NAVIGATING UNCERTAINTY

A STUDY ON THE IMPACT OF POLICY UNCERTAINTY ON STOCK RETURNS, FIRM INVESTMENT, AND INVESTOR SENTIMENT IN THE UNITED STATES

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Navigating Uncertainty: A Study on the Impact of Policy Uncertainty on Stock Returns, Firm Investment, and Investor Sentiment in the United States

Abstract:

We investigate how US policy uncertainty is related to US stock returns, firm investments, and investor sentiment - in order to shed light on the responses made by firms and investors when faced with higher uncertainty. Leveraging the economic policy uncertainty index, we find that policy uncertainty is negatively correlated with US stock returns in the same month following a shock to uncertainty, and propose evidence that points towards policy uncertainty potentially being a source of return predictability in the US. Our results also point towards policy uncertainty having effects on the demand for downside protection by looking at how investors respond to shocks in uncertainty, but find no conclusive evidence regarding its effects on market wide investor sentiment. We find a delayed and negative impact on firm investment, implying that policy uncertainty could have an impact on firms' investment decisions as they defer investments in favor of waiting for more information.

Keywords:

Economic policy uncertainty, US stock returns, firm investments, investor sentiment

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1 Introduction

The United States' economic and political landscape has been surrounded by a great deal of uncertainty during the past decades. The global financial crisis in 2008, the 2011 debt-ceiling dispute, turbulent elections, Covid-19, and the recent signs of deteriorating trust in the banking system following the collapse of Silicon Valley Bank, are all examples of events that have had an adverse effect on the predictability of future policy action. Events like these trigger a need for political intervention, highlighted by actions such as the resulting bailouts of the 2008 crisis or lockdowns and extreme quantitative easing following Covid-19. Such interventions or policy decisions are often surrounded by major uncertainty regarding both the direction and magnitude of government action. The dramatic run-up to the 2016 presidential election is a good example, illustrating how the future direction of US policies and trade relations was dependent on the outcome of a highly uncertain election. This uncertainty made its mark on financial markets leading up to the election, and on the day following the final result, the chief strategist at a large US broker was quoted by CNBC saying “Overnight was all about uncertainty. Today we know” when commenting on the 250-point surge in the Dow after Trump’s victory (Imbert and Cheng, 2016).

This unpredictability in policy action has arguably been further amplified by the nature of the US political system, which has several times been characterized by partisan gridlock and political polarization. The current state makes it inherently difficult to reach a consensus on major policy decisions and can lead to delays, inaction, or uncertainty regarding said policies. For instance, the 2011 debt-ceiling dispute resulted in a downgrade of the US credit rating by Standard & Poor's, which fueled uncertainty in the market. Currently, in May 2023, there is another debt-ceiling dispute looming, with the US Secretary of Treasury, Janet Yellen, warning that the US may run out of cash by the beginning of June (Debusmann, 2023). Understanding the consequences of ambiguity in economic policy on financial markets is crucial for policymakers, as it can have real economic- and financial implications. Likewise, from an investor perspective, it is without a doubt important to understand the various factors that affect financial markets.

Blattner, Catenaro, Ehrman, Strauch, and Turunen (2008) stress the importance of predictability in monetary policy particularly, and the dire effects of uncertainty on inflation, asset pricing, and overall economic welfare. The authors highlight four potential sources of information asymmetry which impair predictability in policy actions. First, private market participants may not be fully aware of the central bank’s objectives, making it hard to predict the timing and direction of policy decisions. Following this, it becomes hard to deduce whether a certain policy decision is a result of changes in objectives or rather due to changes in the economic outlook of the central bank, or both. Second, market participants may not be fully aware of which indicators, and third, how these indicators are being interpreted by central bankers. Finally, there may be general uncertainty regarding the workings and construction of monetary policy. These four sources rely on the level of transparency and method of forward guidance that central banks employ, meaning uncertainty does not necessarily stem from agents’ own lack of predictability regarding economic variables (such as inflation), but also from the level of efficiency in communication and transparency between market participants. Important to highlight is that this insight is not restricted to central banks and monetary policy but could very well be generalized to cover other government bodies constructing different types of policy as well. Policymakers do not only have to consider the direct effects of their policy decisions but also how they manage expectations, as it affects each actor’s ability to accurately forecast and assign probabilities to future outcomes. This predictability has, according to the authors, implications on both macroeconomic variables but also consequences for asset pricing, capital allocation, and the size of uncertainty-related risk premiums in financial markets.

The bulk of prior research on the topic of uncertainty has been dedicated to studying the macroeconomic implications of policy uncertainty (e.g., Bloom, 2009; Bachmann, Elstner, and Sims, 2013; Jones and Olson, 2013), or its effect on real investments. Bernanke (1983) made important contributions to the uncertainty literature by considering the effects of uncertainty on firm investments through the lens of real options theory. In his paper, he provides a theoretical framework that shows how the implicit real option value associated with deferring irreversible investments in favor of waiting for more information increases with uncertainty. Such theory would imply that firms are more cautious when making investment decisions in periods of high uncertainty, which we will test empirically in this paper. Even though the vast majority of the literature has focused on the effects of uncertainty on macroeconomic variables and real investment, there is a growing body of literature dedicated to the relationship between policy uncertainty and financial markets.

Progress in the studies of policy uncertainty and its implications for firms and financial markets was made when Baker, Bloom, and Davis (2013) developed and published the economic policy uncertainty index, a method to measure and quantify policy uncertainty.[1] Later, Baker, Bloom, and Davis (2016) show that firms with more exposure to government purchases face higher stock price volatility, lower investments, and lower employment growth when policy uncertainty is higher. Specifically, they find that firms within the defense, healthcare, and financial sectors are particularly sensitive to changes in uncertainty.

After Pástor and Veronesi (2013) published their theoretical contributions on uncertainty and its effects on financial markets, more empirical research has been published to test the validity of their theoretical findings. Pástor and Veronesi's equilibrium model presents several interesting predictions for how stock markets react to what they refer to as "political uncertainty".[2] The main findings of their model and brief empirical work are that higher political uncertainty leads to increased volatility of returns and higher correlation among stocks. Political uncertainty also demands an equity risk premium. All of these effects are further predicted to have a stronger impact during worse economic conditions. They manage to find some empirical evidence to support the predictions of their model, however, the bulk of empirical work comes from other sources.

Kelly, Pástor, and Veronesi (2016) continue on the path of empirical research on the topic and study how uncertainty during national elections and global summits impacts option pricing. Their empirical findings imply that options whose duration span major political events on average are more expensive (around 5.1%) compared to neighboring options not spanning such events, suggesting that political uncertainty is priced into the options market. They also find that the value of option protection against price risk, tail risk, and variance risk is higher during less favorable economic conditions (one-month at-the-money options are 8% more expensive during weak economic times compared to only 1% more expensive during favorable economic conditions).

Brogaard, Dai, Ngo, and Zhang (2020) study the cross-border implications of global political uncertainty surrounding US presidential and midterm elections and find that equity returns in non-US markets on average fall during the period leading up to a US election.

This paper aims to expand the scope of empirical research on the broad topic of policy uncertainty and its implications for firms, investors, and financial markets. With the focal point being on stock returns in particular, our results will also provide answers to questions regarding

[1] The index, underlying data, and more information about the index and its authors is available at www.policyuncertainty.com

[2] Political uncertainty in their study is focused on the uncertainty regarding future government policies. We consider this to be equivalent to the term "policy uncertainty" which we will use throughout this paper.

market efficiency in periods of doubt and the return predictability of economic policy uncertainty. To gain such insights, the bulk of this paper will be dedicated to studying how policy uncertainty directly impacts (i) stock returns, (ii) firm investments, and (iii) investor sentiment.

1.1 Research question and hypotheses

While our work largely serves as an extension of the work carried out by the researchers cited above, our targeted focus on empirically investigating the implications and predictive power of policy uncertainty on US stock returns allows us to explore the following question.

How, and to what extent, does economic policy uncertainty impact stock returns?

We do this by addressing and investigating the credibility of the following hypotheses:

> H1: Changes in policy uncertainty adversely impact realized stock returns and can be used to predict future stock returns.

One of the key predictors of Pástor and Veronesi's (2013) theoretical model is that political uncertainty commands a risk premium. They proceed to conduct some simple empirical analysis but find, at best, modest support for that prediction when considering the 3-, 6-, and 12-month market excess return. We aim to expand on their empirical analysis through the use of a larger dataset with firm-level stock returns and a decade of additional return- and uncertainty data. As previously mentioned, during the past decade, the US has been subject to major uncertainty shocks which further validate the relevance of this analysis. Beyond testing for any potential predictive power of policy uncertainty on future returns, we also test the hypothesis that a positive change in policy uncertainty is associated with lower returns for the same month.

The rationale for our hypothesis is based on Pástor and Veronesi's (2013) theoretical equilibrium model, and subsequent research on the topic (e.g., Brogaard and Detzel 2015; Brogaard et al. 2020; Kelly et al. 2016). Further, it is reasonable to suggest that portfolio managers and investors, when faced with a shock in policy uncertainty, adjust their beliefs regarding the future performance of firms and the perceived risk of financial investments. Here we argue, in line with most of the prior research, that an increase in policy uncertainty generally leads to expectations of weaker firm performance and increased risk.

> H2: These effects are more prominent during times with less favorable economic conditions.

Pástor and Veronesi's (2013) theoretical model mentioned above also predicts that the impact of political uncertainty is more prominent during times with less favorable economic conditions. However, regarding the potential risk premium they also discuss the value of a potential put protection stemming from the government's tendency to intervene and support financial markets in economic downturns. Naturally, the theoretical framework suggests that the value of this protection is higher with worse economic conditions as the potential government intervention (i) becomes more likely, and (ii) becomes more valuable to match the severity of the downturn. The financial crisis of 2008 and the Covid-19 pandemic provide good illustrations of how the government provides put protection for financial markets. In 2008, failing banks were bailed out to prevent a collapse of the financial system, while in 2020, extensive fiscal and monetary policies were implemented to mitigate the impact of the pandemic on the economy and support financial markets. In both situations, the Federal Reserve carried out large programs of quantitative easing to inject liquidity into financial markets and facilitate economic recovery.

Rational investors should consider the value of this government put protection when pricing stocks which could reduce the risk premium in less favorable economic conditions, according to Pástor and Veronesi (2013). During economic downturns, the aforementioned put protection depresses the equity premium, whereas policy uncertainty has the opposite effect. However, it is unclear to them what force should prevail as it is entirely dependent on the parameters in their theoretical model.

We argue that amidst challenging economic circumstances, a shock to policy uncertainty would have the same impact as in H1, but stronger due to the economic circumstances. Our hypothesis builds on the assumption that a shock to policy uncertainty negatively impacts the expected value of the put protection as the probability of protective government policy should decrease when policy uncertainty is higher. To illustrate, imagine a state with no uncertainty where investors are perfectly informed about the put protection provided by the government. In such a state, investors would account for the fact that they, to some degree, are protected against downside risk. When policy uncertainty grows, investors can no longer assume the same protection and will adjust their required return accordingly. Hence, as the put protection is more valuable during recessions, we hypothesize that policy uncertainty shocks during periods of economic downturn will have a greater effect on stock returns, compared to times of strong economic conditions.

H3: Changes in policy uncertainty negatively impact firm investments, and

H4: Changes in policy uncertainty negatively impact investor sentiment.

In their recent paper, Brogaard et al. (2020) suggest that uncertainty surrounding US elections can influence equity returns through two fundamental channels; (i) expected cash flows, and (ii) discount rates (expected returns). They find evidence supporting the discount rate channel as the main driver of the lower returns leading up to elections. We adopt a similar framework by investigating how uncertainty affects two underlying components that could have an impact on stock returns, namely (i) firm investments, and (ii) investor sentiment. However, our analysis is grounded in a more action-based perspective, meaning we want to study how policy uncertainty impacts actual, put-into-action, investment decisions among firms and investors. One key reason why such a perspective is useful is because it yields actionable insights into the tangible, real-world consequences of policy uncertainty, rather than merely focusing on theoretical constructs. Important to note, however, is that both of these hypotheses are theoretically motivated by established finance- and economic research.

The investment-driven effect can be intuitively motivated by considering that each irreversible investment opportunity gives rise to a real option to defer investments in favor of waiting for more information, and has an inherent *option value* that increases with uncertainty. Bernanke (1983) makes the case that, assuming NPV-maximization (risk-neutrality), the expected value of "bad news" (e.g., an unfavorable policy change) determines the option value of deferring an irreversible investment decision and waiting for new information. In simple terms, the benefits of deferring an investment are higher when uncertainty regarding parameters impacting the outcome is high. In periods with perfect information, firms will always choose to invest in projects with the highest NPV due to the option value being zero, but as uncertainty increases so does the value of the real option. If the investment is made, the opportunity cost is represented by the option value at the time of the investment decision, which is zero with perfect information and increases with uncertainty. Assuming that firms only invest in NPV-positive projects, deferring investments pushes cash flows further into the future, which has an adverse effect on their present value.

The sentiment-driven component is theoretically motivated by considering the notion that in an efficient market, investor sentiment, defined as beliefs about cash flow and risk that are not justified by firm fundamentals, should not impact security prices (Baker and Wurgler, 2006, 2007). However, Baker and Wurgler (2006), as well as Huang, Jiang, Tu, and Zhou (2015) find evidence that different measures of investor sentiment can be used to predict stock returns, following the theory that investors make overly optimistic (pessimistic) judgments during times with positive (negative) investor sentiment. This challenges the efficient market hypothesis and poses some questions regarding the rationality of investors. On the topic of rationality, it is reasonable to presume that uncertainty distorts investors' ability to forecast probability distributions (Knight 1921), making it inherently difficult to assess the risk and fair market price of securities accurately, and thus inhibits the ability to make rational investment decisions. Birru and Young (2022) find that when uncertainty is higher, and valuations more subjective, investor sentiment has a significantly larger ability to predict stock returns.

The focus in prior literature has been to study the relationship between sentiment and stock returns, as well as the amplifying effect of uncertainty. The prior literature does not, however, consider a potential direct connection between uncertainty and investor sentiment, leaving a gap in the literature that we deem important to study. Our hypothesis on this relationship is simple. Policy uncertainty creates ambiguity, impairs forecasting capabilities, and reduces investor confidence. These factors, among others, should have an adverse effect on investor sentiment which presumably translates to more pessimistic trading patterns.

1.2 Overview and preliminary findings

To proxy for policy uncertainty, we follow a method commonly adopted in prior literature and use the Economic Policy Uncertainty index (EPU-index) developed by Baker, Bloom, and Davis (2013). To test the first hypothesis, we begin by regressing firm level monthly log-returns on the log-transformed percentage change in the EPU-index. We find that changes in the index are negatively and significantly correlated with monthly realized log-returns. When including lags, we also find suggestive evidence that increases in the EPU-index significantly and negatively predict log-returns for the next month, and positively predict log-returns 3, 4, and 5 months ahead. This could imply that an increase in EPU induces lower realized returns today and subsequently higher expected returns in future periods.

To test for the second hypothesis, we incorporate variables indicating the state of the economy into our model. By leveraging a recession indicator and the Chicago FED National Activity Index, our results suggest that the impact of policy uncertainty shocks on log-returns is amplified during recessions and during periods when the economy is growing below trend. The final part of our main empirical analysis examines whether changes in EPU trigger a response when it comes to firm-level investments and shifts in investor sentiment. To proxy for investor sentiment, we utilize both the Total Exchange Put/Call Ratio from CBOE, and the sentiment index developed by Baker and Wurgler (2006). Our findings on capital expenditures are somewhat ambiguous but points toward policy uncertainty having a delayed negative effect on capital expenditures, significant at the two-quarter lag. Our analysis of investor sentiment suggests that there is a negative relationship between policy uncertainty and the Put/Call Ratio. However, we find no significant relationship between Baker and Wurgler's (2006) investor sentiment and the EPU-index.

After finding preliminary results suggesting that uncertainty might have an impact on US stock returns and firms on an aggregated level, we proceed to study if this impact takes different shapes depending on the industry, based on the theory that the relationship is not heterogeneous.

The paper is divided into 7 sections and is organized as follows. Section 2 explains our data and descriptive statistics. Section 3 describes the empirical framework used to investigate our research question and hypotheses and section 4 presents the results. Section 5 discusses the results, while section 6 presents a short industry analysis and tests the external validity of our results. Section 7 concludes.

2 Data and descriptive statistics

Our main set of data consists of monthly stock returns and various firm characteristics for stocks listed on the New York Stock Exchange (NYSE) during 1985-2022, available through Compustat via WRDS. For convenience and to eliminate any potential issues with outliers and stocks with low trading volumes we limit our dataset to only include securities with at least USD 2bn in market cap. We exclude extreme outlier returns from our dataset. All firm-level accounting data is gathered from Compustat. The Subsequent list includes 2,535 mid- and large-cap stocks for a total period of 456 months and contains both live as well as dead stocks to ensure that the data is free of survivorship bias.

Components of the Fama-French three-factor model are downloaded from Kenneth French's website. To proxy for stock market volatility, we use the VIX index, available from 1990 via the Chicago Board Options Exchange (CBOE). As the VIX is only available from 1990 and onwards our final dataset is limited to only include monthly observations since 1990.

To capture the policy uncertainty, we follow Pástor and Veronesi (2013), and several others, using the Economic Policy Uncertainty index developed by Baker, Bloom, and Davis (2013). The US index is available with a monthly frequency from 1985 until the present. The index is constructed through a weighted average of three underlying components designed to measure policy uncertainty. The first component quantifies the coverage of policy-related uncertainty in 10 large US newspapers, using a keyword search method for words related to policy uncertainty. The other two components measure disagreement among forecasters regarding the US economic outlook, such as inflation and government spending, and the total number of US federal tax codes that are due to expire within the next ten years. Data on the disagreement between economic forecasters are drawn from the Philadelphia FED survey of professional forecasters. Since the start of the US index, there have been spikes in the EPU-index around major US political events and economic turbulence. These events include the Dot-com crash, the global financial crisis of 2007-08, the 2011 debt-ceiling dispute, and recently the Covid-19 pandemic and subsequent lockdowns.

We identify a few advantages in using this measure for policy uncertainty above other methods used in prior literature (such as global elections or summits), partly following the reasoning of Brogaard and Detzel (2015). First, the EPU-index provides a continuous measure of policy uncertainty. With historical data from 1985, combined with the consistent methodology used to construct the index, this approach yields a more nuanced and consistent measure that does not rely on the assumption of homogeneity regarding the level of uncertainty between isolated political events. The EPU-index has been used to identify statistical relationships in prior literature, which we deem strengthens its validity and speaks of its predictive power. Further, during the construction of the index, Baker, Bloom, and Davis conducted an extensive audit including 12,000 randomized newspaper articles, and find a 0.93 correlation between the human- and computer-generated indexes. However, the index cannot be seen as entirely uncontroversial. Kelly et al. (2016) mention the inherent difficulties in isolating exogenous variation in uncertainty. It is, for instance, not impossible to imagine that major stock market events such as the 1987 "Black Monday" or 2010 "Flash Crash" can trigger responses in the EPU-index, and not just the other way around. We also recognize that the index may be a source of collinearity between itself and other variables within our models. Furthermore, its strong dependence on news media could potentially bias the index due to *uncertainty* being an attention-inducing media buzzword. However, given the widespread use of the index and the robust method used to construct it, our stance is that the EPU is an adequate proxy of policy uncertainty for this paper.

To measure the state of the US economy we will rely on the monthly recession indicator published by the St. Louis FED (FRED) and the Chicago Fed National Activity Index

(CFNAI), which comprises 85 different measures of economic activity in the U.S. These measures can be divided into four broad categories: Employment, Industrial Production, Personal Consumption, and Manufacturing and Trade Sales. The index is designed to show deviations from the expected growth trend on a monthly basis and is structured so that a value of 0 indicates that the economy is growing in line with the trend. The St. Louis FED recession indicator is an interpretation of data released by the National Bureau of Economic Research (NBER). The recession indicator is expressed in the form of a dummy variable, returning a value of 1 in recessionary periods. NBER defines a recession as "a significant decline in economic activity that is spread across the economy and that lasts more than a few months". Albeit the lack of specificity in this definition, we deem it to be sufficient for this paper, especially since the indicator is consistent, commonly used, and easily accessible. Since the start of the EPU-index in 1985 there have been 40 months of recession in the US, spread across different periods: The 1990-91 recession, the Dot-com bubble burst, the global financial crisis, and the short 3-month recession during the start of the Covid-19 pandemic.

For the second part of our analysis, we also include the volume-based Total Exchange Put/Call Ratio to measure market wide investor sentiment. The Put/Call Ratio gives an intuitive and simple interpretation of overall sentiment on financial markets and is calculated by dividing the trading volume of put options by the volume of call options in a given period, yielding a ratio that signals whether investors are bearish (buying puts) or bullish (buying calls) given the current market conditions. The data is publicly available via CBOE and dates back to September 1995. As the Put/Call Ratio is published with daily frequency we manually calculate a monthly average to match the structure of the EPU-index. Furthermore, to address concerns stated in prior literature regarding the ability to construct a reliable measure of investor sentiment, we also use the composite sentiment index constructed by Baker and Wurgler (2006, 2007), henceforth denoted as the BW-index. This index is available on Jeffrey Wurgler's website, and the data covers our entire sample period with monthly frequency.[3]

The data on firm level capital expenditures (CAPEX) used in the later stage of our analysis is available with a quarterly frequency via Compustat. Since the data is only reported on a YTD basis, we manually calculate the isolated quarterly capital expenditures.

To ensure consistency in our subsequent empirical analysis, before moving on we remove all observations with one or more missing values. Summary statistics are reported in Table 1. In Table 2 (see Appendix 1.A), we show summary statistics for the four periods of recession that are included in our sample period. Figure 1 (Appendix 1.B) plots the economic policy uncertainty index with recessions shaded in red.

[3] The data is available at https://pages.stern.nyu.edu/~jwurgler/

Table 1: Descriptive Statistics

Variable	Mean	Median	St.Dev	Min	Max
Return (%)	1.29	1.13	11.25	-84.24	153.28
EPU	115.18	107.10	39.84	57.20	350.46
Put/Call ratio	0.86	0.88	0.16	0.44	1.21
CFNAI	-0.04	0.02	0.67	-7.35	4.44
VIX	19.77	18.16	7.62	9.51	59.89
CAPEX	114.24	18.73	395.76	-4,871.00	11,613.00
ROCE	0.13	0.14	5.50	-1,569.18	105.21
D/A	0.28	0.26	0.21	0.00	4.48

This table represents summary statistics for our variables of interest (return, instead of log returns for illustration purposes). Returns are monthly returns of all stocks listed on NYSE during 1990-2022. EPU is the Economic Policy Uncertainty Index by Baker, Bloom and Davis (2013), Put/Call ratio is the total exchange volume based put options divided by call options from CBOE. CFNAI is the 3 month moving average of the Chicago Fed National Activity Index, VIX is the S&P 500 implied volatility. CAPEX is the quarterly capital expenditures is millions of USD. ROCE and D/A is the firm level return on capital employed and debt-to-assets respectively.

3 Empirical method

3.1 H1: Policy uncertainty and stock returns

The main dependent variable in our core model is the monthly realized log returns for the stocks in our sample. To then investigate the relationship between policy uncertainty and stock return we run several different linear regressions, beginning with a simple OLS.

$$Log\ Return_{i,t} = \beta_0 + \beta_1 Log\ \Delta EPU_t + \beta_2 X_{i,t} + \varepsilon_{i,t} \quad (1)$$

Where *Log Return*$_{i,t}$ is the natural logarithm of firm-specific monthly stock returns, and *Log* ΔEPU is the natural logarithm of the monthly percentage change in the economic policy uncertainty index. The reason for using *Log* ΔEPU is to avoid issues with non-stationarity and eliminate the presence of a unit root within the EPU time series. Using the EPU index in this way is preferred and supported by the results from an Augmented Dickey-Fuller test where we can reject the null hypothesis of the presence of a unit root at the 1% level. Furthermore, KPSS tests on both versions of the EPU confirm the results, where we fail to reject the null hypothesis of stationarity for ΔEPU, but not for the raw index. This method of transforming our time series is also consistent with the way we treat stock data, i.e., using stock returns instead of monthly closing prices to induce stationarity. The way we treat the EPU-index differs from some of the other approaches seen in prior literature on the topic. For example, Pástor and Veronesi (2013) uses the raw values of the index but scales it down by a factor of 100.

Gulen and Ion (2016) suggest that using the change in the EPU-index is more appropriate when attempting to answer the question of how firms are affected by short-term shocks to policy uncertainty. While they opt to use the level of uncertainty rather than the change in EPU (for reasons specific to their investigation on capital expenditures), we are interested in studying how investors and firms react to uncertainty shocks. Hence, the change in the EPU-index appears to be an appropriate independent variable for our purposes. Further, our view is that our approach reduces the risk of spurious regressions and biased estimators caused by non-stationarity issues in our time-series variables.

The variable $X_{i,t}$ is a vector of control variables containing the three-month moving average of the Chicago Fed National Activity Index (CFNAI), the natural logarithm of the monthly percentage change in the implied volatility series on the S&P 500 (Log ΔVIX), and the components of the Fama-French 3-factor model (SMB, HML, R_m-R_f). To capture the effects of firm-specific characteristics on stock returns we also include control variables for profitability (*ROCE*) and leverage (*D/A*).

To account for heterogeneous effects stemming from unobservable firm characteristics that could also impact the monthly realized log returns for each stock in our sample, we extend the model to include fixed effects on the firm level. Due to the structure of our data, where our main variable of interest and the majority of controls are constant across each entity in the cross-section but vary over time, we do not add any time-fixed effects - as these effects would mechanically absorb the potential explanatory power of the EPU-index. Following Gulen and Ion (2016) we instead control for macroeconomic factors via the CFNAI. For robustness, we compute Huber-White heteroskedasticity-robust standard errors. Equation (2) shows the final regression equation, where α_i captures firm-specific fixed effects. Complete outputs of all tests are reported in Table 3.

$$Log\ Return_{i,t} = \beta_0 + \beta_1 Log\ \Delta EPU_t + \beta_2 X_{i,t} + \alpha_i + \varepsilon_{i,t} \quad (2)$$

3.2 H1: Predictability of stock returns

The second part of our first hypothesis is that policy uncertainty should positively predict future returns as investors sell stock in response to an increase in policy uncertainty, driving down prices and increasing expected returns. To address this question, we construct a set of lagged variables of the EPU-index which we incorporate into our model. Deciding on the number of lags to consider is somewhat discretionary and different methods have been applied in the literature. Pástor and Veronesi (2013) opted for a 3, 6, and 12-month lag. Brogaard and Detzel (2015) considered 1–3-, 6-, and 12 months. For this paper, the main focus is on the short-term effects on stock returns, and we hence opt to consider 1–6 months of lag in the EPU index. This decision is further supported by the high volatility in the index with spikes persistent only for a short number of periods, as illustrated in Figure 1.

When testing the predictability of the EPU-index on stock return we run regressions with the following specifications

$$Log\ Return_{i,t} = \beta_0 + \beta_1 Log\ \Delta EPU_{t-k} + \beta_2 X_{i,t} + \alpha_i + \varepsilon_{i,t} \qquad (3)$$

Where $Log\ \Delta EPU_{t-k}$, denotes the monthly percentage change in the EPU-index by Baker, Bloom, and Davis (2013), and $k \in \{1,2,3,4,5,6\}$ indicating the number of lags. $X_{i,t}$ denotes the vector of control variables used in equation (1). Similar to equation (2), we include firm level fixed effects.

3.3 H2: Policy uncertainty and adverse economic conditions

To test for the second hypothesis, that policy uncertainty has a larger impact during worse economic conditions, we run a similar fixed effects regression as above but include an interaction term between *Log ΔEPU* and two indicators on the state of the economy.

$$Log\ Return_{i,t} = \beta_0 + \beta_1 Log \Delta EPU_t E_t + \beta_2 X_{i,t} + \beta_3 Log \Delta EPU_t + \beta_4 E_t + \alpha_i + \varepsilon_{i,t} \qquad (4)$$

E_t is the indicator of economic activity, either the monthly recession indicator published by the St. Louis FED or the three-month moving average of the Chicago Fed National Activity Index. *Log ΔEPU* is the same as in equation (1). $X_{i,t}$ is the vector of the same control variables as in equation (1). For the regression that includes the interaction effect, we exclude the CFNAI-variable from the set of control variables, as it is already present in E_t.

The recession indicator is a dummy variable that takes the value of 1 during recessions and 0 otherwise. Since higher values of the recession dummy indicate less favorable conditions, and higher values of *Log ΔEPU* indicate an increase in uncertainty, our hypothesis is that $\beta_1 < 0$.

For the interaction with CFNAI, we use a slightly different specification to make the interaction term easier to interpret. As both the CFNAI and *Log ΔEPU* can take on negative and positive values the interpretation of the β-coefficient would become very ambiguous.[4] To avoid this ambiguity and make the coefficient easier to interpret we use log-EPU instead of *ΔEPU* in equation (4). As positive values of CFNAI indicate a stronger economy and negative values indicate a weaker economy our hypothesis is that $\beta_1 > 0$.

[4] For example: in a strong economy (CFNAI > 0) and with decreasing EPU ($\Delta EPU < 0$), the interaction term would be < 0 and we would expect positive returns (meaning, $\beta < 0$). However, in a weak economy (CFNAI < 0) and with increasing EPU ($\Delta EPU > 0$), the interaction term would also be < 0 but we would expect negative returns (meaning, $\beta > 0$).

3.4 H3: Policy uncertainty and firm investments

For our purposes, firm investments are measured by using data on capital expenditures, available on a quarterly basis for the firms in our dataset. We then run the following regression.

$$CAPEX_{i,t} = \beta_0 + \beta_1 \Delta EPU_t + \beta_2 X_{i,t} + \alpha_i + \varepsilon_{i,t} \tag{5}$$

Where $CAPEX_{i,t}$ is the quarterly capital expenditures expressed in USD millions. Opting for the raw values of capital expenditures is a consequence of the structure of the capital expenditures data. As the capital expenditures in our dataset take on both negative and positive values, calculating the % change would yield inaccurate values for mathematical reasons which would impact the accuracy of our models. Another approach would be to follow Gulen and Ion (2016) and use the investment intensity (capital expenditures divided by sales). However, assuming that capital expenditures are stickier compared to sales, the dependent variable could change simply as a result of changes in sales without any conscious decision from the firm to change its investment behavior.

$X_{i,t}$ is a vector of control variables including ΔVIX, CFNAI, ROCE, and D/A. Similar to equation (2), to isolate the within-entity change in capital expenditures for the firms in our sample, we include firm fixed effects. Since the EPU-index is reported on a monthly basis compared to the quarterly CAPEX data, we adjust ΔEPU to match the frequency of reported capital expenditures. To find values that most accurately describe the uncertainty during a quarter, we argue that the mean of the EPU-index during the quarter is appropriate to use, as it represents the average level of policy uncertainty under which firms operate during a given quarter. By only considering the end-of-quarter levels of policy uncertainty, one would neglect short-term EPU shocks that may occur within each quarter, which would impair the predictive power of the model. The method of using the arithmetic mean of the EPU-index also follows prior literature on this topic (see Gulen and Ion, 2016). After calculating the quarterly mean, we proceed to compute the quarter-on-quarter change in the EPU-index, which is the ΔEPU. We expect a negative coefficient, implying that firms cut back on investments when uncertainty is higher.

It is reasonable to assume that the effects of policy uncertainty on capital expenditures are delayed rather than instant because firms may need time to gather and analyze information about policy changes, assess the potential impacts on their business, and adjust their investment plans accordingly. Furthermore, the actual investment process often involves a series of time-consuming steps, including managerial and board approval, obtaining financing, making projections, and executing the investment plan. This should result in a lag between changes in policy uncertainty and corresponding changes in capital expenditures. Hence, it is highly relevant to further investigate if policy uncertainty shocks have a delayed impact on firm investment beyond any potential impact during the same quarter.

We test for this by simply replacing ΔEPU_t with ΔEPU_{t-k} in equation (5), where $k \in \{1, 2, 3, 4\}$ and denotes the number of quarterly lags applied in the model.

3.5 H4: Policy uncertainty and investor sentiment

We proceed to investigate if the EPU-index negatively impacts investor sentiment, through the use of two different proxy variables, the Put/Call Ratio, and the BW-index. The Put/Call Ratio, as mentioned in section 2, is the total volume of put options traded, divided by the total volume of call options, which yields a simplistic but easy-to-interpret measure of how investors respond to changes in uncertainty. A value larger than 1 means that higher relative volumes of put options are being traded which could be interpreted as market wide skepticism regarding stock prices, following an increased demand for protection against downside risk.

It is to be noted that the approach of using the Put/Call Ratio has its clear limitations. Baker and Wurgler (2007) briefly discuss the difficulties in identifying a reliable and uncontroversial proxy for investor sentiment. They opt for creating a composite index based on components suggested in prior literature, the BW-index as mentioned above in section 2. To address these concerns, we run identical models with the BW-index instead of the Put/Call Ratio to see if the results are consistent when substituting the measure for investor sentiment to a more robust and less noisy proxy.

To test for the hypothesis that policy uncertainty negatively impacts investor sentiment we run the following regression.

$$Sentiment_t = \beta_0 + \beta_1 \Delta EPU_t + \beta_2 X_t + \varepsilon_t \tag{6}$$

Where $Sentiment_t$ represents both measures for investor sentiment, the Put/Call Ratio and BW-index, respectively. For this regression, the control variables included in X_t are ΔVIX and CFNAI, in the same form as previously used. Our hypothesis suggests that an increase in EPU would lead to a relative increase in the volume of traded puts, as demand for hedging against downside risk increases, hence a $\beta_1 > 0$. Conversely, the BW-index increases when sentiment is higher, which means that we would expect a negative β_1.

4 Results

The following section briefly presents the results from our empirical analysis. Further interpretations and critical reflections are presented in section 5.

4.1 Policy uncertainty and log-returns

Table 3: Policy uncertainty and log returns

	Log return			
	OLS			Fixed Effects
Model	(1)	(2)	(3)	(4)
LogΔEPU	-0.069***	-0.005***	-0.005***	-0.006***
	(-46.68)	(-4.429)	(-4.429)	(-4.545)
$(R_m - R_f)$		0.011***	0.011***	0.011***
		(177.5)	(177.5)	(177.7)
SMB		0.003***	0.003***	0.003***
		(35.20)	(35.21)	(34.90)
HML		0.005***	0.005***	0.005***
		(59.05)	(59.06)	(60.05)
LogΔVIX		0.002	0.002	0.002
		(1.519)	(1.516)	(1.533)
CFNAI		-0.001***	-0.001***	-0.001**
		(-3.607)	(-3.603)	(-3.093)
ROCE			0.000	-0.000
			(0.7354)	(-1.021)
D/A			-0.002*	-0.003
			(-2.301)	(-1.552)
Fixed-Effects:	No	No	No	Yes
Observations	258,801	258,801	258,801	258,801
R2	0.01240	0.22398	0.22400	0.23227
Within R2	–	–	–	0.22543

This table presents the regression results for the relation between changes in policy uncertainty and realized log returns. The dependent variable is monthly log returns of stocks listed on the NYSE since 1990. Our main variable of interest, LogΔEPU, is the log-transformed monthly percentage change in the Economic Policy Uncertainty Index (EPU-index) developed by Baker, Bloom and Davis (2013), where an increase in the index indicates larger uncertainty. As control variables we include: ΔVIX which is the change in S&P 500 implied volatility, $(R_m - R_f)$ which is the market excess return, SMB and HML which are the remaining two components of the Fama-French Three Factor Model, CFNAI which is the 3 month moving average of the Chicago Fed National Activity Index, ROCE which is the return on capital employed, and D/A which is the debt-to-asset ratio. Model (1) is a univariate OLS regression whereas models (2)-(3) include market-wide and firm-specific controls respectively. Model (4) includes firm-level fixed effects. T-statistics are shown in parenthesis, and calculated using Huber-White standard errors. ***, **, *, . represent significance at the 0.1%, 1%, 5%, and 10% level

The regression output in Table 3 shows the estimates and related t-statistics for our independent variables when testing their relationship with log-returns as the dependent variable for both regular OLS- and fixed effect regressions. Our model suggests a negative and significant relationship between economic policy uncertainty and log-returns - while controlling for market wide risk factors, implied market volatility, the state of the US economy, and firm-specific characteristics for profitability and capital structure, as well as firm-level fixed effects. The model suggests that a 1% increase in ΔEPU is associated with a -0.069% change in returns for the same month.

Based on the output in Table 3, we find suggestive evidence in support of the hypothesis that economic policy uncertainty does in fact negatively impact stock returns on an aggregated level in the United States. The estimates for the ΔEPU are significant at the 0.1% level with all specifications of the model.

4.2 The predictive power of policy uncertainty

The output presented in Table 4 shows the results from equation (3) and suggests that policy uncertainty may have a degree of predictive power on log-returns, beyond the immediate effects shown in Table 3. Lags 3, 4, and 5 of ΔEPU are positively correlated with log returns, and significant at the 1%, 0.1%, and 1% levels respectively. The one-month lag of ΔEPU is negatively correlated with log-returns, significant at the 0.1% level.

Table 4: Policy uncertainty and log returns

Model	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Log}\Delta\text{EPU}_{t-1}$	-0.008***					
	(-7.138)					
$\text{Log}\Delta\text{EPU}_{t-2}$		0.000				
		(0.1976)				
$\text{Log}\Delta\text{EPU}_{t-3}$			0.003**			
			(2.581)			
$\text{Log}\Delta\text{EPU}_{t-4}$				0.004***		
				(3.348)		
$\text{Log}\Delta\text{EPU}_{t-5}$					0.004**	
					(3.213)	
$\text{Log}\Delta\text{EPU}_{t-6}$						-0.001
						(-1.308)
--------	------	------	------	------	------	------
Fixed-Effects:	Yes	Yes	Yes	Yes	Yes	Yes
Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Observations	258,801	258,801	258,801	258,801	258,801	258,801
R2	0.23236	0.23219	0.23221	0.23223	0.23223	0.23220
Within R2	0.22553	0.22535	0.22537	0.22539	0.22539	0.22536

This table presents the regression results for the relation between changes in policy uncertainty for previous periods and realized log returns. The dependent variable is monthly log returns of stocks listed on the NYSE since 1990. Our main variable of interest, LogΔEPU, is the log-transformed monthly percentage change in the Economic Policy Uncertainty Index (EPU-index) developed by Baker, Bloom and Davis (2013). The model include 6 lags of the variable. As control variables we include: ΔVIX which is the change in S&P 500 implied volatility, $(R_m - R_f)$ which is the market excess return, SMB and HML which are the remaining two components of the Fama-French Three Factor Model, CFNAI which is the 3 month moving average of the Chicago Fed National Activity Index, ROCE which is the return on capital employed, and D/A which is the debt-to-asset ratio. We include firm level fixed effects for all regressions. T-statistics are shown in parenthesis, and calculated using Huber-White standard errors. ***, **, *, . represent significance at the 0.1%, 1%, 5%, and 10% level

The coefficients imply that a 1% increase in ΔEPU is associated with a 0.003%, 0.004%, and 0.004% increase in returns 3, 4, and 5 months ahead. Also, a 1% increase is associated with a -0.008% change in return for the following month. These results support our hypothesis that EPU shocks positively predict future log-returns, after a short-term decrease.

4.3 Policy uncertainty and log returns during adverse economic conditions

Table 5 shows the regression results of equation (4) where we test the hypothesis that the effect of policy uncertainty on log-returns is stronger during adverse economic conditions. The output suggests that policy uncertainty has a larger impact during recessions as the coefficient of the interaction term between LogΔEPU and the recession dummy is negative and significant at the 0.1% level. The coefficient of -0.0495% suggests that a 1% increase in ΔEPU is associated with a -0.0495% change in return during recessions.

Table 5: Policy uncertainty, economic conditions and log returns

Model	(1)	(2)
LogΔEPU*Recession	-0.0495***	
	(-10.44)	
LogΔEPU	0.003*	
	(2.183)	
Recession	-0.004***	
	(-3.637)	
LogEPU*CFNAI		0.003***
		(3.563)
LogEPU		-0.006***
		(-8.754)
CFNAI		-0.0177***
		(-3.890)
- - - - - - - - - - -	- - - - - - - -	- - - - - - - -
Fixed-Effects:	Yes	Yes
Controls:	Yes	Yes
Observations	258,801	258,801
R2	0.23326	0.23246
Within R2	0.22643	0.22563

This table presents the regression results for the relation between changes in policy uncertainty interacted with indicators of economic conditions, and log-returns. The dependent variable is monthly log returns of stocks listed on the NYSE since 1990. Our main variables of interest are LogΔEPU*Recession, and LogEPU*CFNAI. LogΔEPU is the log-transformed monthly percentage change in the Economic Policy Uncertainty Index (EPU-index) developed by Baker, Bloom and Davis (2013). LogEPU is the log-transformed monthly level of the same index. Recession is the recession indicator from the St. Louis FED, a recession dummy which takes on a value off 1 during times of recession and 0 otherwise. CFNAI is the 3 month moving average of the Chicago Fed National Activity Index. As control variables we include: ΔVIX which is the change in S&P 500 implied volatility, $(R_m - R_f)$ which is the market excess return, SMB and HML which are the remaining two components of the Fama-French Three Factor Model, ROCE which is the return on capital employed, and D/A which is the debt-to-asset ratio. We include firm level fixed effects in both regressions. T-statistics are shown in parenthesis, and calculated using Huber-White standard errors. ***, **, *, . represent significance at the 0.1%, 1%, 5%, and 10% level

The interaction term between CFNAI and LogEPU is positive and significant at the 0.1% level, which further supports the hypothesis of amplified effects during economic downturns, as the CFNAI is >0 when the economy is growing above trend. As mentioned in section 3.3, we use Log-EPU instead of ΔEPU in the second regression to avoid the ambiguity that otherwise would arise regarding the interpretation of the coefficient given the structure of the variables. With the current structure, the interpretation is that when the economy is strong, the interaction term will be positive and vice versa. Hence, a positive coefficient indicates that positive returns are observed during stronger economic periods, and negative returns are associated with a weaker economy.

4.4 Policy uncertainty and firm investment

Table 6: Policy uncertainty and capital expenditures

Model	(1)	(2)	(3)	(4)	(5)
ΔEPU_t	0.1775***				
	(3.680)				
ΔEPU_{t-1}		0.1157*			
		(2.565)			
ΔEPU_{t-2}			-0.1826***		
			(-4.112)		
ΔEPU_{t-3}				-0.0199	
				(-0.4526)	
ΔEPU_{t-4}					-0.0251
					(-0.5837)
Fixed-Effects:	Yes	Yes	Yes	Yes	Yes
Controls:	Yes	Yes	Yes	Yes	Yes
Observations	83,419	83,162	82,897	82,627	82,359
R2	0.75929	0.76044	0.76160	0.76263	0.76356
Within R2	0.00071	0.00060	0.00081	0.00065	0.00071

This table presents the regression results for the relation between quarterly capital expenditures and changes in policy uncertainty. The dependent variable is the quarterly capital expenditures. ΔEPU_t is the percentage change in the quarterly average values of the Economic Policy Uncertainty Index (EPU-index) developed by Baker, Bloom and Davis (2013) We include 4 quarters of lags in model (2)–(5) respectively. As control variables we include: ΔVIX which is the change in S&P 500 implied volatility, CFNAI which is the 3 month moving average of the Chicago Fed National Activity Index, ROCE which is the return on capital employed, and D/A which is the debt-to-asset ratio. We include firm level fixed effects in all regressions. T-statistics are shown in parenthesis, and calculated using Huber-White standard errors. ***, **, *, . represent significance at the 0.1%, 1%, 5%, and 10% level

When testing the hypothesis that policy uncertainty has an adverse impact on firm investment on a quarterly basis, the results presented in Table 6 show evidence in support of H4. Based on the results of the model, changes in policy uncertainty have a negative and highly significant effect on firm-level capital expenditures two quarters in the future, whereas the same-quarter and the immediately following quarter are positively associated with shocks in policy uncertainty. In short, a 1% increase in policy uncertainty is related to a 0.1826 USD million lower capital expenditures two quarters in the future. The same 1% increase in the EPU-index is also associated with 0.1775 USD million in higher capital expenditures for the same quarter, followed by 0.1157 USD million in higher capital expenditure for the following quarter.

4.5 Policy uncertainty and investor sentiment

Table 7: Policy uncertainty and investor sentiment

Model	Put/Call	BW-index
ΔEPU	0.0011**	0.0011
	(2.709)	(0.4874)
ΔVIX	-0.0007	0.0011
	(-1.481)	(0.7014)
CFNAI	-0.0770***	0.0966*
	(-4.073)	2.418
Observations	289	391
R2	0.07844	0.01328
Adj. R2	0.06874	0.00563

This table presents the regression results of an OLS regression testing the relationship between changes in policy uncertainty and investor sentiment. The dependent variable is the monthly average total exchange Put/Call Ratio (volume based) from CBOE. Our main variable of interest, ΔEPU, is the monthly percentage change in the Economic Policy Uncertainty Index (EPU-index) developed by Baker, Bloom and Davis (2013). As control variables we include: ΔVIX which is the change in S&P 500 implied volatility, CFNAI which is the 3 month moving average of the Chicago Fed National Activity Index. T-statistics are shown in parenthesis. ***, **, *, . represent significance at the 0.1%, 1%, 5%, and 10% level

Table 7 presents the results of an OLS model testing the hypothesis that policy uncertainty has a negative impact on investor sentiment, using the volume-based total exchange Put/Call-ratio as the dependent variable. The model suggests a positive and statistically significant relationship between changes in policy uncertainty and the ratio of traded put and call options. A 1% increase in policy uncertainty triggers a 0.0011 increase in the Put/Call Ratio, implying that more put options are traded relative to call options, signaling that investors become more skeptical. We find no significant relationship between the BW sentiment index and the EPU-index for the same period.

5 Discussion

The following section aims to further dissect and critically analyze the results presented in the previous section, as well as highlight any potential limitations of our data and research design that may give rise to biased results.

5.1 Policy uncertainty and its implications on stock returns

The empirical results presented in Table 3 under Section 4 suggest that we can confirm our hypothesis that changes in policy uncertainty are negatively associated with US stock returns for the same month. The result is expected and consistent with findings in previous literature on the topic of uncertainty and stock returns (Pástor and Veronesi 2013; Brogaard and Detzel 2015; Brogaard et al. 2020).[5] As shown in Table 4, one lag of the change in EPU is also negatively and significantly correlated with stock returns which further supports the thesis that increases in policy uncertainty are associated with negative returns in the immediate and short term. This implies that the economic policy uncertainty index has the ability to negatively predict stock returns for the month following an uncertainty shock. From an intuitive point of view, we could explain these results as investors failing to immediately and accurately estimate the implication of uncertainty. Given the nature of a shock to policy uncertainty, it is reasonable to expect that there is some uncertainty surrounding the actual level and implication of uncertainty, making it difficult for investors to rationally account for the implication of the uncertainty. Then, as the implications of the uncertainty shock become more observable it allows investors to better account for the policy uncertainty. Our results are valuable as they suggest that investors in general (in the same month) underestimate uncertainty.

As alluded to in section 4, our model suggests that policy uncertainty also has a positive predictive power on stock returns further in the future. Specifically, Table 4 shows the positive predictive power of policy uncertainty on stock returns in the 3–5 months following the policy uncertainty shock. The results are again in line with the findings in prior literature. On one hand, it could imply that investors are indeed rational and identify a change in risk, or adjust their forecasts as a result of a change in policy uncertainty. This change would then likely have implications on their estimates of the fair value of the asset, or the required return of holding that asset. If that is the case, the asset price would change to reflect that. Another explanation could be that investors are irrational and overreact to the noise stemming from major shocks to policy uncertainty, which subsequently leads to a reversal in returns for the following periods when rational investors take advantage of arbitrage opportunities following potential mispricing. In section 3 we also discussed that uncertainty makes it difficult for investors to forecast probability distributions which can interfere with the ability to make rational investment decisions. In short, the result could both be a result of behavioral biases from investors, and a result of the uncertainty altering probability distributions with unknown consequences. Another aspect to consider is the structure of the EPU-index. As illustrated in Figure 1, the index is rather volatile and does not tend to remain at highly elevated levels for long periods of time. Hence, another explanation of our results could be that as the uncertainty is reduced after a couple of months, investors readjust their expectations with the new information, and asset prices adjust accordingly.

Brogaard et al. (2020) found that returns tended to revert and increase again after the outcome of an uncertain election was revealed. They also find evidence that it is the discount

[5] These authors take slightly different approaches in their empirical work. Pástor and Veronesi (2013) and Brogaard and Detzel suggest policy uncertainty demands a positive risk premium which is consistent with stock prices immediately dropping as the policy uncertainty increases. Brogaard et al. (2020) find that stock returns are negatively impacted during the period leading up to US elections.

rate that drives the impact of uncertainty on returns. This resonates well with our theory that investors, when faced with uncertainty (either through a shock or an upcoming election) are unable to accurately predict probability distributions and when the uncertainty is resolved they are once again able to make better predictions which is reflected in stock returns.

It is important to note that we have found no evidence of causality, or proved that policy uncertainty is what causes the movements on the US stock market. The relatively low explanatory power of our models further suggests that we likely excluded important control variables, which could have a material impact on our statistical model.

In section 2 we also mention that finding a truly exogenous measurement of policy uncertainty is complicated (Kelly et al. 2016). Given how the EPU-index is structured, with two of the three components likely being sensitive to changes in other variables (newspaper component and disagreement amongst forecasters) it is possible that we are failing to identify variables that could have a causal impact on both the EPU-index and stock returns. There is also the possibility that significant stock market events, bankruptcies, and scandals could raise a need for policy intervention which in turn leads to an increase in uncertainty, i.e., we could face a form of reverse causality. However, it is important to note that we do not find any evidence for that kind of alternative interpretation of our results.

Another important limitation of our models is related to the sample selection bias. As we only include mid- and large-cap firms listed on NYSE (> $2bn in market capitalization) we disregard both smaller firms and firms listed on other exchanges. Thus, we are not able to make any broader inferences for the entire US stock market or firm universe, but only on stocks filling the above-mentioned criteria.

An interesting and perhaps slightly counterintuitive observation is that the β-estimate for the CFNAI is negative, meaning that a better state of the economy has a negative correlation with stock returns. One explanation for this could simply be inaccuracies in our model. Another possible explanation can be provided by Pástor and Veronesi (2013) where they discuss the potential value of what they refer to as the "Greenspan Put" or the "Government put protection". I.e., the fact that governments are more likely to intervene during worse economic times, which provides a put protection on asset prices and hence could mitigate the negative impact of worsening economic conditions. A somewhat related aspect also highly relevant for asset prices is the federal funds rate. As seen during the past months of the rate-hiking cycle, indications of better economic conditions can imply that the Federal Reserve will increase rates further or at a higher pace to "cool off" the economy and bring inflation down to the target. This in turn could lead to lower liquidity and higher interest rates which all else equal should drive prices down. In short, when the economy is strong and growing above trend it might lead to the expectation of higher interest rates which depress asset prices. However, we do not aim to make any definite conclusions here, and for the purpose of this paper, we will not investigate this relationship any deeper.

5.2 Policy uncertainty, adverse economic conditions, and log-returns

As Pástor and Veronesi's (2013) theoretical model suggests, we find that the correlation between policy uncertainty and stock returns is significant and negative during periods of adverse economic conditions. As discussed above in section 5.1 and in section 1.1 there is a possibility that the put protection during recessions could counteract the effect, but the result seems more supportive of our hypothesis that the expected value of this protection decreases when there is a policy uncertainty shock during recessionary periods, as it becomes uncertain if this government put protection still exists to the same extent. In short, the findings in this section support our second hypothesis that investors are more sensitive to uncertainty shocks during periods of adverse economic conditions. However, it is important to notice that the limitations of our model mentioned above in section 5.1 still apply to the empirical analysis.

5.3 Policy uncertainty and firm investments

Our study provides suggestive evidence of a delayed relationship between changes in policy uncertainty and capital expenditures, most significant at the two-quarter lag. These results are in line with our hypothesis and consistent with the notion that the value of deferring investments increases as firms are faced with higher uncertainty. The intuition behind such results is, as previously mentioned, that uncertainty distorts agents' ability to accurately assess and forecast the risks and outcomes of capital investments. However, a potential problem arises as we are only including mid-and large cap firms listed on NYSE in our sample. This selection bias limits our ability to make inferences that apply to a wider variety of firms, such as early start-ups and scale-up firms where the decision-making process for investments may look entirely different. One could argue that such firms have less flexibility when it comes to deferring investments that are crucial for scaling operations in the early stages of their life cycle, which is not captured in our empirical analysis. Firms may also differ substantially in their ability to reverse investments, and the associated cost of doing so. The value of deferring an investment is not relevant if investments can be easily reversed, as no benefits can be seized by waiting for more information. Gulen and Ion (2016) find empirical evidence that supports this claim by controlling for four different measures of investment irreversibility and find that higher investment irreversibility amplifies a firm's sensitivity to policy uncertainty in the context of corporate investments. Furthermore, as firms operate in different industries with varying levels of capital intensity, among other things, our model is unable to comment on sector characteristics that may impact firms' sensitivity to policy uncertainty. Baker et al. (2016) find that firms that operate within policy-sensitive sectors such as defense, health care, and financial services are especially responsive to policy uncertainty, as they are highly dependent on government contracts and are more exposed to shifts in regulatory policy. Such industry differences undoubtedly affect the relationship between uncertainty and firm investment, and it would be of great value to conduct sector-level analyses with a more heterogeneous sample of firms to address issues of this nature.

We also find that the short-term relationship between capital expenditures and policy uncertainty is positive, which to us appears somewhat surprising as it contradicts our hypothesis that we would find a negative relationship between policy uncertainty and firm investments. This also contradicts the findings from Gulen and Ion (2016), but one should note that we are using a different method and studies the actual capital expenditures and not the intensity relative to sales. One potential explanation, although very speculative, could be that firms increase their short-term investments to hedge for a potential increase in the cost of capital as a result of the uncertainty. One could also consider a scenario where firms operating in favorable regulatory environments increase their immediate capital expenditures to capture the benefits from existing opportunities that could be at risk following an uncertainty shock.

5.4 Policy uncertainty and investor sentiment

As hypothesized, our results suggest a positive correlation between changes in policy uncertainty and the Put/Call Ratio, or in other words; a negative relationship between policy uncertainty and market wide investor sentiment. As the levels of policy uncertainty grow higher, it's reasonable to assume that the demand for hedging the risk of unfavorable outcomes grows as a result. Kelly et al. (2016) show that option protection is more valuable, and as a result more expensive, if a major political event lies within the option's life span. Their results imply a significant and positive relationship between put prices and political uncertainty, which is amplified in weak economic conditions. Our findings act as a complement to these results, as it shows how the demand for downside protection increases in response to higher uncertainty, even though put options are priced higher in these periods. Combined, these results suggest that uncertainty increases the value of put protection in financial markets and that investors are willing to pay for it – as demonstrated by the significant relationship with the Put/Call Ratio.

Interestingly, we do not find any significant correlation between economic policy uncertainty and the BW sentiment index. This could simply be a consequence of a rather limited sample size, or that there is no significant relationship between that sentiment proxy and uncertainty. The latter case could highlight that the Put/Call Ratio is not as suitable of a proxy for investor sentiment as the more robust BW-index. However, we still believe that the results we find are valuable as the Put/Call Ratio clearly illustrates the response of investors when uncertainty changes, through the lens of tangible trading data, which matches the action-based perspective that we aim to develop through our empirical methodology. The BW-index may be a less noisy and more appropriate proxy for overall sentiment in the market, but since we are interested in investors' actions, and not the overall market attitude, the Put/Call Ratio paints a clear and intuitive picture of investors' actions following a shift in sentiment or beliefs.

Given the relatively simple empirical method, there is a possibility that important control variables are omitted from our model. Hence, a more robust statistical analysis of the relationship would be valuable for future researchers to consider.

Despite the different and arguably less sophisticated proxy for investor sentiment used in this study, the possibility to find interesting conclusions on the back of prior research still exists. Both Baker and Wurgler (2006) and Huang, Jiang, Tu, and Zhou (2015) find empirical evidence that investor sentiment has a degree of predictive power on stock returns. The latter find that a positive sentiment leads to overly optimistic estimates and judgments, which is predictive of lower returns in future periods. Combining this result with the correlation we find between policy uncertainty and the Put/Call Ratio there is an argument to be made that policy uncertainty can have an impact on investor sentiment which in turn is driving some of the predictive power of future returns. Another relevant aspect to consider from Huang, Jiang, Tu, and Zhou (2015) is their findings regarding which underlying channel drives return predictability. Their empirical results suggest that investor sentiment negatively and significantly predicts future cash flows (using dividend growth as a proxy), which drives the predictability of the returns. But they find no evidence for investor sentiment being able to forecast the dividend-price ratio (a proxy for discount rate), implying that it is the cash-flow channel that is driving the predictability in the US. A plausible interpretation would be that positive investor sentiment is associated with optimistic beliefs about future cash flows that are not justified by fundamentals. When the true state of the cash flows then is revealed, stocks adjust accordingly.

Interestingly, Brogaard et al. (2020) find that the impact of election uncertainty on stock returns is mainly driven by the discount-rate channel. At first, this might appear contradicting, but when considering the notable difference between our proxy for uncertainty (EPU-index) and theirs (federal elections), the result does not have to be counterintuitive. On one hand, it is perfectly reasonable that investors, when facing uncertainty regarding the outcome of an election, would demand a higher return for holding stocks leading up to the election. On the other hand, when faced with a shock to uncertainty, such as Covid-19, it is also plausible that investor sentiment rapidly decreases and investors as a consequence overestimate the negative impact on future cash flow, rather than demanding higher returns for holding stocks during the time of uncertainty. Further disentangling which of the traditional channels explains the predictive power of EPU-index on returns could be a meaningful extension of our analysis.

6 Robustness & external validity

The following section presents a brief discussion of the robustness and external validity of the results gathered in previous sections by applying our methodology to different contexts. Section 6.1 presents a short and selective non-US study to see if our results apply to European economies, and Section 6.2 considers potential heterogeneous effects in a subset of 30 different US industries.

6.1 Policy uncertainty and index returns in Sweden and the United Kingdoms

To test the validity of our results outside of the US, we extend our methodology to a European setting by testing whether Swedish and UK index returns are sensitive to policy uncertainty. To do this, we download monthly value-weighted returns for Sweden and the United Kingdom from WRDS monthly World Indices database, and the corresponding policy uncertainty indexes for both countries.[6] We then proceed to regress these index returns on both the US economic policy uncertainty and the respective countries' economic policy uncertainty, to capture both domestic uncertainty effects and potential spillovers from the US. Brogaard et al. (2020) showed that uncertainty surrounding elections has cross-border implications, which warrants a quick investigation if that transfers to the economic policy uncertainty index as well. Our results are in line with the results we present in section 4 and prior research on this topic. Shocks in the US economic policy uncertainty and the country-specific economic policy uncertainty are negatively and significantly correlated with same-period returns in both Sweden and the United Kingdom.

6.2 Policy uncertainty and industry heterogeneity

In section 4 above we found suggestive evidence that shocks to policy uncertainty are associated with a negative impact on stock returns. While we, in our regressions, controlled for firm fixed effects we disregard industry belonging and thus ignore potential heterogeneous effects that may be of importance. Prior studies have shown that some sectoral returns are only weakly predictable or unpredictable (see Phan, Sharma, and Tran, 2018) in relation to uncertainty. Hence, it is unlikely that the relationship between uncertainty and stock returns is homogeneous across all industries. Due to this, investigating if the relationship differs across industries is both relevant and interesting to understand, as there may be potential heterogeneous effects that affect cross-industry sensitivity to policy uncertainty.

Baker et al. (2016) found that industries that are relatively exposed to government spending are more sensitive to changes in policy uncertainty. More specifically they find that volatility for these firms increases, while investments and employment decrease during times of high policy uncertainty. In their paper, they specifically refer to policy-sensitive industries such as defense, health care, finance, and infrastructure construction. They also proceed to study industry-specific uncertainty and find that defense, health care, and financial sectors are especially sensitive to each own industry uncertainty measure.

Other research on this topic finds similar results. Gulen and Ion (2016) show that the relationship between firm-level capital expenditures and policy uncertainty is significantly stronger for firms that are more dependent on government spending and for firms with a high degree of investment irreversibility. From an intuitive standpoint, the degree of irreversibility is likely different across industries. For example, industries that require large up-front

[6] The monthly index return data is available from 1986–2022 for both countries. The Swedish economic policy uncertainty index covers the entire period. For the United Kingdom, the economic policy uncertainty data is available from 1998 and onwards.

commitments/investments such as ship- or aircraft-manufacturing, construction, or oil and gas might face higher irreversibility and thus also be more sensitive to policy uncertainty.

Boutchkova, Doshi, Durnev, and Molchanov (2012) study how the return volatility of different industries is sensitive to political events. Their results indicate that industries that are more dependent on trade, contract enforcement, and labor intensity show greater return volatility when local political risks are higher.

To find industry returns we download the Fama-French value-weighted 30-industry portfolios, which classify industries using 4-digit SIC codes. The dataset and industry-specific control variables are available via Compustat.

We run regressions for each of the 30 industries with specifications similar to that of equation (1) where log-returns instead are the log-transformed value-weighted average return for each industry, and the firm-specific controls are replaced by industry averages. Results are reported in Table 8, showing all significant coefficients of interest and excluding the rest.

We find modest evidence for the theory that industries are heterogeneous in their sensitivity to policy uncertainty shocks, and our results are not entirely consistent with prior literature on volatility and investment. For example, Baker et al. (2016) suggested that the volatility, investment, and employment growth in the health care, defense, and financial services industries would be more sensitive to a higher level of uncertainty. Our model, however, suggests that the relationship between policy uncertainty and same-period returns for the health care industry is positive. Despite us studying returns, not volatility and investments, one could reasonably expect that the results would be somewhat transferable in terms of which industries are most sensitive to policy uncertainty. This could imply that the results from the investment, volatility, and employment literature are not completely transferable to the study of stock returns, but it could also be the case that our limited sample size and industry classifications impair our ability to accurately compare these studies against our own results.

On the other hand, Gulen and Ion (2016) find that investments in firms with a higher degree of investment irreversibility are more sensitive to higher uncertainty levels. More specifically, they consider industries that produce durable goods to be associated with a high degree of investment irreversibility. Shleifer and Vishny (1992) provide the intuition behind this methodology by showcasing that firms in industries characterized by a high degree of cyclicality, such as producers of durable goods, should be simultaneously affected by negative demand shocks as the main buyers of these goods tend to operate within the same industry. When hit by a negative demand shock, or in our case - uncertainty, firms operating in highly cyclical industries disinvest and become more financially constrained, hence lowering the demand and recovery value of their assets, which could, in turn, explain the lower returns following uncertainty shocks. Studying our output in Table 8, several of the industries with negative and significant relationships between returns and policy uncertainty shocks do seem to belong to industries that produce durable goods, suggesting that the results have some degree of theoretical support from the literature on uncertainty and capital expenditures.

Table 8: Log returns and policy uncertainty by industry

Industry	Log-ΔEPU	Adj. R2
Automobiles and Trucks	-0.032. (-1.8165)	0.5767
Business Equipment	-0.023. (-1.9141)	0.7741
Aircraft, Ships and Railroad Equipment	-0.038* (-2.3502)	0.5970
Fabricated Products and Machinery	-0.021. (-1.9180)	0.7717
Healthcare, Medical Equipment and Pharmaceutical Products	0.019* (2.3436)	0.5392
Retail	0.017* (2.0003)	0.6404
Textiles	-0.040* (-2.5129)	0.5867

This table presents all significant coefficients from OLS regressions testing the effects of changes in log-transformed policy uncertainty on value weighted log-returns for the Fama-French 30 industry portfolios. Industries are classified using 4-digit SIC-codes. Our main variable of interest, LogΔEPU, is the log-transformed monthly percentage change in the Economic Policy Uncertainty Index (EPU-index) developed by Baker, Bloom and Davis (2013). As control variables we include: ΔVIX which is the change in S&P 500 implied volatility, all components of the Fama-French three factor model (SMB, HML, $(R_m - R_f)$), CFNAI which is the 3 month moving average of the Chicago Fed National Activity Index, industry average debt-to-asset ratio and industry average return on capital employed. Standard errors are heteroskedasti. T-statistics are shown in parenthesis, and calculated using Huber-White standard errors. ***, **, *, . represent significance at the 0.1%, 1%, 5%, and 10% level

It is important to highlight that 23 out of the 30 industries did not yield any significant results between policy uncertainty and value-weighted industry log returns. This could imply that there are no significant relationships for those 23 industries, or that 395 monthly observations are not enough to find any statistically significant relationships. However, it is strange given the highly significant results presented in section 4 that we do not find more significant results in this section. If the reality is that there are no significant relationships between uncertainty and returns in 23 out of 30 industries, the ability to translate our aggregated results into actionable insights for policymakers and investors is notably impaired.

7 Conclusion

This paper provides additional evidence regarding the relationship between policy uncertainty and stock returns, firm investment, and investor sentiment. First, we show that policy uncertainty is negatively correlated with same-period stock returns and that this effect is amplified in times of worsening economic conditions. Second, we show that policy uncertainty positively predicts stock returns in the 3–5 months past an uncertainty shock, providing support to the theory and evidence of policy uncertainty demanding a risk premium. Our models show mixed evidence when testing the effects of policy uncertainty on capital expenditures, but suggest a delayed negative effect two quarters into the future, implying that uncertainty may be a factor affecting investment decisions within firms. Furthermore, our study highlights how policy uncertainty impacts investor behavior and increases demand for downside protection in financial markets through its effect on the Put/Call Ratio, but fails to establish a statistically reliable correlation with a more robust measure of investor sentiment.

In conclusion, our study has contributed to the understanding of how stocks, firms, and investors are impacted by economic policy uncertainty. By better understanding how these market actors react to ambiguity and lack of transparency surrounding policy decisions, policymakers can take steps to mitigate uncertainty and avoid its negative effects on the economy and financial markets. With our results in mind, market participants can better anticipate, assess, and manage risks stemming from uncertainty, ultimately leading to more rational and informed decision-making.

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Appendix 1

1.A

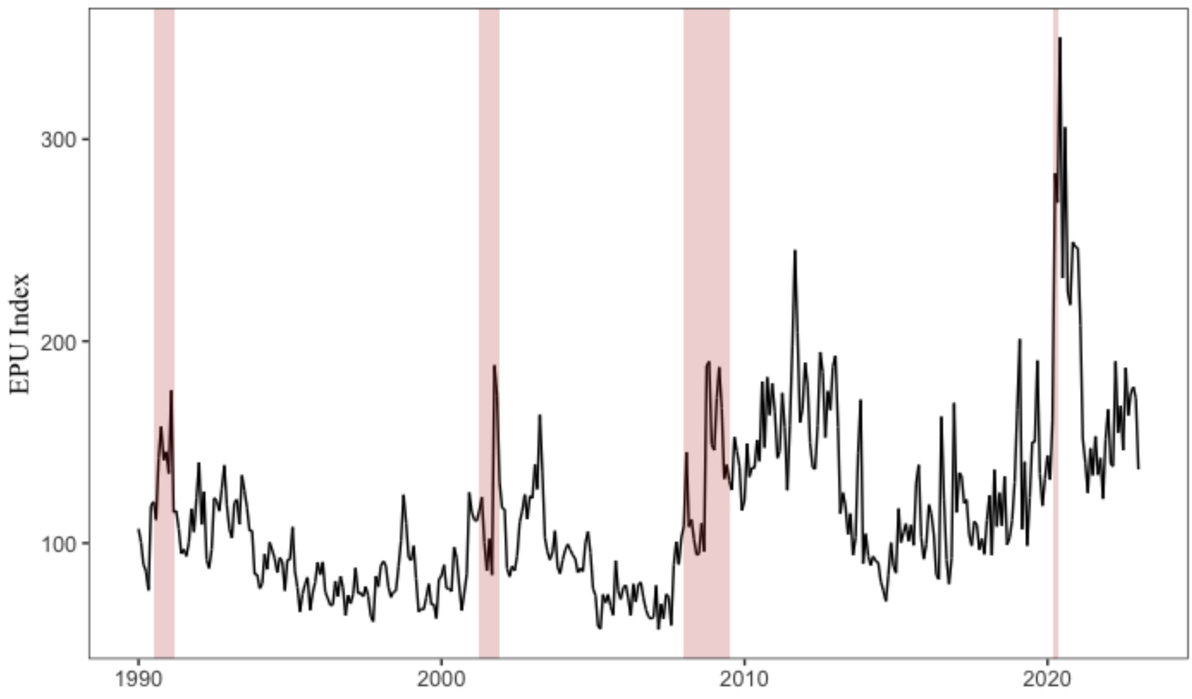
Table 2: Descriptive Statistics, Recession Periods

	1990-91 Recession			Dot-com Bubble			2008 Financial Crisis			Covid-19		
	Mean	Median	St. Dev	Mean	Median	St. Dev	Mean	Median	St. Dev	Mean	Median	St. Dev
Return (%)	0.85	0.80	12.29	0.09	0.00	12.93	-1.06	-1.24	17.87	-16.75	-13.33	16.59
EPU	140.40	141.64	20.94	121.64	109.08	38.85	135.51	135.33	34.15	221.83	221.83	86.71
Put/Call	-	-	-	0.73	0.72	0.08	0.98	0.98	0.10	-	-	-
CFNAI	-0.72	-0.79	0.36	-0.65	-0.65	0.05	-1.29	-1.32	0.73	-0.76	-0.76	0.91
VIX	24.58	24.27	4.95	25.38	24.38	4.99	33.71	27.73	12.60	43.84	43.84	13.71
CAPEX	74.83	9.10	252.81	103.84	16.80	380.83	137.34	25.64	427.00	141.68	24.33	431.71
ROCE	0.17	0.15	0.15	0.14	0.15	0.50	0.16	0.15	0.36	0.12	0.11	0.22
D/A	0.29	0.27	0.20	0.28	0.28	0.17	0.26	0.24	0.21	0.35	0.33	0.23

This table represents summary statistics for our variables of interest during the four recessions covering our dataset. The recession indicator is from the St. Louis FED. Returns are monthly returns of all Stocks listed on NYSE during 1990-2022. EPU is the Economic Policy Uncertainty Index by Baker, Bloom and Davis (2013), Put/Call ratio is the total exchange volume based put options divided by call options from CBOE. CFNAI is the 3 month moving average of the Chicago Fed National Activity Index, VIX is the S&P 500 implied volatility. CAPEX is the quarterly capital expenditures is millions of USD. ROCE and D/A is the firm level return on capital employed and debt-to-assets respectively.

1.B

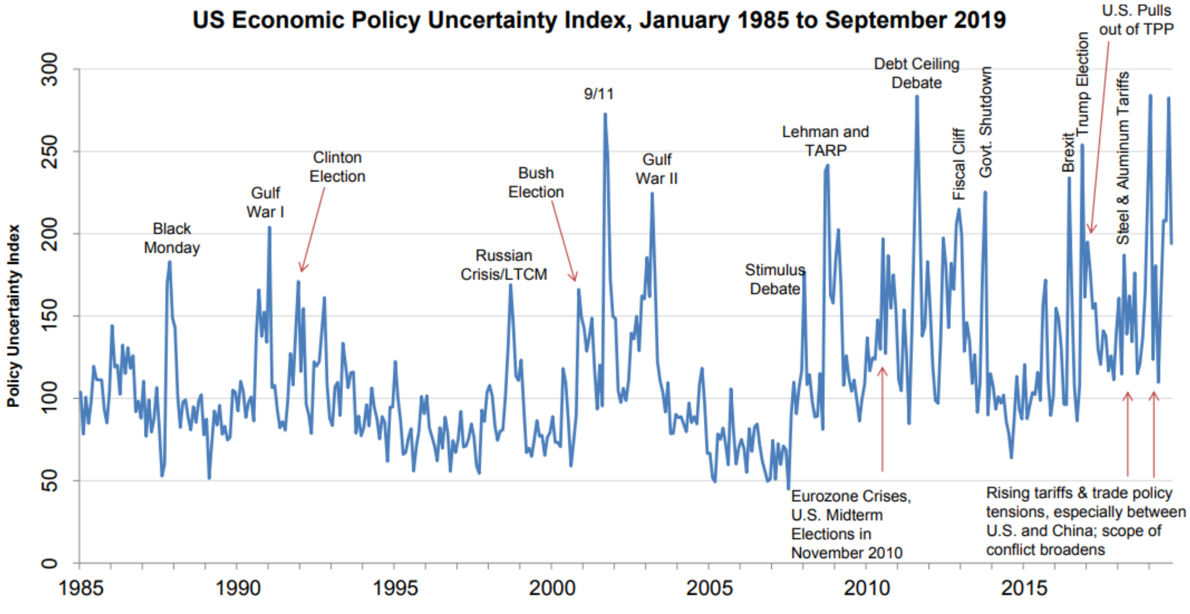
Figure 1: Economic Policy Uncertainty Index



This graph illustrates the US policy uncertainty index developed by Baker, Bloom, and Davis (2013) between 1990 and 2022. Recessions, classified by the St. Louis FED recession indicators, are highlighted in red. For an annotated index, see below.

1.C

Figure 2: Annotated US policy uncertainty index between 1985 and 2019, with major events highlighted



Source: "Measuring Economic Policy Uncertainty" by Scott R. Baker, Nicholas Bloom and Steven J. Davis, as updated at www.policyuncertainty.com. Monthly data normalized to 100 prior to 2010.