# THE EFFECTS OF POLITICAL UNCERTAINTY ON OPTIONS

## AN EMPIRICAL STUDY OF S&P 500, EURO STOXX 50, AND S&P SECTORS AROUND POLITICAL EVENTS

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**The effects of political uncertainty on options: An empirical study of S&P 500, Euro Stoxx 50, and S&P sectors around political events**

Abstract:

We study options spanning political events and examine whether a price premium, associated with the political uncertainty from events, exists. First, we use recent data and replicate parts of Kelly, Pastor, and Veronesi (2016) by analysing how the price risk, variance risk, and tail risk associated with political events, affect equity options on the S&P 500 and Euro Stoxx 50 indices. Our results indicate a price premium on options spanning political events, and this premium is also larger when the economic conditions are weaker. Second, we apply the analysis to S&P sectors with varying political exposure by examining if sectors that are more affected by political uncertainty, also exhibit higher implied volatility premium during political events, compared to less exposed sectors. In fact, we find a pattern supporting this, however, the empirical evidence is too weak to draw any firm conclusions. Also, we do not find any support that this implied volatility premium difference between the more and less exposed sectors, would be any larger when the economy is weaker.

Keywords:

Political uncertainty, Options, Implied volatility, Sectors.

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Before a thrilling political event, the uncertainty about the outcome and subsequent policy changes, can affect the financial market and lead to market turmoil. Considering that options provide protection against bad outcomes, whether and how options are influenced by political uncertainty, is therefore a topic of importance. Our understanding of the effects of political uncertainty on options, however, is still limited.

In this paper, we study S&P 500, Euro Stoxx 50, and S&P sector equity options, by examining the protection options provide against political risks. We base our empirical design, mainly, on the findings of Kelly, Pastor, and Veronesi (2016), called KPV hereafter. Using options data across 20 countries, they conclude that options spanning political events are relatively more valuable compared to options not spanning the events. Furthermore, they find that the impact of these events on options is stronger in a weaker economy. To empirically examine the effects of political uncertainty, KPV use a model developed by Pastor and Veronesi (2013), called the PV model hereafter. The PV model provides a broad theoretical framework with mechanisms for how political uncertainty results in different types of shocks which can drive the implied volatility, variance risk premium, and implied volatility slope for options spanning political events. These are associated with three types of political risks specified by KPV, namely, the price risk, variance risk, and tail risk. The main prediction of the PV model is that implied volatility, variance risk premium and implied volatility slope should all be larger for options during political events, compared to bordering options that do not span the event. Furthermore, the framework predicts that the effect is larger in magnitude during weak economic conditions.

Using the PV model as a theoretical guideline, we replicate parts of KPV with updated data for the U.S. and Eurozone to study this timely topic. Hence, we include recent political events, such as the enthralling 2016 and 2020 U.S. presidential elections, Brexit referendum and the many economically relevant summits during the U.S. – China trade war. Additionally, we further complement KPV's findings by applying the implications of the framework to S&P sectors. We select this scope by arguing that the model predictions, also, would apply across sectors with varying political risk exposure. Specifically, we focus on the model predictions regarding the implied volatility difference between options spanning the event and bordering options (*IVD*). Also, by studying the literature, we find that the amount of empirical work covering this topic is very modest. Indeed, such research could be valuable, particularly for investors making investment decisions amidst political uncertainty, or during a recession. Moreover, politicians and regulators could benefit when suggesting economic policy changes, for instance, regarding trade agreements that would affect industries differently. Therefore, our sector-level analysis widens the implications of the PV model and better captures the uncertainty induced by government policy changes or during elections. Thus, we contribute by studying the topic with an industry-specific scope, in order to better understand the financial effects of political uncertainty on equity options across industries with varying political risk exposure. For this analysis, we divide the sectors into two groups, using the findings of Yu et al. (2017). More specifically, Financials, Materials, and Information Technology are politically more exposed since their industry betas are significantly affected by the risks related to economic policy changes. On the other hand, Energy, Utilities and Consumer Staples, are the least affected by this uncertainty amongst the S&P sectors.

By constructing a data sample consisting of national elections and global summits related to the U.S. and Eurozone between 1996-2020, six S&P sectors, economic conditions, and options data, we design a variety of tests all aimed to capture the effects of political risks in the equity options market. In short, our tests show empirical evidence that political uncertainty is priced in the options market for the U.S. and Eurozone, which is shown by the increase in implied volatility, variance risk premium and implied volatility slope for options spanning political events. Furthermore, we find support that the effects are even larger given that the economic conditions are weaker. These conclusions are mostly similar to KPV's. We then apply the analysis to sectors and find a pattern supporting that sectors that are more politically exposed exhibit a relatively higher *IVD* compared to the less exposed. Hence, we identify a trend indicating that Information Technology, Financials, and Materials, exhibit a larger *IVD*, on average, than Consumer Staples, Utilities, and Energy. However, since we do not find any significant results in most of these tests, we cannot confidently state that this effect exists in the population. Also, we do not find any empirical evidence that the *IVD* difference between the more and less exposed sectors would increase during weak economic conditions. Furthermore, we discuss our findings and identify possible explanations for our results, relating to specific events, model mechanisms, data limitations, and the literature. Also, we conduct robustness checks and find that the majority of our predictions for the U.S. and Eurozone, survive the tests. However, by recognizing the paper's limitations, we also acknowledge the importance of further research with larger sample sizes especially for the sector-level analysis, in order to get a more accurate understanding of the topic.

Our paper is divided into six sections. Section I clarifies the contribution of this paper and its connection to the existing literature. Section II specifies our theoretical framework. Section III describes the empirical design by detailing our data, methodology, variables, and hypotheses. Section IV presents and interprets our empirical results. Section V further discusses our findings, including their limitations. Section VI concludes.

## I. Literature Review

There is a prevalent amount of literature focusing on the relation between politics and its effects on the economy. For instance, several papers examine how politics may impact general macroeconomic outcomes (Alesina and Rodrik, 1994; Olters, 2001). While they cover the phenomenon of politics and economy, our study is narrowed to the financial effects. Therefore, our paper is strictly related to studies covering uncertainty induced by politics in the financial market. A few examples include papers focusing on political uncertainty stemming from national elections. Pantzalis, Stangeland, and Turtle (2000) analyse stock market behaviour across 33 countries and discover extraordinarily high-levels of stock returns in the two-week-period preceding elections. Another study, with an almost similar sample size (27 countries), points to an insignificant equity premium (Bialkowski, Gottschalk, and Wisniewski, 2008). On the other hand, Li and Born (2006) show significant results, though, they solely include U.S. presidential elections. Furthermore, Goodell and Vahamaa (2013) state that the VIX rises when the probability of an eventual winner increases. Additionally, Gemmill (1992) analyses the FTSE 100 implied volatility in relation to the 1987 British parliamentary election and conclude that the index surged two weeks in advance. Although our paper considers fairly similar topics as the above studies, we broaden the scope of political uncertainty and include non-electoral political events. Therefore, our paper is also linked to papers focusing on non-electoral political uncertainty. Some examples include Bittlingmayer (1998) and Voth (2002) who both conclude that a positive link relating the uncertainty to stock market volatility existed in-between the two world wars. Another paper studies the government's spending policies and their effects on stock returns and find that firms experience lower stock returns during Republican presidencies (Belo, Gala, and Li, 2013). While our paper is thematically related to the above studies, none of them examine options, however.

Other prominent papers focusing on the financial impact of political uncertainty include Erb, Harvey, and Viskanta (1996) and Brogaard and Detzel (2015). The former focuses on different measures of country risk and their importance to investors. They find a relation, albeit rather weak, between political risk and future stock returns. The latter, instead, relates stock data to economic policy uncertainty, and conclude that government policy changes are considered a risk factor for equities. Pastor and Veronesi (2012) focus particularly on the reaction of the stock market to the government announcement of a policy change and find similar results. In a later study, they, instead, analyse the price response of equities to political signals relating to the outcome of a future policy change (Pastor and Veronesi, 2013). Hence, they specifically study the asset pricing implications and find, inter alia, that the financial effects are stronger given a weaker economy. Our study is heavily related to their paper since we use its main theoretical framework, the PV model, as guideline. Thus, contrary to the above papers, we build our empirical analysis with a clear theoretical framework.

Additionally, we specifically study the asset pricing implications of political uncertainty, similar to Pastor and Veronesi (2013). Sialm (2006) has a similar scope and examines the impact of stochastic taxes on the pricing of equity securities and concludes that investors get compensated for the political risk stemming from possible changes in tax policies. Also, Croce at al. (2012) analyse the impact of fiscal policies on asset pricing. However, compared to the aforementioned two papers, we consider a wider set of government choices and policy changes, including elections, in addition to using a theoretical model with the inclusion of Bayesian learning. Excluding Pastor and Veronesi (2013), the closest study to our paper is KPV. They use the PV model as a theoretical guide but reinterpret the measure of political uncertainty by including national elections, expanding the sample to include global events, and studying equity options. KPV find strong evidence for the model predictions and conclude that options spanning political events are more valuable since they give protection for investors against the price risk, variance risk and tail risk, created by political events. This effect is also stronger in a weaker economy and given that the election uncertainty is higher. Indeed, many papers seem to show a link between political uncertainty and financial market behaviour. However, in a later study, Pastor and Veronesi (2017) analyse the VIX and argue for a weakened effect over time. They explain that the Trump administration’s political signals have been difficult to interpret from an investor’s perspective. Nevertheless, by studying recent events, one could contribute with an updated belief on the financial effects of this uncertainty.

The literature on this topic is growing in scope. Some studies showcase the link to firm behaviour and firm-specific differences. For instance, Bloom, Bond, and Reenen (2007) argue that regulatory changes affect firms' investment dynamics. In addition, Julio and Yook (2012) find that political uncertainty stemming from national elections could lead to low investment spending levels. Other studies have explored the effects on firm-level foreign direct investments (Nguyen, Kim, and Papanastassiou, 2017). Their conclusions indicate that firms increase their foreign direct investments level in countries where there are low levels of economic policy uncertainty, in relation to their home country. Although several papers cover political uncertainty in the above contexts, few have empirically analysed the effects on industries. Indeed, since there are firm-level differences to political uncertainty, a similar link could be studied for industries. Boutchkova et al. (2012) focus on how local and global political risks impact U.S. subsector return volatility. They conclude that industries that are more dependent on trade and labour often show greater return volatility when the uncertainty induced by national elections is higher. Moreover, Yu et al. (2017) use the EPU-index developed by Baker, Bloom and Davis (2016) in relation to the different S&P 500 industries and rank the sectors based on which sectors are the most affected by economic policy uncertainty. Furthermore, Hill, A. Korczak and P. Korczak (2019) find that firms within finance and customer-facing sectors were the most sensitive to political uncertainty during Brexit. Nevertheless, by studying the existing literature, we expect some sectors to be more affected by political events, and the implications of this uncertainty on sector equity options is therefore worth studying. Thus, to accurately understand political uncertainty and its effects in the options market, we add an industry-specific scope. Also, we include recent political events in order to accurately examine this timely topic. In short, our contribution to the existing literature comes in two ways. First, we examine political uncertainty and its effects on equity options while considering recent years events. Second, we study the sector-level impact of political uncertainty using clear theoretical principles. To the best of our knowledge, our paper is the first to extend KPV by applying the model predictions on recent data in addition to having a sector-level focus.

## II. Theoretical Framework

In the following section, we introduce the main theoretical guidelines for our paper. We build our theoretical framework based on KPV by presenting the PV model and its implications, as well as relating the model fundamentals to our sector-level focus.

### A. Model Introduction

The following subsection presents the PV model which is used to analyze political uncertainty during policy changes, which for example occurs during global summits. Following KPV, the PV model is a general equilibrium model, where companies' average profitability depends on which policy's the government has in place. This can be seen in *Equation 1,* which describes the development of firm's profitability, where $g_t$ represents the impact of any given policy on the profitability. All else equal, a higher $g_t$ implies higher profitability.

$$d\Pi_t^i = (\mu + g_t)dt + \sigma dZ_t + \sigma_1 dZ_t^i \qquad \textit{Equation (1)}$$

Moreover, the PV model assumes that there is no information asymmetry. How any policy selected by the government will impact overall profitability is uncertain for the investors (investors own the firms in the economy) and the government, but they will learn about it through Bayesian learning when they observe the realized profitability. At time $t = \tau$, which is when the political event takes place, the government decides whether or not they want to change the current policy in place, and also what new policy will be implemented in case of a change. If the government decides to change policy, investors will update their beliefs about how profitability will be impacted by taking the new policy into account. Consequently, the actors will learn and update their beliefs accordingly about the impact of the new policy on profitability by observing realized profitability.

The government is "quasi-benevolent", as specified by KPV, meaning that it aims to maximize the size of the economy (by increasing firm profitability), which is defined as the final value of total capital in the economy. However, they also consider the political cost associated with choosing a specific policy. An example of such a cost is that a selected policy might decrease the probability of the current government being re-elected. Namely, the investors wish to maximize the wealth function expressed in *Equation 2,* but the government's selection of policy will instead maximize a very similar function, shown by *Equation 3*, where $C^n$ is introduced, representing the political cost or benefit of a given policy. If $C^n$ were to be 1 for all *n* policies, *Equation 2* and *3* would be the same, meaning that the government would select policies which would be optimal from investors viewpoint.

$$u(W_T^j) = \frac{(W_T^j)^{1-\gamma}}{1-\gamma} \qquad Equation\ (2)$$

$$\max_{n\in\{0,\ldots,N\}} \left\{ \left[ E_\tau \frac{C^n W_T^{1-\gamma}}{1-\gamma} \mid policy\ n \right] \right\} \qquad Equation\ (3)$$

In the PV model, $C^n$ is not fully known before $t = \tau$, and investors cannot predict with certainty what policy will be selected by the government. The unpredictability surrounding $C^n$, which could distort politicians' incentives, results in uncertainty regarding the government's selection of policy which is the main origin of political uncertainty. This uncertainty partly forces an increase in stock volatility. Agents learn about $C^n$ by interpreting the flow of political signals through news related to the event. These signals could, for example, occur when politicians speak about an approaching summit which gives information about what policy the government might select. These signals cause so called political shocks, which is the main channel explored in the model. We describe political shocks in more detail in subsection B.

The framework can also be interpreted for elections, as explained by KPV. We use the election interpretation when analysing political elections as opposed to the above interpretation which is used when analysing global summits. The model equations and dynamics stay the same, only the interpretation changes. First, the timepoint of the political event, $\tau$, now represents the election date where the government is elected. Second, the political uncertainty stems from which government will be selected. Third, the people who vote do not only care about economic motives, but also other aspects about the candidates such as their personality or their view on pressing questions (for instance regarding the topic of migration). Fourth, instead of learning about how a selected policy will impact the profitability of firms, actors learn about the impact that the elected government will have.

### B. Model Implications

In this subsection, we summarize the fundamental implications of the PV model by, firstly, introducing a number of relevant equations presented by KPV and, secondly, outlining the key implications of the model.

*B.1. Relevant Equations*

$$dS_t = \mu_S(S_t)dt + \sigma_S(S_t)dW_{S,t} \qquad \textit{Equation}\ (4)$$

In *Equation 4*, $S_t$ represents a vector of state variables, that follows a generic stochastic process.

$$S_t = (\hat{g}_t, \hat{c}_t, \dots, \hat{c}_t^N, t) \qquad \textit{Equation}\ (5)$$

As shown in *Equation 5*, $S_t$ includes the above state variables prior to the timepoint $\tau$. $\hat{g}_t$ denotes the perception about the currently set policy's impact, which captures the state of the economy. Intuitively, a high $\hat{g}_t$ represents a strong economy. In addition, $\hat{c}_t^N$ represents the perception of the political cost related to each policy *n*. Furthermore, political shocks are the driving factor of $\hat{c}_t^N$.

$$\frac{dM_t}{M_t} = \mu_M(S_t)dt + \sigma_M(S_t)dW_{M,t} + J_{M,\tau}1_{t=\tau} \qquad \textit{Equation}\ (6)$$

$$\frac{d\pi_t}{\pi_t} = \sigma_\pi(S_t)dW_{\pi,t} + J_{\pi,\tau}1_{t=\tau} \qquad \textit{Equation}\ (7)$$

In *Equation* 6 the stock market's market value $M_t$ which, intuitively, can be viewed as stock prices, and the stochastic discount factor $\pi_t$, both follow a generic stochastic process with jumps at time $t = \tau$ when policy selection is made. $1_{t=\tau}$, represents an indicator function which is 1 at $t = \tau$ and otherwise 0. $J_{M,\tau}$ and $J_{\pi,\tau}$ represents the jumps at $t = \tau$ when the policy selection is made.

As seen in *Equation 6* and *7*, the discount factor and stock prices also depend on the state variables which partly includes $\hat{c}_t^N$ and $\hat{g}_t$ from *Equation 5*. More specifically, stock prices and the discount factor react to $\hat{c}_t^N$ and $\hat{g}_t$. In the model, there are two central shocks that are related to these state variables. The first type of shock is the impact shock, which occurs when investors update their perception about the current policy's impact on profitability resulting in an updated $\hat{g}_t$. If investors observe that profitability is increasing under any current policy $n$, they revise $\hat{g}_t$ upwards, and thus their expectations regarding profitability in the future are higher, leading to an increase in stock prices. The second type of shock that drives stock prices and the discount rate is political shocks. Political shocks occur when investors receive signals prior to the political event, for example when politicians speak, updating investors' beliefs about political costs ($\hat{c}_t^N$) and thus their assigned probabilities that a given policy will be implemented. The larger these shocks are, the larger the stock price volatility will be. These shocks and their subsequent impact are discussed in more detail below.

*B.2. Main Implications*

The probability of a specific policy being implemented depends partly on the political cost. When the political costs associated with the policy are higher, the probability of implementing the policy is lower. Another fundamental implication is that when the economy is weak, the probability of the government replacing the prevailing policy is relatively high. A low $\hat{g}_t$ simply indicates that the prevailing policy is not working well, and thus the probability of replacing the policy is higher. If $\hat{g}_\tau$ is relatively high, the probability of changing the currently set policy at t = $\tau$ is lower. When $\hat{g}_\tau$ is very high, sticking to the prevailing policy is expected, and thus stock prices would not react to such a decision. In this case, there would be a small or no jump in $J_{M,\tau}$, hence no jump in the discount factor or stock price in *Equation 6* or *7*. Implementing another policy when $\hat{g}_\tau$ is very high is most likely negative news for the stock market since the deviation from retaining the successful policy is most likely driven by political costs rather than what is best for the stock market. If $\hat{g}_\tau$ is low, however, keeping the old policy is negative for the stock market, and changing to a perceived low risk policy will most likely lead to a positive jump in stock prices.

Following KPV, the implied stock market volatility, also called implied volatility or IV, is higher when there is uncertainty regarding whether or not a new policy will be implemented, since any news signal prior to the event would be of more importance leading to larger political shocks impacting *Equation 6* or *7*. In contrast, political signals prior to the event would be of very little importance if $\hat{g}_t$ is very high, leading to relatively low stock market volatility. The reason for the low volatility is because investors stop caring about the signals prior to the event, since they know that the government will almost certainly not change the prevailing policy given that $\hat{g}_t$ is extremely high. In such a case, political shocks that impact *Equation 6* and *7* are much smaller.

The key takeaway from the above two paragraphs is that expectations about what policy will be implemented are partly driven by $\hat{g}_t$ and $\hat{c}_t$. Also, higher uncertainty regarding whether or not a new policy will be implemented results in higher volatility, since signals preceding the event carries more information about what policy the government might introduce.

*B.2.1 Implications on IV, VRP and Slope*

In the sections below we firstly, in *B.2.1.1*, explain how option prices are derived in the framework, utilizing the Black-Scholes formula, and considering some of the state variables. In *B.2.1.2 – B.2.1.4*, we discuss three quantities that in a measurable manner capture the different model predictions. Similar to KPV, these are all used to construct our variables for our analysis, which we explain in-depth in Section III. More precisely, they are utilised to empirically test whether or not the model predictions occur in reality. To shortly summarize this, IV is selected since it is a way to measure the predictions regarding the increased stock volatility during political events that makes options more valuable. We also discuss the prediction that options are more valuable in weak economic conditions, compared to strong economic conditions. The model also predicts that the variance risk, which is defined in *B.2.1.3*, should be higher during political events. Furthermore, the model predicts that the variance risk should be higher in weak economic conditions compared to strong economic conditions. Since the variance risk premium, or VRP, is generally higher when investors are ready to pay much for the protection against the variance risk, VRP allows us to test these predictions. As explained by KPV, analysing the VRP would indicate if political uncertainty affects the state price density. Lastly, we include the implied volatility slope, or Slope. Since the model predicts that the risk of a very bad policy change (tail risk) is larger during weak economic condition, Slope should also be larger during weak economic condition. The reason for this is explained in *B.2.1.4*.

*B.2.1.1. Option Price Formula*

Investors assign probabilities that any given policy choice *n* would be implemented by the government at t = τ. Depending on the state variables, such as $\hat{g}_t$ and $\hat{c}_t$, investors' assigned probability of each policy will differ. Following KPV, the price of a put option is derived by firstly calculating the different Black–Scholes prices given the expected outcome of each potential policy. Thereafter, the prices are probability-weighted using the investors assigned probabilities to arrive at the option price. *Equation 8* gives the put option price.

$$Put(S_t, m, K) = E\left[\frac{\pi_m}{\pi_t}\max(K - M_m, 0) \mid \mathrm{S}_t\right] \qquad Equation\ (8)$$

In the above equation, m represents the option's maturity, $M_m$ is the market value (stock price) of the underlying index at maturity, K represents the strike price, and S captures the state variables such as $\hat{g}_t$ and $\hat{c}_t$.

*B.2.1.2. Implied Volatility (IV)*

As stated by KPV, much of the value of an ATM option stems from the protection it provides against an unfavourable, from the perspective of an investor, policy choice at t = τ, which would descend stock prices. For bordering options not spanning the political events, there is no risk of a policy change that would be perceived as unfavourable, since there is no event during the control group's options' lifespan. Thus, all else equal, options that span the political event are of relatively higher value compared to bordering ones due to the protection they provide against the increased price risk related to potential policy changes, which we capture through a higher IV. IV is also higher when there is more uncertainty regarding the policy selection (as discussed above in B.2.*)*, which naturally drives IV for options spanning the event higher.

Recall that when the economy is very strong and $\hat{g}_t$ is very high, the probability of a policy change is very low. This means that the uncertainty regarding policy selection is low, making IV lower compared to options in weak economic condition. If the probability of a policy change is low, then the probability of a policy change that would be perceived as unfavourable is also low, hence, all else equal, options spanning the political event during strong economic condition are of relatively lower value compared to options in weaker economic conditions. Because of this, implied volatility is also relatively low during strong economic conditions.

*B.2.1.3. Variance Risk Premium (VRP)*

In the theoretical framework, the variance risk premium is normally high if investors are ready to pay much for the protection against the variance risk. According to KPV, variance risk can be decomposed into the variance in stock returns and the risk of a price jump at t = τ. The variance in stock returns prior to the event stems from different political shocks. The price change at t = τ occurs because investors now know what policy is selected and adjust market prices accordingly. The selected policy, and whether its economic consequences after being implemented is considered more or less uncertain, will impact the variance after t = τ. Policies with higher uncertainty will normally result in a price drop at t = τ and an increase in variance after t = τ.

For bordering options, there is no risk of political shocks or price jumps related to a policy change since no event occurs during the options' lifespan. Therefore, the variance risk is lower during the options lifespan, meaning that, all else equal, VRP is expected to be lower compared to options spanning event.

When the economy is strong, VRP is expected to be relatively low. A strong economic state implies that the current policy will most likely be kept, hence, investors pay very little attention to the signals they receive prior to the event since they know that the current policy is most likely going to be kept. More specifically, the political shocks prior to the event are less impactful, decreasing the variance risk compared to when the economy is weak. Furthermore, since it is anticipated that the government will not change their current policy, there is also low probability of a big price change at t = τ, decreasing the variance risk further. This can be clearly illustrated using an extreme case presented by KPV: if $\hat{g}_t$ is infinitely high, all agents know that the government will not change the current policy, thus no signals prior to the event matters and no political shocks therefore occur. Furthermore, there will not be any price reaction at t = τ since all investors know that the government will keep its current policy.

*B.2.1.4. Implied Volatility Slope (Slope)*

In the case of implied volatility slope, the value becomes larger when OTM options are relatively more expensive compared to ITM options. As stated by KPV, the important differentiating factor between the two is that OTM options deliver better protection against very bad outcomes, which in this model occurs when, for example, the government changes to a policy with very high uncertainty regarding its impact on the economy. Since there is no policy change during the lifespan of options not spanning the event, the risk of a very bad policy selection outcome does not exist, resulting in implied volatility slope being lower for bordering options.

As previously explained, the PV model assumes that the probability of a new policy being implemented is much lower when the economy is strong. Therefore, the risk of a very bad policy being implemented is also lower during strong economic condition, making Slope lower during strong economic condition.

## C. Sector-specific Predictions

In this subsection, we utilize the PV model to make predictions regarding how sectors with different level of political exposure will react around major political events.

*C.1. Comparison between More and Less Exposed Sectors*

As discussed in the literature, for instance by Boutchkova et al. (2012) and Yu et al. (2017), some industries are more exposed to political uncertainty, and are thus more sensitive (profitability wise) to political events. To connect this to our theoretical guidelines, we know that depending on what policy the government sets, firm profitability will be affected in different ways. Furthermore, as explained in subsections A and B, the uncertainty about what policy the government will implement at $t = \tau$ contributes to uncertainty about how future firm profitability will be impacted by the event, driving IV. Since the more exposed sectors' profitability would to a greater extent be affected by what policy the government sets, IV is predicted to be larger for these sectors compared to the less exposed sectors. We expect that this greater profitability dependency will lead to more volatility prior to the political event. The relatively higher volatility prior to the event is expected to occur because every political signal in the form of political shocks, which updates investors' beliefs about what policy the government might select, will be larger for the more exposed sectors. The political shocks are larger for the more exposed sectors since their profitability is more sensitive to the selection of the policy. An easy way to illustrate this is through an extreme case: assuming that the less exposed industries' profitability does not depend at all on what policy the government sets, then, the flow of information prior to the event produces no political shocks for these industries, thus not increasing IV. On the other hand, these signals would still matter for the more exposed industries whose profitability is more dependent on the selection of policy, driving IV and making it, all else equal, relatively larger compared to the less exposed industries. In Section III, we thoroughly define the IV difference (*IVD*), for any given event, between options spanning the event and nearby options not spanning the event. Using the PV model, we therefore predict the *IVD* to be larger for the more exposed industries.

*C.2. The Impact of Economic Conditions*

We also argue that the *IVD* difference between the more and less exposed sectors, described above, will be smaller in a stronger economy. We arrive at this prediction by using the PV model. A simple way to illustrate this is through an extreme case described by KPV: when the economy is in an infinitely good state, the probability that the government will change the currently set policy is 0%. In this case, the flow of information prior to the event produces no political shocks for any industry that would update investors beliefs about what policy the government might select. This is because all investors know that the government will not change the current policy due to the extremely good economic state. The absence of any political shocks, would mean that the mechanism where political signals matter more for exposed sectors, would totally disappear. Thus, this extra IV stemming from exposure differences between the sectors would not exist, meaning that the extra *IVD* difference between the more and less exposed sectors would also disappear. Following KPV, when the economy is weak, the probability of a policy change increases. Therefore, we predict that these signals prior to the event start to matter relatively more for the more exposed sectors again, as explained in *C.1*, increasing IV and subsequently *IVD* relatively more for the exposed sectors.

## III. Empirical Design

In the following section, we specify our empirical design, and in the process, we describe our variables of interest and data in more detail. The empirical design follows the main sections of KPV and incorporates the principal findings of Yu et al. (2017) in our procedure for the sector-level analysis.

### A. Data Description

*A.1. Options*

Similar to KPV, we use the U.S. database in OptionMetrics for options data spanning 1996-2020. For data covering U.S. political events, we use the country's most followed stock market index, namely, the S&P 500 index. For data covering events relevant to the Eurozone, we use the Euro Stoxx 50 index. While KPV does not include this index, we argue that it can be used as a proxy for the region. In fact, this is considered Europe's leading blue-chip index for the Euro area and it is made up by 50 of the largest stocks from 8 countries in the Eurozone (Qontigo, 2021). Lastly, for our industries, we use available indices for the S&P 500 sectors (the selection of these sectors is further explained in *A.4*). The start-dates of the Eurozone and industry options data differ from the start-date on the S&P 500 index. For Eurozone data, we use options from 2008 to match our events of interest, and for our industries, we use options data from 2000 since OptionMetrics does not provide S&P sector-level data earlier than that.

Our options data set includes, inter alia, quotidian data on implied volatilities, deltas, and open interest. Also, besides OptionMetrics, we use the Oxford-Man Institute's Realized Library for data on realized variances. We use the options data to construct our options variables of interest.

*A.2. Economic Conditions*

We use the economic conditions data to construct our macroeconomic variables (*GDP, CLI, FST* and *MKT*); these are further explained in subsection B. We use the International Monetary Fund (IMF), Organization for Economic Cooperation and Development (OECD), and FactSet. Regarding OECD and FactSet, we use their online databases, while the data from IMF is hand-collected from different World Economic Outlook reports ranging from 1996 to 2020.

*A.3. Political Events*

In our analysis, we relate data on a list of relevant political elections and global summits to our option market and macroeconomic variables. To better capture political uncertainty, these events strictly follow the main criteria set by KPV and, hence, must be political in nature and lead to substantial policy shifts. Also, the event dates must be determined far in advance (at least four weeks prior to the event date) so that they are publicly known on the dates at which we examine the options spanning the relevant events.

First, we select data on national elections ranging from 1996 to the presidential election of 2020 for the U.S. and our sectors. These include both the U.S. senate elections and the presidential elections since the U.S. president has executive control over changes in government policy. In addition, similarly to KPV excluding other countries' elections in the U.S.-analysis, we cannot include U.S. elections in the Eurozone-analysis or vice versa. Also, we cannot include the different national elections of Eurozone countries in our analysis (since an election in Finland will generally not cause a major impact on the Euro Stoxx 50, for instance). However, we deviate slightly from this logic when we include three additional national elections of special importance for the Euro area. As mentioned by KPV, the two Greek elections of 2012 had a profound impact on the future of Eurozone, mostly due to a possible Greek exit from the area and subsequent impact on the future of endangered economies such as Spain and Italy. Additionally, we include the 2016 United Kingdom EU membership referendum in the sample. This extraordinary event created major political uncertainty among Eurozone member states and is thus of importance (Graziano, Handley and Limao, 2021). Table AI in Appendix summarizes our list of election events, including their dates and option availability.

Second, we consider four types of global summits, namely, the G7/G8/G20 summits and European summits. Since we include post-2011 data, as opposed to KPV, we include G7 summits due to the 2014 Crimean crisis and subsequent exclusion of Russia from the member list. Not all summits are used in the empirical analysis however, instead, the allowed summits should primarily focus on economic issues and have the possibility of leading to major changes in economic policy, as stated by KPV. We have, besides from including the summits used by KPV, also identified recent events by studying the summit agendas and the content of the final announcements to support our selections. For each potential summit, we study the topics and final announcements using available information from the G7 Research Group, G20 Research Group, European Council, and Council of European Union. Regarding the European summits, we consider both EU and Eurozone summits. Since all Eurozone countries are members of the EU, our inclusion of EU summits fits perfectly well in the Eurozone analysis. In our sample, we include all global summits except the European summits for the USA, while the Eurozone analysis is based on all relevant summits since the EU member states are all part of the G20 meetings. In addition, France, Germany, and Italy are part of the G7/G8 group. Although they are a minority of the Eurozone, France and Germany are, by far, the largest economies in the Euro area. Also, all three contribute to 75% of the Euro Stoxx 50 index, as of March 2021

(Qontigo, 2021). Thus, it would be wise to include all economic relevant G7/G8 summits in the Eurozone-analysis to capture the uncertainty of those meetings on the major members and, thereafter, indirectly on the Eurozone. Furthermore, our S&P sectors' options data are related to U.S. events only, as the European summits are not relevant for the U.S. analysis and thus irrelevant for the sectors. Table AII in appendix presents our list of summits, including their dates, topics, and option availability.

*A.4. Sectors*

We collect industry options data spanning U.S. events starting in 2000 and use an identical test procedure to the U.S.- and Eurozone analysis. To fully test the predictions introduced in Section II, we compare the different industries by sorting our group of sectors based on different levels of political sensitivity. Apart from the PV model, we use the main findings of Yu et al. (2017) to guide this analysis. In their study, they investigate how economic policy uncertainty (EPU) drives the different betas of the S&P 500 industries. The EPU-index, developed by Baker, Bloom and Davis (2016), is an index on uncertainty related to economic policy. Although EPU and political uncertainty are not directly interchangeable, as stated by KPV, this index has been used as a proxy for political uncertainty by Pastor and Veronesi (2017). Furthermore, we argue that all our political events are strongly related to EPU as this is a main criterion when selecting events. All political events have been thoroughly chosen studying their topics and/or the different decisions taken, hence, these events should lead to both EPU and political uncertainty. Thus, the inclusion of EPU as a guidance in our analysis is suited with regard to theory and our event sample.

Yu et al. (2017) conclude that the betas of Financials, Materials, and Inf. Tech., are most likely higher than other industries in their tests. Hence, they conclude that these industries are significantly affected by uncertainty related to economic policy changes. On the other hand, Energy, Utilities and Con. Staples, are less affected by this uncertainty and, therefore, have betas that are least driven by EPU, implying that they are politically less exposed. The U.S. industry ranking, presented by Yu et al. (2017), is shown in Table AI, in Appendix. Following their findings, we include the aforementioned sector indices and divide them accordingly in subsequent analysis. Indeed, we recognize that our industry sample is narrowed to S&P sectors. However, even though our scope is limited, the inclusion of other market's sectors is currently problematic since there is a lack of empirical studies on the relationship between political uncertainty and non-U.S. sectors in terms of exposure. Although Hill, A. Korczak and P. Korczak (2019) rank UK sectors, their tests are limited to the Brexit referendum, as mentioned in Section I. Nevertheless, we hesitate to design a broader analysis covering other markets due to the limited literature.

## B. Variable Description

In the following subsection, we construct our variables and further clarify their function in our empirical analysis.

*B.1. Implied Volatility Difference (IVD)*

Using implied volatility introduced in our theoretical framework, we construct our first option variable. Following KPV, we specify implied volatility for an option that is ATM at time $t$ and matures at time $m > t$, as $IV_{t,m}$. For each option, OptionMetrics calculates the implied volatility value. In subsequent tests, we focus primarily on options with accompanying $IV_{t,m}$ for which $t < \tau < m$ holds, for each political event with the date $\tau$. When choosing this data, we first find the two expiration dates, called $a$ and $b$, that surround $\tau$. More specifically, these dates must fulfil $a < \tau < b$ (note that $b$ is the expiration date for options spanning the event). In the selection of appropriate dates, we examine the distance from the event to the nearest expiration date. If this distance is six days or more, we select $a$ and $b$ so that they are one month apart. However, if the distance is five days or less, the two dates should be two months apart. As KPV mentions, this requirement helps us avoid using "ultra-short-maturity options" and dealing with political uncertainty that gets settled a few days from the event date. Thereafter, we choose the expiration date following $b$ which is denoted $c$ (note that this expiration date must always be one month apart $b$ regardless of the distance between $a$ and $b$ according to KPV). Both $a$ and $c$ are expiration dates of the control groups. Hence, options with $b$ as expiration date (treatment group) are related to bordering control group options in subsequent calculations and tests.

Options included in our sample must satisfy three criteria specified by KPV. First, they must be ATM options with deltas less than 0.5 but greater than 0.4, in terms of absolute values. Second, they must have positive open interest. Finally, all options must have $s$ days until the relevant expiration date, $a, b$ or $c$. Hence, within each group, we consider implied volatilities from multiple dates that are $s$ days from the relevant expiration date. For instance, in our treatment group, the event date is in-between $b - s$ and $b$, or more precisely, $b - s < \tau < b$. Following KPV, we define $IV_{b-s,b}$ and adjust it to make it more robust. First, we modify by computing $IV_{b-s,b} - 0{,}5 * (IV_{a-s,a} + IV_{c-s,c})$. Thereafter, we replace the aforementioned three components, for any given $s$, by averages of $IV$-values across multiple different $s$-values. We conduct this modification to reduce the "noise in the estimation", as stated by KPV. Subsequently, we create $\overline{IV}_b$, $\overline{IV}_a$ and $\overline{IV}_c$. For instance, we express $\overline{IV}_b$ as

$$\overline{IV}_b = Mean\,\{IV_{b-s,b} : b - s \in [\tau - 20, \tau - 1]\} \qquad Equation\ (9)$$

Following KPV, $\overline{IV}_b$ is the average implied volatility over all acceptable options up until $\tau - 1$, that expire at $b$. More precisely, it is the (equal-weighted) average of $IV_{b-s,b}$ across all acceptable options and where $b - s$ is in the 20-trading-day window preceding the event. We follow KPV and select the specific length of this window to account for the "day-to-day option price fluctuations". Thereafter, we repeat the procedure and adjust the timeframe accordingly for the control groups, in order to create $\overline{IV}_a$ and $\overline{IV}_c$. Finally, we define our first option variable, namely, the implied volatility difference (*IVD)* as

$$IVD_\tau = \overline{IV}_b - 0{,}5 * (\overline{IV}_a + \overline{IV}_c) \qquad \textit{Equation (10)}$$

Following the PV model, if this value is above 0, for any given event, it would indicate that options with $b$ as expiration date, have higher implied volatility values, on average, than bordering options belonging to the control groups.

*B.2. Variance Risk Premium Difference (VRPD)*

Our second option variable is denoted $VRPD_\tau$ and is the variance risk premium difference (*VRPD*) for event date $\tau$. First, we define the variance risk premium at time $t$ for an acceptable option maturing at time $m > t$ as

$$VRP_{t,m} = IV_{t,m}^2 - RV_{t,m}^2 \qquad Equation\ (11)$$

In the above equation, $RV_{t,m}^2$ denotes the (average) realized variance between $t$ and $m$, and it is used to construct the quotidian list of $VRP_{t,m}$. As KPV states, this variable provides an impartial and fair measure of the expected variance across an option's life. When calculating *VRPD*, we choose $a, b$ and $c$, in the same fashion as in the above section. Thereafter, we utilize the following equation:

$$VRPD_\tau = \overline{VRP}_b - 0{,}5 * (\overline{VRP}_a + \overline{VRP}_c) \qquad Equation\ (12)$$

where the three components are computed in the same way as in *B.1*. Note that the acceptable options sample for our $VRPD$ calculations is the same as for $IVD$ since the criteria do not change. If *VRPD* is positive, for any given political event, KPV suggests that investors value the insurance against the variance risk for options spanning the event date relatively more, compared to bordering options in the control groups.

*B.3. Implied Volatility Slope Difference (SlopeD)*

Our final option variable, *SlopeD*, is constructed by the slope coefficient of the function that links implied volatility to an option's Black-Scholes delta, as specified by KPV. From our data sample, we construct a quotidian list of slopes, namely, $Slope_{t,m}$. Also, we follow KPV and change the criteria for our acceptable options. Specifically, we include put options at time $t$ with positive open interest and deltas less than -0,1 but greater than -0,5. Also, these options are OTM.

When calculating $Slope_{t,m}$, we construct a regression that relates the options' implied volatilities against their deltas. However, we only compute the slope coefficient given that at least three acceptable options exist for any time $t$, as KPV states. Thereafter, we compute our variable with the following equation:

$$SlopeD_{\tau} = \overline{Slope}_b - 0{,}5 * (\overline{Slope}_a + \overline{Slope}_c) \qquad\qquad Equation\ (13)$$

The above three components are defined and calculated in the same manner as their counterparts in *B.1*. If the value is above 0, for any given event, KPV suggests that investors pay a higher price for protection against the tail risk, for options in the treatment group compared to bordering options not spanning the event.

*B.4. Macroeconomic Variables (GDP, CLI, FST, and MKT)*

Similar to KPV, we relate our option variables to the economic conditions data to test whether the pricing of political uncertainty is influenced by the state of the economy. A high value of any these variables indicates that the economic conditions are strong. We use the OECD database for data on the seasonally adjusted real GDP growth in the same quarter as the event date for each observation. This variable is called *GDP* onward. Also, we import data on the Composite Leading Indicator, *CLI*, in the same month as the event for each observation. More specifically, this variable identifies signals of turning points in business cycles, as stated by KPV. Our next macroeconomic variable, *FST*, is the most recent real GDP growth forecast for the following year from the event date of each observation, and it is obtained from the IMF. Finally, we use FactSet for the stock market index return over the previous three months from the date of the event for each observation, called *MKT* in our analysis.

**C. Hypotheses**

Based on our theoretical framework and empirical design, we formulate four hypotheses related to the three risks associated with events related to the U.S., Eurozone, and S&P sectors. We exclude *VRPD* and *SlopeD* from our sector-level analysis, as the relevant data on realized variance is not available for the S&P sectors. In addition, there is a lack of industry options data for *SlopeD* due to the variable criteria. Therefore, our hypotheses and subsequent tests for the sector-level analysis slightly differ from the U.S.- and Eurozone analysis. We specify our hypotheses, including their predictions, below.

*Hypothesis (1): On average, the option variables (IVD, VRPD, and SlopeD) are all positive. Namely, the uncertainty stemming from major political events is priced in the options market.*

*Hypothesis (2): On average, the option variables (IVD, VRPD, and SlopeD) are greater when the economic conditions are weaker. Namely, political uncertainty has larger effects on options when the economy is weaker.*

*Hypothesis (3): On average, IVD is greater for sectors that are more sensitive to political uncertainty. Namely, political uncertainty has larger effects on the implied volatility of options in sectors with higher exposure to political uncertainty.*

*Hypothesis (4): On average, the IVD difference between the more and less exposed sectors is greater when the economic conditions are weaker. Namely, political uncertainty has larger effects in terms of IVD on the more exposed sectors, when the economy is weaker.*

## IV. Empirical Results

In the following section, we present and interpret our main empirical results from our tests. We divide our findings into regions and sectors.

### A. U.S. and Eurozone analysis

**Table I.**

**Option market variables**

| | *IVD* | *VRPD* | *SlopeD* |
|---|---|---|---|
| Mean (All observations) | 0,029 | 0,018 | 0,021 |
| P-value two-tailed | 0,0013 | 0,0066 | 0,0240 |
| t-statistic | 3,40 | 2,84 | 2,35 |
| Obs. | 86 | 84 | 69 |
| Std. error | 0,0086 | 0,0062 | 0,0087 |

| | *IVD* | *VRPD* | *SlopeD* |
|---|---|---|---|
| U.S. mean | 0,016 | 0,0057 | 0,016 |
| Eurozone mean | 0,037 | 0,024 | 0,024 |

*In Table I, we test if IVD, VRPD and SlopeD are significantly different from 0. “Mean” represents the mean of IVD, VRPD and SlopeD across all events (U.S. plus Eurozone). Furthermore, the p-values, t-statistics, numbers of observations and standard errors refer to the test where all events (U.S. plus Eurozone) are included. The p-values also refer to the two tailed p-value. We use standard errors that are clustered on a monthly basis, since IVD, VRPD and SlopeD for events that occur during the same month, occur during similar conditions, and are therefore correlated with each other. IVD, VRPD and SlopeD are reported in decimals, meaning that 0.029 represents a 2.9 percentage-point difference between the treatment and control group. We also report the mean for the U.S. and Eurozone subsamples.*

*A.1. Option variables during Political Events*

The first hypothesis states that political uncertainty is priced in the option market. For this to hold true, *IVD*, *VRPD* and *SlopeD* should all be larger than 0, on average. Table I summarizes the empirical results related to the first hypothesis. Similar to KPV we find support for the prediction stating that all three option variables are larger than 0, on average.

*A.1.1. IVD prediction*

The positive *IVD* in Table I represents the price premium for options spanning the political event, since an increase in implied volatility results in higher option prices. More specifically, *IVD* represents the extra cost for the protection against the political uncertainty related to political events. Accounting for all observations across the U.S. and Eurozone, we observe an average *IVD* of 0.029 (p-value = 0.0013). This represents a price premium for a put option during an average political event of roughly 12% compared to the control group. As stated by KPV, a percentage increase in implied volatility for ATM put options approximately result in the same percentage increase in the put option's price. Hence, 12% is calculated by taking the *IVD* divided by the average IV of the control group. Furthermore, we observe a 0.016 *IVD* in the U.S. subsample and a 0.037 *IVD* for Eurozone. Possible explanations for the difference between the U.S. and Eurozone results are presented in Section V.

*A.1.2. VRPD prediction*

We also observe a positive *VRPD* on an aggregate level and across both the U.S. and Eurozone samples. The observed *VRPD* across all events is 0.018 and is statistically significant (p-value = 0.0066), implying that the variance risk associated with the political events results in a price premium for options spanning the event, affecting the state price density. *VRPD* is 0.024 in the Eurozone sample and 0.0057 in the U.S. sample. Once again, we observe a higher value for Eurozone.

*A.1.3. SlopeD prediction*

As shown in Table I, Slope is 0.021 higher in the treatment group compared to the control group (p-value = 0.024), indicating that the tail risk associated with political events is priced in the treatment options. Consequently, this supports the first hypothesis. The average value of *SlopeD* is 0.016 in the U.S. sample and 0.024 in the Eurozone sample. Once again, we observe a higher value in the Eurozone sample.

**Table II.**

**Option market variables regressed against economic conditions**

***IVD***

| | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.022*** | -0.021*** | -0.018** | -0.031*** |
| P-value (coef.) | 0.002 | 0.004 | 0.013 | 0.00 |
| t-statistic | -3.16 | -2.99 | -2.53 | -4.72 |
| $R^2$ | 0.106 | 0.096 | 0.071 | 0.212 |
| Obs. | 86 | 86 | 86 | 85 |
| Std. error | 0.0069 | 0.0070 | 0.0070 | 0.0066 |

***VRPD***

| | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.012** | -0.010* | -0.0070 | -0.014*** |
| P-value (coef.) | 0.018 | 0.052 | 0.156 | 0.004 |
| t-statistic | -2.4 | -1.97 | -1.43 | -2.92 |
| $R^2$ | 0.066 | 0.045 | 0.024 | 0.094 |
| Obs. | 84 | 84 | 84 | 84 |
| Std. error | 0.0048 | 0.0048 | 0.0049 | 0.0048 |

***SlopeD***

| | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.033*** | -0.030*** | -0.028*** | -0.020** |
| P-value (coef.) | 0.000014 | 0.000104 | 0.000380 | 0.0120 |
| t-statistic | -4.69 | -4.13 | -3.74 | -2.59 |
| $R^2$ | 0.247 | 0.203 | 0.173 | 0.092 |
| Obs. | 69 | 69 | 69 | 68 |
| Std. error | 0.0071 | 0.0073 | 0.0074 | 0.0079 |

*In Table II, we run a OLS regression. Each of the four economic condition variables, placed on the x-axis, are one by one regressed, firstly, against IVD, which is on the y-axis. We then run the same test but swap IVD for SlopeD and VRPD. Each coefficient represents the slope coefficient in each standalone regression. We run 12 different regressions (4 economic measures * 3 options market variables). For example, the slope coefficient of -0.022 in the above table means that a one increase, which represents one standard deviation, in the GDP metric would result in a 0.022 decrease in IVD. Recall that GDP, CLI, FST and MKT is zero mean and unit variance standardized. The interpretation is the same for CLI, FST and MKT. All observations where data is available for both U.S. and the Eurozone are included. The p-values and t-statistics refer to the test if the slope coefficients are significantly different from 0. The p-values represent the two-tailed p-value.*

** p-value < .1, ** p-value < .05, *** p-value < .01*

### *A.2. Option variables in Relation to Economic Conditions*

The second hypothesis states that *IVD*, *VRPD* and *SlopeD* are all relatively larger in weaker economic conditions, compared to stronger economic conditions. From our OLS regressions in Table II, we find a clear relationship, where larger values of *IVD*, *VRPD* and *SlopeD* are associated with a relatively weaker economic condition. As shown by the graphs in Figures I - III and in Table II, there is a negative slope coefficient when *IVD*, *VRPD* and *SlopeD*, are each regressed against the four different macroeconomic variables. These outcomes thus support the PV model's prediction that political uncertainty has a larger impact on the option variables during weak economic conditions. In conclusion, we find support for the second hypothesis. The only two regressions where the slope coefficient is not statistically significantly negative on the

5% level are when *VRPD* is regressed against *CLI* (p-value = 0.052) and when *VRPD* is regressed against *FST* (p-value = 0.156). Similar to KPV, we find that the effects of the option variables are larger during weak economic conditions, the only difference being that KPV also finds significance when *VRPD* is regressed against *FST* and *CLI*. Since all economic metrics are standardized to zero-mean and with unit variance, a one standard deviation decrease in the GDP metric would result in a 0.022 *IVD* increase, as an example (see slope coefficient in Table II).

*Figure I-III are graphical illustrations of the OLS regressions in Table II. The x-axis represents standard deviations of each economic metric. The y-axis represents the values of the three option variables in decimal form.*

**Figure I.**

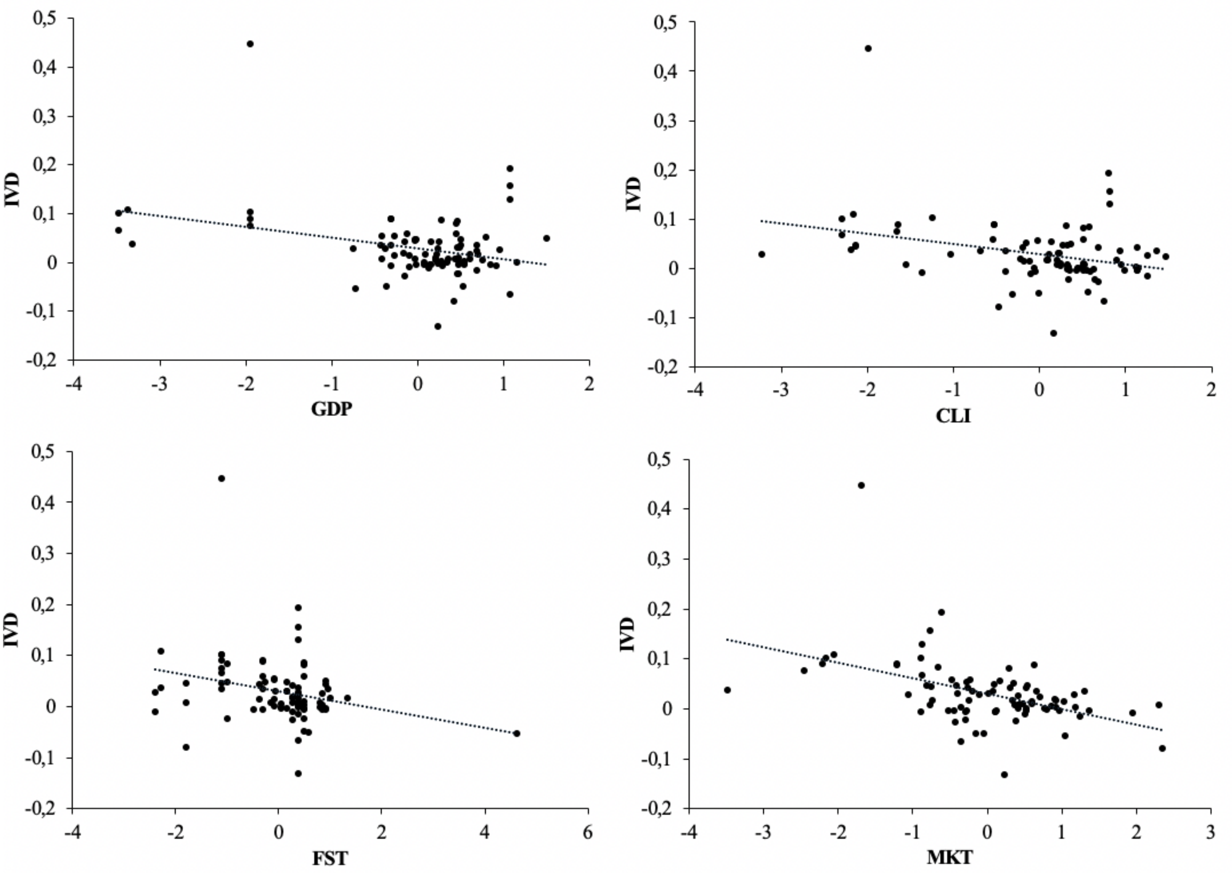


**Figure II.**

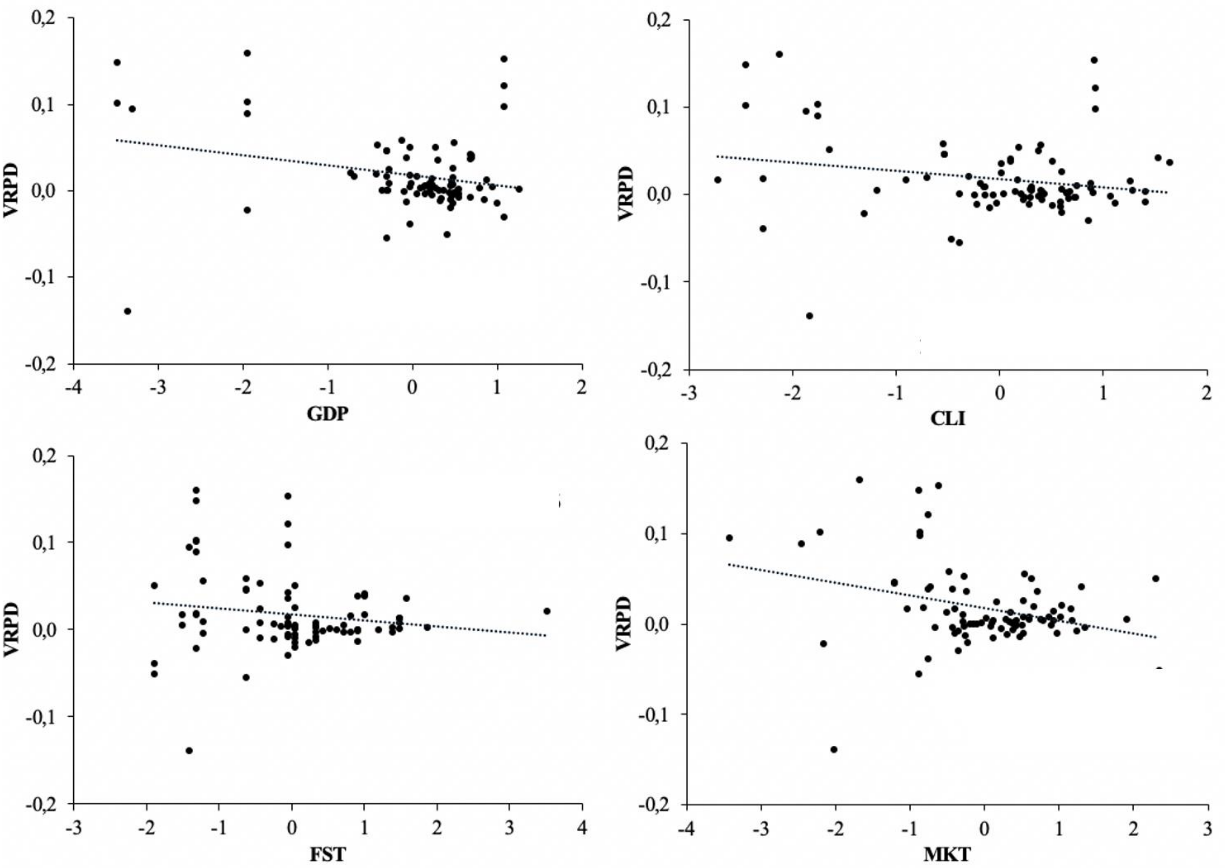
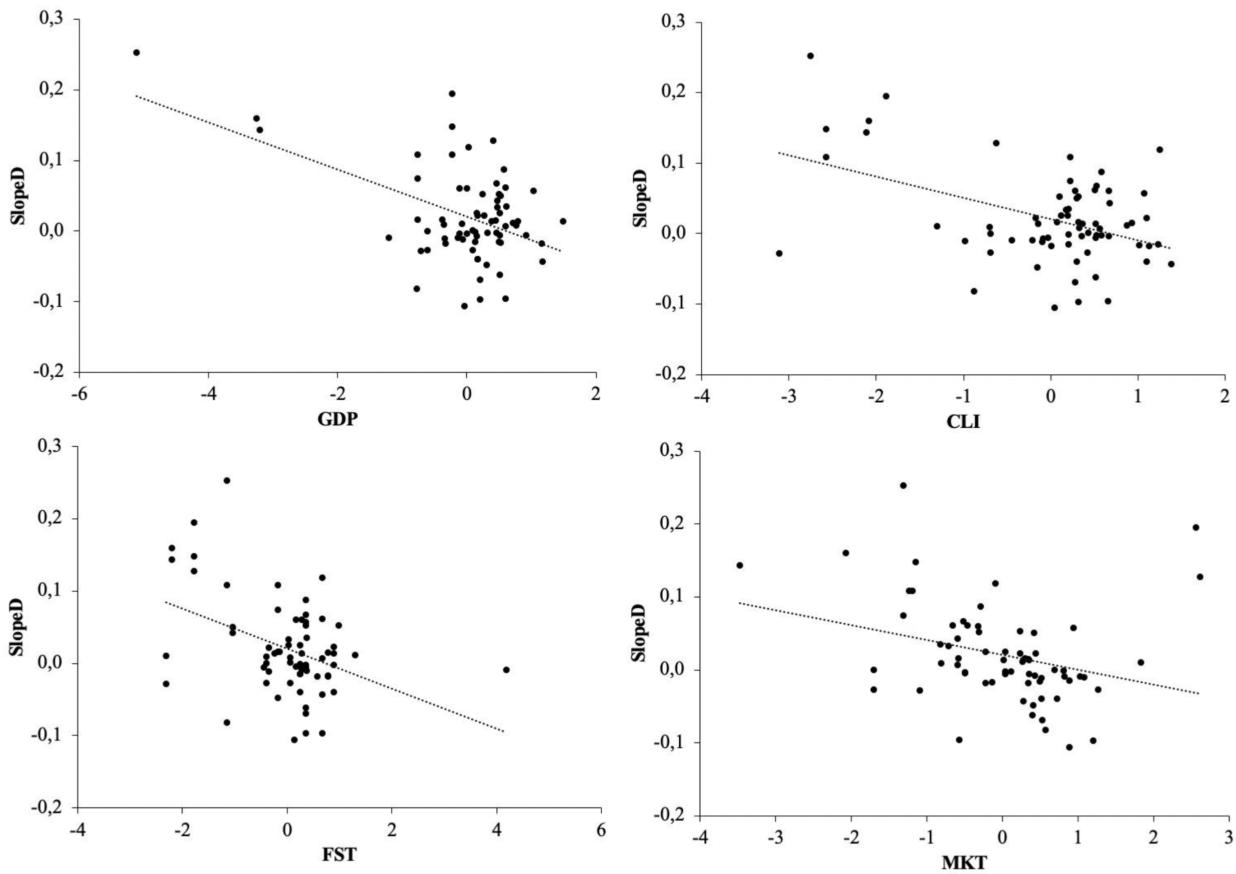



**Figure III.**



## B. Sector-level Analysis

### *B.1 IVD Difference between More Exposed and Less Exposed Industries*

### Table III.

**IVD mean on industry level**

| | Aggregate | More exposed group | Less exposed group | Materials | Energy | Inf. Tech. | Financials | Utilities | Con. Staples |
|---|---|---|---|---|---|---|---|---|---|
| *IVD* mean | 0.016** | 0.018** | 0.014* | 0.021*** | 0.020** | 0.016** | 0.017** | 0.012* | 0.0090* |
| P-value two-tailed | 0,036 | 0,013 | 0,085 | 0,005 | 0,027 | 0,012 | 0,028 | 0,075 | 0,061 |
| t-statistic | 2,23 | 2,67 | 1,79 | 3,07 | 2,34 | 2,69 | 2,32 | 1,85 | 1,95 |
| Obs. | 180 | 90 | 90 | 30 | 30 | 30 | 30 | 30 | 30 |
| Std. error | 0,0071 | 0,0066 | 0,0077 | 0,0067 | 0,0086 | 0,0059 | 0,0072 | 0,0067 | 0,0046 |

*In this table, we display each U.S. industry's average IVD during all US events for which data is available. The aggregate IVD mean is the average IVD including all events for all industries. 180 observations come from 6 industries * 30 events per industry. Furthermore, the p-value, t-statistic and numbers of observations refer to testing if IVD is different from 0. The p-value also refer to the two- tailed p-value. The test for the aggregate mean uses standard errors clustered on a monthly basis. The reason we use clustering on the aggregate sample is because each industry observation results in one observation for the aggregate sample, which means that during each event, 6 datapoints are used (one for each industry). These data points are naturally correlated to each other since they occur during the same month, making clustering relevant. The more exposed and less exposed samples also use standard error clustered on a monthly basis due to the same reasoning as for the aggregate.*

** p-value < .1, ** p-value < .05, *** p-value < .01*

### Table IV.

| High exposure group *IVD* - low exposure group *IVD* | |
|---|---|
| Mean IVD difference | 0,0039 |
| P-value | 0,10 |
| t-statistic | 1,69 |
| Obs. | 30 (180) |
| Std. error | 0,0023 |

*In this table, the mean refers to the average difference between the average IVD of the more exposed group and the less exposed group (0.018-0.014 from Table III = 0,0039). Each observation therefore includes 3 observations from the exposed group, and 3 observations from the less exposed group. Each observation in the "Mean IVD difference" is constructed by grouping these 6 industry IVD values per event into the less exposed and more exposed group. We then compute the difference between the two groups' average IVD during every event. Specifically, we receive 1 "Mean IVD difference" observation per event, and thus 30 data points in total. The p-value (two-tailed) and t-statistic refer to testing if these 30 measures of the IVD difference between the two groups is significantly larger than 0, which would indicate a higher IVD for the more exposed group. The standard errors are not clustered in this table since all industry IVD observations during each event are together constructed into 1 data point for the test. 180 refers to all IVD data points on an industry level, which are used to construct the 30 points used in the test. See description in Table V for an alternative to this test, utilizing 270 observations which are instead clustered, yielding the exact same results as this table.*

**Table V.**

| Mean IVD difference between more and less exposed group | | | | |
|---|---|---|---|---|
| | | More exposed group | | |
| | | Inf. Tech. | Financials | Materials |
| Less exposed group | Utilities | 0,003 | 0,004 | 0.008** |
| | Energy | -0,004 | -0,003 | 0,001 |
| | Con. Staples | 0.007*** | 0,008 | 0.012*** |

*In this table, we compute the mean IVD difference between each sector in the more exposed group and each sector in the less exposed group. -0.003 in the middle of the table therefore represents the mean IVD in Financials minus the mean IVD in Energy. We also test if there is a significant difference between each pair of sectors. More specifically, we compute the IVD difference between the two chosen sectors during each event, resulting in 30 total IVD differences. In the next step we test if these IVD differences are significantly larger than 0. Standard errors are not clustered for the same reason as in table IV. Another way to construct the test in Table IV it to compute each high exposure industry minus each low exposure industry as in this table, which would give 9*30 = 270 observations. These 270 observations are then clustered on an event basis. We then test if the 270 observations on an aggregate lever is greater than 0. When conducting this test, we observe exact same results as in Table IV, with the exact same p-value, mean IVD difference and standard errors.*

** p-value < .1, ** p-value < .05, *** p-value < .01*

As shown in Figure III, the more exposed basket, which includes Materials, Inf. Tech., and Financials, displays a *IVD* of 0.018, compared to 0.014 for the less exposed basket. This difference of 0.004 is not statistically significant (p-value = 0.10). In Table V, we also compute the mean IVD difference between each sector in the more exposed group and each sector in the less exposed group**.** As displayed, all sectors exhibit larger *IVD* values in the more exposed group compared to the less exposed group, except for when Energy is compared to Inf. Tech. and Financials. The difference between Inf. Tech. and Con. Staples, as well as the difference between Materials and Con. Staples are significant on a 1% level, while the difference between Materials and Utilities is significant on a 5% level. To conclude the results, we find a pattern supporting our prediction that the more exposed sectors will display a higher *IVD* during political events, but we cannot confidently state that this pattern exists in the real population due to the p-value being too high in majority of the comparisons. The low power of the test could be a potential issue. This is discussed in more details in Section V.

In Table III, we provide a ranking of the individual sectors in terms of *IVD*. As displayed, Materials, Inf. Tech. and Financials represent the three of the four sectors with highest *IVD*. What is interesting is that Energy, which we classified in the less sensitive basket, is the sector with the second highest *IVD*. This is further discussed in Section V.

We also test if *IVD* on an aggregate level in the different samples are larger than 0, to ensure that political uncertainty is priced on a sector level. We find that the average *IVD* across all observations is 0.016, which is statistically significant on a 5% level.

*B.2. IVD Difference between More Exposed and Less Exposed Industries in Relation to Economic Conditions*

**Table VI.**

| *(High exposure group IVD - low exposure group IVD) regressed against economic conditions* | | | | |
|---|---|---|---|---|
| | ***GDP*** | ***CLI*** | ***FST*** | ***MKT*** |
| Slope coefficient | 0,005 | 0,002 | 0,001 | 0,006 |
| P-value (coef.) | 0,023 | 0,402 | 0,541 | 0,015 |
| t-statistic | 2,40 | 0,85 | 0,62 | 2,6 |
| $R^2$ | 0,171 | 0,025 | 0,014 | 0,195 |
| Obs. | 30 | 30 | 30 | 30 |
| Std. error | 0,0022 | 0,0023 | 0,0024 | 0,0021 |

*In Table VI, we run a standard OLS regression. Each of the four economic condition variables, placed on the x-axis, are one by one, in separate regressions, regressed against the IVD difference between the more exposed and less exposed group. Each coefficient represents the slope coefficient. For example, the slope coefficient of 0.005 under GDP means that a one standard deviation increase in the GDP metric would result in a 0.005 increase in the IVD difference between the more exposed and less exposed group. The p-values and t statistics refer to the test if the slope coefficients are significantly different from 0.*

Table VI displays the test for our final industry hypothesis, namely, that the *IVD* difference between the more and less exposed sectors will be smaller in a stronger economy. We run a simple OLS regression with the difference in *IVD* between the two groups against the economic condition variables. We are looking for a negative slope coefficient, which would indicate a decrease in the difference in *IVD* when the economy is stronger. Based on our sample, we see no evidence of this expected prediction. No coefficient is negative; hence we cannot find any empirical evidence for the fourth hypothesis.

# V. Discussion

In the following section, we discuss our empirical results in relation to the theory, as well as assessing the robustness of our analysis and presenting limitations worth acknowledging.

## A. Comparison between the U.S. and Eurozone

When interpreting our results in Table I, we spot an eye-catching finding related to the U.S.- and Eurozone-analysis. Namely, *IVD*, *VRPD* and *SlopeD* are all, on average, clearly larger in the Eurozone sample compared to the U.S. sample. While there are several potential explanations, we discuss a few factors that the PV model would point towards below. Firstly, economic condition is, as can be viewed in Table II and Figures I-III, clearly negatively related to the size of *IVD*, *VRPD* and *SlopeD*. We observe that all four macroeconomic variables are noticeably lower in the Eurozone sample compared to the U.S. sample. For example, the average seasonally adjusted real GDP growth in the given quarter is 0.45% in the U.S. and 0.01% in Eurozone, meaning that the difference in the option variables between the two groups could partly be explained by the difference in economic condition. Using the slope of -0.027 in the regression of *IVD* against the non-standardized quarterly GDP growth (See Figure AI in Appendix), we can infer that a 1 percentage-point decrease in GDP growth would, according to the regression, result in a 2.7 percentage-points higher *IVD*. The average GDP growth in the Eurozone sample is 0.44 percentage-points lower compared to the U.S., which implies that there should be a 1.2 percentage-points higher *IVD* in the Eurozone sample (2.7 * 0.44 = 1.2). This can be compared to the realized difference of 2.1 percentage-points. Surely, our regression is not a perfect representation of the population effect, but it clearly indicates that economic conditions could play a role in explaining the difference.

Another potential factor that could cause differences in the three option variables is how unpredictable politicians are regarding policy changes, in the two regions. As discussed in the theoretical framework, more uncertainty would lead to larger shocks. Since we lack a measure to capture this, we avoid drawing any further conclusions.

## B. Insights from Extraordinary Events

From our results, we identify several abnormally high *IVD* values, especially for the U.S. and Eurozone, compared to their averages. Interestingly, these values often occur during extraordinary events. Thus, we further discuss our results with accompanying potential explanations using the intuition from our theoretical framework. Hence, by studying these observations in-depth, we can better assess our results in relation to the model mechanisms. The first example concerns the second 2012 Greek election where the Eurozone *IVD* was 0.09 (which is almost three times the average *IVD* in our sample). We illustrate this case in Figure AII. This event occurred during the peak of the financial crisis from Greece's perspective. In fact, we find that the economic conditions in Eurozone were substantially lower compared to other events, especially against post-2012 summits. Naturally, given our model predictions, these weaker conditions increase *IVD*. Furthermore, major uncertainty regarding the future of the Eurozone was present during this period. First, the political situation in Greece was heavily troublesome with considerable election uncertainty, especially after the May election in which no party took an absolute majority of the seats. Second, the two Greek legislative elections also induced uncertainty within the Eurozone (Dimitrakopoulos, 2012). In short, it is possible that this very uncertain environment would lead to higher implied volatility as predicted by our theoretical framework, thus, making options spanning the event date more valuable and increasing the protection against the price risk. As a result, *IVD* becomes abnormally high. Other events during the peak of the Eurozone crisis (2010-2012) also include such values. In this case, the economic conditions were also substantially lower compared to other years. In addition, many of the global summits discussed the crisis implying a general uncertainty about possible government interventions which indicates a strengthening of the political shocks. For instance, the Eurozone *IVD* reached 0.13 in the 2010-06-26 G20 summit which included the recovery from the debt crisis on the agenda (in comparison, the U.S. *IVD* was less than 0.01). Furthermore, we see that the Eurozone *IVD* surged to 0.09 during the Brexit referendum of 2016. Compared to the aforementioned events, the economic conditions were not relatively weaker and are, therefore, not the main driver for the relatively higher *IVD*. In fact, there was a deep uncertainty among policymakers, investors, and within the general public, regarding the election outcome and subsequent consequences on the relationship between the UK and EU. Consequently, this could potentially lead to larger political shocks, driving *IVD*. Furthermore, companies dependent on the UK-EU relationship (which surely include Eurozone firms) were unsure regarding the impact on their businesses in terms of profitability given a Brexit outcome. Since the realized outcome was to leave the EU, this future profitability uncertainty is expected to have strengthened the impact shocks. Additionally, as Hill, A. Korczak and P. Korczak (2019) states, several sectors were deeply affected by the political risk surrounding the event (mainly because of firm-level uncertainty about profitability). Though this study is limited to the UK, non-UK firms dependent on the relationship could have also been affected by this uncertainty. Nonetheless, the impact shocks were most likely noteworthy which could explain the high *IVD*.

Other extraordinary events include the different elections and summits surrounding the global financial crisis starting in 2007. In December 2008, the Eurozone *IVD* peaked at almost 0.45, and the U.S. *IVD* surged to 0.11 a month earlier in the 2008 U.S. presidential election (in which battling the financial crisis was a critical theme). In fact, the economic conditions were relatively weaker during this period. Furthermore, we see similar findings for the U.S. presidential elections 2016 and 2020. In the former, the U.S. *IVD* was 0.03 (more than twice the average), and in the latter, it was almost five times the average. Though the economic conditions were not notably weaker, major election uncertainty could have surrounded both events which possibly strengthened the political shocks.

### C. Investigating the Sectors

While we observe a pattern supporting our third hypothesis, we do not identify significant results in the majority of our tests. However, we observe interesting findings about our sectors that could explain some of our results. For instance, the case of the Energy sector is striking and worth analyzing in-depth. Comparing the sectors on an event-to-event basis, we find abnormal values for many events, and in particular the 2008 U.S. presidential election. In fact, the *IVD* value of over 0.20 for Energy was 10 times its average while the other sectors show *IVD* values between 0.09-0.13. According to Table AIII, Energy's beta measuring the systematic risk is expected to be the least affected by political uncertainty, amongst our sectors. However, we observe that the average *IVD* value for Energy is the second highest in our sample, surpassing both Inf. Tech. and Financials. The aforementioned observation has, most likely, driven this conflicting case due to its magnitude. Interestingly, Yu et al. (2017) comment that during periods of turmoil (pointing at the financial crisis starting in 2007), the betas of our sectors are expected to be less driven by EPU. Instead, other factors impacting the betas and that occur simultaneously are worth acknowledging, such as market and funding liquidity or general macroeconomic distress. Whether these factors contribute to political uncertainty can be further discussed, however, we emphasize that the factors, surely, could be of economic relevance and could induce both policy and election uncertainty. Nonetheless, considering the changed relation between EPU and industry betas during periods of turmoil, it is likely that other factors can explain the anomalies for Energy. Regarding the 2020 election, we also see a case in which Energy has the highest *IVD* value of all sectors. We argue that it is possible that the case could be explained by studying Trump's politics. Prior to the 2020 election, the Trump and Biden administrations were distinctly different from each other which certainly created policy uncertainty in the Energy sector. More specifically, the Republicans favored an "energy dominance agenda" while the Democrats suggested a vision dominated by investments in clean energy and an increased focus on decarbonization (Goldwyn and Clabough, 2020). Thus, the increased *IVD* relative to the more exposed sectors could be explained by a general policy uncertainty amongst firms in the Energy sector, which possibly strengthened the shocks for these companies from the election.

Another case concerns the *IVD* values relating to the 2018-11-30 G20 summit. While the main talk was the U.S.-China trade war, one of the main outcomes included the U.S.-Mexico-Canada agreement (UMCA) which replaced the North American Free Trade Agreement (NAFTA). Interestingly, although these topics are of economic relevance for trade and the general economy, the three most exposed sectors have the lowest *IVD* in this event and we find no support for our predictions. However, it was expected that UMCA would positively affect the U.S. economy on an aggregate level and many export-dependent sectors, such as Materials, would be benefitted according to the United States International Trade Commission (2019). In addition, the report also states that the new agreement would be notably cost-effective in terms of operating costs for U.S. financial firms. Also, within-industry groups related to information technology reported their support for the agreement prior to the announcement, particularly amongst the big internet companies. Thus, by studying the agreement, the level of uncertainty surrounding the event compared to other events, could have been lower for Inf. Tech, Materials and Financials. Another potential explanation could be difficulties in interpreting the political signals, pointing back to Pastor and Veronesi (2017). However, we hesitate to make any firm and conclusive comments in this subsection since the above examples are solely possible explanations.

### D. Robustness tests

To assess the robustness of our empirical results, we conduct two critical tests. The results are presented in Tables AIV-AVI, in Appendix. First, we follow KPV and repeat our tests while excluding a group of events in which there is uncertainty about the event dates. Specifically, we remove these because we cannot fully be certain whether the dates were announced at least 20-trading-days prior, with regard to the criterion listed by KPV. Only six events from Table AII are affected by this exclusion since political events, in general, are scheduled many months or even years in advance. The affected events are the European summits that occurred on 2008-11-07, 2009-03-01, 2010-05-07, 2011-07-21 (also excluded due to data unavailability), 2011-10-26 (also excluded due to data unavailability), and 2015-06-22. Thus, we repeat our tests for the hypotheses concerning Eurozone. We obtain very similar findings in most cases. The key difference concerns the prediction of *VRPD* in the second hypothesis. Contrary to our main results, we find insignificance on a 0.05-level for *GDP* against *VRPD.* In addition, the p-values have dramatically increased when *CLI* and *FST* are regressed against *VRPD.* Although one could argue that the excluded events could have driven *VRPD*, we still find strong empirical evidence for the other predictions.

Second, we conduct a robust regression instead of OLS regression for the second hypothesis. The results are presented in Table AVI. KPV do not use robust regression when comparing the option variables to the economic conditions, however, we argue that this is critical due to the presence of the almost striking outliers seen in Figures I-III. Thus, we use this method to handle our outliers and compare the analysis to the OLS regression. From our robust regression tests, we obtain different results for *VRPD* and *SlopeD* compared to our main analysis in terms of significance. For the former, we now find insignificant results for *GDP*, and for the latter, we find insignificance against *MKT*, both on a 0.05-level. Thus, we recognize that the presence of outliers in an already small sample size could have had an effect on our main findings.

### E. Limitations

Several limitations are worth considering when interpreting our results. For instance, being limited to events solely relevant to the U.S. and Eurozone, reduces the size of our data sample (which is smaller than KPV's). Hence, the statistical power of our tests for all hypotheses is a salient limitation worth recognizing in our analyses, particularly for sectors. Indeed, this increases the risk of type II errors. We discuss the potential issues with effect size and power specifically for the industry comparison, utilizing Lakens (2013). To the best of our knowledge, it exists no previous literature to determine whether the effect size is expected to be large, small, or non-existent in the *IVD* industry comparison (specifically for our third hypothesis). The effect size in our sample from Table IV, by calculating Cohen's D to 0.114, is definitely considered small. If the effect size from our sample in Table IV were to be close to the real population effect size, the test would require a relatively larger sample size to detect the effect. Even if the population effect size were to be double the difference of our sample, Cohen's D would be around 0.2, which is still considered small. Surely, we cannot use our sample to determine the effect size of the population in the industry comparison, because it could very well not exist an effect at all. Thus, we are not arguing that the effect would exist in a larger sample, but that it is worth noting that there could be potential issues with low power in our test if it exists a small effect in the population. This is not a problem we can solve, due to the fact that the indices tracking the S&P sectors have not existed long enough to capture events before the year 2000. Furthermore, there has not occurred a sufficient number of relevant events in the U.S. between 2000-2020 to make the sample larger.

Additionally, we acknowledge that the option data availability is unbalanced when comparing the S&P 500 index to the other indices. For instance, there are far more acceptable options to include in the U.S. analysis compared to the Eurozone- or the sector-level analysis. Also, in some cases, there is a considerable variation among our treatment and control groups in terms of number of acceptable options. Surely, this might have had an impact on the construction of the option variables and consequently on our results. Another limitation concerns the exclusion of the third hypothesis of KPV which states that the price of political uncertainty is higher when the uncertainty is higher. Although this is one of the key predictions of KPV, the exclusion of these tests does not impact our results. In addition, KPV states that the uncertainty variable, *UNC*, only applies to elections. In our event sample, our election sample size is substantially smaller than for summits. Hence, the construction of *UNC* would be problematic. Nevertheless, given a larger election sample, and by testing whether high uncertainty levels would impact options, a broader result, and a more precise replication, could be obtained.

## VI. Conclusion

We empirically examine the pricing implications of political uncertainty on U.S., Eurozone, and S&P sector equity options. First, by replicating parts of KPV using recent data, we find empirical support consistent with the key predictions of the PV model, similar to the authors. Our results imply that political uncertainty is priced in the option market, hence, commanding an option price premium stemming from the price risk, variance risk, and tail risk, associated with political events relevant to the regions U.S. and Eurozone. Also, we conclude that this premium is greater during weak economic conditions.

Second, we introduce a sector-specific scope to the PV model, and use the model predictions to test if *IVD* is larger for industries that are more sensitive to political uncertainty. In fact, we find a pattern that more exposed S&P sectors, show higher *IVD* during major political events, compared to less exposed sectors. More specifically, we identify a trend indicating that the *IVD* for Inf. Tech, Financials, and Materials, are larger than corresponding values for Con. Staples, Utilities, and Energy. However, since we do not find any significant results in most of the tests, we cannot confidently state that these effects exist in the real population. Also, we do not find any empirical evidence for the *IVD* difference between the two groups to increase, during weak economic conditions. Thus, we find no empirical evidence for the main predictions when analyzing political uncertainty and equity options, by comparing more exposed sectors to less exposed. After further discussing our findings, we identify possible explanations for our results, relating to specific events, model mechanisms and the literature. Also, we recognize that several limitations are worth considering, especially concerning the data. In order to better test the model predictions, future research could use a larger sample size, particularly in the industry-level analysis. Additionally, by including other markets' industries, a wider understanding of the financial effects on sector equity options, could be obtained.

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# Appendix

## Table AI.

**Elections**

| Event type | Date | Option data in OptionMetrics |
|---|---|---|
| U.S. Presidential Election | 1996-11-05 | Yes |
| U.S. Senate Elections | 1998-11-03 | Yes |
| U.S. Presidential Election | 2000-11-07 | Yes |
| U.S. Senate Elections | 2002-11-05 | Yes |
| U.S. Presidential Election | 2004-11-02 | Yes |
| U.S. Senate Elections | 2006-11-07 | No |
| U.S. Presidential Election | 2008-11-04 | Yes |
| U.S. Senate Elections | 2010-11-02 | Yes |
| Greek legislative election | 2012-05-06 | Yes |
| Greek legislative election | 2012-06-17 | Yes |
| U.S. Presidential Election | 2012-11-06 | Yes |
| U.S. Senate Elections | 2014-11-04 | Yes |
| United Kingdom EU membership referendum | 2016-06-23 | Yes |
| U.S. Presidential Election | 2016-11-08 | Yes |
| U.S. Senate Elections | 2018-11-06 | Yes |
| U.S. Presidential Election | 2020-11-03 | Yes |

*This table lists all elections considered in our data sample between November 1996 and November 2020 together with their dates and option availability information. These elections are parliamentary and/or presidential. Note that in those cases U.S. Senate and Presidential elections occur on the same date, we consider the events as a single observation, similar to KPV. We include all elections with available options data in our empirical analysis.*

## Table AII.

### Global summits

| Event type | Date | Topics of economic relevance | Option data in OptionMetrics |
|---|---|---|---|
| European summit | 2008-10-15 | Economic and financial situations | Yes |
| European summit | 2008-11-07 | Global financial crisis | Yes |
| G20 summit | 2008-11-14 | Global financial crisis | Yes |
| European summit | 2008-12-11 | Economic and financial situations | Yes |
| European summit | 2009-03-01 | Global financial crisis | Yes |
| European summit | 2009-03-19 | Economic, financial, and social situation | Yes |
| G20 summit | 2009-04-02 | Global stimulus | Yes |
| European summit | 2009-04-05 | Economic, financial, and social situation | Yes |
| European summit | 2009-06-18 | Economic, financial, and social situation (and related institutional issues) | Yes |
| G20 summit | 2009-09-24 | World economic recovery | Yes |
| European summit | 2009-12-10 | Economic, financial, and employment situation | Yes |
| European summit | 2010-02-11 | Greek financial crisis | Yes |
| European summit | 2010-03-25 | Greek financial crisis | Yes |
| European summit | 2010-05-07 | Greek financial crisis | Yes |
| European summit | 2010-06-17 | Jobs and economic growth after the financial crisis | Yes |
| G8 summit | 2010-06-25 | Recovery from global recession and European debt crisis | Yes |
| G20 summit | 2010-06-26 | Recovery from global recession and European debt crisis | Yes |
| European summit | 2010-09-16 | Economic governance (strategy and task force) | Yes |
| European summit | 2010-10-28 | Economic governance (strategy and task force) | Yes |
| G20 summit | 2010-11-11 | Global economic recovery and financial regulation | Yes |
| European summit | 2010-12-16 | Europan economic policy | Yes |
| European summit | 2011-02-04 | European economic situation | No |
| European summit | 2011-03-11 | Europan economic policy | No |
| European summit | 2011-03-24 | Europan economic policy | No |
| European summit | 2011-06-23 | Europan economic policy | No |
| European summit | 2011-07-21 | Greek financial crisis | No |
| European summit | 2011-10-23 | Europan economic policy | No |
| European summit | 2011-10-26 | Crisis strategy | No |
| G20 summit | 2011-11-03 | Recovery from global recession and European debt crisis | Yes |
| European summit | 2011-12-08 | Europan economic policy | No |
| European summit | 2012-01-30 | Europan economic policy and Greek financial crisis | Yes |
| European summit | 2012-03-02 | Greek financial crisis | Yes |
| G8 summit | 2012-05-18 | Euro crisis | Yes |
| G20 summit | 2012-06-18 | Euro crisis; International economic governance | Yes |
| European summit | 2012-06-29 | Financial stability in the Euro area | Yes |
| European summit | 2013-03-14 | Economic policy and crisis strategies (EU-Russia and Syria) | Yes |
| G20 summit | 2013-09-05 | Global economic growth; Crisis strategy | Yes |
| G7 summit | 2014-06-04 | Global economy and trade; Crimean crisis response | Yes |
| European summit | 2014-10-24 | Jobs and economic growth | Yes |
| G20 summit | 2014-11-15 | Jobs and global economic growth | Yes |
| G7 summit | 2015-06-07 | Global economy and trade | Yes |
| European summit | 2015-06-22 | Economic governance and crisis strategy (Greece-Turkey) | Yes |
| European summit | 2015-07-07 | European Stability Mechanism; European economic policy | Yes |
| European summit | 2015-07-12 | European Stability Mechanism; European economic policy | Yes |
| G20 summit | 2015-11-15 | Global economic growth; Investment strategies | Yes |
| G7 summit | 2016-05-26 | Global economy and trade | Yes |
| G20 summit | 2016-09-04 | G20 growth agenda; Innovative economic policies | Yes |
| G20 summit | 2017-07-07 | Sustainable economic growth and job creation | Yes |
| European summit | 2017-12-15 | Euro reform strategy | Yes |
| European summit | 2018-03-23 | Fiscal capacity; European Stability Mechanism | Yes |
| European summit | 2018-06-29 | European Stability Mechanism; Banking union | Yes |
| European summit | 2018-10-18 | Europan economic policy | Yes |
| G20 summit | 2018-11-30 | Global trade; International tax policies | Yes |
| European summit | 2018-12-14 | Europan economic policy | Yes |
| European summit | 2019-06-21 | Europan economic policy | Yes |
| G20 summit | 2019-06-28 | Global trade | Yes |
| G7 summit | 2019-08-24 | Global trade | Yes |
| European summit | 2019-12-13 | European Stability Mechanism; Banking union | Yes |
| European summit | 2020-12-11 | Crisis response (COVID-19); Financial stability | Yes |

*This table lists all global summits considered in our data sample between October 2008 (same start-date as by KPV) and December 2020. These summits are either of the type European, G7, G8 or G20. Also, we list the topics discussed in the meetings by studying the press announcements or the different decisions taken at the summits. Note that several events occurring in 2011 lack options data. We include all summits with available options data in our main empirical analysis.*

## Table AIII.

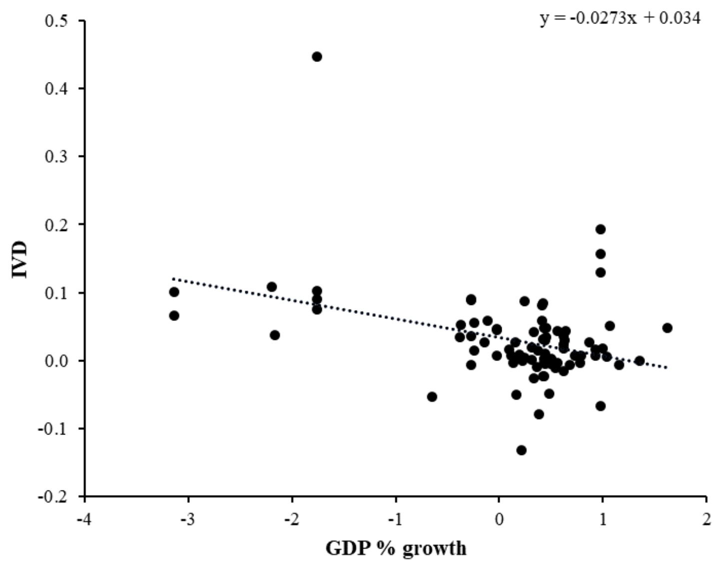
**Industry ranking**

| Industry | Mean (β) | Mean (Ranking number) | Group |
|---|---|---|---|
| Inf. Tech. | 2.087 | 9.500 | More exposed |
| Financials | 1.772 | 9.273 | More exposed |
| Materials | 1.279 | 8.080 | More exposed |
| Utilities | 0.633 | 3.000 | Less exposed |
| Con. Staples | 0.552 | 2.000 | Less exposed |
| Energy | 0.142 | 1.000 | Less exposed |

*In this table, we summarize the key points used in our empirical analysis from "Table 2: Summary statistics of industry beta and its ranking group" in Yu et al. (2017). They estimate the industry betas by using the DCC-MIDAS-EPU model. The information above lists the S&P sectors used in our analysis, as well as their means (for their industry betas and their relative ranking numbers). Similar to Yu et al. (2017), we divide these sectors into two groups based on exposure to EPU. As an example, the industry beta mean of Inf. Tech. is the largest from their sample which implies that the industry beta is most affected by EPU. The ranking numbers suggest that the betas of Inf. Tech, Financials, and Materials, mostly remain relatively more driven by EPU, implying that those sectors are significantly exposed to EPU, as Yu et al. (2017) states.*

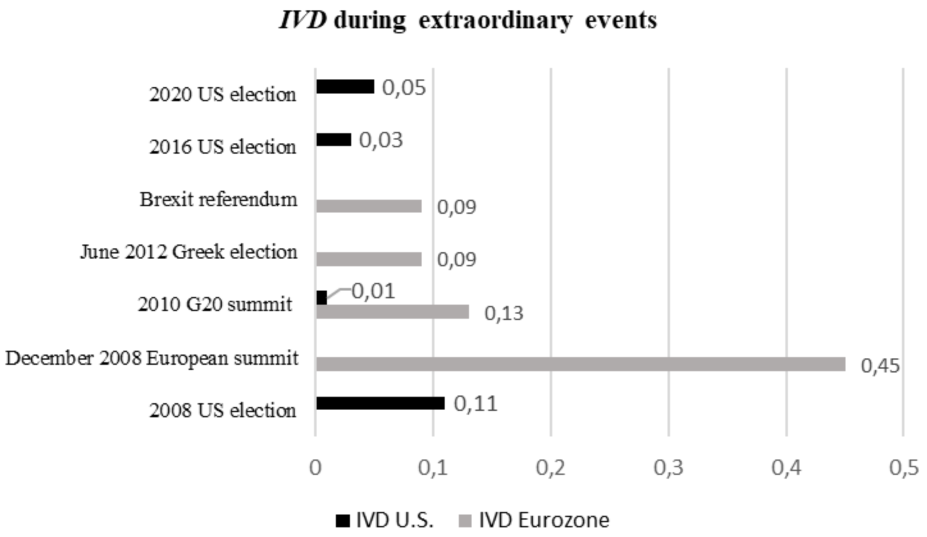
## Figure AI.

**Regression IVD against non-standardized GDP**




*In this figure, we run the same regression as in Figure I for the GDP regression, where the only difference is that we do not standardize the GDP metric to zero mean with unit variance. Hence, the figure shows the regression of IVD against non-standardized GDP. The x-axis in this graph thus illustrates the GDP percentage growth. 1 on the X axis represents a 1% GDP growth during the given quarter that the event is taking place.*

## Figure AII.




*In this figure, we illustrate the computed IVD values from our data sample for specific extraordinary events. Note that the U.S. average IVD across all events is 0.016, and the corresponding value for Eurozone is 0.037. We calculate this data following the method described by KPV, which is presented in Section II in this paper.*

## Table AIV.

**Option market variables regressed against economic conditions**

| *IVD* | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.022 | -0.020 | -0.017 | -0.032 |
| P-value (coef.) | 0.006 | 0.010 | 0.025 | 0.00 |
| t-statistic | -2.81 | -2.64 | -2.28 | 4.62 |
| $R^2$ | 0.09 | 0.0802 | 0.0612 | 0.2125 |
| Obs. | 82 | 82 | 82 | 81 |
| Std. error | 0.0079 | 0.0075 | 0.0072 | 0.0068 |

| *VRPD* | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.007 | -0.005 | -0.005 | -0.012 |
| P-value (coef.) | 0.226 | 0.311 | 0.355 | 0.020 |
| t-statistic | -1.22 | -1.02 | -0.93 | -2.38 |
| $R^2$ | 0.02 | 0.01 | 0.01 | 0.07 |
| Obs. | 80 | 80 | 80 | 80 |
| Std. error | 0.0054 | 0.0051 | 0.0049 | 0.0049 |

| *SlopeD* | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.033 | -0.030 | -0.028 | -0.020 |
| P-value (coef.) | 0.0000174 | 0.000125 | 0.000439 | 0.0130 |
| t-statistic | -4.63 | -4.08 | -3.7 | -2.56 |
| $R^2$ | 0.25 | 0.20 | 0.17 | 0.09 |
| Obs. | 68 | 68 | 68 | 67 |
| Std. error | 0.0072 | 0.0074 | 0.0075 | 0.0080 |

*In this table we run the exact same test as in Table II, the only difference being that we exclude the European summits occurring on 2008-11-07, 2009-03-01, 2010-05-07 and 2015-06-22, in order to assess the robustness of our results.*

## Table AV.

**Option market variables**

| | *IVD* | *VRPD* | *SlopeD* |
|---|---|---|---|
| Mean | 0.030 | 0.017 | 0.021 |
| P-value two-tailed | 0.0010 | 0.0090 | 0.022 |
| t-statistic | 3.39 | 2.73 | 2.38 |
| Obs. | 82 | 80 | 68 |
| Std. error | 0.0087 | 0.0061 | 0.0088 |

*In this table we run the exact same test as in Table I, the only difference being that we exclude events: 2008-11-07, 2009-03-01, 2010-05-07 and 2015-06-22, for the same reason as for Table AIV.*

## Table AVI.

**Option market variables regressed against economic conditions**

***IVD***

| | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.022** | -0.021** | -0.018** | -0.031*** |
| P-value (coef.) | 0.036 | 0.046 | 0.018 | 0.001 |
| t-statistic | -2.13 | -2.02 | -2.41 | -3.34 |
| $R^2$ | 0.106 | 0.096 | 0.071 | 0.212 |
| Obs. | 86 | 86 | 86 | 85 |
| Std. error | 0.0102 | 0.0103 | 0.0074 | 0.0093 |

***VRPD***

| | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.011 | -0.010 | -0.0070 | -0.014** |
| P-value (coef.) | 0.270 | 0.211 | 0.217 | 0.047 |
| t-statistic | -1.11 | -1.26 | -1.24 | -2.02 |
| $R^2$ | 0.061 | 0.045 | 0.024 | 0.094 |
| Obs. | 84 | 84 | 84 | 84 |
| Std. error | 0.0105 | 0.0075 | 0.0056 | 0.0069 |

***SlopeD***

| | *GDP* | *CLI* | *FST* | *MKT* |
|---|---|---|---|---|
| Slope coefficient | -0.033*** | -0.030*** | -0.028*** | -0.020 |
| P-value (coef.) | 0.00 | 0.009 | 0.0089 | 0.133 |
| t-statistic | -5.34 | -2.67 | -2.69 | -1.52 |
| $R^2$ | 0.247 | 0.203 | 0.173 | 0.092 |
| Obs. | 69 | 69 | 69 | 68 |
| Std. error | 0.0062 | 0.0113 | 0.0103 | 0.0134 |

*In this table we construct the exact same test as in Table II, the only difference being that we instead run a robust regression instead of a standard OLS regression in order to examine the robustness of our main results for the second hypothesis.*