{I_{it}}{K_{it}}\Big)$. $\square$

$$\mathbb{E}\Big[R_{i,t+1}\Big] = \frac{\alpha}{\beta}\frac{Y_{i,t+1}^{\frac{1-\beta}{\beta}} I_{i,t}^{-\frac{\alpha}{\beta}}\mu - 1}{\frac{I_{it}}{Y_{i,t+1}}\Big(1 + a\frac{I_{it}}{K_{it}}\Big) - \frac{\alpha}{\beta r_{ft}}} \tag{31}$$

A.1 Energy Price Uncertainty and Investment - Alternative Formulation

In this section I develop a small model based on Stewart (1978). Consider a representative firm that uses two inputs, capital (K) and energy (E) to produce a final product. The firm purchases energy in a competitive market at a price w_e per unit and combines energy with capital (e.g. property plant equipment PPE) to produce its final product, and all other factors required such as labor are maximized out of the equation. The firm's profit at any period is given by

$$\pi = pq - w_e E - rK \tag{32}$$

where p is the output price, q is the quantity produced, and r is the unit cost of capital including opportunity costs, or financing costs. I assume that input substitution between energy and capital is possible. In fact, as documented by Tovar and Iglesias (2013), translog analysis of production costs and factors such as capital, energy, labor, and intermediate materials in the US yield negative estimates of cross-price elasticities between energy an capital which are consistent with a systematic increase in energy efficient capital. More precisely, if the firm uses technology $q = f(K, E)$ to convert capital and energy into the final product, substitution implies that for any fixed output q and capital K, the quantity of energy required

$$E = g(q, K) \tag{33}$$

satisfies $\partial g/\partial K < 0$. I assume that the firm's PPE configuration is not instantaneously adjustable, so that capital has to be determined in advance, and that the price of energy w_e follows a mean preserving spread process

$$w_e = \beta\nu + \theta \tag{34}$$

where β and θ are constant shift parameters, and ν is a positive random variable. Finally, I assume the firm's manager is risk averse and maximizes expected utility over profit π with a standard von Neumann-Morgenstern utility function U. If we express the optimization problem in terms of capital and output

$$pq - w_e g(q, K) - rK \tag{35}$$

a necessary condition for utility maximization is therefore

$$\mathbb{E}[U'(\pi)(-w_e \frac{\partial g}{\partial K} - r)] = 0 \tag{36}$$

To study how uncertainty on energy prices impacts investment, I consider first the benchmark case in which the manager is risk neutral so $U'(\pi)$ is a constant. In this situation the first order condition of profit maximization implies the manager chooses next period capital satisfying

$$-\frac{\partial g}{\partial K} = \frac{r}{\mathbb{E}[w_e]} \tag{37}$$

equating the marginal rate of technical substitution to the expected factor price ratio. On the other hand, a risk averse manager with concave utility function will depart from this first order condition. Expressing (36) in covariance form yields

$$\mathbb{E}[U'(\pi)(-w_e \frac{\partial g}{\partial K} - r)] = \mathbb{E}[U'(\pi)]\mathbb{E}[(-w_e \frac{\partial g}{\partial K} - r)] + cov([U'(\pi), (-w_e \frac{\partial g}{\partial K} - r)) = 0 \tag{38}$$

U is a concave function so $U'(\pi)$ is increasing in w_e, and since the term $-w_e\frac{\partial g}{\partial K}-r$ is also increasing in w_e we have that the covariance term in (38) is strictly positive, which implies

$$\mathbb{E}[(-w_e\frac{\partial g}{\partial K}-r)]<0\rightarrow-\frac{\partial g}{\partial K}<\frac{r}{\mathbb{E}[w_e]} \tag{39}$$

so a risk averse manager demands more capital than its risk neutral counterparty.

B Robustness Analysis to the Information Set

B.1 Theoretical Setup

In this section I explain how I construct a measure of energy policy uncertainty using U.S. political agenda data. To keep the notation self-contained I explain an extension of the forecasting model based on Jurado et al. (2015), including extra political variables in the forecasting exercise. For technical details I refer the reader to the original paper. Policy uncertainty arises from the impossibility of economic agents to perfectly forecast politician's decisions. I follow the literature on uncertainty and define energy policy uncertainty as the conditional volatility of the unforecastable component of the number of energy related executive orders from the point of view of an economic agent. In particular, given investor's information set I_t, I define the k-period ahead energy political uncertainty on topic i as

$$\mathcal{U}_t(k)=\sqrt{\mathbb{E}[(\mathrm{eo}_{t+k}^{energy}-\mathbb{E}[\mathrm{eo}_{t+k}^{energy}|I_t])^2|I_t]} \tag{40}$$

where eo_t^{energy} is the total number of executive orders signed by the U.S. President during month t. To model the information set I_t, I use a large battery of macroeconomic and financial time series, as well as political information.[41] The information set comprises variables that help forecast the number of executive orders within a one month, one quarter, and one year horizons. I include the current political agenda, the number of public laws and executive orders being passed on each topic. I use information about the party in power in each one of the two chambers as well as the president's affiliation. This allows me to control for differences in the agenda of both parties, which

[41] As noted by Jurado et al. (2015), many proxies of economic uncertainty fail to account for the forecastable component of the time series being analysed, which pervades the uncertainty estimations with predictive variation.

are reflected in next periods' political decisions. Finally I include the original 132 time-series of macroeconomic variables and the 147 financial variables presented in Ludvigson and Ng (2009) and Ludvigson and Ng (2007), and used in Jurado et al. (2015) for the uncertainty estimations.

The forecasting procedure is explained as follows. Let $\mathcal{P}_\mathbf{t} = (\mathrm{pl}_{1t}, ..., \mathrm{pl}_{Nt})$ be a vector containing the number of public laws for every topic, and $\mathcal{E}_\mathbf{t} = (\mathrm{eo}_{1t}, ..., \mathrm{eo}_{Nt})$ a vector containing the number of executive orders for every topic i. Also, let $\mathbf{X_t^{JLN}} = (X_{1t}^{JLN}, ..., X_{Nt}^{JLN})'$ denote the original macroeconomic and financial predictors used by Jurado et al. (2015) after suitable transformations to ensure the series are stationary. Let $\mathbf{X_t} = (\mathbf{X_t^{LN}}, \mathcal{P}_t, \mathcal{E}_t, \mathrm{House}_t, \mathrm{Senate}_t, \mathrm{President}_t)$ be the whole set of predictors in the forecastable model consisting of the original 132+147 predictors in Jurado et al. (2015), 30 time series regarding the number of public laws, executive orders for every of the 20 topics defined in the Comparative Agenda project, plus three dummy variables House, Senate, and President which take the value of one if at month t the House of Representatives has a Republican Majority, the Senate has a Republican Majority, or the President is Republican. This last three variables are then transformed in first differences to ensure stationarity. It is assumed predictor $X_{it} \in \mathbf{X_t}$ has an approximate factor structure

$$X_{it} = \Lambda_i^{F'} \mathbf{F_t} + e_{it}^X \tag{41}$$

where $\mathbf{F_t}$ is a vector of r_F common factors, and e_{it}^X is an idiosyncratic error. To compute uncertainty on the number of executive order related to energy $\mathrm{eo}_t^{energy} \in \mathcal{E}_t$

$$\mathrm{eo}_{t+1}^{energy} = \phi_j^e(L)\mathrm{eo}_t^{energy} + \gamma_j^F(L)\hat{\mathbf{F}}_\mathbf{t} + \gamma_j^W(L)\mathbf{W_t} + v_{t+1}^e \tag{42}$$

where $\mathbf{W_t}$ is a set of extra predictors including square terms of the principal components, and $\phi^e(L), \phi^F(L), \phi^W(L)$ are polynomials on the lag operator L of order n_e, n_f, n_w respectively. Let $\mathbf{Z_t} = (\hat{\mathbf{F}}_\mathbf{t}, \mathbf{W}_t)'$ and define $\mathcal{Z}_t = (\mathbf{Z}'_\mathbf{t}, ..., \mathbf{Z}'_\mathbf{t-q+1})$, as well as $E_t = (\mathrm{eo}_t^{energy}, ..., \mathrm{eo}_{t-q+1}^{energy})'$, the forecasting model can then be expressed as:

$$\begin{bmatrix} \mathcal{Z}_t \\ E_t \end{bmatrix} = \begin{bmatrix} \Phi^{\mathcal{Z}} & 0 \\ \Lambda' & \Phi^E \end{bmatrix} \begin{bmatrix} \mathcal{Z}_{t-1} \\ E_{t-1} \end{bmatrix} + \begin{bmatrix} \mathcal{V}_t^{\mathcal{Z}} \\ \mathcal{V}_t^E \end{bmatrix} \tag{43}$$

or in compact notation

$$\mathcal{Y}_t = \mathbf{\Phi}^{\mathcal{Y}}\mathcal{Y}_{t-1} + \mathcal{V}_t^{\mathcal{Y}} \tag{44}$$

and by the assumption of stationary and under quadratic loss the optimal k-period ahead forecast is the conditional mean

$$\mathbb{E}_t[\mathcal{Y}_{t+k}] = (\mathbf{\Phi}^{\mathcal{Y}})^k\mathcal{Y}_t \tag{45}$$

the forecast error variance-covariance matrix is

$$\Omega_t^{\mathcal{Y}}(k) = \mathbb{E}_t[(\mathcal{Y}_{t+k} - \mathbb{E}_t[\mathcal{Y}_{t+k}])(\mathcal{Y}_{t+k} - \mathbb{E}_t[\mathcal{Y}_{t+k}])'] \tag{46}$$

the $k > 1$ ahead forecast error variance matrix evolves accordingly to

$$\Omega_t^{\mathcal{Y}}(k) = \mathbf{\Phi}^{\mathcal{Y}}\Omega_t^{\mathcal{Y}}(k-1)\mathbf{\Phi}_{\mathbf{j}}^{\mathcal{Y}\prime} + \mathbb{E}[\mathcal{V}_{t+k}^{\mathcal{Y}}\mathcal{V}_{t+k}^{\mathcal{Y}\prime}] \tag{47}$$

where $\Omega_t^{\mathcal{Y}}(1) = \mathbb{E}[\mathcal{V}_{t+1}^{\mathcal{Y}}\mathcal{V}_{t+1}^{\mathcal{Y}\prime}]$. The political uncertainty estimation can then be estimated as:

$$\mathcal{U}_t(k) = \sqrt{1'_{energy}\Omega_t^{\mathcal{Y}}(k)1_{energy}} \tag{48}$$

where 1_{energy} is an adequate selector operator. Finally the components in $\mathbb{E}[\mathcal{V}_{j,t+h}^{\mathcal{Y}}\mathcal{V}_{j,t+h}^{\mathcal{Y}\prime}]$ can be estimated imposing a stochastic volatility structure on the residuals in $\mathbf{Z_t}$ and E_t assuming an autoregressive behaviour of the elements of $\mathbf{Z_t}$:

$$Z_t = \Phi^Z Z_{t-1} + v_t^Z \tag{49}$$

where $Z_t \in \mathbf{Z_t}$, the residual term admits $v_t^Z = \sigma_t^Z\epsilon_t^Z$ and $\epsilon_t^Z \sim N(0,1)$ and the forecast residual $v_{t+1}^y = \sigma_{t+1}\epsilon_t^y$, the stochastic volatility model used assumes an AR(1) process on the square of the log volatility

$$\log(\sigma_t^Z)^2 = \alpha^Z + \beta^Z\log(\sigma_{t-1}^Z)^2 + \tau^Z\eta_t^Z \tag{50}$$

$$\log(\sigma_{t+1}^y)^2 = \alpha + \beta\log(\sigma_t^y)^2 + \tau^e\eta_{t+1} \tag{51}$$

where parameters $(\alpha^Z, \beta^Z, \tau^Z, \alpha, \beta, \tau^e)$ are estimated via MCMC. The stochastic volatility model allows us to express the volatility as:

$$\mathbb{E}_t[\sigma^Z_{t+k}] = \exp\left[\alpha^Z \sum_{s=0}^{k-1}(\beta^Z)^s + \frac{(\tau^Z)^2}{2}\sum_{s=0}^{k-1}(\beta^Z)^{2s} + (\beta^Z)^k \log(\sigma^Z_t)^2\right] \tag{52}$$

and

$$\mathbb{E}_t[\sigma^y_{j,t+k}] = \exp\left[\alpha^y_j \sum_{s=0}^{k-1}(\beta_j)^s + \frac{(\tau_j)^2}{2}\sum_{s=0}^{k-1}(\beta_j)^{2s} + (\beta_j)^k \log(\sigma^y_{jt})^2\right] \tag{53}$$

elements in $\mathbb{E}[\mathcal{V}^{\mathcal{Y}}_{j,t+k}\mathcal{V}^{\mathcal{Y}'}_{j,t+k}]$ are estimated using the fact that $\mathbb{E}_t[\sigma^y_{j,t+k}]^2 = \mathbb{E}_t[v^y_{j,t+k}]^2$ and $\mathbb{E}_t[\sigma^Z_{t+k}]^2 = \mathbb{E}_t[v^Z_{t+k}]^2$.

B.2 Estimation

I follow Jurado et al. (2015) and set $r_F = 10$, and $\mathbf{Z}_t = [\mathbf{F}_t, \mathbf{F}^2_t, G_t]$ where G_t is the first principal component of $\mathbf{X}^2_t$. The polynomials on the lag operator used in the forecasting regressions are assumed to have degrees $n_y = 4, n_f = 2, n_w = 2$, and lags $q = \lfloor 4(\frac{T}{100})^{2/9}\rfloor$. On a first stage the elements of $\mathbf{Z}_t$ are pruned to keep only those ones that provide individual significance with t-statistics greater than 2.575 in the multivariate forecasting regression of y_{t+1} on the candidate predictors known at time t. Once residuals are estimated, the parameters in the stochastic volatility model are estimated via a Markov Chain Montecarlo Method.[42]

[42] I thank Serena Ng for making available the code used in Jurado et al. (2015) on her webpage.

Table 9: Return predictability regressions - Complete Information Set

	(1) $R_{t\to t+1}$	(2) $R_{t\to t+3}$	(3) $R_{t\to t+12}$	(4) $R_{t\to t+36}$
$\mathcal{U}_{t\to t+1}$	-0.197	-0.484**	-2.246*	-2.216**
	(0.169)	(0.212)	(1.247)	(0.894)
$d-p$	2.350**	5.490***	28.952***	36.681**
	(1.045)	(2.019)	(7.410)	(14.889)
Republican President	-0.897**	-1.617**	-5.578**	-9.919
	(0.357)	(0.639)	(2.441)	(6.874)
Republican House	1.462**	3.154***	19.682***	24.346**
	(0.658)	(1.213)	(5.179)	(10.330)
Republican Senate	0.903**	1.325*	4.140	2.827
	(0.442)	(0.795)	(3.101)	(5.865)
smb*	-0.437	-0.442	-2.837	12.728
	(0.787)	(1.533)	(5.825)	(11.027)
hml*	0.467*	0.613	3.710**	6.925
	(0.278)	(0.477)	(1.777)	(4.435)
R^{oil}	0.925	2.663	-10.572	-7.796
	(2.491)	(3.993)	(8.468)	(9.615)
Constant	10.406***	22.849***	120.568***	180.340***
	(3.419)	(6.549)	(24.477)	(42.521)
Observations	715	715	715	691
Adjusted R^2 %	1.370	3.120	16.020	44.960
Sample	1959m6-2018m12	1959m6-2018m12	1959m6-2018m12	1959m6-2016m12

Note: This table presents results from the return predictability regressions using energy related U.S. executive orders. The econometric model is: $R_{t\to t+k} = a + b \times \mathcal{U}_t + \gamma X_t + \epsilon_{t\to t+k}$ where $R_{t\to t+k}$ is the cumulative log return between month t and $t+k$. Newey West standard errors for k lags reported in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Estimation sample of the predictability regression is 1959m6 to 2018m12.

Table 10: Consumption growth regressions - Complete Information Set

$$g(\theta) = \frac{1}{T}\sum_t \left\{ \begin{matrix} \ln\left(\frac{c_{t+k}}{c_t}\right) - \gamma_0 - \gamma_1 \mathcal{U}_{t\to t+1} - \gamma_2 R_{t\to t+k} - \gamma_3 \text{term}_t \\ R_{t\to t+k} - \delta_0 - \delta_1 (d-p)_t - \delta_2 \text{term}_t - \delta_3 \text{def}_t \end{matrix} \right\} \times \text{Instruments}_t = 0$$

	(1) $\ln\left(\frac{c_{t\to c+12}}{c_t}\right), R_{t\to t+12}$	(2) $\ln\left(\frac{c_{t\to c+36}}{c_t}\right), R_{t\to t+36}$	(3) $\ln\left(\frac{c_{t\to c+60}}{c_t}\right), R_{t\to t+60}$	(4) $\ln\left(\frac{c_{t\to c+72}}{c_t}\right), R_{t\to t+72}$
γ_0	5.86***	17.07***	29.65***	36.23***
	(0.17)	(0.49)	(0.80)	(0.96)
γ_1	0.74***	1.28***	1.42***	1.21***
	(0.15)	(0.36)	(0.44)	(0.38)
γ_2	-0.61***	-2.67***	-4.77***	-5.87***
	(0.07)	(0.20)	(0.31)	(0.36)
γ_3	0.06***	0.12***	0.12***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)
δ_0	344.25***	342.41***	449.26***	477.57***
	(21.72)	(15.00)	(16.71)	(16.18)
δ_1	85.72***	83.01***	109.85***	114.58***
	(5.69)	(3.85)	(4.48)	(4.43)
δ_2	14.22***	16.35***	19.42***	18.65***
	(1.23)	(0.94)	(1.12)	(1.20)
δ_3	-38.87***	-27.41***	-22.63***	-23.65***
	(3.79)	(2.69)	(2.41)	(2.19)
Observations	672	648	624	612
Sample	1962m1-2017m12	1962m1-2015m12	1962m1-2013m12	1962m1-2012m12
Hansen's J	190.33	222.96	251.24	257.91
p-value	0	0	0	0

Note: Parameters $\theta = \{\gamma_0, \gamma_1, \gamma_2, \gamma_3, \delta_0, \delta_1, \delta_2, \delta_3\}$ minimize $g(\theta)' I g(\theta)$ and Instruments: Constant, $\mathcal{U}_{t\to t+1}$, term, $d-p$, def. And, I is the identity matrix. This table presents results from the return and consumption growth predictability regressions using energy related U.S. executive orders. The econometric model estimates via GMM the following equations: $R_{t\to t+k} = \delta_0 + \delta_1 X_t + \epsilon_{t\to t+k}$ and $\ln(c_{t+k}/c_t) = \gamma_0 + \gamma_1 \mathcal{U}_t + \gamma_2 R_{t\to t+k} + \gamma_3 X_t + \upsilon_{t\to t+k}$ where $R_{t\to t+k}$ is the cumulative log return between month t and $t+k$. $\mathcal{U}_t = \sqrt{\hat{p}_t(1-\hat{p}_t)}$ is the conditional volatility of random variable Y_t conditional on information set $I_{t-1} = \{R_{m,t-1}, wti_{t-1}, R^{oil}_{t-1}\}$, X_t is a vector of controls including the log dividend to price ration $d-p$, the term structure (term), the default spread (def). $\ln(c_{t+k}/c_t)$ is the growth on consumption between month t and $t+k$ measured as the personal consumption expenses. Newey West standard errors for k lags reported in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Estimation sample of the predictability regression is 1980m1 to 2018m12.

Table 11: Cross-sectional return regressions - Complete Information Set

	Size and Book-to-Market				
	(1)	(2)	(3)	(4)	(5)
μ_{mktrf}	0.007***	0.006***	0.006***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
γ_{mktrf}	2.301*	2.609*	4.786**	5.182***	8.620***
	(1.359)	(1.507)	(1.941)	(1.741)	(2.290)
μ_{smb}		0.001	0.001		
		(0.001)	(0.001)		
γ_{smb}		2.575	5.586**		
		(2.080)	(2.587)		
μ_{hml}		0.003**	0.003**		
		(0.001)	(0.001)		
γ_{hml}		3.941	0.806		
		(2.496)	(5.442)		
μ_{cma}			0.285***		
			(0.091)		
γ_{cma}			0.046		
			(0.105)		
μ_{rmw}			0.341***		
			(0.107)		
γ_{rmw}			0.107**		
			(0.046)		
μ_{me}				0.002	0.002
				(0.001)	(0.001)
γ_{me}				5.977***	10.443***
				(2.167)	(2.761)
μ_{ia}				0.003***	0.003***
				(0.001)	(0.001)
γ_{ia}				9.064**	2.380
				(4.349)	(5.291)
μ_{roe}				0.005***	0.006***
				(0.001)	(0.001)
γ_{roe}				11.250***	-3.314
				(4.259)	(6.553)
μ_{eg}					0.008***
					(0.001)
γ_{eg}					42.471***
					(14.441)
μ_{pol}	0.492***	0.491***	0.492***	0.489***	0.484***
	(0.041)	(0.041)	(0.043)	(0.043)	(0.043)
γ_{pol}	-1.525***	-1.429***	-1.079***	-0.898**	-0.890**
	(0.413)	(0.461)	(0.401)	(0.385)	(0.423)
Observations	468	468	468	468	468
MAE %	.26	.15	.12	.11	.09

Note: This table presents results from estimating the price of risk in expected return - covariance form by extending the CAPM model, Fama and French three and five factor models, and the q^4 and q^5 models. Estimations are performed via GMM in which factor loadings (covariances) and covariance prices of risk are estimated jointly. Factors smb, hml, cma, rmw, correspond to the Fama and French factors related to size, book-to-market, investment and profitability. Factors, me, ia, roe, and eg, correspond to factors related to size, investment, profitability, and expected investment growth. Factor pol corresponds to the innovations to energy policy uncertainty. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Estimation sample of the cross-sectional regression is 1956m1 to 2018m12.

Table 12: Investment Cross-sectional Regressions - Complete Information Set

	(1) Inv	(2) Inv	(3) Inv	(4) Inv	(5) Inv	(6) Inv
Profitability	6.40***	3.15***	6.40***	3.15***	6.41***	3.16***
	(0.63)	(0.33)	(0.63)	(0.33)	(0.63)	(0.32)
Size	-0.09***	-0.12***	-0.09***	-0.12***	-0.09***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathcal{U}_{t\to t+1}$	738.32**	622.93**	1423.31**	1330.91**	539.05**	411.38**
	(307.96)	(274.52)	(655.34)	(641.47)	(248.13)	(202.12)
$\log(q)$	0.54***	0.62***	0.54***	0.62***	0.52***	0.60***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\mathcal{U}_{t\to t+1}$ × Size			-88.80	-91.79		
			(75.69)	(73.55)		
$\mathcal{U}_{t\to t+1}$ × $\log(q)$					502.01*	533.08**
					(285.55)	(267.26)
Constant	1.90***	2.21***	1.87***	2.18***	1.90***	2.21***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)
Observations	335541	335541	335541	335541	335541	335541
Adjusted R^2 (%)	4.35	24.41	4.35	24.41	4.36	24.42
Industry F.E.	No	Yes	No	Yes	No	Yes
From	2000m1	2000m1	2000m1	2000m1	2000m1	2000m1
To	2018m10	2018m10	2018m10	2018m10	2018m10	2018m10

Note: This table presents results from regressing investment defined as capital expenditures over total assets (Compustat Quarterly items capxy/atq × 100) on profitability, book-to-market ratio, size, energy political beta, oil beta, gas beta, and leverage. Profitability is defined as net operating income after depreciation as a fraction of total assets (Compustat Quarterly items oiadp/atq), the book to market is defined as shareholder's equity as a fraction of market capitalization (Compustat quarterly items seq/(prccq × cshoq)), The beta from energy is computed using a 60 month rolling window of running firm's returns on the market return and innovations on the energy political uncertainty measure. $R_{it} = a + bR_{mt} + \beta^{energy}\Delta\mathcal{U}_t + \epsilon_{it}$ where R_{mt} is the return on the CRSP Value Weighted Market Portfolio, and $\Delta\mathcal{U}_t^{energy}$ is the innovation on the conditional variance of the stochastic process defined as 1 if there is at least one executive order in a month and zero otherwise. The innovation is computed as the residual of regression $(p_{t+1} - p_{t+1}^2) = \phi_0 + \phi_1(p_t - p_t^2) + \nu_t$. Oil beta β^{oil} is defined as the slope of regressing firm returns on the market return and the West Texas Intermediary monthly return using a 60 month rolling window. $R_{it} = a + bR_{mt} + \beta^{oil}R_t^{oil} + \epsilon_t$. Gas betas are computed using the return on the monthly Henry Hub Natural Gas Spot price $R_{it} = a + bR_{mt} + \beta^{oil}R_t^{gas} + \epsilon_t$, Leverage is computed as total debt = Compustat Quarterly items (dlcq+dlttq) over total debt plus market equity (prccq × cshoq). Oil and gas prices come from the Federal Reserve Economic Data at St. Louis. Clustered standard errors at the month level reported in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.