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# The Effect of Economic Policy Uncertainty on US stock returns: a cross-sectional analysis

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## Abstract

After a decade of unprecedented economic growth and relative calmness, the world has faced a new crisis. The recent COVID-19 crisis has induced a massive spike in Economic Policy Uncertainty (EPU). This paper investigates the relationship between EPU and the cross-section of US stock returns. The main question that this paper tries to answer is whether EPU is priced in the cross-section of US stock returns. Furthermore, this paper also tries to get an understanding of how EPU behaves over presidential cycles and across different industry sectors. My analyses show no evidence of the presence of an EPU risk factor in the US market over a recent and relatively long period from 1987 to 2019. The excess returns show a U-shaped pattern across decile portfolios formed on EPU. My results also show no evidence of a statistical difference in returns across presidential cycles or industry sectors. Potential explanations for not finding the associated risk premium of EPU are Market efficiency, a U-shaped pattern of volatility for imprecise signals and the difficulty of predicting betas

*Keywords:* Economic Policy Uncertainty; Cross-section of stock returns; ICAPM; Finance

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# 1. Introduction

After more than ten years of economic expansion, the bull market has come to an end. The world has experienced a decade of unprecedented growth after the havoc of the great financial crisis. However, recently the world and financial markets have shaken up as a result of the outbreak of the new coronavirus. The world is already in the middle of a global recession, and this crisis might even lead to a new era in financial markets. After a period of relative calmness, economic uncertainty has spiked once again.

The uncertainty about the future economy has implications for economic agents' behaviour (Bloom, 2009). Merton (1973) provided the foundation of the link between macroeconomics and economic agent's behaviour. He developed the intertemporal capital asset pricing model, which is an alternative to the traditional CAPM. The ICAPM acknowledges that investors hedge against potential shifts/shortfalls in consumption and the investment opportunity set. Bali et al., (2017) mention that: "state variables that are correlated with changes in consumption and investment opportunities are priced in capital markets such that an asset's covariance with these state variables is related to its expected returns". Macroeconomic factors are a perfect fit for those 'state variables' since they are heavily correlated with changes in consumption and the investment opportunity set. Governments are the primary playmakers in macroeconomics by setting fiscal, regulatory or monetary policy. They, therefore, have a significant influence on uncertainty (Brogaard & Detzel, 2015). Baker et al., (2016) acknowledged that as well and developed an index to measure the economic policy uncertainty (EPU) for the United States and eleven other major economies. They investigated the relationship between EPU and stock price volatility, investment rates, employment growth and aggregate investments. Their findings highlight the adverse economic effects of uncertainty shocks.

Baker et al., (2014) document that US policy uncertainty has risen since 1960 and the authors try to find an explanation for this striking pattern. Firstly, the authors attribute that policy-related economic uncertainty rises when government spending and taxes relative to GDP increases. The complexity of government actions is also a potential contributor to a rise in EPU. The authors further document that the major parties in the US have become more polarized. The ideological gap between Republicans and Democrats has been increasing since the 1960s, increasing economic policy uncertainty

Baker et al., (2012) propose the question of whether economic policy uncertainty has hampered the recovery after the great financial crisis in 2008. The economic policy uncertainty index spikes when abnormal political or extraordinary events occur like the attack on 9/11, presidential elections and financial crises. The index decreases gradually after those type of events. However, after the financial crisis of 2008, the index remained at a high level for several years. The authors argue that this is mostly due to concerns about taxes and monetary policy. The authors further document that economic policy uncertainty matters for the economy and the effects of EPU can run through multiple channels. Firstly, uncertainty makes firms more anxious about committing to making investments which are costly to reverse. Secondly, people are more likely to postpone spending when uncertainty is high; people tend to build up a buffer of liquid assets during uncertain times. Thirdly, higher uncertainty raises the financing costs of firms. Lastly, Higher uncertainty leads to greater co-movement in firm-level equity prices. This greater co-movement makes it harder for an investor to diversify risks. economic policy uncertainty might even induce a specific equity risk premium, which is more pronounced in weaker economic conditions. (Pastor & Veronesi, 2011)

The relationship between the EPU and presidential cycles/elections is also fascinating since economic policy uncertainty is tightly linked to policymakers. Santa-Clara & Valkanov (2003) documented an interesting pattern for US stock returns. The authors were the first to document the "Presidential Puzzle" and showed that stock returns were much higher under Democratic administrations than under Republican administrations. The average excess return of a value-weighted portfolio was 2% when the Republican party was in power and 11% when the Democratic party was in power—an economically and statistically significant difference of 9% per year.

Since the financial crisis of 2008, a vast amount of academic literature has been presented that examines economic policy uncertainty and its effects on a variety of economic variables. However, the amount of papers that investigate whether EPU is associated with an equity risk premium is quite scarce. I, therefore, wish to contribute to this field of research by examining whether economic policy uncertainty is priced in the cross-section of US stock returns for a recent and long period. Additionally, I will investigate the relationship between economic policy uncertainty, political cycles and industry sectors in the US. Investigating the potential significance of EPU is of great importance. The world has become interconnected due to globalization and the development of new technologies. As a result, the world has also become more sophisticated over the last couple of years. We have experienced quite some crises over the previous decade like the Arab Spring, Russia's annexation of Crimea, tensions between the US and North Korea and Brexit. Furthermore, the global political playing field is also changing. China is entering the stage as the world's new superpower, and that has scared the US. All these events show a striking pattern, a potential crisis in one part of the world can have severe effects for other parts of the world (Al-Thaqeb & Algharabali, 2019). A recent example of effects being severe is the crisis around COVID-19. The outbreak of this pandemic in China has had a severe impact on the world economy, and on the way, people live and work across the globe.

To conduct all the necessary analyses for this particular research, I extracted data for US stock returns from CRSP and accounting data from Compustat. I used data from January 1985 until December 2019. I estimated uncertainty betas for every stock in my sample by using rolling regressions of 60 months of excess returns on innovations of the EPU index. Stocks were required to have a least 24 months of observations (Fama & French, 1992). Decile portfolios were formed based on those uncertainty betas. I regressed these decile portfolios against various asset pricing models like the CAPM, the Fama & French 3 factor model (FF3), the Carhart 4 factor model and the Fama & French 5 factor model (FF5). I also extended the CAPM and the Fama & French 3 factor model by making a factor mimicking portfolio on the VIX. The VIX index is one of the oldest and most commonly referred to when looking at the volatility in stock prices and returns. It has been used for many years as a measure of market uncertainty in equity markets (Al-Thaqeb & Algharabali, 2019). I control for the VIX index in this research to isolate the potential effect of innovations in the EPU index on US stock returns. I also examined the relationship between stock returns and other firm characteristics by using Fama-Macbeth cross-sectional regressions (1973). In these regressions I controlled for firm size, market beta, book-to-market (Fama & French, 1992), momentum (Jegadeesh and Titman, 1993) the reversal effect (Jegadeesh, 1990) and lastly, I controlled for the betas of stocks formed against the VIX index. Additionally, I investigated whether returns on an EPU factor-portfolio differ across presidential cycles and eleven different industries in the US. In the last part of my research, several robustness tests are conducted.

The main analyses show that EPU is not priced in the cross-section of US stock returns. The excess returns show a U-Shaped pattern across decile portfolios and a long/short portfolio formed on EPU does not deliver significant abnormal returns. I further show that EPU has no significant explanatory power in Fama-Macbeth regressions, and I am also not able to find any statistical difference over presidential cycles or across different industries in the US market.

This paper is organized as follows. Section 2 provides an academic literature review about EPU and its relation to the cross section of stock returns. Section 3 describes the data and variables used in this research. Section 4 describes the methodology of this thesis. The results are presented in section 5 of this paper. Section 6 presents several robustness tests. The results are discussed in section 7 of this paper, and the conclusion is drawn in section 8.

# 2. Literature review

## 2.1 Efficient Market Hypothesis

Financial literature that considers the cross-section of stock returns has evolved quite substantially over the past 50 years. Fama (1970) documented the efficient market hypothesis (EMH). The EMH implies that asset prices fully reflect all available public and private information at any given point in time. The EMH provides the basis for the financial theory known today. However, the EMH is not specified in a specific model an is untestable. Academics have, therefore focussed on certain deviations from the original EMH documented by Fama (1970). These deviations are known as anomalies. These anomalies are quantified as distortions in returns which oppose the EMH.

Traditionally one would argue that macro-economic factors like EPU are part of the market factor in asset pricing models and that adding a new proxy for measuring economic uncertainty shouldn’t add any value. However, the proxy for the market portfolio isn’t perfect, and hence the relation between consumption and the marginal utility of consumption is not as perfect as the CAPM suggests. Studies have been conducted where a factor related to macroeconomics was added to asset pricing models. For instance, Driesprong et al., (2008) found that changes in oil prices strongly predicted future stock market returns in many countries in the world. Their results are economically significant and robust over time. Lettau & Ludvigson, (2001) studied fluctuations in the aggregate consumption-wealth ratio and their role in predicting stock returns. The authors find that changes in the consumption-wealth ratio of investors predict stock returns. They also find that their variable is a better forecaster of future returns than other famous asset pricing anomalies like the dividend yield or the dividend pay-out ratio (Naranjo et al., 1998). Smajlbegovic, (2019) also acknowledged that macroeconomic variables are potential candidates for risk factors in the cross-section of stock returns. He studied the relationship between stock returns and regional macroeconomic information. The author finds that regional economic activity forecasts positively predict the cross-section of stock returns in the US market. A long/short portfolio formed on predicted regional activity yields a risk-adjusted return of approximately 5% per year.

## 2.2 ICAPM

One of the most important breakthroughs in financial literature was when the Sharpe-Lintner-Mossin mean-variance equilibrium model was developed, commonly known as the capital asset pricing model. This model has provided the fundamentals for many important academic papers known today. However, it has had its critics. The CAPM predicts that the returns of an asset are proportional with the covariance of the return of the market, or in other words with its beta. Jensen, Black & Scholes (1972) showed, for instance, that the CAPM does not always hold. They demonstrated that low beta assets provided higher returns than high beta assets. However, the CAPM model is still widely used due to its simplicity, and academic evidence shows that the model explains a significant amount of variation in asset returns. Merton (1973) also criticized the assumptions of the CAPM, and he, therefore, developed an alternative. Namely, the intertemporal capital asset pricing model (ICAPM). Bali et al., (2017) documented that: "investors have incentive to hedge against future stochastic shifts in consumption and investment opportunity sets". For investors, this means that innovations in state variables that forecast the investment opportunities would influence expected excess returns. Hence, changes in those state variables affect the accumulated wealth of investors (Brogaard & Detzel, 2015). The equilibrium between risk and return for Merton's ICAPM is as follows:

$$E_t\left(r_{it+1} - r_{ft+1}\right) = A * Cov_t(r_{it+1}, r_{mt+1}) + B * Cov_t(r_{it+1}, \Delta x_{t+1}) \quad (1)$$

In this equation $r_{f,t+1}$ represents the risk-free rate, $r_{it+1}$ is the return on asset i, $r_{mt+1}$ is the return on the market, and $x_{t+1}$ is a vector of state variables that shift the investment opportunity set. $Cov_t\ (r_{it+1}, r_{mt+1})$ represents the covariance of conditional information available at time $t$. The term A stands for the relative risk aversion of investors, and the term B represents the covariance price of risk for shifts in the investment opportunity set of investors $x_t$. (Brogaard & Detzel, 2015). The equilibrium relationship described in equation (1) has an interesting implication. Investors will have a greater demand for assets that have a positive intertemporal correlation with changes in the future returns of investments, bidding up the prices of those assets and driving down the expected returns.

## 2.3 Economic Policy Uncertainty

Pastor & Veronesi, (2011) (2012) propose the question of whether uncertainty about future government actions affects market prices. The authors developed an equilibrium model and investigated the effect of political uncertainty on stock prices. In their model, Firm profitability is defined by a stochastic process, and the mean of profitability is influenced by government policies. The authors mention that governments are motivated by economic and non-economic motives when making decisions. Governments face a trade-off; on the one hand, they should maximize the investors' welfare, as a socially-oriented entity would. On the other hand, governments are required to deal with the political costs (or benefits) associated with the adoption of different policies. The authors show that the costs are uncertain since investors cannot fully anticipate on policies that governments are going to implement. The source of uncertainty in the model of Pastor & Veronesi (2011) (2012) therefore, comes from the political costs. The authors describe that political shocks can occur when investors learn about the political costs associated with the implementation of certain policies. These political shocks even demand a specific equity risk premium since investors demand compensation for the outcomes of policy events. The authors show that this premium is more pronounced during weaker economic conditions. Governments are more likely to implement changes during a weaker state of the economy. During times like these investors are more likely to process news regarding new policies, increasing the political shocks, and increasing the impact on equity prices. (Pastor & Veronesi; 2011, 2012)

Baker et al., (2016) extended this part of academic literature by publishing a paper about measuring economic policy uncertainty. They developed an index of economic policy uncertainty (EPU). Prior efforts were made by other academics to construct such an uncertainty index, but those were not extensive enough and only measured certain parts of uncertainty. Therefore, Baker et al., (2016) constructed a broad index that would measure uncertainty from news, policy, market and economic indicators (Al-Thaqeb & Algharabali, 2019). For the construction of this index, Baker et al., (2016) used three types of components. (1) newspaper coverage of policy-related economic uncertainty. This component represents the search results of the ten largest newspapers in the US. This component is used for showing the number of news articles that discuss economic policy uncertainty. (2) temporary federal tax code provisions. This component is related to reports written by the Congressional Budget Office; they provide lists of federal tax code provisions. This component represents a measure of uncertainty about the path of federal taxes for the future. (3) Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. This component is used to show the dispersion between predictions about the Consumer Price Index, Federal Expenditures and State and Local Expenditures. The authors use this component to highlight the relationship between EPU and several micro and macro-economic factors. They find that EPU is associated with higher price volatility in stock prices. They further find that EPU leads to a decrease in investments and employment. This effect is most pronounced in policy-related sectors of the economy like defence, health care, finance and infrastructure

Several other studies also highlight these facts and show that economic policy uncertainty can affect asset prices; this can occur in multiple ways. Firstly, EPU is negatively related to capital investments. This implies that EPU might change or delay important decisions taken by specific firms (Gulen and Ion, 2014). Kang et al., (2013) show that economic policy shocks have a significant adverse effect on firm-level investments in interaction with firm-level price volatility in the long run. However, the authors do not find a significant effect for the largest firms (top 20%). Liu & Zhang, (2015) investigate the predictability of EPU to stock market volatility. In-sample the authors show that higher EPU leads to higher stock market volatility. Out-of-sample the authors show that including EPU as a volatility parameter significantly improves the forecasting abilities of volatility models, and this improvement is robust.

I previously highlighted that innovations in state variables that forecast the investment opportunities would influence expected excess returns of investors. Earlier studies show that economic (policy) uncertainty can be quantified as a relevant state variable, which affects the consumption and investment opportunity set of investors in the ICAPM. (Pastor & Veronesi, 2011, 2012; Bali et al., 2017; Bloom, 2009; Jurado, Ludvigson, and Ng, 2015; Bekaert and Engstrom, 2017; Brogaard & Detzel, 2015)

Bali et al., (2017) examined the role of general economic uncertainty in the cross-section of stock returns from July 1977 to December 2014. The authors use the general uncertainty index created by Jurado, Ludvigson, and Ng (2015). Their index is based on a variety of macroeconomic and other financial variables. For every month and each stock, Bali et al.,

(2017) estimate uncertainty betas from a 60-month rolling regression of excess returns on the economic uncertainty index. Stocks are required to have at least 24 monthly observations. The authors perform portfolio sorts where stocks are divided into deciles based on their uncertainty beta. A strategy of going long in the lowest decile of stocks and short in the highest decile of stocks delivers an annual return of approximately  6%, after controlling for a variety of risk factors. The authors find that this premium arises since stocks with a negative uncertainty beta outperform and stocks with a positive uncertainty beta underperform. The authors further conduct Fama & McBeth cross-sectional regressions. Those regressions show that there exists a significant negative relationship between economic uncertainty and future stock returns. With the use of the Fama & McBeth regressions, they are able to show that the uncertainty beta has predictive power. The uncertainty beta can predict future stock returns until 11 months into the future. Bali et al., (2017) provide several explanations for their striking results. They argue that an increase in economic uncertainty reduces investors' optimal consumption. Investors will alter their consumption and investments, in such a way that they can hedge against a worsening of economic activity. From the cross-section of stock returns, this implies that investors prefer holding stocks that have a higher covariance with economic uncertainty. Investors are able to compensate for potential losses by making a portfolio of stocks that correlate positively with economic uncertainty. This, in turn, leads to an increase in demand for stocks with a high covariance with economic uncertainty, which leads to higher prices. Stocks with a high uncertainty beta, therefore, have lower expected returns. This phenomenon can be strengthened by well-established literature on ambiguity aversion and the expected utility theory. Ellsberg (1961) shows that investors prefer known risk to uncertain or unknown probabilities. Bali et al., (2017) documented that investors demand a higher risk premium for holding the market portfolio when the correct probability law to the market return is uncertain. The state of the economy influences the future return distribution, leading to economic uncertainty entering an investor's utility function. The results from Bali et al., (2017) give rise to a possible preference-based explanation of the general uncertainty premium.

Since the financial crisis, a growing amount of literature has been presented that researches the potential effects of economic policy uncertainty. Arouri et al., (2016) contribute to that part of the academic field by studying the relationship between EPU and stock market returns. They study the relationship for the US stock market over a long period from 1900 – 2014. The authors show that EPU significantly reduces stock returns, and they also show that this relationship is non-linear by using a Markov Switching model. The effect of EPU on stock returns is more pronounced and persistent in high volatile periods. They argue that it could be interesting to extend their research and investigate the relationship during the presidential or midterm elections.

Brogaard & Detzel, (2015) also investigate the impact of EPU on stock returns, but they extend the research of Arouri et al., (2016) by examining the effect of EPU in the cross-section of stock returns. They argue and show that EPU is generally different from general economic uncertainty based on the paper of Pastor & Veronesi, (2012). As mentioned before the uncertainty in their model reflects agents learning about political costs associated with implementing policies. The perceived shocks are primarily driven by news shocks which are orthogonal to those related to economic fundamentals. In asset pricing, the perceived shocks are essentially what commands risk premiums. The authors document that it is ex-ante, not evident that a news shock driving policy uncertainty carries the same price of risk as a shock driving general economic uncertainty. The authors, therefore, argue that in terms of the ICAPM, EPU should carry a negative price of risk. An investor should be compensated with positive expected returns when he is long in stocks with a low covariance with EPU and short in stocks a high covariance with EPU. The authors employ a stochastic discount factor based GMM technique to estimate the EPU risk premium. The authors control for another uncertainty measure by controlling for the VXO, which is: “the Chicago Board Options Exchange monthly index of implied volatility on the S&P 100 index”. The authors use the Fama-French portfolios formed on size and momentum as base assets in their analysis and find that a portfolio with stocks with the highest EPU betas underperforms a portfolio with stocks with the lowest EPU betas, the underperformance is approximate 5.53% annually. The findings of Brogaard & Detzel, (2015) show the importance of EPU as a risk factor for equities.

Bekiros et al., (2016) investigates whether EPU matters for the prediction of the US equity risk premium. The authors account for instabilities and nonlinearities in their research. They perform quantile regressions over a monthly timeframe from 1900 – 2014. Incorporating the EPU proxy in the quantile regressions enhances the out of sample predictability of stock returns significantly. The authors further attribute that this effect is present during times where market sentiment is neutral but not when the sentiment turns highly bullish.

## 2.4 International evidence

There has also been international evidence for the relationship between EPU and stock returns. For instance, Chen et al., (2017) study how economic policy uncertainty in China influences Chinese stock returns. They find that on average, a higher EPU will lead to lower future stock returns; this relationship is statically significant. The results from Chen et al., (2017) suggest that the Chinese stock market is inherently different from the US stock market. Chen et al., (2017) further find that the effect of EPU is more pronounced in small-cap, value and momentum portfolios. Li, (2017) extends the research from Chen et al., (2017) and investigates whether China's EPU commands a positive or negative risk premium. The Chinese stock market can be characterized by excessive speculative trading. (Pan et al., 2016; Xiong & Yu, 2011). Li, (2017) mentions that Chinese investors are very risk-seeking and are prone to behavioural biases. The assumptions of the ICAPM do not hold because of these facts. Hence, the relationship between excess returns and EPU should be opposite compared to the US. Therefore, the author formulates that Chinese Investors have a greater demand for stocks with negative EPU betas compared to stocks with positive EPU betas. Li, (2017) follows the study of Brogaard & Detzel, (2015) and also accounts for other measures of uncertainty as state variables, again to isolate the effect of uncertainty provided by EPU. The author documents that in China, EPU commands a positive risk premium. Implying that investors are compensated with abnormal returns when going long in a portfolio of stocks with positive EPU betas, and short in a portfolio of stocks with negative EPU betas. Over the sample period from 1997 – 2014, the authors find that a factor-mimicking portfolio on EPU delivers a premium of 11.99% per year. This study shows that stock market characteristics are also important in explaining the relationship between EPU and stock returns.

Phan et al., (2018) also investigated whether EPU can predict stock market returns. The authors perform a cross country analysis. The authors look at the relationship between the innovations in EPU and monthly excess returns on the most popular equity indices in 16 countries. Furthermore, the authors perform a sector-based analysis for 10 sectors in the US market. The industry sectors are characterized by their unique CIGS code from the Datastream database. The authors find predictability in 10 out of 16 countries; they also show that EPU influences industries differently. For instance, the returns in the basic materials and utility sector are not affected by changes in EPU. Gomes et al., (2007) documented that non-durable goods are less cyclical than durable goods. The authors show that the cash flows and stock returns of durable goods are more exposed to systematic risk. Gomes et al., (2007) quantify durable goods as "commodities" that have an average life of at least three years. Examples are furniture, household equipment and other durable goods. Non-durable goods are quantified as "commodities" with an average service life of at most three years. Examples are clothing, food, fuel, oil and other non-durable goods. Bali et al., (2017) build on this paper and show that their economic uncertainty premium is statistically and economically significant in the Durable, Energy, Hi-Tech, Telecom, Shops and in the Other industry group. They find that the premium is statistically weak in the Health, Utilities and the Non-durable industry group.

Additionally, over the past couple of decades, globalisation increased significantly. So, a sound understanding of economic policy uncertainty and its effect on equity prices is essential because the spillover effects can be severe. Colombo (2013) proposes the question of whether EPU in the US matters for the Eurozone. She shows that: "a one standard deviation shock to US economic policy uncertainty leads to a statistically significant fall in the European industrial production and prices of −0.12% and −0.06%, respectively". She further shows that a US uncertainty shock has a more substantial impact on the Eurozone than a shock that originates in the Eurozone itself. This particular research highlights the importance of political transparency and stability to prevent negative uncertainty shocks on the economy/stock market.

Li & Peng (2017) also research the potential spillover effects. They investigate the co-movements between Chinese and US stock markets. The authors attribute that there is a growing interest in studying and understanding the relationship of EPU and financial risk management. Papers related to this topic are among the most cited and downloaded in finance and financial economics. Additionally, the Chinese A-share stock market has become more integrated within the international market and has become more accessible for investors. Correlations in asset markets play a crucial role in constructing an optimally diversified portfolio. The authors examine the impact of US EPU changes on four different US-China stock market correlations. They consider four stock markets in China. (1) Shanghai A-share, (2) Shanghai B-share, (3) Shenzhen A-share and (4) Shenzhen B-share. The authors show that absolute changes negatively influence the co-movements in the US EPU index. Investors whose portfolio compromise of US and Chinese stocks may draw implications from these results. For gaining diversification benefits, investors need to interpret the US EPU index carefully and act accordingly.

Based on the ICAPM and various other influential papers, I reason that EPU is a relevant state variable which can affect the consumption and investment opportunity set of investors. I, therefore, expect that investors prefer holding stocks with a higher covariance with innovations in EPU. This, in turn, leads to higher demand and higher prices for these particular stocks and brings down their expected returns. A portfolio that is long in stocks with a low covariance with innovations in EPU and short in stocks with a high covariance with innovations in EPU should be compensated with positive expected returns (Brogaard & Detzel, 2015; Bali et al., 2017). I further reason that this implies that a hedge portfolio (long decile 1, short decile 10) should deliver positive abnormal returns in the US market (Brogaard & Detzel, 2015). Therefore, I expect the following:

***H1****: A low EPU beta portfolio shows significantly higher excess returns than a high EPU beta portfolio in the US stock market*

***H2:*** *An EPU hedge portfolio of long decile 1 and short decile 10 will earn positive abnormal returns in the US stock market*

Brogaard & Detzel, (2015) do not conduct Fama-Macbeth regressions in their research. So, I decided to include such an analysis in this paper. Li, (2017) shows that loadings of an EPU factor portfolio positively forecast the cross-section of stock returns in China. She acknowledges that the Chinese market is inherently different from the US market. The hypothesised sign is opposite from the US market because the ICAPM does not hold in the Chinese stock market due to speculative trading. Bali et al., (2017) show that general economic uncertainty and the cross-section of future stock returns have a negative and significant relationship. The authors show that this relationship holds across all regression specifications, allowing for other firm characteristics and industry effects. I expect that EPU carries a negative price of risk, meaning that future expected returns decrease significantly when a stock moves from the 1st to the 10th decile of $\beta EPU$. Therefore, my third hypothesis is the following:

***H3:*** *The loadings on the EPU factor-portfolio will negatively forecast the cross-section of future stock returns in the US stock market*

Durable goods are more exposed to systematic risk due to having a more cyclical nature. (Gomes et al., 2007). Bali et al., (2017) show that the general economic uncertainty premium is statistically and economically significant in the cyclical sectors of the economy. However, the relationship is statically weak in the non-cyclical sectors of the economy. Investors have a greater incentive to hedge against potential reductions when holding cyclical stocks (Gomes et al., 2007). This leads to a greater demand for cyclical stocks that have a higher covariance with innovations in EPU. In turn, leading to higher prices and lower expected returns. I, therefore, formed the following hypothesis:

***H4**: The EPU Premium is more pronounced in cyclical sectors of the US economy*

## 2.5 Presidential cycles

As mentioned earlier, the interaction between economic policy uncertainty and presidential cycles is also fascinating. Santa-Clara & Valkanov, (2003) documented the "presidential puzzle" and investigated the relationship between stock returns and political cycles in the US. The authors conduct their research over a relatively long period from 1927 – 1998. They find that the excess returns are significantly higher under Democratic presidencies than under Republican presidencies. The excess return of a CRSP value (equal) weighted portfolio is on average 9% (16%) higher under Democratic ruling. Business cycle variables cannot explain the observed difference in excess returns between administrations. Santa-Clara & Valkanov, (2003) further show that there are no significant deviations in excess returns around presidential elections. The authors also show that volatility in the markets is a bit higher during Republican administrations. Pastor & Veronesi, (2017) agree with Santa-Clara & Valkanov, (2003) and show that the return gap is even more significant for a more recent period. From 1999 – 2015 the return gap is 17.5%. The authors explain the source of the return gap. They emphasize that it is not about what presidents do, but it rather depends on the moment when they get elected. The authors developed an equilibrium model where the "presidential puzzle" emerges endogenously. The model is built on the assumption of time-varying risk aversion. When expected future returns are high or when risk aversion is high, people tend to elect a Democratic president. When risk aversion is low people tend to choose a Republican president. Therefore, the authors argue that risk aversion is higher under Democratic presidents leading to a higher equity risk premium which leads to higher returns. The authors look at recent history to get a sound understanding of changes in leadership during several crises. During the great depression a Republican president was replaced by a Democratic president and during the financial crisis of 2008 George Bush (REP) was replaced by Barack Obama (DEM). The results of the model imply that stocks returns, as well as economic growth, are higher under Democratic presidencies than under Republican presidencies. Belo et al., (2013) extends this area of research and relate political cycles to the cross-section of stock returns. They investigate how political cycles influence the cross-section of stock returns through the government spending channel. The authors conduct their research in the US over the period from 1947 until 2002. The authors show that firms with a lot of government exposure significantly outperform firms with little government exposure. This outperformance is approximate 6.1% on an annual basis. However, this effect is reversed under a Republican administration. When the Republican party is in power, firms in industries with a lot of government exposure underperform relative to firms in industries with little government exposure. This underperformance is approximate 4.8% annually. This pattern is robust after controlling for firm-level characteristics. The results from this paper imply that the presidential puzzle, documented by Santa-Clara & Valkanov, (2003) is more pronounced in sectors that have high exposure to government spending relative to industries that have low exposure to government spending. For guidance industries that have a high exposure are; Shipbuilding & repairing, Oil & Gas extraction. Industries that have a low exposure are for example; Tobacco product manufactures, Soft drink and ice manufactures. Belo et al., (2013) also constructed an investment strategy that tries to exploit the presidential cycle effect. During Democratic presidencies, the authors go long in a portfolio of companies with a lot of government exposure and short in a portfolio of companies with low government exposure. When the Republican party is in power, one does the opposite. This strategy yields an abnormal return of 6.9% annually. This outperformance is mainly concentrated during the second and third year of presidencies.

Linking presidential elections to economic policy uncertainty is relatively new in the academic field. But, Goodell et al., (2020) recently investigated the relationship between election, policy and market uncertainty. They showed that changes in the election probability of the party of incumbency heavily influences how election uncertainty impacts political and financial uncertainty.

Pastor & Veronesi, (2017) show that the return gap documented by Santa-Clara & Valkanov, (2003) is explained by when presidents get elected and not by the specific actions of presidents. The authors argue that Democratic presidents tend to get elected when risk aversion is high. During these times, investors demand extra social insurance and that is provided by Democratic administrations. During crises or global turmoil, risk aversion typically rises, resulting in a victory for the Democratic party. During crises or global turmoil, EPU increases as well. Based on the academic evidence presented above, I formed the following hypothesis:

***H5**: The excess returns of an EPU factor-portfolio are more pronounced during Democratic presidencies than during Republican presidencies*

# 3. Data

This research revolves around the question of whether and how economic policy uncertainty is priced in the cross-section of stock returns in the United States. In this section, I will explain the data that is used for conducting this particular research. Brogaard & Detzel, (2015) were the first to present evidence on this relationship. However, no further research has been conducted for the US market after the publication of their paper. I intend to build on the evidence presented by Brogaard & Detzel, (2015). I will investigate the relationship between EPU and the cross-section of stock returns for an extended and more recent period.

I will investigate the link between EPU and the cross-section of stock returns from February 1987 until December 2019, and I will use data from January 1985 until December 2019. The monthly stock returns are obtained from the CRSP database. My analysis includes all common stocks (CRSP share code 10 and 11) either listed on the NYSE, AMEX or NASDAQ. Accounting variables of firms are extracted from the Compustat. Several adjustments are made to the dataset consistent with other academic literature that performs research in the cross-section of stock returns. Firstly, financial firms are excluded from my analysis. Financial firms are characterized by high leverage and this makes them hard to compare against non-financial firms. High leverage in non-financial firms typically indicates distress. (Fama & French, 1992). Secondly, all observations of a stock during a year are dropped when it has a share price that is lower than $ 5 in a month during that specific year. These "Penny" stocks are dropped due to illiquidity reasons and can otherwise lead to distortions in the data. Lastly, stocks in the bottom 20% of market capitalization listed on the NYSE are dropped. These are mainly micro-cap stocks, including those type of stocks can lead to distortions when making long-short portfolios. These distortions can also be quantified as illiquidity reasons.

For measuring EPU, I will use the dataset provided by Baker et al., (2016). The dataset is listed on their website. As mentioned before, the authors constructed their index from three types of components: (1) News Coverage about policy-related Economic Uncertainty. (2) Tax Code

Expiration Data. (3) Economic Forecaster Disagreement. Their index starts in January 1985 and is updated every month. The data regarding the VIX index is extracted from the FRED database of Economic Research. This index started in January 1990.

Data regarding several asset pricing models is extracted from the Kenneth French's data library. I will extract the excess returns of the market (MKT), the factors high-minus-low (HML), small-minus-big (SMB), winner-minus-losers (UMD), robust-minus-weak profitability (RMW) and conservative-minus-aggressive Investments (CMA). The specifics regarding the industry sectors are also extracted from the Kenneth French's data library.

# 4. Methodology

In this section of my research, I will explain the specifics about how I perform my research. Firstly, in figure 1 in the appendix one can see how the EPU index and the VIX vary over time. The correlation between these two indices is approximately 40%. The EPU index can be quantified as a persistent index. Therefore, it is common to look at the changes/innovations in the index instead of looking at the total index values. This is also documented by Brogaard & Detzel, (2015), they mention: "From the EPU time-series we must extract innovations because shocks to risk factors are what commands risk premiums". I estimate an AR (1) process for EPU with equation (2). From these time-series, I will extract the innovations in EPU ($\epsilon_t^{EPU}$) and use these in my research for performing the asset pricing tests. I intend to follow papers that are closely related to mine. Therefore, I will also account for general market uncertainty as measured in the US by the VIX. For the VIX, I also estimate an AR (1) process computed with equation (3).

$$EPU_t = \alpha + \beta_1 EPU_{t-1} + \epsilon_t^{EPU} \tag{2}$$

$$VIX_t = \alpha + \beta_1 VIX_{t-1} + \epsilon_t^{VIX} \tag{3}$$

To test whether EPU commands a specific equity risk premium, I calculate the EPU beta ($\beta^{EPU}$) for every stock in every month in my sample using a time-series regression model. I estimate the EPU betas from rolling regressions of excess stock returns on the innovations in the economic policy uncertainty index over a 60-month period after controlling for the market factor of the CAPM. Stocks are required to have at least 24 observations (Fama & French, 1992). Equation (4) is used for estimating the EPU betas ($\beta_1$) of stocks. I form a factor mimicking portfolio factor on the VIX, to control for general market uncertainty. I measure the betas of stocks in my sample against the VIX using equation (5). $\Delta VIX$ represents the innovations in the VIX as calculated with equation (3).

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \Delta EPU + \beta_2 \left(R_{m,t} - r_{f,t}\right) + \epsilon_t \tag{4}$$

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \Delta VIX + \beta_2 \left(R_{m,t} - r_{f,t}\right) + \epsilon_t \tag{5}$$

$R_{i,t}$ represents the return on stock *i* during a specific month and $r_{f,t}$ is the risk-free rate. $\Delta EPU$ represents the innovations in the EPU index as calculated with equation (2). $R_{m,t} - r_{f,t}$ is the excess market return. After obtaining the individual EPU betas, I construct decile portfolios based on EPU betas of stocks. I follow Bali et al., (2017) by using the EPU betas in month *t* for the prediction of stock returns in month *t+1*. I will make decile portfolios where decile 1 represents stocks with the lowest EPU beta, and decile 10 represents stocks with the highest EPU beta. Based on the assumptions of the ICAPM and the academic literature presented in this paper, I will make a long/short portfolio which is long in decile 1 and short in decile 10. The factor mimicking portfolio on the VIX is made by making decile portfolios based on stocks their VIX betas and then going long in decile 1 and short in decile 10. The next step in my analysis is testing the significance of the excess returns across deciles and for the long/short portfolio. Furthermore, I will verify whether the proposed strategy is able to produce alpha. Tests will be performed against various known asset pricing models: CAPM, FF3, Carhart 4 factor model and the FF5. I will also extend the CAPM and the FF3 by controlling for general market uncertainty as measured with the factor mimicking portfolio on the VIX. The different regression equations are represented below:

$$R_{i,t} - r_{f,t} = \alpha + \beta\left(R_{m,t} - r_{f,t}\right) + \epsilon_t \tag{6}$$

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \left(R_{m,t} - r_{f,t}\right) + \beta_2 UNC + \epsilon_t \tag{7}$$

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \left(R_{m,t} - r_{f,t}\right) + \beta_2 SMB + \beta_3 HML + \epsilon_t \tag{8}$$

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \left(R_{m,t} - r_{f,t}\right) + \beta_2 SMB + \beta_3 HML + \beta_4 UNC + \epsilon_t \tag{9}$$

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \left(R_{m,t} - r_{f,t}\right) + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + \epsilon_t \tag{10}$$

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \left(R_{m,t} - r_{f,t}\right) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \epsilon_t \tag{11}$$

$R_{i,t} - r_{f,t}$ represents the excess return of a portfolio sorted on EPU betas, $R_{m,t} - r_{f,t}$ represents the market risk premium as in the CAPM, $SMB$ is the size factor (Small minus Big) commonly used in asset pricing models, $HML$ is the Book to Market factor (High minus Low), $UMD$ is the momentum factor as in the Carhart 4 factor model, $RMW$ is the difference in profitability (Robust minus Weak), the $CMA$ factor shows the investment intensity (Conservative minus Aggressive) and the $UNC$ factor represents the factor mimicking portfolio formed on the VIX.

After my portfolio sort analysis, I will run Fama-Macbeth regressions on a stock level basis, Bali et al., (2017) argues that a cross-sectional analysis based on portfolios has potential disadvantages. Firstly, a portfolio-level analysis has the potential to discard a vast amount of information due to aggregation. Secondly, the authors argue that a portfolio-level analysis is a setting, which makes it is difficult to control for a variety of effects simultaneously. In the Fama-Macbeth regressions, I will account for individual stock market betas. I follow Fama & French (1992) by estimating the market beta of stocks by using a rolling window of returns over the past 60 months, and stocks are required to have at least 24 observations. I will also include firm size and B/M; size is computed as the product of the share price and the number of shares outstanding. B/M ratio is the book value of equity divided by the market value of equity of a firm. In this paper book value of equity is computed as the book value of stockholder equity plus deferred taxes and investment tax credit minus preferred stock capital. For some observations, those variables were not available. In such a case, the book value of equity was computed by subtracting total assets from total liabilities. I also account for market uncertainty by including the betas of the individual stocks formed against the VIX. I further account for momentum as pioneered by Jegadeesh and Titman, (1993). Momentum is defined as the cumulative return over a period of 11 months in the past. The computation of the cumulative return start at *t-12* and ends at *t-1*. Lastly, I will account for the short-term reversal effect, which can be present in stocks. As pioneered by Jegadeesh (1990) the reversal effect is formed by lagging the excess return of a stock for one month. I follow the approach of Bali et al., 2017 by investigating the ability of EPU to forecast future returns. The monthly cross-sectional regression equation is given in equation (12).

$$R_{i,t+1} - r_{f,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{EPU} + \lambda_{2,t} \cdot \beta_{i,t}^{UNC} + \lambda_{3,t} \cdot X_{i,t} + \varepsilon_{i,t+1} \quad (12)$$

$R_{i,t+1} - r_{f,t+1}$ stands for the excess return on stock *i* in month *t+1*. $\beta_{i,t}^{EPU}$ is the EPU beta of stock *i* in month *t*. $\beta_{i,t}^{UNC}$ is the beta of stock *i* formed against the VIX during month *t*. $X_{i,t}$

represents a vector, which stands for the different firm-specific variables at time *t* for stock *i*. These variables are the market beta, the natural log of market cap, the natural log of B/M, momentum and short-term reversal. I account for heteroskedasticity and autocorrelation by reporting the t-statistics following Newey and West, (1987). I follow the research of Brogaard & Detzel, (2015) by reporting the error terms with four lags.

I will sort stocks in quintiles based on their EPU betas to examine how the relationship between stock returns and EPU behaves across industry sectors. I will use the 12-industry classification list to quantify the different industries. This list can be obtained from the Kenneth French data library. The industry of a stock is quantified by the Standard Industrial Classification (SIC) code. I will take 11 sectors into account since financials are excluded in this research. The list of different industries and their description is reported in table 1 in the appendix. I will perform a double sorting process by making quintile portfolios for 11 different sectors (5x11). I will investigate whether the EPU premium is more pronounced in cyclical sectors of the economy.

To check my last hypothesis, I will make a dummy variable for quantifying whether there is a Democratic or a Republican president in charge. When a Republican is in charge the value will be 0 and when a Republican is in charge the value will be 1. I will extend the portfolio sort analysis in the first part of my research by investigating whether the excess returns of a strategy based on EPU are statistically different from one political party to the other.

# 5. Results

## 5.1 Summary statistics

Table I in this research shows the summary statistics of uncertainty related variables like EPU and VIX. It also shows the summary statistics for the different firm characteristics I accounted for in my research, and it shows the various asset pricing factors used in my research. My final sample included 13439 firms. The EPU index has a mean value of 109.15, and the mean absolute difference from month to month is very close to zero. I can reject that the EPU index has a unit-root since the Dickey–Fuller unit-root test shows a t statistic of -5.67, making it significant at all critical levels. This indicates that the EPU Index is very persistent, implying that one has to take changes in the index into account instead of looking at the total index. The innovations in the EPU index are presented in figure 2 in the appendix. One can observe that the values usually are very close to zero with some exceptions during specific events like 9/11.

Another observation is that the index has become more volatile over the last decade compared to the years before 2010. Furthermore, the index reached its lowest point during a period of relative tranquillity just before the great financial crisis (GFA) started, and the index reached its highest level during the sovereign debt crisis in 2011. For comparison the VIX also reached its lowest point during the period just before the GFA and reached its highest level in 2008 in the middle of the GFA, implying that VIX is more associated with general market uncertainty. The firm characteristics are reported in Panel B of the table. The mean of betas formed against EPU and the VIX is relatively low. The mean market beta of stocks in my sample is close to one, and that is consistent with what one would expect. The summary statistics on other firm characteristics are consistent with previous studies that investigated the cross-section of stock returns. Panel C. shows the summary statistics for the different asset pricing factors included in this paper. I reported two different SMB factors (SMB3 & SMB5), I used two different SMB factors in this research because the factor loading on SMB varies when considering the Fama & French 3 factor model compared to the Fama & French 5 factor model. However, as one can observe the difference between the two variables are small.

Table II reports the correlation coefficients of different stock characteristics in my sample. The beta of stocks formed against EPU has a weak positive correlation with the beta of stocks formed against the VIX (0.2324). Further, in the first row of the table, one can observe that the EPU beta of stocks has a slight positive correlation with the market beta of stocks (0.0068), although this coefficient is very close to zero. The EPU beta of stocks is slightly positively correlated with the natural logarithm of the market cap of companies (0.0784) and negatively correlated with book to market (-0.0275) and momentum (-0.0384). However, these coefficients are again very small. The correlation coefficient of EPU and short-term reversal is also very close to zero (0.0017). The correlations coefficients of VIX betas and other firm characteristics are also very low. Li, (2017) also documented the low correlations between the uncertainty betas and other firm characteristics. She mentions that low correlations are a positive thing. She argues that if correlations were high, the predictive power of EPU for expected returns might be driven by the correlations of EPU and other return factors. However, table II shows that this concern is not relevant, given rise to the suggestion of EPU possibly adding new information to asset pricing models.

## Table I
## Summary Statistics of Explanatory Variables and Asset Pricing Factors

This table shows the summary statistics (mean, standard deviation, median, min and max) of the variables in the dataset. Panel A shows the summary statistics for the uncertainty-related variables: The general EPU Index, as provided by Baker et al., (2016), the monthly absolute difference of the EPU Index, the AR(1) EPU Index which represents the innovations in the EPU Index and is calculated with equation (2). Panel A also shows the statistics for the VIX and AR(1) VIX Index shows the innovations of the VIX index as computed with equation (3). Panel B shows the summary statistics for specific firm characteristics used throughout the analysis. βEPU, βUNC and βMKT are calculated using rolling regressions over a 60-month period with a minimum of 24 months (Fama & French, 1992). SIZE represents the natural log of the market capitalization of a company and BM is the natural log of the book to market ratio. MOM represents the momentum effect which can be present in specific stocks and is calculated according to the framework of Jegadeesh and Titman, (1993). REV represents the reversal effect is calculated by lagging the monthly excess return for one month as pioneered by Jegadeesh, (1990). Panel C displays the summary statistics for the most important asset pricing factors used in this paper MKTRF, SMB3, HML3, UMD, SMB5, HML5, RMW5 and CMA5. The sample period is from February 1987 to December 2019.

| Variable | Mean | SD | Median | Min | Max |
|---|---|---|---|---|---|
| *Panel A. Uncertainty-Related Variables* | | | | | |
| EPU Index | 109.15 | 31.86 | 102.66 | 57.20 | 245.13 |
| Absolute difference EPU Index | 0.04 | 20.28 | -1.06 | -94.13 | 103.77 |
| AR (1) EPU Index | 6.95e-06 | 19.23 | -2.65 | -75.62 | 99.72 |
| VIX Index | 19.15 | 7.44 | 17.37 | 10.13 | 62.64 |
| AR (1) VIX Index | -1.39e-09 | 3.48 | -0.43 | -8.34 | 32.24 |
| *Panel B. Firm Characteristics* | | | | | |
| $\beta EPU$ | -0.00018 | 0.0014 | -0.0001 | -0.03 | 0.02 |
| $\beta UNC$ | -0.00079 | 0.0090 | -0.0007 | -0.09 | 0.18 |
| $\beta MKT$ | 1.09 | 0.70 | 1.02 | -9.36 | 9.80 |
| SIZE | 13.27 | 1.94 | 13.27 | 7.53 | 20.99 |
| BM | -0.81 | 0.81 | -0.73 | -10.004 | 2.98 |
| MOM | 0.15 | 0.40 | 0.12 | -2.30 | 5.19 |
| REV | 0.01 | 0.13 | 0.007 | -0.83 | 4.16 |
| *Panel C. Asset Pricing Factors* | | | | | |
| MKTRF | 0.0072 | 0.04 | 0.0119 | -0.23 | 0.12 |
| SMB3 | 0.0004 | 0.03 | 0.0002 | -0.17 | 0.22 |
| HML | 0.0015 | 0.03 | -0.0007 | -0.11 | 0.13 |
| UMD | 0.0052 | 0.05 | 0.0061 | -0.34 | 0.18 |
| SMB5 | 0.0006 | 0.03 | -0.0001 | -0.15 | 0.18 |
| RMW5 | 0.0036 | 0.02 | 0.0041 | -0.18 | 0.13 |
| CMA5 | 0.0023 | 0.02 | 0.0006 | -0.07 | 0.10 |

**Table II**
**Correlations of Stock Characteristics**

This table reports the Pearson correlations between the different firm characteristics. βEPU, βEPU and βMKT are calculated using rolling regressions over a 60-month period with a minimum of 24 months (Fama & French, 1992). SIZE represents the natural log of the market capitalization of a company and BM is the natural log of the book to market ratio. MOM represents the momentum effect according to the framework of Jegadeesh and Titman, (1993). REV represents the reversal effect as pioneered by Jegadeesh, (1990). The sample period is from February 1987 to December 2019.

| | $\beta UNC$ | $\beta MKT$ | SIZE | BM | MOM | REV |
|---|---|---|---|---|---|---|
| $\beta EPU$ | 0.2324 | 0.0068 | 0.0784 | -0.0275 | -0.0384 | 0.0017 |
| $\beta UNC$ | | 0.0667 | 0.0700 | -0.0721 | 0.0164 | 0.0143 |
| $\beta MKT$ | | | 0.0608 | -0.1305 | 0.0554 | 0.0106 |
| SIZE | | | | -0.3476 | 0.0791 | 0.0290 |
| BM | | | | | -0.2626 | -0.0912 |
| MOM | | | | | | -0.0267 |

## 5.2 Portfolio analysis

Table III presents the monthly excess returns of decile portfolios formed on EPU betas. For each month in my sample, I created decile portfolios based on stocks their EPU beta of the previous month. Column one presents the deciles. The second column of Table III shows the average EPU beta per decile. One can observe that the betas increase per decile. The third column of the table shows the monthly excess return. The expectation was that the excess return would be highest in decile 1 and that the returns would decrease monotonically per decile. However, the observed pattern in excess returns is more U-shaped. The average excess return of the 1st decile is 1.43%, the 5th decile shows a return of 0.97%, and the 10th decile shows a return of 1.34%. Decile 6 shows an increase in excess return, but in decile 7, it decreases again. A long-short portfolio of going long in decile 1 and short in decile 10, results in an average monthly excess return of 0.09%. This difference is not economically significant, and the associated t-statistic shows that the difference is not statistically different from zero. Therefore, I am not able to accept my first hypothesis of this paper. Figure 3 in the appendix gives a graphic representation of monthly excess returns across the deciles. The fourth column of table III presents the standard deviation of the excess returns. One can observe that the standard deviation is highest in decile 1 and then decreases monotonically, from decile 8 onwards the volatility rises again. An explanation for the U-shaped pattern in decile portfolio returns can be found by looking at this volatility pattern. Veronesi, (2000) published an influential paper about information quality and its effect on stock returns. He argues that the precision of signals affects the equilibrium of unconditional return volatility. When signals are imprecise, volatility is first decreasing and later increasing according to the level of risk aversion of investors. Veronesi,

(2000) further mentions the following: "When signals are imprecise, dividend realizations have an impact on investors' hedging demand which tends to decrease the volatility of returns compared to the dividend volatility. However, for a sufficiently high risk-aversion coefficient, the indirect effect on the hedging demand dominates increasing return volatility again hence the U-shaped function of volatility with respect to the coefficient of risk aversion".

Basic modern portfolio theory (MPT) (Markovitz, 1952) describes that investors expect to earn higher returns when investing in riskier assets. Hence, the U-shaped function of volatility for imprecise signals in combination with MPT might explain the observed dispersion in excess returns across decile portfolios. Columns five and six show the risk-adjusted returns of the EPU beta portfolios against the Fama & French 3 factor model and the Fama & French 5 factor model. One can observe a similar U-shaped pattern in the alphas as in the excess returns. The alphas generally decrease until decile 8, with decile 6 being the exception.

**Table III**
**EPU Decile Portfolio Returns**

This table presents the average returns of each of the 10 deciles portfolios and the long/short portfolio formed on the EPU Betas of stocks. These EPU betas are estimated with the following equation:

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 \Delta EPU + \beta_2 \left(R_{m,t} - r_{f,t}\right) + \epsilon_t.$$

The EPU betas using a rolling regression window of 60 months with a minimum of 24 months. For each decile, the average EPU Beta, Monthly Excess Return (%), Standard Deviation (%), Fama & French 3 factor-alpha (%), Fama & French 5 factor-alpha (%) and Sharpe ratio are reported. Column D1-D10 represents the long/short portfolio, and that is formed by the difference in monthly excess return between the 1st and 10th decile. The t statistics are reported in parentheses. The sample period is from February 1987 to December 2019. *Significance at the 10% level. **Significance at the 5% level. ***Significance at the 1% level.

| Deciles | EPU Beta | Excess Return | SD | $\alpha^3$ | $\alpha^5$ | Sharpe Ratio |
|---|---|---|---|---|---|---|
| D1 | -0.0025 | 1.43*** (4.20) | 6.78 | 0.60*** (5.55) | 0.75*** (6.81) | 0.17 |
| D2 | -0.0013 | 1.08*** (3.87) | 5.53 | 0.32*** (3.84) | 0.31*** (3.68) | 0.15 |
| D3 | -0.0008 | 1.05*** (4.18) | 5.01 | 0.35*** (4.48) | 0.27*** (3.67) | 0.14 |
| D4 | -0.0005 | 1.03*** (4.23) | 4.85 | 0.34*** (5.00) | 0.24*** (3.71) | 0.16 |
| D5 | -0.0003 | 0.97*** (4.19) | 4.60 | 0.31*** (4.50) | 0.19*** (2.96) | 0.16 |
| D6 | -0.00003 | 1.04*** (4.66) | 4.45 | 0.39*** (6.13) | 0.28*** (4.65) | 0.18 |
| D7 | 0.0002 | 0.95*** (4.33) | 4.38 | 0.31*** (4.55) | 0.14*** (2.38) | 0.16 |
| D8 | 0.0005 | 1.03*** (4.64) | 4.42 | 0.39*** (5.48) | 0.26*** (3.79) | 0.18 |
| D9 | 0.0009 | 1.05*** (4.37) | 4.80 | 0.38*** (5.00) | 0.27*** (3.67) | 0.17 |
| D10 | 0.0021 | 1.34*** (4.53) | 5.89 | 0.60*** (7.07) | 0.62*** (7.21) | 0.23 |
| D1-D10 | -0.0046 | 0.09 (0.66) | 2.65 | 0.0006 (0.00) | 0.13 (1.02) | -0.02 |

From decile 8 onwards, the alphas increase again. The difference between the abnormal returns of decile 1 and 10 are 0.0006 (0.00) and 0.13 (1.02). Both are not economically significant and statistically different from zero. The last column shows the Sharpe ratios of the portfolios. The

Sharpe ratio is computed by subtracting the risk-free rate from the excess return of the portfolio and dividing that by the standard deviation. For this calculation, the average risk-free rate over my sample period was used; the average risk-free rate was 0.25% per month. There does not seem to be a clear pattern in Sharpe ratios across deciles. However, it is interesting to note that the highest Sharpe ratio is achieved in decile 10.

## 5.3 Time-Series regression

Table IV presents the results of the time-series regressions of EPU portfolios against various asset pricing models. Column 1 to 3 in Panel A presents the results for equal-weighted portfolios tested against the CAPM. In isolation, both portfolios are able to generate significant positive alphas. However, column 3 shows that a long/short portfolio formed on EPU is not able to generate any significant alpha. Column 3 also indicates that the market factor (0.1827) is highly significant, implying that the market factor already captures the variation in returns of a portfolio on EPU. Column 4 to 6 presents the results for the Fama & French 3 factor model. The same pattern emerges since no significant alpha can found for the hedge portfolio. Again, the market factor is highly significant in FF3 model. Decile 1 has a negative loading on the HML factor, however insignificant and decile 10 shows a positive and significant loading on the HML factor (0.0887). Implying that returns in decile 10 are more associated with value firms. The long/short portfolio, therefore, shows a significant and negative loading on the HML factor (-0.1302). This implies that the returns of the hedge portfolio are more associated with growth firms than with value firms. The SMB factor is positive and significant in both deciles, indicating that the returns are associated with smaller companies. However, the result becomes insignificant for the long/short portfolio. Panel B shows the same analysis while controlling for the VIX uncertainty factor. Column 3 and column 6 show that the long/short portfolios are still not able to produce significant alphas. Furthermore, in both models, the VIX factor is highly significant. Implying that this other uncertainty factor captures a part of the cross-sectional variation in returns. In both models, the market factor is still highly significant, and the portfolio still loads negatively on the HML factor. Panel C shows the results for the portfolios when tested against the Carhart 4-factor model and the Fama & French 5 factor model. Column 3 and 6 again show higher alphas compared to the previous asset pricing models. However, the alphas are still insignificant and therefore, indistinguishable from zero. Another observation is that the long/short portfolio still has a negative loading on the HML factor when tested against the Carhart 4 factor model. The long-short portfolio also loads negatively on the momentum factor, and this effect is highly significant. This comes from the fact that decile 1 loads very negatively on momentum (-0.1564). This shows that stocks that have a low covariance with innovations in EPU generally show low momentum. Column 4 to 6 in panel C shows that the HML factor becomes redundant when the RMW and CMA factor are included. This is consistent with Fama & French, (2015). They showed that the value factor became redundant when the two other factors were included. The time-series of the value factor are entirely explained by the exposure to the other four factors in the model. From the FF5 model, one can further observe that the long/short portfolio loads significantly negative on the RMW and CMA factor. The negative loadings in decile 1 are a potential explanation for this pattern. Negative slopes on RMW and CMA identify firms that invest aggressively and are unprofitable. Fama & French, (2015) show that these negative slopes help to explain the low average stock returns associated with high beta and highly volatile returns. The portfolio in decile 1 has the highest market beta of all portfolios, and this portfolio is also the most volatile, as could be observed in table III. This implies that a portfolio with firms that have the lowest covariance with EPU can be quantified as firms with a high market beta which are volatile, unprofitable and invest aggressively. These characteristics are not rewarded with significant outperformance over stocks that have a higher covariance with EPU. The average $R^2$ values are reported below the output of every regression. One can observe that the Carhart 4 factor model explains the highest amount of variation in returns for the long/short portfolios (17.9%). One would maybe expect that the FF5 model would explain the highest amount of variation in returns. However, the 5-factor model has its drawbacks. Namely, it is unable to capture the low average returns of small-cap firms which invest aggressively despite being unprofitable (Fama & French, 2015). All in all, I am not able to accept my second hypothesis after conducting the tests against the various asset pricing models. In all six regressions, the alphas of the long/short portfolios are not statistically different from zero. This result is not consistent with the paper of Brogaard & Detzel, (2015) who found proof for the presence of an EPU premium in the cross-section of US stock returns.

## 5.4 Fama-Macbeth cross-sectional regressions

Next to examining the cross-sectional relationship between EPU and US stock returns on a portfolio level, I also examined it from a stock level perspective. This is done with the use of the well-known Fama-Macbeth cross-sectional regressions. Table V shows the output of those regressions. I followed the paper of Bali et al., (2017) by investigating the predictive power of EPU on US stock returns. For every month, the excess return of *t+1* was regressed on a set of specific firm characteristics at time *t*. The univariate regression in column 1 shows that the average slope of monthly regressions of returns on $\beta EPU$ is -0.045. the value of EPU beta becomes positive, after including book to market as a firm characteristic in column 5. However, in all regressions, the value for the EPU beta is insignificant. So, I am not able to draw any conclusions on the economic magnitude of the effect of EPU on a stock level basis as a predictor of future returns. The individual stock betas formed against the VIX ($\beta UNC$) are also insignificant across all regressions. The individual market beta coefficient of stocks becomes significant (p<0.10) after including the natural logarithm of size. The economic significance of the relationship between the market beta and the expected stock return yields: an increase in future monthly return of 0.20% (0.29 * 0.7), when considering a one standard deviation increase in the market beta of stocks (Table I). Column 5 shows that the effect is even stronger when the natural logarithm of the book to market ratio is added to the regression. A one standard deviation increase in the market beta of stocks leads to an increase in future monthly return of 0.26% (0.37 * 0.7). Column 4 further shows that the size factor is negative and significant across all models where the natural logarithm of market cap is included. Its economic significance varies from -0.21% (-0.11 * 1.94) to -0.35% (-0.18 * 1.94). implying that a one standard deviation increase in size leads to a reduction in the future stock return of 0.21% to 0.35%. The last characteristic that is significant across all regressions is the natural log of the book to market ratio. That factor is highly statistically significant, and the economic significance varies from 0.43% to 0.44%. A one standard deviation increase in the natural log of the book to market ratio leads to an increase of 0.43% to 0.44% in one-month future stock return. The average $R^2$ are relatively low. However, Lewellen, (2014) documented that it is not correct to interpret the $R^2$ in Fama-Macbeth regressions as informative for the predictive power of the included variables. In Fama-Macbeth regressions the $R^2$ shows the fraction of contemporaneous volatility explained by the included characteristics. The $R^2$ values are consistent with other papers that conduct Fama-Macbeth cross-sectional regressions. The general expectation was that EPU beta loadings would negatively forecast the cross-section of US stock returns. This hypothesis was formed based on previous academic research (Bali et al., 2017; Li, 2017; Brogaard & Detzel, 2015). However, I am not able to find results consistent with previous research, and I am therefore not able to accept my third hypothesis.

# Table IV
# EPU Portfolio Time-Series Regression

This table presents the alpha and regression coefficients of portfolios formed on EPU Betas. 1, corresponds to decile one which consists of stocks that have a low EPU Beta. 10, corresponds to decile ten which consists of stocks that have a high EPU Beta. The column 1-10 is the long-short strategy. Panel A reports the results of the equal-weighted portfolios when tested against the CAPM and Fama-French 3 factor model. Panel B reports the results of the equal-weighted portfolios when tested against the CAPM and Fama-French 3 factor model controlling for another uncertainty measure, namely the VIX. Panel C reports the results of equal-weighted portfolios against the Carhart 4-factor model and the Fama-French 5 factor model. Below every regression, the average $R^2$ is given. The alphas are given in %, and the t statistics are given in parentheses. The sample period is from February 1987 to December 2019. *Significance at the 10% level. **Significance at the 5% level. ***Significance at the 1% level.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 1 | 10 | 1-10 | 1 | 10 | 1-10 |
| *Panel A. Equal Weighted Portfolio vs CAPM & FF3 Factor model* | | | | | | |
| α | 0.55*** | 0.58*** | -0.03 | 0.60*** | 0.60*** | 0.0006 |
| | (3.13) | (3.72) | (-0.24) | (5.55) | (7.07) | (0.00) |
| MKTRF | 1.3428*** | 1.1601*** | 0.1827*** | 1.1837*** | 1.0226*** | 0.1611*** |
| | (33.24) | (32.40) | (6.19) | (46.00) | (50.70) | (5.31) |
| SMB | | | | 0.9008*** | 0.8723*** | 0.0286 |
| | | | | (24.72) | (30.54) | (0.66) |
| HML | | | | -0.0415 | 0.0887*** | -0.1302*** |
| | | | | (-1.08) | (2.94) | (-2.87) |
| Avg $R^2$ | 0.7376 | 0.7276 | 0.0889 | 0.9020 | 0.9204 | 0.1117 |
| *Panel B. Equal Weighted Portfolio vs CAPM & FF3 controlling for VIX* | | | | | | |
| α | 0.60*** | 0.59*** | 0.01 | 0.60*** | 0.55*** | 0.05 |
| | (3.02) | (3.28) | (0.06) | (4.94) | (5.86) | (0.38) |
| MKTRF | 1.3928*** | 1.1672*** | 0.2256*** | 1.2349*** | 1.0227*** | 0.2122*** |
| | (29.75) | (27.45) | (6.71) | (41.90) | (45.26) | (6.21) |
| SMB | | | | 0.8924*** | 0.9081*** | -0.0157 |
| | | | | (22.65) | (30.06) | (-0.34) |
| HML | | | | -0.0515 | 0.1025*** | -0.1540*** |
| | | | | (-1.26) | (3.27) | (-3.25) |
| UNC | 0.0474* | -0.0092 | 0.0566*** | 0.0283* | -0.0317** | 0.0585*** |
| | (1.78) | (-0.38) | (2.97) | (1.74) | (-2.42) | (3.10) |
| Avg $R^2$ | 0.7280 | 0.6935 | 0.1413 | 0.8990 | 0.9189 | 0.1684 |
| *Panel C. Equal Weighted Portfolio vs Carhart 4 factor & FF5 Factor model* | | | | | | |
| α | 0.72*** | 0.60*** | 0.12 | 0.75*** | 0.62*** | 0.13 |
| | (6.86) | (6.93) | (0.95) | (6.81) | (7.21) | (1.02) |
| MKTRF | 1.1390*** | 1.0235*** | 0.1155*** | 1.1174*** | 1.0098*** | 0.1076*** |
| | (44.95) | (48.85) | (3.81) | (39.52) | (45.93) | (3.20) |
| SMB | 0.9111*** | 0.8720*** | 0.0391 | 0.8633*** | 0.8864*** | -0.0230 |
| | (26.31) | (30.46) | (0.94) | (21.79) | (28.77) | (-0.49) |
| HML | -0.1049*** | 0.0900*** | -0.1948*** | -0.0452 | -0.0518 | 0.0066 |
| | (-2.78) | (2.88) | (-4.32) | (-0.89) | (-1.31) | (0.11) |
| UMD | -0.1564*** | 0.0031 | -0.1595*** | | | |
| | (-6.63) | (0.16) | (-5.65) | | | |
| RMW | | | | -0.2003*** | -0.0367 | -0.1637*** |
| | | | | (-3.82) | (-0.90) | (-2.63) |
| CMA | | | | -0.2421*** | 0.0113 | -0.2534*** |
| | | | | (-3.23) | (0.19) | (-2.85) |
| Avg $R^2$ | 0.9119 | 0.9204 | 0.1790 | 0.9068 | 0.9255 | 0.1404 |

**Table V**
**Fama-MacBeth cross-sectional regressions**

This table reports the results of the Fama-Macbeth cross-sectional regressions (1973) using the following model:

$$R_{i,t+1} - r_{f,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{EPU} + \lambda_{2,t} \cdot \beta_{i,t}^{UNC} + \lambda_{3,t} \cdot X_{i,t} + \varepsilon_{i,t+1}$$

These results are obtained by regressing the monthly excess returns of month *t+1* on the EPU betas of firms and other firm characteristics at time *t* (βUNC, βMKT, SIZE, BM, MOM and REV). Below every regression, the average $R^2$, number of observations and number of periods are given. The t statistics are reported in parentheses and are computed using the methodology of Newey and West (1987). The sample period is from February 1987 to December 2019. *Significance at the 10% level. **Significance at the 5% level. ***Significance at the 1% level.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Intercept | 0.0111*** | 0.0114*** | 0.0084*** | 0.0332*** | 0.0262*** | 0.0270*** | 0.0275*** |
| | (4.66) | (4.54) | (4.33) | (6.41) | (5.22) | (5.33) | (5.36) |
| $\beta EPU$ | -0.0448 | -0.1701 | -0.0354 | -0.0225 | 0.0490 | 0.1739 | 0.3043 |
| | (-0.12) | (-0.39) | (-0.09) | (-0.05) | (0.12) | (0.42) | (0.78) |
| $\beta UNC$ | | -0.0191 | -0.0429 | -0.0073 | -0.0005 | -0.0096 | -0.0040 |
| | | (-0.36) | (-0.79) | (-0.14) | (-0.01) | (-0.20) | (-0.08) |
| $\beta MKT$ | | | 0.0026 | 0.0029* | 0.0037** | 0.0032** | 0.0029** |
| | | | (1.50) | (1.65) | (2.32) | (2.19) | (2.04) |
| ln(SIZE) | | | | -0.0018*** | -0.0011*** | -0.0011*** | -0.0012*** |
| | | | | (-5.32) | (-3.07) | (-3.26) | (-3.28) |
| ln(BM) | | | | | 0.0054*** | 0.0054*** | 0.0053*** |
| | | | | | (5.30) | (6.12) | (6.32) |
| MOM | | | | | | 0.0006 | 0.0002 |
| | | | | | | (0.32) | (0.11) |
| REV | | | | | | | -0.0062 |
| | | | | | | | (-1.34) |
| Avg $R^2$ | 0.0037 | 0.0070 | 0.0326 | 0.0403 | 0.0485 | 0.0559 | 0.0602 |
| No. of obs. | 615808 | 538128 | 538128 | 538128 | 538128 | 538018 | 538005 |
| No. of periods. | 395 | 335 | 335 | 335 | 335 | 335 | 335 |

## 5.5 Presidential administration analysis

Table VI reports the average monthly excess and risk-adjusted returns of EPU portfolios across different presidential administrations. A Republican president was in power in 203 months in my sample, and in 192 months a Democratic president was in control. The second column shows the excess returns in Democratic years, and the fourth column shows the monthly excess returns in Republican years. I also find the U-shaped pattern in decile returns across different presidential administrations. Figure 4 in the appendix gives a representation of the returns across deciles for the two political parties. For both political parties, a long/short portfolio does not yield statistically significant returns indistinguishable from zero. Column six shows that the monthly excess returns are higher in Democratic years than in Republican years. This effect is consistent across all deciles. However, the difference is only statistically different from zero in decile 5, 6 and 9. Furthermore, there is practically no difference in returns on a formed long/short portfolio for different presidential administrations. The average monthly excess return is 0.09% for both political parties. Column 3 and 6 show the 3-factor alphas of a strategy on EPU in Democratic and Republican environments. During Democratic administrations, I find that a hedge portfolio produces negative risk-adjusted return (-0.10%). However, this value is insignificant and therefore, indistinguishable from zero. For Republican administrations, I find that a long/short portfolio produces a positive risk-adjusted return of 0.06%. However, this value is also statistically insignificant. So, across both administrations, I am not able to find the associated risk premium with EPU. Belo et al., (2013) showed that government spending was a sound channel trough which political parties could influence stock returns. I expected EPU to be a relevant channel of influence as well. This expectation was based on the paper of Pastor & Veronesi, (2017) and the assumption of time-varying risk aversion. A Democratic president tends to get elected when expected returns are high or in other words, when risk aversion is high. However, my results show otherwise. I am, therefore, not able to accept the drawn hypothesis.

**Table VI**

**Monthly average returns of EPU portfolios presidential administrations**

This table reports the time-series of returns of equal-weighted decile portfolios formed on EPU Betas. The table reports the average monthly returns for all the years in my sample. This table also reports the average monthly excess and risk-adjusted returns across Democratic (Dem) and Republican (Rep) administrations. The column RETRF Dem-Rep represents the difference in monthly excess returns between the administrations across deciles and the p-value for those differences are given in the column "RETRF Dif p-value". D1-D10 is the long-short portfolio of going long in stocks with a low EPU Beta and short in stocks with a high EPU Beta. The p-values of the long-short portfolios are given in the last row. The sample period is from February 1987 to December 2019

| Deciles | RETRF Dem | $\alpha^3$ Dem | RETRF Rep | $\alpha^3$ Rep | RETRF Dem-Rep | RETRF Dif p-value |
|---|---|---|---|---|---|---|
| D1 | 1.93 | 0.52 | 0.96 | 0.65 | 0.96 | (0.16) |
| D2 | 1.48 | 0.21 | 0.70 | 0.41 | 0.78 | (0.16) |
| D3 | 1.48 | 0.31 | 0.66 | 0.38 | 0.82 | (0.10) |
| D4 | 1.38 | 0.24 | 0.70 | 0.44 | 0.67 | (0.17) |
| D5 | 1.43 | 0.35 | 0.54 | 0.29 | 0.89 | (0.05) |
| D6 | 1.43 | 0.38 | 0.67 | 0.44 | 0.75 | (0.09) |
| D7 | 1.28 | 0.20 | 0.65 | 0.42 | 0.63 | (0.15) |
| D8 | 1.35 | 0.31 | 0.73 | 0.50 | 0.62 | (0.17) |
| D9 | 1.49 | 0.39 | 0.64 | 0.39 | 0.84 | (0.08) |
| D10 | 1.84 | 0.62 | 0.87 | 0.59 | 0.97 | (0.10) |
| D1- D10 | 0.09 | -0.10 | 0.09 | 0.06 | 0.00 | (1.00) |
| P-value | (0.66) | (0.61) | (0.61) | (0.70) | (1.00) | |

## 5.6 Industry analysis

For my final analysis, I examined the effect of economic policy uncertainty across 11 different industries in the US stock market. Table VII presents the monthly alphas of equal-weighted portfolios formed on EPU betas across 11 different industries. I sorted stocks based on their four-digit Standard Industrial Classification (SIC) code, and I used the sectors quantified by the industry list obtained from the Kenneth French data library. Table 1 in the appendix shows all included industries and their description. After the quantification of the different industries, I formed quintile portfolios on stock their EPU beta of the previous month. Panel A shows the monthly alphas from the CAPM. Column 2 to 6 shows the quintile portfolios alphas, and column 7 shows the alpha of the long-short portfolio per industry. The last column shows the average computed EPU beta per industry. I am not able to find an EPU risk premium that is statistically different from zero in any of the different industries. Furthermore, no clear pattern in quintile portfolio returns can be observed. In some sectors, I again find a U-shaped pattern (Non-durable, Durable, Tech, Other). Some other sectors show a different picture with no clear trend in their quintile returns. Phan et al., (2018) showed in their paper that EPU was not able to predict returns for Basic Materials (Manufacturing & Chemicals) and the Utilities sector. The manufacturing sector shows a slight positive premium in this analysis; however, not statistically different from zero. The Chemicals and Utilities sector even show a negative premium associated with EPU. However, this is also not statistically significant. So, I am not able to draw any conclusions based on these results. My main prediction was that the EPU premium would be more pronounced in cyclical (Durable) sectors of the economy than in the non-cyclical (Non-durable) sectors. This prediction was based on the evidence presented by Bali et al., (2017) and Gomes et al., (2007). The highest positive alphas are achieved in the Durable and Tech sectors. However, again these alphas are not statistically different from zero. Panel B shows the alphas extracted from the Fama & French 3 factor model. The alphas of the long/short portfolios across the 11 industries do not become significant when considering this other asset pricing model. This industry analysis does not support my drawn hypothesis of an EPU premium, which should be more pronounced in cyclical sectors of the economy.

## Table VII
## Monthly alphas of equal-weighted EPU portfolios for 11 different industries

Stocks are divided into 11 different industries based on their 4 digits SIC code. For every month stocks in each sector were sorted into 5 quintile portfolios. Panel A shows the alphas extracted from the CAPM. Where quintile 1 contains stocks with the lowest EPU beta and quintile 5 contains stocks with the highest EPU beta. The column 1-5 (Low-High) shows the trading strategy of going long in quintile 1 and going short in quintile 5. The last column shows the average EPU beta per industry sector. Panel B presents the alphas extracted from the Fama-French 3 factor model. The t statistics are given in parentheses. The sample period is from February 1987 to December 2019. *Significance at the 10% level. **Significance at the 5% level. ***Significance at the 1% level.

| Industry | 1 | 2 | 3 | 4 | 5 | 1-5 (Low-High) | Avg. EPU Beta |
|---|---|---|---|---|---|---|---|
| Panel A. CAPM alphas (%) | | | | | | | |
| Non-durable | 0.45** | 0.37** | 0.34** | 0.35*** | 0.41** | 0.04 | -0.00015 |
| | (2.41) | (2.43) | (2.47) | (2.68) | (2.25) | (0.20) | |
| Durable | 0.52** | 0.003 | 0.13 | 0.08 | 0.30 | 0.23 | -0.00028 |
| | (1.99) | (0.01) | (0.67) | (0.35) | (1.16) | (0.75) | |
| Manufacturing | 0.32* | 0.35** | 0.32** | 0.29* | 0.32* | 0.006 | -0.00038 |
| | (1.74) | (2.34) | (2.28) | (1.88) | (1.70) | (0.04) | |
| Energy | 0.34 | 0.28 | 0.49* | 0.22 | 0.50 | -0.15 | -0.00029 |
| | (0.92) | (0.92) | (1.66) | (0.66) | (1.24) | (-0.44) | |
| Chem | 0.17 | 0.44** | 0.36** | 0.40** | 0.40 | -0.24 | -0.00025 |
| | (0.73) | (2.36) | (2.15) | (2.45) | (1.53) | (-0.82) | |
| Tech | 0.57** | 0.52*** | 0.39** | 0.41** | 0.47** | 0.10 | -0.00023 |
| | (2.33) | (2.64) | (2.18) | (2.17) | (2.35) | (0.65) | |
| Telecom | 0.41 | 0.19 | 0.35* | 0.26 | 0.76*** | -0.34 | -0.00006 |
| | (1.39) | (0.87) | (1.72) | (1.41) | (3.04) | (-0.97) | |
| Utilities | 0.42 | 0.37 | 0.51*** | 0.56*** | 0.46** | -0.04 | 0.00018 |
| | (1.16) | (1.60) | (3.43) | (3.66) | (2.46) | (-0.10) | |
| Shops | 0.39** | 0.26 | 0.37** | 0.34** | 0.49*** | -0.11 | -0.00017 |
| | (2.00) | (1.61) | (2.54) | (2.37) | (2.63) | (-0.62) | |
| Health | 0.76*** | 0.84*** | 0.84*** | 0.64*** | 0.93*** | -0.17 | 0.00003 |
| | (2.90) | (3.61) | (3.70) | (3.70) | (3.94) | (-0.79) | |
| Other | 0.46*** | 0.31** | 0.34** | 0.23 | 0.39** | 0.07 | -0.00017 |
| | (2.84) | (2.21) | (2.60) | (1.64) | (2.29) | (0.46) | |

Panel B. Fama-French 3 factor model alphas (%)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Non-durable | 0.38** | 0.30** | 0.26** | 0.28** | 0.33* | 0.05 | -0.00015 |
| | (2.27) | (2.19) | (2.08) | (2.34) | (1.96) | (0.25) | |
| Durable | 0.42* | -0.12 | 0.03 | -0.06 | 0.22 | 0.20 | -0.00028 |
| | (1.71) | (-0.71) | (0.16) | (-0.31) | (1.03) | (0.65) | |
| Manufacturing | 0.26* | 0.26** | 0.23* | 0.18 | 0.23* | 0.02 | -0.00038 |
| | (1.73) | (2.20) | (2.05) | (1.56) | (1.75) | (0.14) | |
| Energy | 0.23 | 0.14 | 0.35 | 0.09 | 0.38 | -0.14 | -0.00029 |
| | (0.65) | (0.50) | (1.27) | (0.28) | (1.00) | (-0.41) | |
| Chem | 0.11 | 0.35** | 0.26* | 0.32** | 0.27 | -0.16 | -0.00025 |
| | (0.51) | (1.98) | (1.73) | (2.01) | (1.06) | (-0.55) | |
| Tech | 0.72*** | 0.63*** | 0.48*** | 0.51*** | 0.56*** | 0.16 | -0.00023 |
| | (4.62) | (4.54) | (3.70) | (3.69) | (4.12) | (1.10) | |
| Telecom | 0.44 | 0.23 | 0.36* | 0.27 | 0.75*** | -0.31 | -0.00006 |
| | (1.53) | (1.11) | (1.82) | (1.42) | (3.02) | (-0.85) | |
| Utilities | 0.42 | 0.30 | 0.47*** | 0.50*** | 0.34* | -0.08 | 0.00018 |
| | (1.16) | (1.29) | (3.24) | (3.30) | (1.89) | (-0.21) | |
| Shops | 0.31 | 0.19 | 0.32** | 0.28** | 0.43** | -0.11 | -0.00017 |
| | (1.91) | (1.38) | (2.46) | (2.20) | (2.59) | (-0.66) | |
| Health | 0.88*** | 0.93*** | 0.92*** | 0.69*** | 1.01*** | -0.13 | 0.00003 |
| | (4.23) | (4.77) | (4.95) | (4.52) | (5.11) | (-0.61) | |
| Other | 0.43** | 0.25** | 0.29*** | 0.16 | 0.36*** | 0.07 | -0.00017 |
| | (3.8) | (2.18) | (2.64) | (1.43) | (2.99) | (0.45) | |

# 6. Robustness

I conducted several robustness tests to test the persistence of the insignificance of EPU in the cross-section of stock returns in the US. Panel A of table VIII presents the results for equal-weighted portfolios on innovations on EPU for a period just before the great financial crisis (GFA) (1987-2007). Column 2 shows that the excess return on the hedge portfolio (0.23) is higher than the excess return of the hedge portfolio over the total sample period (0.09), as can be observed from table III. However, the monthly excess return over the period before the GFA is still not significant, and I am therefore not able to draw any conclusions. Columns 4 and 5 show the abnormal returns extracted from the FF3 and FF5. The abnormal returns are also higher over the pre-financial crisis period than over the total sample period. Furthermore, the long-short portfolio shows a slightly significant ($p < 0.10$) alpha when tested against the FF5 model—implying that the strategy would yield an annual risk-adjusted return of 3.6% when using the FF5 model. Furthermore, one can again observe the U-shaped pattern across excess returns and abnormal returns. Panel B shows the results of equal-weighted portfolios on EPU over the post-financial crisis period. Interestingly, the EPU strategy shows a different picture compared to the pre GFC period. The excess return of the hedge portfolio is negative; however, not significant and therefore not indistinguishable from zero. So, I am not able to draw any conclusions based on the excess returns of this strategy in the period after the GFC. The excess returns again show the similar U-shaped pattern across the deciles. Column 4 and 5 again show the risk-adjusted returns; these also turn negative for the hedge portfolio in the post-financial crisis period. The 3-factor alpha of the long-short portfolio is slightly significant ($p < 0.10$). These results show that a strategy based on EPU would yield a risk-adjusted return of -4.08% in the post-financial crisis period when using the FF3 model. Another interesting observation is that the U-shaped pattern across deciles disappears for the risk-adjusted returns in the post GFC period, especially when looking at the 3-factor alphas. Those alphas are not significant in the two lowest deciles. Implying that investors are not compensated for investing in stocks that have a low covariance with innovation in EPU. Panel C shows another robustness test that I conducted. I made value-weighted portfolios instead of equal-weighted portfolios over the total sample period. One can observe that the results are quite similar when looking at table III for comparison. So, making value-weighted portfolios does not seem to change the results over the total sample period. Table 2 in the appendix shows the time-series regressions of value-weighted portfolios against various asset pricing models. The different factor loadings also do not change significantly when making value-weighted portfolios on the innovations on EPU. Lastly, I want to mention that I considered making quintile portfolios instead of decile portfolios. However, this also did not lead to significant changes in the results.

## Table VIII
## Robustness tests

This table presents the various robustness tests conducted in this research. Column one presents the deciles, column two shows the excess returns of the portfolios, column three presents the standard deviation of the portfolios, column four shows the FF3 factor-alpha. Column five shows the FF5 factor-alpha. All the values are reported in %. Panel A shows the results of equal-weighted portfolios over the pre-financial crisis period. Panel B shows the results of equal-weighted portfolios over the post-financial crisis period, and panel C shows the results of value-weighted portfolios over the total sample period. The t statistics are given in parentheses. The sample period is from February 1987 to December 2019. *Significance at the 10% level. **Significance at the 5% level. ***Significance at the 1% level.

| Deciles | Excess Return | SD | $\alpha^3$ | $\alpha^5$ |
|---|---|---|---|---|
| *Panel A: Equal Weighted Portfolio Pre-Financial Crisis 1987 – 2007* | | | | |
| D1 | 1.56*** (3.58) | 6.89 | 0.85*** (5.72) | 1.01*** (6.68) |
| D2 | 1.09*** (3.22) | 5.39 | 0.36*** (3.20) | 0.39*** (3.54) |
| D3 | 1.02*** (3.29) | 4.93 | 0.29*** (2.66) | 0.26** (2.46) |
| D4 | 0.98*** (3.31) | 4.71 | 0.28*** (2.93) | 0.21** (2.37) |
| D5 | 0.90*** (3.21) | 4.43 | 0.23*** (2.44) | 0.14 (1.56) |
| D6 | 0.98*** (3.63) | 4.27 | 0.31*** (3.50) | 0.23*** (2.80) |
| D7 | 0.91*** (3.47) | 4.14 | 0.25*** (2.74) | 0.11 (1.34) |
| D8 | 0.97*** (3.71) | 4.13 | 0.34*** (3.47) | 0.23** (2.53) |
| D9 | 1.06*** (3.76) | 4.46 | 0.43*** (4.19) | 0.33*** (3.35) |
| D10 | 1.33*** (3.59) | 5.87 | 0.69*** (7.07) | 0.71*** (5.99) |
| D1-D10 | 0.23 (1.32) | 2.76 | 0.16 (0.95) | 0.30* (1.76) |
| *Panel B: Equal Weighted Portfolio Post-Financial Crisis 2008 – 2019* | | | | |
| D1 | 1.21** (2.20) | 6.59 | 0.16 (1.03) | 0.29* (1.94) |
| D2 | 1.05** (2.17) | 5.79 | 0.12 (1.02) | 0.11 (0.88) |
| D3 | 1.11** (2.57) | 5.18 | 0.27*** (3.40) | 0.23*** (2.91) |
| D4 | 1.11*** (2.61) | 5.10 | 0.29*** (4.04) | 0.23*** (3.16) |
| D5 | 1.10*** (2.69) | 4.90 | 0.33*** (3.83) | 0.25*** (2.97) |
| D6 | 1.16*** (2.93) | 4.76 | 0.40*** (5.59) | 0.32*** (4.51) |
| D7 | 1.04** (2.60) | 4.79 | 0.29*** (3.43) | 0.19** (2.31) |
| D8 | 1.14*** (2.80) | 4.90 | 0.40*** (4.52) | 0.31*** (3.42) |
| D9 | 1.05** (2.36) | 5.35 | 0.28*** (2.87) | 0.22** (2.21) |
| D10 | 1.36** (2.75) | 5.96 | 0.49*** (4.26) | 0.52*** (4.33) |
| D1-D10 | -0.15 (-0.76) | 2.45 | -0.34* (-1.71) | -0.23 (-1.13) |
| *Panel C: Value Weighted Portfolio 1987-2019* | | | | |
| D1 | 1.42*** (4.19) | 6.75 | 0.60*** (5.51) | 0.75*** (6.81) |
| D2 | 1.07*** (3.87) | 5.48 | 0.32*** (3.85) | 0.30*** (3.67) |
| D3 | 1.09*** (4.33) | 5.01 | 0.38*** (4.96) | 0.30*** (4.07) |
| D4 | 0.99*** (4.09) | 4.83 | 0.30*** (4.54) | 0.19*** (3.11) |
| D5 | 0.96*** (4.16) | 4.58 | 0.30*** (4.36) | 0.19*** (2.92) |
| D6 | 1.07*** (4.78) | 4.44 | 0.42*** (6.38) | 0.30*** (4.88) |
| D7 | 0.94*** (4.29) | 4.36 | 0.30*** (4.47) | 0.13** (2.22) |
| D8 | 1.03*** (4.62) | 4.45 | 0.40*** (5.40) | 0.26*** (3.79) |
| D9 | 1.05*** (4.36) | 4.78 | 0.38*** (4.95) | 0.26*** (3.60) |
| D10 | 1.34*** (4.55) | 5.86 | 0.60*** (7.20) | 0.62*** (7.32) |
| D1-D10 | 0.08 (0.61) | 2.63 | -0.009 (-0.07) | 0.13 (0.97) |

## 7. Discussion

My research and expectations are based on an extensive amount of academic literature that investigates the relationship between an uncertainty factor and the cross-section of stock returns. However, I am not able to find results consistent with previous literature. This section of the thesis bridges the gap between the results and existing literature. The main research question of this paper was whether "EPU is priced in the cross-section of stock return". The foundation of this research question is based on the ICAPM (Merton, 1973). The ICAPM allows for the incorporation of investment behaviour and acknowledges that investors hedge assets against potential reductions in their consumption or their investment opportunity set. In that model, investors prefer holding stocks which have a higher covariance with EPU. This increase in demand leads to higher prices and lower returns. Contrary to the work of Brogaard & Detzel, (2015) I am not able to find the associated risk premium with EPU in the US market consistent with the assumptions of the ICAPM. My analyses show a U-shaped pattern in decile portfolio (risk-adjusted) returns. This implies that stocks that have a low covariance with EPU show high returns as well as stocks with a high covariance with EPU. This U-shaped pattern in portfolios formed on EPU has not been documented before and has interesting implications. A possible explanation could be found in the paper of Veronesi, (2000). The author documented that when signals are imprecise, the realizations of the dividends influence the hedging demand of investors. The authors further argue that imprecise signals lead to a U-shaped pattern in volatility with respect to the coefficient of risk aversion. This U-shaped pattern in volatility can also be observed in table III of my research. MPT consists of the assumption of investors expecting to earn higher returns when investing in riskier assets (higher volatility) (Markovitz, 1952). I reason that MPT, in combination with the U-shaped function of volatility for imprecise signals could be an explanation for the fact that I am not able to find a significant relationship between EPU and US stock returns.

Another potential explanation for the results of this paper can be found in the paper of Barahona et al., (2018). The authors investigate how risk premiums are affected by risk exposure predictability (Beta). The authors argue that investors need to predict future betas to gain exposure to a particular risk factor. Barahona et al., (2018) mention that there are risk factors which are hard to quantify like market crash risk. Their results imply that when betas are less predictable, hedging demand of investors decreases, leading to a reduction of the associated risk premium. The authors focus their research on relative downside betas and VIX betas.

However, the authors attribute that their predictability model fits a broader spectrum of asset pricing models related to hedging demands of investors like the ICAPM (Merton, 1973). The fact that I am not able to find an associated risk premium with EPU in this study might imply that investors have problems with the prediction of EPU betas.

There is also a more straightforward explanation for the fact that I am not able to find an EPU risk premium; this stems from the principle of market efficiency. Many academics argue that anomalies in the markets tend to decrease significantly after being documented (Marquering et al., 2006) (Cotter & McGeever, 2018). Due to behavioural biases and the slow diffusion of information anomalies arise. However, after a while, investors realize that there are potential alphas in the market. This, in turn, leads to anomalies getting arbitraged away.

I further want to address that the methodology of forming the portfolio on EPU differs from the work of Brogaard & Detzel, (2015) and Li, (2017). Li, (2017) mentions that it is appropriate to create factor-mimicking portfolios when investigating the risk premium of an uncertainty factor. Boogaard and Detzel (2015) argue that: “it is convenient in empirical work to form mimicking portfolios for a proposed discount factor because they can reduce measurement error and filter out the information that is irrelevant to the prices of the test assets”. Several studies suggested that creating a factor-mimicking portfolio rather than a hedge portfolio, is common practise when investigating the risk premium of a state variable (Ang et al., 2006; Lamont, 2000). However, due to the feasibility of the scope of work, I decided to follow the methodology presented by the influential paper of Bali et al., (2017). The fact that I created hedge portfolios instead of factor-mimicking portfolios can be seen as a potential limitation of this study.

# 8. Conclusion

This study examined whether EPU is priced in the cross-section of US stock returns. This paper also investigated the behaviour of EPU across different presidential cycles and industry sectors. I observed a U-shaped pattern in the monthly excess returns of decile portfolios. The monthly average excess return of a long-short portfolio on EPU was 0.09%. However, this value is statistically insignificant. The performed tests against various asset pricing models also showed no significant risk-adjusted returns for an EPU hedge portfolio. The factor loadings in the time-series regressions implied that other factors in the market already captured EPU portfolio returns. The time-series regressions, however, showed interesting results regarding the characteristics of EPU beta portfolios. A low EPU beta portfolio can be quantified as a portfolio with small-cap firms which have a high market beta. The results further show that firms in the bottom decile are unprofitable and invest aggressively. Stocks in a low EPU beta portfolio also show a negative momentum effect. The Fama-Macbeth cross-sectional regressions show that EPU betas have no predictive power. The reported values for EPU betas are insignificant also after controlling for different firm characteristics. I am also not able to find statistical proof of a difference in portfolio returns across presidential administrations, and my last analysis shows that the EPU premium is statistically insignificant across all industry sectors. My research is not consistent with various other papers related to this topic (Brogaard & Detzel, 2015; Bali et al., 2017). Therefore, possible explanations have to be addressed carefully. Firstly, these results can be attributed to the fact that imprecise signals in the economy lead to a U-shaped pattern in volatility with respect to the coefficient of risk aversion of investors. (Veronesi, 2000). Secondly, investors might have problems with predicting the betas formed on the innovations on EPU. Less predictable betas lead to a reduction in hedging demand which leads to a reduction in the associated risk premium (Barahona et al., 2018). Lastly, the fact that I am not able to find an EPU risk premium might simply be due to market efficiency.

There are still interesting areas for future research, although I am not able to find that EPU is priced in the cross-section of stock returns. One can potentially investigate the relationship between EPU and other assets like cryptocurrency. An increase in EPU might lead to higher Bitcoin returns. Another suggestion for future research is to consider time variation in EPU betas. My robustness tests showed that the risk premium on EPU varies over time. The returns on a hedge portfolio were positive in a pre-financial crisis period and negative in a post-financial crisis period. Pieterse-Bloem et al., (2016) studied time variation in betas. They showed that there is significant time variation in country and industry factors in the corporate bond market in Europe. They show that breaks in time-variation match with essential events of European market integration. Investigating time variation in EPU betas could lead to a better understanding of its effects. Lastly, the EPU index has surged to new highs due to the recent crisis around COVID-19. I wish I could have included this period in my research. However, the CRSP data was not yet available. Investigating the relationship of EPU and stock returns during this crisis could be very interesting for future research.

The equity market is continuously evolving, and having a sound understanding of the potential drivers of the variation in the cross-section of stock returns will always be very important. New factors will emerge, as others will disappear due to behavioural biases and market efficiency.

So, research that considers the zoo of factors (Harvey & Liu, 2019) will always be present and important. In the end, investors will always keep chasing abnormal returns.

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# APPENDIX

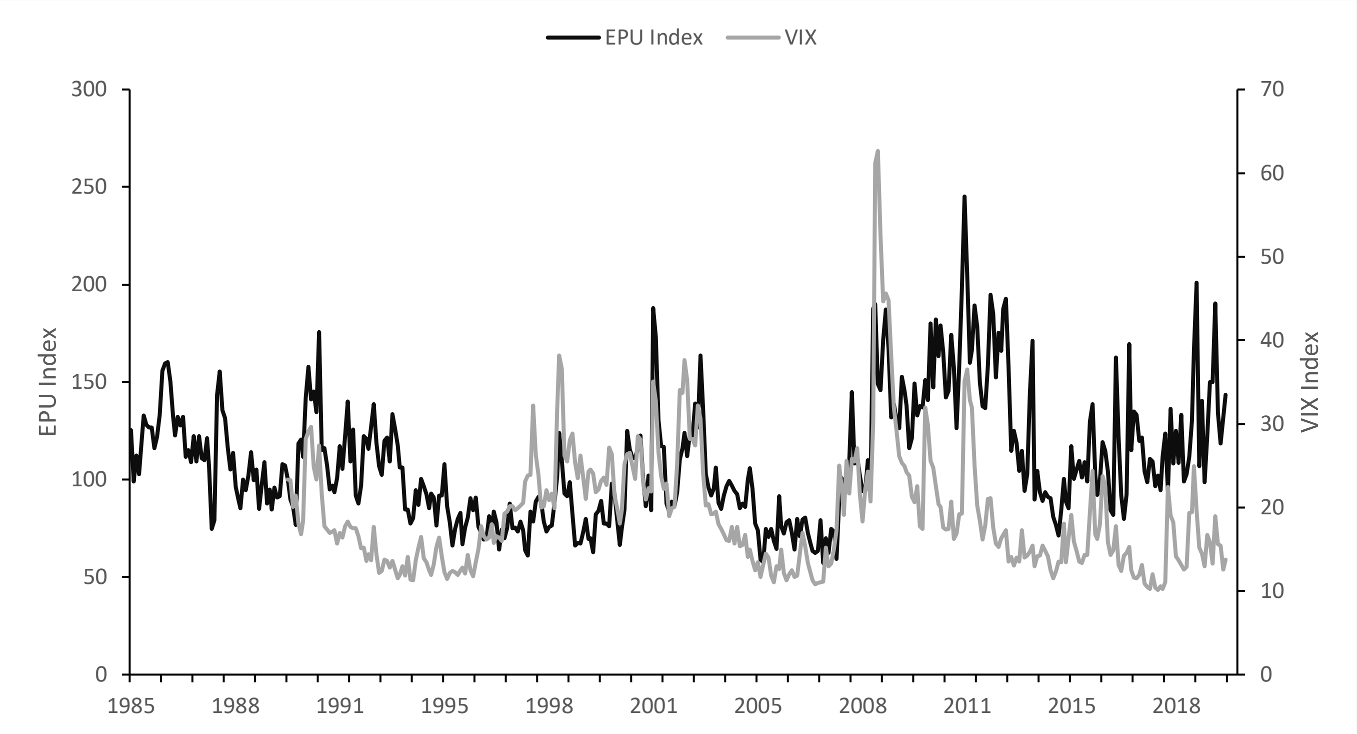


*Figure 1. This figure represents the EPU index as created by Baker et al., (2016) from 1985 – 2019 and the VIX index from 1990 – 2019.*

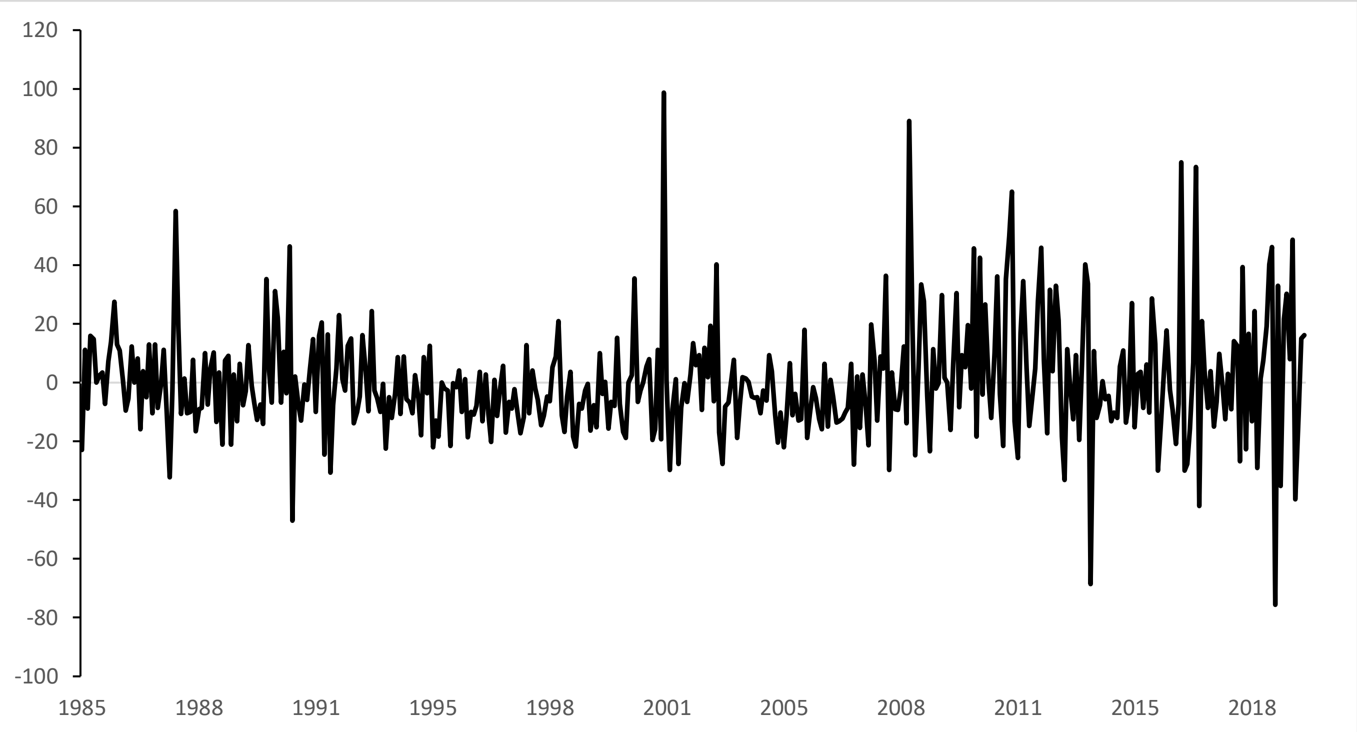


*Figure 2. This figure represents the innovations on the EPU Index as calculated with a AR (1) process using the following equation:* $EPU_t = \alpha + \beta_1 EPU_{t-1} + \epsilon_t^{EPU}$; $\epsilon_t^{EPU}$ *represents the innovations on the EPU index.*

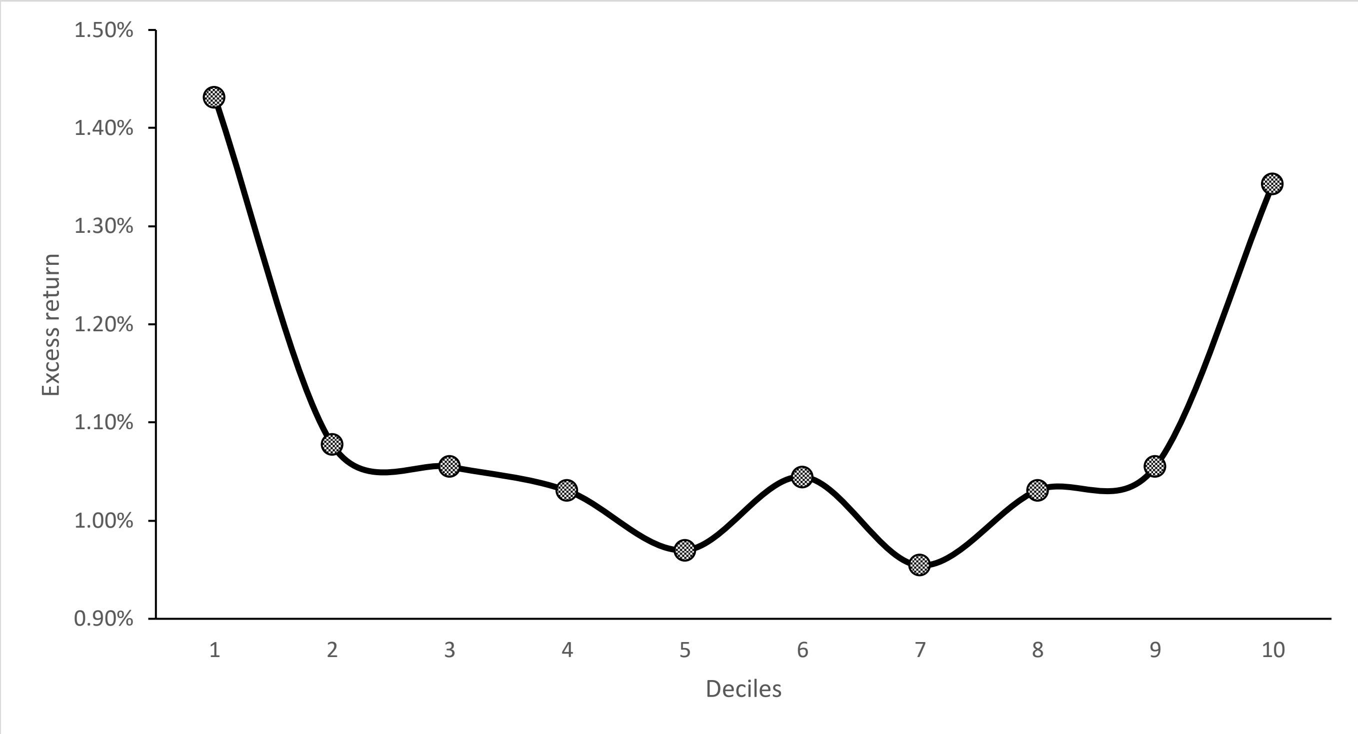

*Figure 3. This figure represents the monthly excess returns of EPU beta portfolios across deciles from 1987 - 2019*

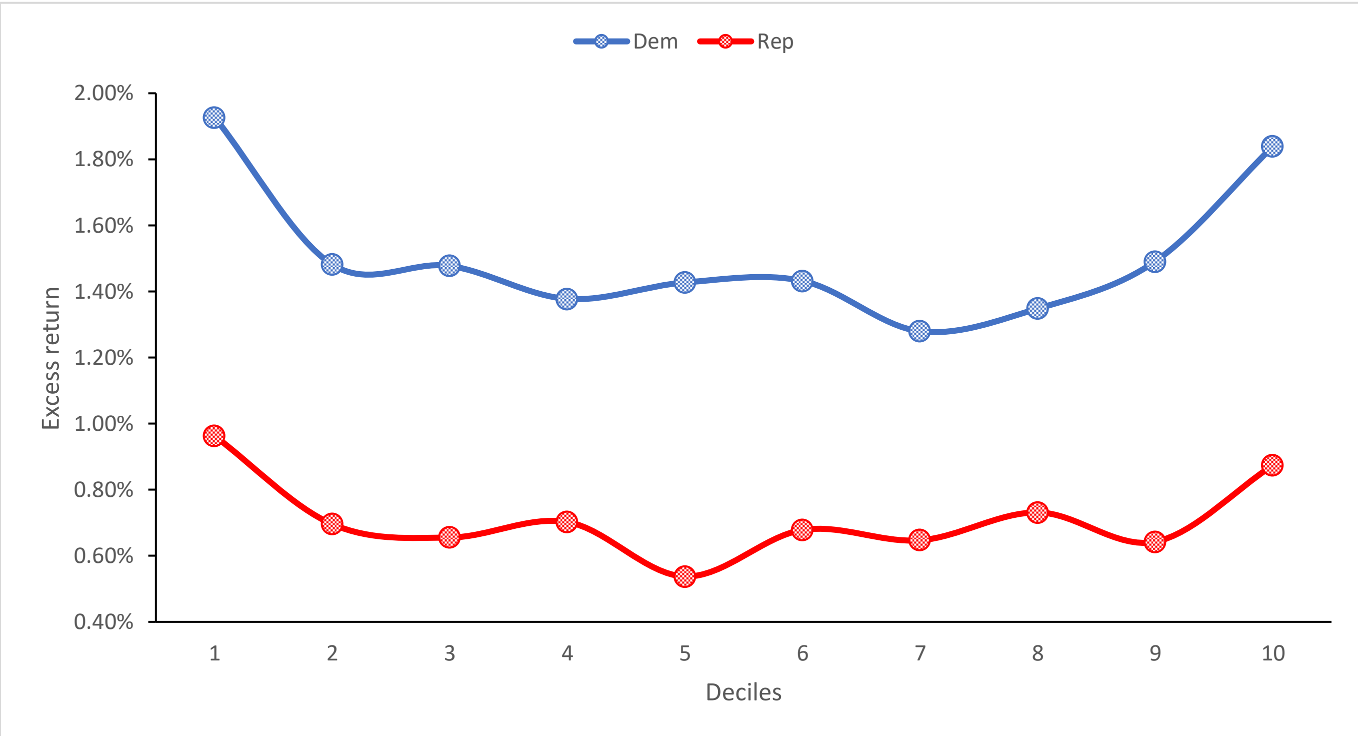

*Figure 4. This figure presents the monthly excess returns of EPU beta portfolios across deciles for Democratic and Republican administrations from 1987 – 2019.*

| Industry | Description |
|---|---|
| Consumer Nondurables | Food, Tobacco, Textiles, Apparel, Leather, Toys |
| Consumer Durables | Cars, TVs, Furniture, Household Appliances |
| Manufacturing | Machinery, Trucks, Planes, Paper, Commercial Printing |
| Energy | Oil, Gas and Coal Extractions and Products |
| Chemistry | Chemicals and Allied Products |
| Business Equipment | Computers, Software and Electronic Equipment |
| Telecom | Telephone and Television Transmission |
| Utilities | Utilities |
| Shops | Wholesale, Retail and Other Services (Laundries, Repair Shops) |
| Health | Healthcare, Medical Equipment and Drugs |
| Other | Mines, Construction, Transport, Hotels, Business Services, Entertainment |

*Table 1. This table gives a description of 11 industry sectors included in my analysis for testing the significance of the EPU premium across different sectors in the US economy from 1987 – 2019.*

## Table 2
## EPU Value Weighted Portfolio Time-Series Regression

This table presents the alphas and factor loadings of value weighted portfolios formed on the EPU Betas of the previous month. 1, corresponds to a value-weighted portfolio of stocks with a low covariance with EPU. 10, corresponds to a value-weighted portfolio of stocks with a high covariance with EPU. 1-10 represents the long/short portfolio based on the strategy of EPU. Panel A shows the results of a value weighted portfolio against the CAPM and the FF3 factor model. Panel B shows the results of a value-weighted against the CAPM and FF3 factor after controlling for the VIX uncertainty measure. Panel C shows the results of a value-weighted portfolio against the Carhart 4 factor model and the FF5 factor model. The average $R^2$ is given below every regression. The alphas are given in %, and the t statistics are given in parentheses. The sample period is from February 1987 to December 2019. *Significance at the 10% level. **Significance at the 5% level. ***Significance at the 1% level.

| Variable | (1)<br>1 | (2)<br>10 | (3)<br>1-10 | (4)<br>1 | (5)<br>10 | (6)<br>1-10 |
|---|---|---|---|---|---|---|
| *Panel A. Value Weighted Portfolio vs CAPM & FF3 Factor model* | | | | | | |
| α | 0.55*** | 0.59*** | -0.04 | 0.60*** | 0.60*** | -0.009 |
| | (3.10) | (3.76) | (-0.31) | (5.51) | (7.20) | (-0.07) |
| MKTRF | 1.3382*** | 1.1542*** | 0.1840*** | 1.1799*** | 1.0167*** | 0.1632*** |
| | (33.30) | (32.40) | (6.30) | (46.10) | (51.12) | (5.42) |
| SMB | | | | 0.8957*** | 0.8704*** | 0.0254 |
| | | | | (24.72) | (30.90) | (0.60) |
| HML | | | | -0.0425 | 0.0863*** | -0.1288*** |
| | | | | (-1.11) | (2.90) | (-2.86) |
| Avg $R^2$ | 0.7383 | 0.7276 | 0.0916 | 0.9023 | 0.9218 | 0.1138 |
| *Panel B. Value Weighted Portfolio vs CAPM & FF3 controlling for VIX* | | | | | | |
| α | 0.60*** | 0.58*** | 0.02 | 0.61*** | 0.54*** | 0.07 |
| | (3.08) | (3.28) | (0.13) | (5.03) | (5.91) | (0.45) |
| MKTRF | 1.3884*** | 1.1618*** | 0.2266*** | 1.2317*** | 1.0173*** | 0.2144*** |
| | (29.88) | (27.43) | (6.80) | (42.06) | (45.58) | (6.32) |
| SMB | | | | 0.8843*** | 0.9071*** | -0.2273 |
| | | | | (22.59) | (30.40) | (-0.50) |
| HML | | | | -0.0540 | 0.0998*** | -0.1537*** |
| | | | | (-1.33) | (3.22) | (-3.27) |
| UNC | 0.0466* | -0.0089 | 0.0555*** | 0.0278* | -0.0298** | 0.0576*** |
| | (1.77) | (-0.37) | (2.93) | (1.72) | (-2.42) | (3.08) |
| Avg $R^2$ | 0.7297 | 0.6932 | 0.1434 | 0.8994 | 0.9202 | 0.1705 |
| *Panel C. Value Weighted Portfolio vs Carhart 4 factor & FF5 Factor model* | | | | | | |
| α | 0.71*** | 0.60*** | 0.11 | 0.75*** | 0.62*** | 0.13 |
| | (6.85) | (7.06) | (0.88) | (6.81) | (7.32) | (0.97) |
| MKTRF | 1.1348*** | 1.0175*** | 0.1173*** | 1.1130*** | 1.0046*** | 0.1084*** |
| | (45.09) | (49.25) | (3.91) | (39.62) | (46.30) | (3.25) |
| SMB | 0.9062*** | 0.8703*** | 0.0360 | 0.8585*** | 0.8834*** | -0.0249 |
| | (26.35) | (30.83) | (0.88) | (21.81) | (29.06) | (-0.53) |
| HML | -0.1063*** | 0.0874*** | -0.1937*** | -0.0437 | -0.0564 | 0.0127 |
| | (-2.84) | (2.84) | (-4.34) | (-0.87) | (-1.45) | (0.21) |
| UMD | -0.1575*** | 0.0028 | -0.1603*** | | | |
| | (-6.72) | (0.15) | (-5.74) | | | |
| RMW | | | | -0.2008*** | -0.0375 | -0.1633*** |
| | | | | (-3.86) | (-0.93) | (-2.64) |
| CMA | | | | -0.2457*** | 0.0173 | -0.2631*** |
| | | | | (-3.30) | (0.30) | (-2.98) |
| Avg $R^2$ | 0.9124 | 0.9218 | 0.1828 | 0.9073 | 0.9267 | 0.1443 |