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By
DEBORAH B. BEYER

Dr. Zaifeng Fan, Dissertation Chair

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DEDICATION

I'd like to dedicate this dissertation to my husband, Scott, and my daughter, Anna, the two loves of my life. You fill our house with laughter and bring me so much joy. I am very grateful for the unwavering support you have given me every step of my DBA journey. I cherish you both.

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ABSTRACT

In recent decades, rising economic policy uncertainty coupled with increasing levels of political polarization have impacted financial markets and by extension, investors in those markets. Literature has mainly focused its attention on one of these factors or the other, while few studies to date have examined their joint effects on stock market volatility. Yet politics and the economy are profoundly intertwined; they must be considered in tandem. Through a two-essay format, the objectives of this dissertation are to investigate the combined impact of economic policy uncertainty and partisan conflict on stock market volatility and further, to study the impact of partisan conflict in particular on politically sensitive industry volatility.

Findings from Essay 1 provide evidence that economic policy uncertainty increases volatility, whereas partisan conflict reduces it. A deeper examination reveals that partisan conflict's dampening effect exists only during periods of political gridlock. Essay 2 results show that partisan conflict also reduces industry-level volatility. Moreover, partisan conflict has a greater impact on reducing high politically sensitive industry volatility compared to industries with low political sensitivity. Results from both studies are meant to inform government policymakers, analysts, and investors of the effects these politically-related forces have on equity market volatility.

Keywords: volatility, partisan conflict, policy uncertainty, political sensitivity, industry

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ESSAY 1: ECONOMIC POLICY UNCERTAINTY, PARTISAN CONFLICT, AND MARKET VOLATILITY

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ABSTRACT

Despite a prevailing preoccupation among analysts and investors over the economic consequences spurred on by policy uncertainty and political conflict in the United States, few studies have examined their joint impact on financial markets. This essay examines the combined effect of economic policy uncertainty and partisan conflict on two monthly measures of market risk: implied and realized volatility. I employ various regression models to determine the effects of economic policy uncertainty and partisan conflict on market risk, taking into account political variables, namely presidential party and political gridlock, and established volatility predictors. My results report a positive, significant impact of economic policy uncertainty and a negative, significant impact of partisan conflict on both implied and realized volatility. In other words, whereas higher economic policy uncertainty correlates to higher volatility, partisan conflict has a dampening effect. Next, I examine the effects of these two factors during periods of political gridlock versus political harmony. My findings suggest that partisan conflict has a negative and significant effect on market risk during periods of political gridlock, but this effect becomes insignificant during periods of political harmony. Finally, I investigate economic policy uncertainty's impact on volatility when partisan conflict is high (above its median value). My results do not support the literature suggesting that high levels of partisan conflict alter economic policy uncertainty's impact on market risk. Overall, my results indicate that economic policy uncertainty and partisan conflict have opposite, significant effects on volatility and that models including both factors provide additional explanatory power compared to when each one is considered in isolation.

Keywords: volatility, partisan conflict, policy uncertainty, politics, gridlock

Essay 1: Economic Policy Uncertainty, Partisan Conflict, and Market Volatility

Our current world is fraught with increasingly divisive political ideologies and financial uncertainty mirrored in heightened market volatility. Entering the phrase "Stock market volatility today" yielded an astounding 93.2 million hits in a Google search as of April 1, 2022, more than 30 million hits more than the 62.2 million that appeared in the same search on May 25, 2021. Stunningly, entering "political conflict" into Google on April 1, 2022 produced around 4.5 billion results. The sheer magnitude of these search results is indeed reflective of the prevailing preoccupations of our present world. Given that stock market volatility is a critical risk measure of the health and performance of the economy (Schwert, 1989) and a significant source of input for key investment decisions (Christiansen et al., 2012), investors, analysts, and government officials closely monitor its fluctuations. Furthermore, COVID-19 has engendered even greater uncertainty and a growing preoccupation with risk (Altig et al., 2020). As a result, academics and practitioners alike are actively seeking to identify key macroeconomic forces driving this risk, now more than ever.

Of course, while the pandemic has put investors and analysts on high alert, it is clearly not the only factor contributing to changes in stock market volatility. Well before the pandemic, politics and economic policy have been consistently named as contributing factors to stock market performance and risk, measured through various proxies of market volatility. For example, a large stream of research has documented the effects of political party ideologies, party of the president, and political gridlock on stock market returns (e.g., Alvarez-Ramirez et al., 2012; Huang & Wang, 2018; Leblang & Mukherjee, 2005; Lobão, & Guimarães, 2019; Santa-Clara & Valkanov, 2003; Sy & Al Zaman, 2012). Furthermore, the United States' increasingly divided and contentious partisan political system has spurred an uncertain economy and angst among investors. Specifically, a documented growing disparity between Republican and Democratic policies has led to increased political polarization, discord, and at times even greater policy uncertainty (Baker et al., 2014). It is unsurprising that these changes ultimately impact market returns in the United States and globally (Smales, 2019). Recent studies have underscored the significant effects politics and political uncertainty have on stock market returns and volatility (e.g., Pástor & Veronesi, 2017; Tiwari et al., 2019).

Politics and economics are undeniably intertwined. Among many others, Buchanan (1987) and Alesina and Rosenthal (1995) detailed the relationship between politics and economic policy decisions. Alesina and Rosenthal (1995) in particular discussed in great detail the important interplay that exists between politics, particularly with respect to a polarized government, and policy outcomes. More recent studies have examined how politics and economic policy uncertainty both affect different sectors of the economy, notably financial markets (e.g., Al-Thaqeb & Algharabali, 2019; Baker et al., 2014; Brogaard & Detzel, 2012; Hoke, 2019; Jia et al., 2021; Kelly et al., 2016; Pástor & Veronesi, 2013). Baker et al. (2014) discussed the need to consider the role polarization plays alongside policy uncertainty. Many of the aforementioned studies, in fact, associated economic policy uncertainty with political conflict induced by polarization, attesting to the importance of examining these two driving factors together, not one in isolation from the other.

Despite academic discussion surrounding the growing impact of divisive partisan politics and pronounced economic policy uncertainty, few studies have empirically researched how, when combined, each factor affects stock market performance and, as importantly, stock market risk. In order to get a complete and more accurate picture of the effects of polarizing politics and economic policy uncertainty on financial markets, therefore, the two prevalent forces should be examined together. Some past literature (e.g., Kelly et al., 2016; Pástor & Veronesi, 2013) has likened economic policy uncertainty to political uncertainty stemming from political conflict. Indeed, two separate forces are at play that can be captured by two distinct measures of uncertainty and conflict. In fact, the proliferation of content-based measures in academic research has led to the creation of key indices that can proxy for economic policy uncertainty and partisan conflict. Two such recent measures are the economic policy uncertainty index (EPU; Baker et al., 2012, 2016) and the partisan conflict index (PCI; Azzimonti, 2018). While PCI is not a direct measure of political polarization per se, in its original form PCI was called the political polarization index (Azzimonti, 2013) as it captures, in large part, the growing divide between political ideologies at the federal level. So as not to confound EPU and PCI, the authors of these two indices clearly delineated the differences that exist between them. The first essay of this research thus fills a notable gap in the literature by studying the combined effects of economic policy uncertainty and partisan conflict as measured by EPU and PCI on both implied and realized market volatility.

Extending the examination of economic policy uncertainty and partisan conflict effects on volatility, I also investigate their impact during periods of political gridlock versus political harmony. Political gridlock is defined as a situation in which the party of the president in the White House, the majority party of the House of Representatives, and the majority party of the Senate do not all share the same political affiliation (Beyer et al., 2006). Political harmony thus represents a state in which all controlling parties in the White House and Congress are the same. Academics and practitioners disagree on the effects of a gridlocked government on market returns (e.g., Beyer et al., 2015; Kerr, 2018). The argument is a timely one. Significantly, political gridlock in Washington has existed for sixteen of the twenty-two years in this century alone: 2000–2003, 2007–2009, 2011–2017, 2019–2020. Since a gridlocked government can impact both economic policy decisions and partisan conflict, the question naturally arises as to how the effects of partisan conflict and economic policy uncertainty differ during periods of political gridlock versus harmony. This research extends current literature by addressing that question.

A final examination of this study considers the effects that high versus low periods of partisan conflict have on economic policy uncertainty. Recent literature has proposed that higher levels of partisan conflict could impact economic policy uncertainty by reducing the chance of policy enactment (Bechtel & Füss, 2008; Gupta et al., 2018; Jia et al., 2021; Jiang & Shi, 2020; Pham, 2019). These papers forwarded the idea that under higher political conflict, fewer policy changes will be made as an agreement cannot be reached. This study will conclude by investigating the effects of higher levels of partisan conflict on economic policy uncertainty as it relates to stock market volatility.

This study contributes to existing literature in the following ways.

1. It enhances our understanding of the impact of political and economic forces on market risk by examining several important measures of risk.
2. It gives insight into the impact of economic policy uncertainty and partisan conflict on volatility during political gridlock versus harmony periods.
3. It offers information about the impact partisan conflict may have on economic policy uncertainty with regard to volatility.

Overall, the results of this study provide further information to those who track risk, such as investors, portfolio managers, analysts, and government officials. Given recent economic disruptors such as the Global Financial Crisis and the outbreak of Covid-19, this study's focus on the powerful forces of partisan politics and economic policy uncertainty on stock market volatility is clearly a timely and important one.

The findings from this research show evidence of statistically significant correlation between measures. Specifically, consistent with other studies, I found that economic policy uncertainty is positively associated with both implied market volatility and realized volatility. In addition, when controlling for partisan conflict, economic policy uncertainty remained positively and significantly correlated to different volatility measures. I found that partisan conflict, as measured by the PCI, has a statistically significant negative correlation with respect to both implied and realized volatility with EPU in the model. Moreover, in both series of regressions, the magnitude of the PCI coefficient increased with the addition of EPU and other control variables. In other words, the impact of PCI became greater. My findings also suggest that partisan conflict is significantly correlated to both implied and realized volatility only during periods of political gridlock. Partisan conflict is a negative but insignificant factor during periods of political harmony for both implied and realized volatility. This result makes sense given that a divided government should typically lead to greater levels of conflict. Finally, I found that high and low levels of partisan conflict do not impact economic policy uncertainty, which is in contrast to what some research has previously suggested (Bechtel & Füss, 2008; Jia et al., 2021; Jiang & Shi, 2020; Gupta et al., 2018; Pham, 2019). In all cases, the inclusion of both economic policy uncertainty and partisan conflict in the model provides more information about volatility than when each variable is considered separately, as measured by the adjusted R^2. These findings have important implications for analysts, government officials, and investors looking to identify risk factors in the markets.

Literature Review and Hypotheses Development

Theoretical Foundation

The importance of studying factors that affect market returns finds its roots in modern finance. With the advent of modern finance, researchers and investors have sought to identify those factors that impact the magnitude and dispersion of market returns. Several theories in particular have motivated this search for answers. Fisher (1930) introduced basic concepts that united the utility of wealth in the capital markets, explaining that through capital markets, both buyers and sellers benefit. That is, greater savings and more investment opportunities can be realized on both sides of the transaction. Ergo, buying and selling in financial markets proves advantageous to individuals and the overall economy. With the introduction of modern portfolio theory by Markowitz (1952), investors have sought not only to invest but to efficiently optimize portfolios to diversify their market risk.

Shortly thereafter, Sharpe (1964) and Lintner (1965) derived the capital asset pricing model (CAPM), a groundbreaking model for finance that gives a formula for quantifying capital market risk. Under this model, it is assumed that investors' portfolios are well-diversified, to the point that unsystematic risk is immaterial and the sensitivity of a portfolio to systematic risk becomes the important consideration for investors. In that respect, studies of systematic risk factors affecting the economy are highly impactful to investors.

Several models critiqued the CAPM, such as the arbitrage pricing theory (APT) which holds that an asset's expected return is derived from that asset's sensitivity to systematic risk factors. The determination of these factors, or the economic variables they represent, is at the heart of factor analysis, and by extension, much of the finance research today. Merton (1987) contended that research was also needed on the expected return of individual stocks to help investors diversify their unique portfolios. Other researchers such as Levy (1978) and Malkiel and Xu (2002) critiqued the CAPM for its over-generalized assumptions about investor behavior. Levy (1978) argued that investors utilize heterogeneous investment strategies that result in imperfectly diversified portfolios, thereby exposing them to idiosyncratic (firm- or industry-specific) as well as systematic risk. Malkiel and Xu (2002) proposed a new model that reflects the importance of considering idiosyncratic risk. Goyal and Santa-Clara (2003) added to the discussion of risk and return, arguing the need to consider idiosyncratic risk by showing its significance in relation to market returns.

Finally, in another study, Fama (1970) published a seminal paper on the efficient market hypothesis, the idea that security prices in the market reflect varying degrees of available public and private information, according to the strength of the market's efficiency. An efficient market assumes rationality on the part of investors. The efficient market hypothesis gives confidence to investors that assets will be appropriately priced based on the fact that they reflect only relevant market information that will be quickly assimilated into stock prices and market movement.

In response to these important theories of modern finance, researchers have since studied factors that drive return and both systematic and idiosyncratic risk in capital markets. Two risk factors in particular that have surfaced in recent literature include economic policy uncertainty and political, or partisan, conflict. Whereas many studies have examined market volatility in great depth (e.g., Diebold & Yilmaz, 2009; Engle & Rangel, 2008; Mele, 2007; Paye, 2012; Schwert, 1989), the role played by both political conflict and policy uncertainty in volatile markets remains relatively unexplored in the finance literature, yet represents a most timely topic. Increasing political polarization (Baker et al., 2014; Pew Research Center, 2017) and consequent discord in the United States have sparked concern on the part of analysts, investors, and government officials. Events in the recent past, such as the escalating trade policies with China under the Trump administration (Noland, 2020) or the debt ceiling debate in Congress (Aye et al., 2016), clearly portray the ways in which a divisive political climate and economic policy uncertainty coexist. In the face of escalating polarization between political ideologies and stalemates in government policy decision-making, it is more important than ever to study economic policy uncertainty alongside partisan conflict to evaluate the impact they have on stock market volatility.

However, despite the popularity of studies individually focused on economic policy uncertainty and political conflict on market returns, to my knowledge no study to date has empirically examined them jointly using multiple volatility measures. Though often discussed in tandem, the effects of these factors are typically analyzed separately from one another. Therefore, this study investigates the joint effects of economic policy uncertainty and partisan conflict on both implied and realized volatility, as well as their impact under periods of political gridlock versus harmony.

Modern finance theories and previous literature findings form the foundation for this study on the factors driving market risk and return. Moreover, mounting uncertainty around economic policy and marked divisiveness in political ideologies make this research increasingly relevant moving forward. The knowledge gleaned from my study will inform analysts, portfolio managers, and investors of systematic and idiosyncratic risk factors in the markets. In addition, the results of this research have significant implications for policy makers and government officials alike.

Stock market returns are closely related to external, macroeconomic variables, such as corporate bond spread, default yield spread, industrial production growth, inflation growth, and term spread (Chen et al., 1986; Christiansen et al., 2012; Engle et al., 2013; Paye, 2012; Schwert, 1989). Whereas stock market performance impacts investments, stock market volatility has long been recognized as an indicator of investment risk (Mittnik et al., 2015). Models seeking to better identify factors contributing to market volatility have multiplied over the years. Consequently, many macroeconomic variables have also been linked to stock market volatility. Schwert (1989), who noted that volatility represents a measure of the health of the economy, analyzed factors impacting implied volatility in the markets and concluded that certain macroeconomic variables, among them economic policy decisions, increase said volatility. Recently, economic policy uncertainty in particular has been linked to volatility, largely revealing a positive relationship between the two (Antonakakis et al., 2013; L. Liu & Zhang, 2015; Z. Liu et al., 2017).

Unsurprisingly, politics have also been identified as being closely correlated to investment risk (Boutchkova et al., 2012) and financial markets (Addoum & Kumar 2016). A subset of literature has demonstrated the significant impact of presidential elections, partisanship (Bialkowski et al., 2007; Leblang & Mukherjee, 2004; Mnasri & Essaddam, 2021), and political party (Santa-Clara & Valkanov, 2003; Addoum & Kumar, 2016) on stock market performance and market volatility. Moreover, researchers have identified effects from increasing political polarization that has occurred since the late 1960s (Baker et al., 2014; McCarty et al., 2016). As a result, researchers have become particularly interested in the effects of this growing level of political polarization and the measurable effects it creates on financial markets. Indeed, Jiang et al. (2020) specifically noted the importance of studying partisan conflict for investors looking to mitigate their portfolio risk by appropriately diversifying their holdings. Despite the increasing importance of partisan conflict on stock market volatility, little research has yet been done in this area.

Furthermore, whereas a core body of research demonstrates the individual effects of economic policy uncertainty and political variables on stock market performance and volatility, few studies have systematically combined them into a model examining their important effects when considered in tandem. Based on the findings of previous literature, I argue that an examination of the effects of one measure on volatility without the others provides an incomplete analysis. For this reason, I also include party of the president and political gridlock as political forces with the potential to impact markets.

Economic Policy Uncertainty

The world is a complex place, filled with growing uncertainty, accentuated most recently by the terrorist acts of September 11, 2001, the financial crisis of 2008–2009, and the Covid-19 pandemic of 2020–2021. This uncertainty pervades all aspects of society, not the least of which are government policies and financial markets. As a result of prevailing effects on market forces engendered by periods of heightened macroeconomic uncertainty, academics have devised ways of measuring economic policy uncertainty and gauging its impact. The development of these indices is a testament to the growing realization of the deleterious effects of rising policy uncertainty on many sectors of the economy, from the retail investor to the U.S. markets and the risk in these markets.

Several notable indices designed to track patterns of economic uncertainty at the federal level have been created in the past decade alone, including those of Baker et al. (2012, 2016), Carriero et al. (2018), Gilchrist et al. (2014), Jo and Sekkel (2019), Jurado et al. (2015), and Shin and Zhong (2020). Arguably the most frequently cited index, both in academia and in practice, is that of Baker et al. (2012, 2016), who developed a monthly content-based measure of economic policy uncertainty. In constructing the main component of their measure from 1985 onward, the authors drew from 10 leading national newspapers to find articles containing specific reference to a triad of terms capturing the concepts of uncertainty, the economy or economic factors, and policy. To test the robustness of their measure, Baker et al. (2012, 2016) compared their index against other measures of uncertainty, assuring a strong correlation and level of accuracy. Additionally, the authors checked for political bias by verifying consistency in the movements of the index along left-slanted versus right-slanted newspapers. Finally, the uncertainty measure was evaluated against human auditors trained through an elaborate process, with a resultant high correlation between computer- versus human-based generation of the index. The EPU historical index dates back to 1900 and includes six major newspapers instead of 10. A much more detailed description of the construction of the EPU index can be found in Baker et al. (2016).

In the current literature, changes in economic policy uncertainty, as mostly measured by the Baker et al. (2012; 2016) EPU index, have been linked to multiple domestic phenomena. Changes in economic policy uncertainty have been tied to recessions (e.g., Bloom, 2014; Karnizova & Li, 2014), stock market performance (e.g., Arouri et al., 2016; Baker et al., 2016), asset prices (e.g., Brogaard & Detzel 2015), and stock market volatility (e.g., Antonakakis et al., 2013; L. Liu & Zhang, 2015; Pástor & Veronesi, 2012). Economic policy uncertainty is also associated with financial stability (e.g., Phan et al., 2021), gross domestic product (e.g., Baker et al., 2016; Duca & Saving, 2018), political polarization (e.g., Azzimonti, 2018; Baker et al., 2014; Duca & Saving, 2018), and economic growth (e.g., Barrero et al., 2017; Handley & Limão, 2015). At the firm level, EPU impacts corporate cash holdings (Cheng et al., 2018), mergers and acquisitions (Bonaime et al., 2018), financial reporting quality (Bermpei et al., 2019), corporate social responsibility (Ongsakul, Jiraporn, et al., 2021), and corporate governance (Ongsakul, Treepongkaruna, et al., 2021). Finally, EPU has also been shown to impact investor behavior (e.g., Bernanke, 1983; Mian et al., 2015; Zhang, 2019) and investment (e.g., Bloom, 2009; Gulen & Ion, 2016; Azzimonti, 2018).

Economic Policy Uncertainty and U.S. Stock Market Performance

Previous literature has established a correlation between economic policy uncertainty and U.S. stock market performance. In their seminal study, Baker et al. (2016) linked their measure of EPU to stock market performance and found that higher levels of uncertainty correspond to lower stock market returns and higher volatility. Antonakakis et al. (2013) studied time-varying correlations between EPU and stock market returns from 1985 to 2013. The 3-component EPU index is composed of three separate parts: the news-based index discussed previously, the quantity of federal tax code provisions that are set to expire in the future, and professional economic forecaster disagreement (Baker et al., 2012). Antonakakis et al. (2013) found the correlation between EPU and stock market returns to be negative absent the financial crisis of 2008. Kumar and Lee (2006) also revealed a negative relationship between stock prices and EPU. Similarly, Arouri et al. (2016) found that rises in economic policy uncertainty had a negative effect on stock market returns for the extended period of time between 1900 and 2014. Past studies have consistently documented a negative relationship between policy uncertainty and U.S. stock market performance.

Significantly, economic policy uncertainty has been linked not only to stock market performance but also to changes in stock market volatility. Pástor and Veronesi (2013) developed a model demonstrating that higher volatility was engendered by higher periods of uncertainty as measured by the Baker et al. (2012) EPU index. L. Liu and Zhang (2015) used measures of realized volatility to show that higher levels of EPU led to higher volatility in US markets. Using a multifractal volatility model, Z. Liu et al. (2017) concluded that EPU could be used to predict future stock market volatility; they also showed a positive relationship between higher levels of EPU and future volatility. Hoke (2019), on the other hand, remarked an immediate lowering of volatility as measured by implied volatility, or the Chicago Board Options Exchange's Cboe VIX index, when EPU increased. My study tests the robustness of the relationship between EPU and stock market volatility through different measures of volatility, including both implied and realized.

Politics and U.S. Stock Market Performance

An abundance of prior evidence suggests that, along with economic policy uncertainty, politics also plays a significant role in stock market returns and volatility. As early as Hibbs (1977), researchers have sought to identify the relationship between U.S. party of the president and the macroeconomy. Differences in political ideologies and fiscal policies translate into variations in market returns. Numerous studies have linked the party of the president to stock market returns. For example, in a study of stock market performance between 1929 and 1980, Huang (1985) concluded that mean returns are higher under Democratic presidencies. Johnson et al. (1999), for their part, revealed that small-cap stocks enjoy four times the annual returns under Democratic versus Republican presidencies. Santa-Clara and Valkanov (2003), in their study on political party in the White House, discovered a statistically significant differential for both value-weighted and equal-weighted returns between Democratic and Republican presidencies; they found these returns to be consistent in their sample period dating back to 1927. They also identified a presidential puzzle in that the higher returns enjoyed under Democratic presidencies could not be explained by a compensation for risk, since higher stock market volatility was found to exist under Republican presidencies. Li and Born (2006) also discovered a robust correlation between politics and stock market returns. Consistent with Johnson et al. (1999), Sy and Al Zaman (2011) found that small stocks benefit even more than large stocks during Democratic presidencies. Based on their study, they concluded that the presidential premium was in fact compensation for risk. Nickles and Granados (2012) provided further validation to the argument of U.S. presidential party impact on markets, while underscoring the increased need for a better understanding of the relationship between political variables and stock market performance.

In their study on presidential party and the market, Belo et al. (2013) aptly suggested that differences in stock market returns under Republican and Democrat presidencies could be largely attributed to respective differences in government spending, taxes, and support of social programs. Perez-Liston et al. (2014) confirmed the results of previous work indicating that stock market returns have been higher under Democratic presidencies. Furthermore, the authors discovered that politics has a significant impact on those firms having higher book-to-market ratios. More recently still, economists Blinder and Watson (2016) statistically showed that the economy performs better under a Democratic president. Pástor and Veronesi (2017) revisited the presidential puzzle and concluded that the same model showing better stock market returns under Democratic presidencies could also be used to explain how economic growth accelerates under these presidencies. Clearly, based on the results of this body of literature, a non-negligible relationship exists between party of the president and stock market returns. Given the documented impact that presidential party has on the markets, it logically flows that a mounting divergence in political ideology between parties would further affect markets and volatility.

In reality, many news outlets bemoan the growing disparity between Republican and Democratic ideologies and its prevailing impact on many sectors of contemporary society. Jones

(2001) defined political polarization as the extent to which preferences of each party differ. Bonica et al. (2013) pointed to increased polarization between the two parties. Under a state of high polarization, therefore, members of opposing parties will be more likely to disagree on government policy. The Pew Research Center (2017), for its part, noted how the increasing gap between Republican and Democratic ideologies serves to define the current American political system. More recently, Pew Research Center (2020) conducted a study on Americans' views of partisan divisions in the United States. A significant 69% of those surveyed perceived a negatively-construed growing gap between Republican and Democrats. Furthermore, 80% of Americans surveyed claimed to be somewhat or very concerned by this political discord, a troubling percentage that speaks to the current uneasy state of the political economy. Case in point, the most recent presidential election (2020) and the politically polarizing effects brought about as a result of the pandemic plainly underscore the divisive impact partisan politics can have.

Growing levels of political conflict have preoccupied recent academic literature as well. This increased level of political partisanship can be attributed to polarizing ideologies (Pew Research Center, 2017) and political gridlock at the federal level. Academics and practitioners are divided on the effects of gridlock on stock market returns and the economy as a whole. Beyer et al. (2006, 2015) empirically showed that political gridlock is bad for equity investors. On the practitioner side, both Kerr (2018) and Fisher (2019) associated political gridlock with a calming of the markets. Disagreement also appears to exist surrounding the effects of gridlock on economic policy uncertainty. Binder (2003) and Füss and Bechtel (2008) spoke of a calming effect that a divided government has on economic policy change and risk due to a certain inaction on the part of lawmakers. On the other hand, Sojli and Tham (2015) found that increased election probabilities of a divided government were positively associated with Baker et al. (2012)'s EPU measure. Sojli and Tham (2015) focused on policy uncertainty's effect on asset prices, attributing the impact to gridlock in Congress and corresponding legislative productivity. The authors concluded that an increase in legislative uncertainty during the period of a divided government stemmed from a greater number of laws that Congress rejected coupled with a greater percentage of vetoed laws by the president under these conditions.

In addition to market effects under a divided government, current research also has focused on the impact of growing political polarization between Republican and Democrat ideologies. Heltzel and Laurin (2020) found that polarization between political parties has reached its highest levels in recent years. According to Newport (2019), not only has polarization increased but so has its impact. This trend is not limited to just the political realm, however, but has real and significant implications for the economy and financial markets as a whole. Analysts and academics alike speculate on the negative impact of increased divisiveness on stock market performance and on investor confidence (Shiller, 2000). The effects of partisan conflict occupy a central role in concerns over the direction of the economy and financial markets. In fact, as political ideologies between Republicans and Democrats in the United States have diverged and become more divisive, a measure of political conflict becomes a growing requisite in any model examining stock market risk and returns.

Partisan Conflict

In response to this growing discord and increased political gridlock at multiple levels of government, several measures of partisan conflict have since been developed. These measures include those created by McCarty et al. (1997), Poole and Rosenthal (2001), Lindqvist and Östling (2010), and Azzimonti (2018). The latter measure, a monthly news-based measure known as the PCI (Federal Reserve Bank of Philadelphia, 2021), is the one I adopted for this study. Like EPU, the PCI measure is an index based on a semantic search of newspaper articles. The goal of the PCI is to identify political discord within and between parties by identifying the frequency with which articles contain political disagreement among lawmakers on policy. These measures of disagreement ultimately represent varying levels of partisan conflict. For consistency's sake, the search for these articles was performed in Factiva, a digitized platform containing all major newspapers. The index calculates monthly values and is currently available on the Federal Reserve Bank of Philadelphia website.

Notably, recent studies have employed the EPU measure to proxy for both political risk (Pham, 2019) and political instability or uncertainty (Irshad, 2017; Y. Jiang et al., 2020; Kelly et al., 2016; Pástor & Veronesi, 2013). However, PCI and EPU capture different measures of uncertainty (e.g., Azzimonti, 2018; Baker et al., 2016; Huang & Wang, 2018; Pham, 2019). Through a bivariate regression, Huang and Wang (2018) found that the PCI is distinct from other measures of uncertainty, such as EPU. The authors determined that there is a positive relationship between partisan conflict and one-month future market returns. Pham (2019) examined the mediating role that firm-level political connections play between the cost of equity and the PCI measure of political risk. Hoke (2019) also contrasted PCI from EPU and, using Azzimonti's (2018) index, found an inverse relationship between PCI and stock market returns. More specifically, the author found that this political risk was contemporaneously incorporated into stock prices (Hoke, 2019). Given that PCI is a relatively new measure, research using this index is still in its nascent stage. This study extends current knowledge concerning the implications of this measure on financial markets and on volatility in particular.

Prior to the development of the PCI, an extensive body of literature had already established the direct effects of political polarization and resulting partisan conflict on the implementation of government policies. In support of the divided government hypothesis, Kelly (1993) showed how divided government has led to the adoption of fewer innovative policies. Edwards et al. (1997) found that the percentage of important legislation that failed to pass was higher under a divided versus a unified government. Coleman's (1999) research supported the idea that a unified government leads to a greater number of significant policies being enacted. According to Milner and Judkins (2004), increased political partisanship impacts trade policy. Sojli and Tham (2015) found that divided governments negatively impact economic policy enactment. Under the party polarization hypothesis, Jones (2001) found that higher levels of political polarization within and among parties are an instrumental factor in determining legislative gridlock. Binder (2003) also pointed to a rise in political polarization and gridlock at the federal level in thwarting policy implementation. In a follow-up study, Binder (2014) re-emphasized the growing frequency of legislative gridlock stemming from increased partisan polarization. McCarty (2011) discussed the upsurge in political polarization since the 1970s. According to that study, the bifurcation in political stance aggravated by increasingly contrary views on government and Supreme Court appointments, priorities of policy enactments, and impeachable actions makes policy enactment challenging. McCarty et al. (2016) argued that rising political polarization and subsequent gridlock in the United States have served to hamper government policymaking. The argument for considering both measures of partisan conflict and economic policy uncertainty in an examination of stock market volatility is clear. Increased polarization of political ideologies engenders higher levels of partisan conflict that ultimately impact policy gridlock, and possibly by extension, economic policy uncertainty.

Partisan Conflict and Economic Policy Uncertainty

Precedence has already been set for examining measures of partisan conflict and economic policy uncertainty together, further supporting the inclusion of both variables in my model. Cheng et al. (2018) considered the variables side by side when examining their impact on the aggregate cash holdings of U.S. companies. Pham (2019) showed the effects of economic policy uncertainty and partisan conflict on firm financial reports and their cost of equity. The author indicated that heightened or extreme levels of political discord can hinder governmental policy making with deleterious consequences. Furthermore, Jia et al. (2021) postulated, based on previous academic research, that partisan conflict may either stimulate or lessen the effects of economic policy uncertainty. I therefore argue that an examination of economic policy uncertainty absent any consideration of political discord or harmony is, ostensibly, incomplete.

Stock Market Volatility

Stock market volatility has long been recognized as an indicator of investment risk. Macroeconomic variables can have important impacts on market volatility (Engle & Rangel, 2008). Models seeking to better understand volatility in the markets have proliferated over the years. Consequently, a large number of variables have been linked to stock market volatility. Schwert (1989), who noted that volatility represents a measure of the health of the economy, analyzed factors impacting implied volatility in the markets and concluded that certain macroeconomic variables, among them inflation, industrial production growth, and bond yields affected said volatility (see also Engle et al., 2013).

Fleming and Ostdiek (1995) presented the CBOE Volatility Index (VIX) as a new and initial measure for predicting market volatility, showing its usefulness and suitability as a proxy for fluctuations in market returns. The VIX is a forward-looking index, or fear gauge for investors, that measures expected volatility over the approaching 30-day period (Whaley, 2009). As one would suspect, the VIX spikes during unforeseen and impactful world events, such as the October 1987 market crash or the terrorist attacks of 9/11. The VIX is also affected by presidential elections, as evidenced by Li and Born (2006), Goodell and Vähämaa (2013), and most recently Mnasri and Essaddam (2021). Finally, Bekaert et al. (2013) and Bruno and Shin (2015) linked fluctuations in VIX to changes in monetary policy.

Various measures of realized volatility have also been used to proxy for stock market risk. There exists an ongoing debate among academics regarding which volatility measures, implied or realized, provide the most accurate assessment of stock market risk (Kambouroudis et al. 2016). Kambouroudis et al. (2016) found results suggesting that implied and realized volatility measures each contain separate information that proves beneficial when predicting future volatility. In my study, both essays are also novel in the fact that I estimate the effects of economic policy uncertainty and partisan conflict on these two distinct measures of systematic volatility: implied and realized. Additionally, in a separate essay, I consider the effects of these variables on industry-specific idiosyncratic risk, categorized by an industry’s level of political sensitivity as defined by previous research.

By examining the effects of economic policy uncertainty and partisan conflict on multiple measures of volatility, my study makes another important contribution to current knowledge on this topic. Through my analysis, I capture different forms of risk that investors may face when investing. Previous research has focused primarily on one proxy for volatility, thereby providing an incomplete picture of the level and types of risk that occur in financial markets as a result of these economic and political forces.

Economic Policy Uncertainty and Stock Market Volatility

Economic policy uncertainty, as suspected, impacts volatility as well as stock market returns. Several studies have demonstrated a clear positive correlation between economic policy uncertainty and volatility in U.S. markets. Pástor and Veronesi (2013) used Baker et al.'s (2012) EPU index as a proxy for political uncertainty, framing it in the context of the uncertainty of government actions. They discovered that higher political uncertainty leads to more volatile stock prices. In a predictive model, L. Liu and Zhang (2015) and Z. Liu et al. (2017) found that higher levels of EPU forecasted higher daily realized volatility. Baker et al. (2016) found that an increase in their EPU measure corresponded to an increase in firm-level implied volatility. Based on the tenets of the efficient market hypothesis, I expect to find a positive contemporaneous correlation between economic policy uncertainty and monthly implied and realized volatility. Therefore, I posit that economic policy uncertainty is positively correlated with monthly measures of systematic implied and realized stock market volatility. Hence,

H_1: Economic policy uncertainty is positively associated with stock market volatility.

H_{1a}: Economic policy uncertainty is positively associated with implied market volatility.

H_{1b}: Economic policy uncertainty is positively associated with realized market volatility.

Partisan Conflict and Stock Market Volatility

Of the few extant studies on PCI and volatility, Gupta et al. (2018) found that higher levels of PCI led to lower S&P 500 index volatility. The authors' analysis was performed using quantile regression in a time series setting using realized volatility. Cheng et al. (2018) came to a similar conclusion in a tangential finding in their research on the effects of partisan conflict on corporate cash holdings. The idea behind the negative correlation between partisan conflict and volatility is that policymakers do not make impactful decisions when in a state of gridlock or during periods of high conflict. Consequently, it follows that the higher the level of partisan conflict, the lower the advent of volatility in the market and that this finding would be robust to controlling for economic policy uncertainty. Therefore, based on extant research, I forward the following hypotheses:

H_2: Partisan conflict is negatively associated with stock market volatility.

H_{2a}: Partisan conflict is negatively associated with implied market volatility.

H_{2b}: Partisan conflict is negatively associated with realized market volatility.

Political Gridlock, Economic Policy Uncertainty, and Partisan Conflict

Along with the effects of economic policy uncertainty and political polarization, political gridlock can play a key role in determining the impact of these two variables on stock market performance and volatility. Previous studies have discussed the consequences of a divided government on policy determinations and a smoothly functioning economy (Jones, 2001). As defined previously, a state of political gridlock occurs when the majority party in the houses of Congress and the White House are not all the same. Due to the overwhelming prevalence of a state of political gridlock in the past 50 years, academics and practitioners have debated its effects on markets and on the economy as a whole (Beyer et al, 2015; Binder, 2003; Fisher, 2019; Füss & Bechtel, 2008; Sojli & Tham, 2015). The theoretical association made between a divided government and economic policy uncertainty (Baker et al., 2014; Sojli & Tham, 2015) suggests that heightened tensions among lawmakers increase the chances of economic policy uncertainty. Increased economic policy uncertainty has been shown to lead to greater volatility in the markets. I therefore postulate the following:

H_3: Economic policy uncertainty has a greater impact on stock market volatility during periods of political gridlock.

H_{3a}: Economic policy uncertainty has a greater impact on implied volatility during periods of political gridlock.

H_{3b}: Economic policy uncertainty has a greater impact on realized volatility during periods of political gridlock.

A similar theoretical association has been made between a divided government and partisan conflict (Alesina & Rosenthal, 1995; Azzimonti, 2018). This association naturally begets the question of how the effects of partisan conflict would change during periods of political gridlock versus political harmony. Azzimonti (2018) suggested that a divided government should effectively lead to higher levels of partisan conflict. Intuitively, this argument makes sense. The more divided a government, presumably the more conflict and resulting gridlock would result in the decision-making process of that government. When in disagreement, political parties can't reach a compromise, which leads to stalled policy changes. Theoretically, therefore, higher levels of partisan conflict under a state of political gridlock should have a greater impact on reducing stock market volatility than lower levels of conflict occurring during periods of political harmony. Given this logical connection between political gridlock and heightened partisan conflict, I posit that:

H_4: Partisan conflict has a greater impact on stock market volatility during periods of political gridlock.

H_{4a}: Partisan conflict has a greater impact on implied volatility during periods of political gridlock.

H_{4b}: Partisan conflict has a greater impact on realized volatility during periods of political gridlock.

Economic Policy Uncertainty and Partisan Conflict

Finally, despite the low correlation that exists between the EPU and PCI measures, recent literature has discussed the potential impact of partisan conflict on economic policy uncertainty (Füss & Bechtel, 2008, Gupta et al., 2018; Jia et al., 2021; Jiang & Shi, 2020; Pham, 2019). According to these studies, enough evidence exists to argue for possible effects of partisan conflict on economic policy uncertainty. These papers propose that higher levels of partisan conflict can serve to reduce the effects of economic policy uncertainty on financial markets by hindering any policy changes (Bechtel & Füss, 2008; Pham, 2019). In addition, partisan conflict at higher levels can potentially translate into less economic policy uncertainty as investors anticipate fewer shifts in economic policy in the current situation (Jia et al., 2021). Jiang and Shi (2020) also asserted, based on previous studies, that partisan conflict likely reduces economic policy uncertainty. No study to my knowledge, however, has yet tested these effects as they relate to U.S. stock market volatility. Based on the aforementioned studies, I thereby propose the following hypotheses:

H_5: Economic policy uncertainty has a lower impact on stock market volatility when partisan conflict is high.

H_{5a}: Economic policy uncertainty has a lower impact on implied volatility when partisan conflict is high.

H_{5b}: Economic policy uncertainty has a lower impact on realized volatility when partisan conflict is high.

Data and Methodology

The sample period for this study extends from January 1985 to April 2021. The dates were chosen based on the availability of the current Baker et al. (2012, 2016) three-component EPU index. The sample frequency is monthly and consists of a total of 436 months of data.[1] Monthly data for PCI were collected during this same time frame, as were the data for all other variables used in the study.

Main Variables

Economic Policy Uncertainty

Economic policy uncertainty is a term that has gained momentum, particularly since the financial crisis of 2008. Baker et al. (2012, 2016) contended that a majority of recent economic uncertainty centers around policy concerns; hence, they designed a measure to determine the effects of policy uncertainty on the overall economy. The authors created the EPU index based on three separate components (Baker et al., 2012). The first component is a news-based measure of 10 leading U.S. newspapers. The measure captures discussions that include words related to "economic," "policy," and "uncertainty" all in the same article. The index then builds a normalized index of the number of articles from these newspapers. The next component is based on lists of temporary tax code provisions at the federal level, assembled by the Congressional Budget Office. The authors of the index then constructed annual dollar-weighted numbers of those provisions set to expire within the next 10 years. They thereby measure the level of uncertainty by the direction of the future federal tax code. The third and final component of the Baker et al.'s (2012) EPU measure examines disagreement among economic forecasters based

[1] The date for the sample period begins in 1985 in order to exclude the differently-constructed EPU historical data, which extends from 1900 to 1985 and is pure content-based analysis taken from fewer newspapers than the more recent index. Data can be found at www.policyuncertainty.com. Data for this study was retrieved on May 29, 2021.

on information taken from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. This component of the index measures forecaster disagreement over future inflation gauged by the consumer price index and future government expenditures. In the overall monthly EPU index, 50% weight is attributed to the newspaper-based measure, with the remaining 50% divided equally between the expiring tax code provisions and the disagreement over inflation and future government purchases. The EPU index has undergone numerous robustness checks to assure the reliability of the measure (Baker et al. 2012, 2016). The index is available on the "Economic Policy Uncertainty" (n.d.) website, established and maintained by the index's authors. Data for the more recent EPU measure based on the three components is available starting in January 1985.

Partisan Conflict

Increasing political polarization and resultant gridlock at the congressional level have affected the government's ability to reach consensus on important policy and budgetary issues. As a result, Azzimonti (2018) created the PCI to measure the effects of this political discord on financial markets and investments. The PCI is hence a monthly measure of political conflict. The measure is a novel content-based index designed to capture the frequency with which political disagreement over government policy is discussed in newspaper articles. The index was constructed through Factiva, a digital database of all major U.S. newspapers (Azzimonti, 2018). The index is normalized by the number of newspaper articles appearing in 1990. While PCI does not directly represent a political polarization measure per se, increasing polarization is a major contributing factor to the index's performance (Azzimonti, 2018). In other words, a rise in political polarization should naturally translate into a higher level of partisan conflict as differing ideologies create roadblocks to efficient decision-making. Due to the newness of the measure, little research has yet been done documenting its effects on the economy and financial markets. Data for the PCI is available starting in January 1981 (Federal Reserve Bank of Philadelphia, *Partisan conflict index*, 2021).

Stock Market Performance and Volatility

To proxy for stock market performance, I added the risk-free rate to the market premium using CRSP's value-weighted returns (French, n.d.). To measure volatility or risk, I considered both implied and realized volatility. According to Christensen and Prabhala (1998), measures of implied volatility based on the S&P 100 Index (OEX market) are superior to those of historical volatility for predicting future market volatility, especially post-market crash of 1987. Additionally, the authors demonstrated how monthly measures of implied volatility gave additional information beyond that found in monthly realized volatility measures. Since implied volatility is forward looking, it is important to consider EPU and PCI as they relate to this measure to establish a better forecasting model.

For implied volatility, I use the CBOE VIX index (Yahoo! Finance, 2021), a widely accepted measure of volatility in finance literature. Corrado and Miller (2005) and Konstantinidia and Skiadopoulos (2011) showed VIX to be an accurate measure of implied volatility in the market. Moreover, VIX is an index that has frequently been used as a measure of market uncertainty in previous studies (e.g., Goodell & Vähämaa, 2013; Kambouroudis et al., 2016; Wang, 2019); it is highly regarded as a proxy for implied volatility. The VIX calculates the anticipated volatility for the S&P 500 index over the next 30-day period. This measure is determined using values of implied volatility for options on the S&P 500 index (Whaley, 2009). Data for VIX is available starting in January 1990, the creation of the index.

Realized (or historical) volatility, primarily introduced by Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002), is another important measure of volatility based on historical instead of anticipated volatility. To form a more complete picture of the impact of EPU and PCI on volatility, I calculated monthly market realized volatility from daily return data obtained on the French (n.d.) website. Realized volatility estimates past market return volatility in an unbiased and efficient manner (Andersen et al., 2003).

Control Variables

In my study, I controlled for variables shown to have an effect on measures of market volatility. First, since much previous research has focused on the impact of party of the president on stock market returns and volatility (e.g., Leblang & Mukherjee, 2005; Pástor & Veronesi, 2020; Santa-Clara & Valkanov, 2003; Sy & Al Zaman, 2011), I included a dummy variable to represent party of the president in office during the sample period (*Political parties of the presidents*, n.d). Similarly, a state of political gridlock versus harmony in Washington has been shown to have effects on stock market performance (Beyer et al., 2006, 2015; Huang & Wang, 2018; Lobão & Guimarães, 2019). I therefore also included political gridlock versus harmony as a dummy variable in this study. I found information for the majority party in both the U.S. House of Representatives (United States House of Representatives, (n.d.)) and the U.S. Senate (United States Senate, (n.d.)). From this information I noted the periods during which political gridlock occurred (all controlling parties at the federal level were not the same).

Following the literature (e.g., Christiansen et al., 2012; Engle et al., 2013; Paye, 2012; Schwert, 1989), I also included other macroeconomic measures shown to have an effect on market volatility. All data for the following control variables were collected from the Federal Reserve of St. Louis website (Federal Reserve Bank of St. Louis, 2021). The first measure, corporate bond spread (CBS), represents the difference in yields between the AAA (Federal Reserve Bank of St. Louis, *Moody's seasoned Aaa corporate bond yield*, 2021) and the BAA-rated corporate bonds (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield*, 2021). Default yield spread (DYS) measures the difference between the yield on BAA-rated corporate bonds and the yield on long-term government bonds (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield relative to yield on 10-year treasury constant maturity,* 2021). Industrial production growth (IPG) measures the change in the total output manufactured in utility, mining, and manufacturing from one month to the next (Federal Reserve Bank of St. Louis, *Industrial production: total index*, 2021). Inflation growth (PPIG) is calculated using monthly Producer Price Index data (Federal Reserve Bank of St. Louis, *Producer price index by commodity: All commodities*, 2021); it represents the change in inflation from one period to the next. Finally, term spread (TS) is a measure of the difference between the long-term yield on government bonds and the 3-month Treasury bill rate (Federal Reserve Bank of St. Louis, *10-year treasury constant maturity minus 3-month treasury constant maturity*, 2021). Data for all control variables are monthly and span the dates of the study: January 1985 to April 2021.[2]

[2] Additional variables were initially included in this analysis, such as inflation as measured by the consumer price index and earnings (Shiller, 2000), but due to concerns over multicollinearity in the data, these variables were subsequently eliminated.

Methodology

Impact of Partisan Conflict and Economic Policy Uncertainty on Measures of Systematic Risk

I first examined the impact of economic policy uncertainty and partisan conflict on differing measures of stock market volatility. To test Hypotheses 1–5, I employed ordinary least squares (OLS) regression with robust standard errors, to decrease concerns over heteroskedasticity (Engle, 2001). I regressed the natural log value of volatility on a one-period lag of the natural log of volatility, on EPU and PCI, and on a vector of control variables.

My model to test Hypotheses 1 and 2 is represented by the following regression equation:

$$LVOL_t = \alpha + \rho LVOL_{t-1} + \beta_1 EPU_t + \beta_2 PCI_t + \gamma X_t + \varepsilon \qquad (1)$$

Following Christiansen et al. (2012), Paye (2012), and Nonejad (2017), I used the natural logarithm of realized volatility. $LVOL_t$, therefore, denotes the natural logarithm of the return volatility measure in period *t*. Calculating the natural log of volatility normalizes the data for my study. I examined implied and realized volatility; VIX was used as a proxy for implied volatility.

Realized volatility has been presented as a particularly accurate measure of actual volatility in several seminal studies (Andersen & Bollerslev, 1998; Andersen et al., 2000, 2001; Barndorff-Nielsen & Shephard, 2002; Schwert, 1989). Monthly realized volatility was calculated by summing the daily squared S&P 500 returns. The formula for estimating volatility was constructed thusly (Schwert, 1989):

$$\sigma_t^2 = \sum_{i=1}^{N_t} r_{i,t}^2 \qquad (2)$$

where N_t represents the number of daily returns $r_{i,t}$ from the calculated realized volatility measure, in month *t*. I define realized volatility as the square root of σ_t^2.

$$RV_t = \sqrt{\sigma_t^2} \tag{3}$$

The dependent variable in Equation 1, $LVOL_t$, represents the log of the volatility measure: implied volatility (*LVIX*) and calculated realized volatility (*LRV*), respectively. Consistent with the literature (Goodell & Vähämaa, 2013; Paye, 2012), I included the lagged value of each volatility measure, $LVOL_{t-1}$, in my model as a control for last month's volatility effect. $LVOL_{t-1}$, represents the lag of logged VIX (*LLVIX*) or realized volatility (*LLRV*), respectively. My main independent variables include economic policy uncertainty (*EPU*) and partisan conflict (*PCI*). EPU_t represents the level of economic policy uncertainty as captured by the Baker et al. (2012, 2016) index. PCI_t represents the level of partisan conflict as captured by the Azzimonti (2018) index. The efficient market hypothesis forwards the idea that effects on markets will be quickly accounted for in terms of market risk and return. Thus, given the monthly (versus the more frequent daily) frequency of my measures, I used concurrent versus lag variables for EPU and PCI to examine their immediate effect. Finally, γX_t represents a vector of control variables. The control variables employed for the macroeconomy are those suggested from prior literature (Christiansen et al., 2012; Engle et al., 2013; Paye, 2012; Schwert, 1989) and detailed previously, namely corporate bond spread (*CBS*), default yield spread (*DYS*), industrial production growth (*IPG*), inflation growth (*PPIG*), and term spread (*TS*). I also included a dummy variable for party of the president (*PP*) based on past studies showing the impact that this factor has on stock market performance and risk (Blinder & Watson, 2016; Belo et al., 2013; Pástor & Veronesi, 2012, 2013, 2017; Santa-Clara & Valkanov, 2003; Sy & Al Zaman, 2011). A value of 1 represents a Republican president whereas a value of 0 represents a Democrat in office. In addition, based on previous findings on the links between political gridlock or a divided government on market returns and volatility (Beyer et al., 2015; Binder, 2003; Füss &

Bechtel, 2008; Sojli & Tham, 2015), I included a dummy variable for periods of political gridlock (*PG*) where a value of 1 signifies months of gridlock and a value of 0 signifies months of political harmony. In all regressions, I tested for robustness of the models using the Huber/White sandwich estimator of variance. Using this method tests for possible heteroskedasticity within the models. Using Newey–West standard error with three lags to correct autocorrelation provided similar results, which are not shown here but are available upon request.

Impact of Economic Policy Uncertainty and Partisan Conflict during Periods of Political Gridlock versus Harmony

To isolate the impact of partisan conflict and economic policy uncertainty on market volatility during periods of political gridlock versus harmony, I ran separate regressions for all volatility measures (Hypotheses 3 and 4). The following regression model was used:

$$LVOL_t = \alpha + \rho LVOL_{t-1} + \beta_1 EPU_t + \beta_2 PCI_t + \beta_3 EPU_t \, x \, PG_t + \beta_4 PCI_t \, x \, PG_t + \gamma X_t + \varepsilon \qquad (4)$$

The dependent variable, $LVOL_t$ represents the log of the volatility measure examined: implied volatility (*LVIX*) and calculated realized volatility (*LRV*), respectively. $LVOL_{t-1}$, represents last month's volatility effect, the lag of logged VIX (*LLVIX*) or realized volatility (*LLRV*), respectively. EPU_t represents the level of economic policy uncertainty as captured by the Baker et al. (2012, 2016) index. PCI_t represents the level of partisan conflict as captured by the Azzimonti (2018) index. yX_t represents a vector of control variables. These include corporate bond spread (*CBS*), default yield spread (*DYS*), industrial production growth (*IPG*), inflation growth (*PPIG*), and term spread (*TS*). I included a dummy variable for party of the president (*PP*), where a value of 1 represents a Republican president and a value of 0 represents a

Democrat in office. I also included a dummy variable for periods of political gridlock (*PG*), where a value of 1 signifies months of gridlock and a value of 0 signifies months of political harmony. EPU_t x PG_t represents the interaction between economic policy uncertainty and political gridlock at time *t*. PCI_t x PG_t represents the interaction between partisan conflict and political gridlock.

Lastly, to test for the effect of differing levels of partisan conflict on economic policy uncertainty (Hypothesis 5), I performed two separate OLS regressions. I divided the data into two periods: the high PCI and the low PCI period. The high PCI period includes sample periods when PCI is greater than or equal to its median value. The regression equation is as follows:

$$LVOL_t = \alpha + \rho_1 LVOL_{t-1} + \beta_1 EPU_t + \beta_2 HighPCI_t + \beta_3 HighPCI_t \, x \, EPU_t + \gamma X_t + \varepsilon \quad (5)$$

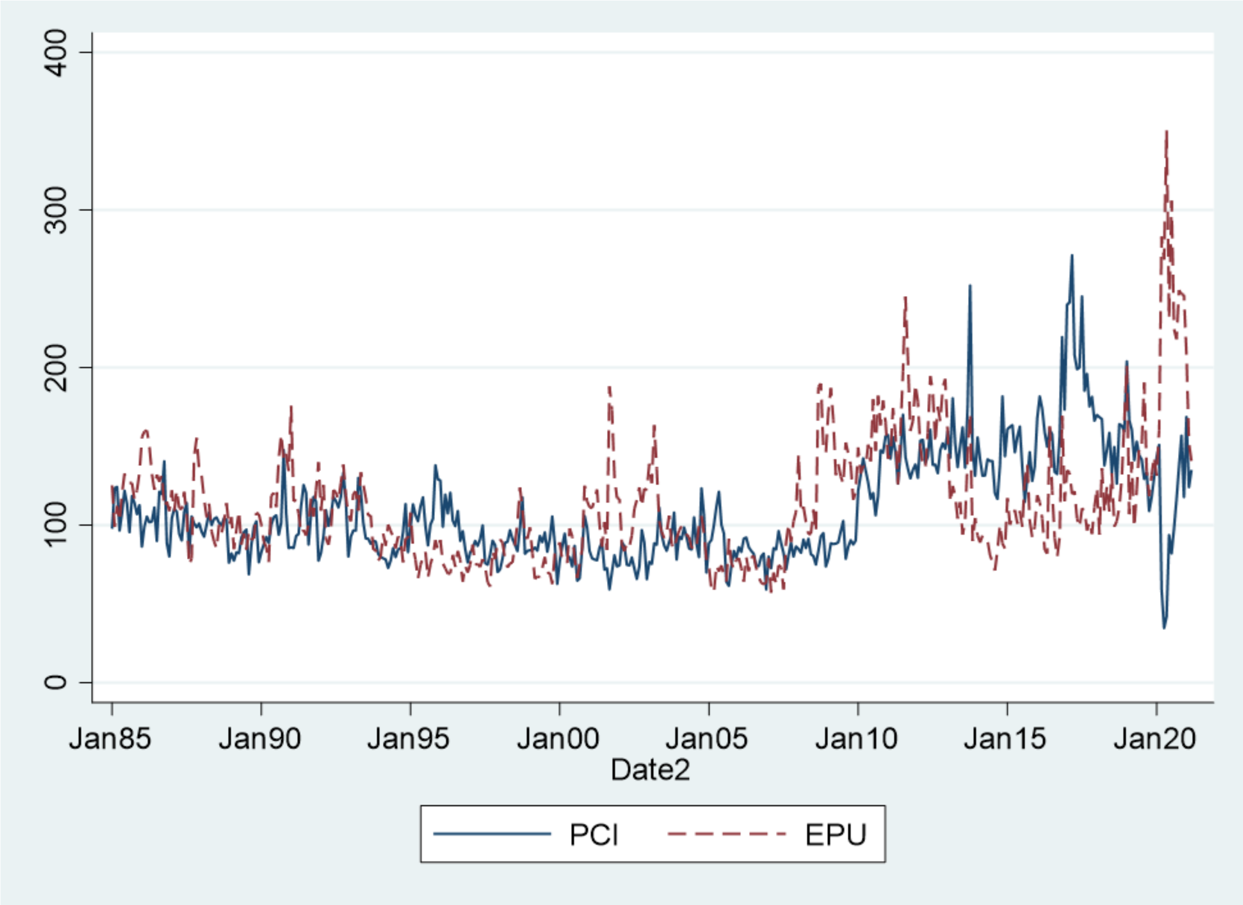
In this model, PCI_t is replaced by $HighPCI_t$, which is a dummy variable whose value is equal to 1 when PCI data points are greater than or equal to the index's median value (99.3899) and 0 otherwise. $HighPCI_t$ x EPU_t is the interaction between $HighPCI_t$ and EPU_t at time *t*. These analyses allowed me to further discern the impact that higher and lower levels of partisan conflict may have on economic policy uncertainty's effect on market volatility. Once again, all models used the Huber/White standard errors to correct heteroscedasticity.

Results

Appendix A provides variable definitions for all variables used in this study. Figure 1 shows the graphical relationship between economic policy uncertainty and partisan conflict. Note that EPU and PCI at times move together but at other times spike in different directions based on events in the political and economic realms. The differing peaks and troughs illustrate the uniqueness of each variable.

Figure 1

Time-Series Plot of Economic Policy Uncertainty and Partisan Conflict Index from May 1985 to April 2021



Note. This figure illustrates the trends of both the economic policy uncertainty index of Baker et al. (2012, 2016), with data taken from www.policyuncertainty.com, and the partisan conflict index of Azzimonti (2018), with data taken from the Federal Reserve Bank of Philadelphia. Both are measured on the y-axis. The date in five-year intervals is represented on the x-axis. The pairwise correlation run on these variables for the sample period of January 1985 to April 2021 revealed a correlation of 23.19%, significant at the 5% level.

Table 1 shows descriptive statistics for each of the variables used in the model. The number of observations captured for each variable ranges from 374 to 436, depending on the available data from the study's sample period of January 1985 to April 2021. The descriptive statistics detail the number of observations, the mean, the standard deviation, and the minimum and maximum values for each variable. Note that in the case of the presidential party dummy variables, the mean for presidential party is 0.550. Recalling that a value of 1 refers to a Republican president, we can see that the sample period contains slightly more months capturing a Republican presidency versus when a Democrat is in office. In a similar vein, the dummy variable for political gridlock with a value of 1 represents a period of gridlock whereas a value of 0 represents a period of harmony. Note that the mean for this variable is 0.757. We can thus conclude that, during the sample period used for this study, slightly more than three quarters of the timeframe exists under a period of political gridlock. This fact confirms that periods of gridlock have been far more pervasive in recent history than periods of political harmony. Consequently, studying the effects of political gridlock can reveal useful information to practitioners and government officials alike.

Table 1

Descriptive Statistics of the Main Variables

Variable	Obs.	*M*	*SD*	Min.	Max.
LVIX	375	2.910	0.347	2.252	4.093
LLVIX	374	2.910	0.347	2.252	4.093
LRV	434	1.338	0.481	0.278	3.291
LLRV	435	1.337	0.480	0.278	3.291
EPU	436	113.302	39.625	57.203	350.460
PCI	436	110.142	34.389	34.74	271.29
PP	436	0.550	0.498	0	1
PG	436	0.757	0.429	0	1
CBS	436	-0.988	0.370	-3.38	-0.55
DYS	436	2.330	0.700	1.29	6.01
IPG	436	2.061	3.478	-0.471	21.586
PPIG	435	0.002	0.010	-0.053	0.030
TS	436	1.703	1.122	-0.700	3.690

Note. This table reports the descriptive statistics for the variables used in this study. The number of observations range from 374 to 436 in the sample period between January 1985 to April 2021. *LVIX* represents the log of implied volatility as measured by volatility index (VIX). *LLVIX* is the log of VIX lagged one period. *LRV* represents the log of monthly realized volatility. *LLRV* is the log of realized volatility lagged one period. *EPU* is measured by the Baker et al. (2012, 2016) index. *PCI* is measured by the Azzimonti (2018) index. Presidential party (*PP*) is a dummy variable where 1 = a Republican in office, whereas 0 = a Democrat. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony. The following control variables are monthly measures that come from the Federal Reserve Bank of St. Louis. *CBS* represents the corporate bond spread, or the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. All collected and calculated data measures are monthly between January 1985 and April 2021. Obs = observations; M = mean; SD = standard deviation; min. = minimum value; max. = maximum value.

I also determined the pairwise correlations between variables to assure the data did not suffer from multicollinearity. Table 2 displays the list of pairwise correlations between measures of overall market implied and realized volatility. The correlations between each volatility measure and its lagged volatility measure were high, as expected. The implied and realized volatility measures were also highly correlated but appeared in different models. Corporate bond spread and default yield spread were highly correlated (-0.8009), but I followed previous literature that included both macroeconomic variables in the same model (e.g., Schwert, 1989, Christiansen et al., 2012) and left them in this study. Correlations between EPU and all volatility measures were significant at a level of 5%. Correlations between PCI and all volatility measures were also significant at a level of 5%. The variables EPU and PCI were significantly correlated as well, but the correlation was low at 23.19%. In addition, neither EPU nor PCI was highly correlated with any key variable in this study. I further tested multicollinearity using the variance inflation factor (VIF) test. I did not find any evidence of multicollinearity in the models. Appendix B reports the results of the VIF test for the variables in the following main regression models (Tables 3 and 4).

Table 2

Correlation Matrix of the Main Variables

	LVIX	*LLVIX*	*LRV*	*LLRV*	*EPU*	*PCI*	*PP*	*PG*	*CBS*	*IPG*	*PPIG*	*TS*
LVIX	1.0000											
LLVIX	0.8415*	1.0000										
LRV	0.8479*	0.7537*	1.0000									
LLRV	0.7176*	0.8479*	0.6478*	1.0000								
EPU	0.4289*	0.4420*	0.3772*	0.3625*	1.0000							
PCI	-0.3142*	-0.2996*	-0.2192*	-0.2256*	0.2319*	1.0000						
PP	-0.0321	-0.0408	-0.0019	-0.0015	0.0671	-0.1676*	1.0000					
PG	0.0943	0.0584	0.0566	0.0270	0.0803	0.2506*	0.0467	1.0000				
CBS	-0.5203*	-0.5631*	-0.4609*	-0.5105*	-0.4178*	0.0989*	-0.1913*	-0.0015	1.0000			
DYS	0.5578*	0.5977*	0.5605*	0.5974*	0.5115*	0.0802	-0.0949*	-0.0346	-0.8009*			
IPG	-0.0422	-0.0590	0.0056	-0.0029	-0.0707	-0.0915	0.0009	-0.5462*	0.0531	1.0000		
PPIG	-0.1562*	-0.1565*	-0.1509*	-0.1842*	-0.0840	0.0204	0.0062	-0.1463*	0.2435*	0.0440	1.0000	
TS	0.0208	0.0539	0.0052	0.0228	0.1334*	0.0772	-0.0893	-0.2574*	-0.2427*	0.1722*	0.0007	1.0000

Note. This table reports the correlation matrix between the variables studied in this research. The natural log of implied volatility (*LVIX*) is calculated as the log of the anticipated volatility for the S&P 500 index over the next 30-day period (VIX index). *LLIX* is *LVIX*, lagged one period. The natural log of realized volatility (*LRV*) is calculated as the square root of the sum of the daily squared S&P 500 returns that occur within each month period. *LLRV* is *LRV*, lagged one period. Economic policy uncertainty is measured by the Baker et al. (2012, 2016) *EPU* index. Partisan conflict is measured by the Azzimonti (2018) partisan conflict index (*PCI*). *PP* stands for party of the president; *PG* represents periods of political gridlock. *CBS* represents the corporate bond spread, or the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. All data measures collected are monthly between January 1985 and April 2021.

*$p < 0.05$.

Multivariate Regression Analysis with Realized and Implied Volatility

Table 3 shows the results of the multivariate regression with the logged value of monthly implied volatility, *LVIX*, as the dependent variable. As expected, in all models, *LLVIX* was positive and significant (at the 1% level). In Model 2, without controlling for other variables, *EPU* was positively associated with *LVIX* and was significant at the 10% level. In Model 3, without controlling for other variables, *PCI* was negatively and significantly associated with *LVIX* (at the 5% level). In Model 4, we see that in the presence of *PCI*, *EPU* remained positively associated with *LVIX* and became significant at the 1% level. We also see that *PCI* remained negatively associated with *LVIX* and also became significant level at the 1% level. In Model 5, in the presence of all control variables, *EPU* remained positively associated with *LVIX* and remained significant (at the 5% level). The magnitude of the coefficient, 0.001, remained the same between the models. In the presence of all control variables in Model 5, *PCI* remained significantly negatively associated with *LVIX* (at the 1% level). Thus, *EPU* had a significant positive impact on implied volatility in Models 2, 4, and 5. I therefore find evidence to support H_{1a}. Moreover, *EPU* had a higher level of significance in the presence of *PCI* and in the presence of other control variables. The variable *PCI* had a significant negative impact on implied volatility in Models 3, 4, and 5. I find evidence to support H_{2a}. Similar to *EPU*, *PCI* had a more highly significant impact on volatility in the models including *EPU* and in the model including the other control variables. In addition, the F statistic revealed that each model tested is significant. Of note, the adjusted R^2 value was highest for the unrestricted Model 5. Furthermore, the adjusted R^2 was higher for all models containing both *EPU* and *PCI*. The results show that presidential party has no impact on volatility, unlike previous studies have suggested. Consistent with the relationship proposed in Beyer et al. (2006), the impact of political gridlock on volatility is positive (at a 1% level of significance). In line with previous studies (Schwert, 1989), I found that default yield spread and industrial production growth are both positive and significant (at the 5% level). I did not find evidence that corporate bond spread, inflation growth, or term spread are significantly correlated to implied volatility. The *F* statistic revealed that each model tested is significant. Of note is the fact that the adjusted R^2 value is highest for the unrestricted Model 5. Moreover, the adjusted R^2 value is higher for models containing both *EPU* and *PCI* than for models containing one variable or the other. The results in Table 3 suggest that together, economic policy uncertainty and partisan conflict provide additional explanatory power about market volatility when added to well-established macroeconomic variables. The finding is robust even after controlling for volatility persistence through *LLVIX*.

Table 4 shows the results of the multivariate regression with monthly realized volatility, *LRV*, as the dependent variable. As expected, in all models, *LLRV* was positive and significant (at the 1% level). In Model 2, without controlling for other variables, *EPU* was positively and significantly associated with *LRV* (at the 1% level). In Model 3, without controlling for other variables, *PCI* was negatively and significantly associated with *LRV* at the 10% level. In Model 4, we see that in the presence of *PCI*, *EPU* remained positively associated with *LRV* and significant (at the 1% level), with a coefficient of increased magnitude (0.003 versus 0.002). We also see that *PCI* remained negatively associated with *LRV* and became significant at the 1% level, also with a more impactful coefficient (-0.002 versus -0.001). In Model 5, in the presence of all control variables, *EPU* remained positively associated with *LRV* and significant (at the 5% level). In the presence of all control variables in Model 5, *PCI* remained negatively and significantly associated with *LRV* (at the 1% level). The variable *EPU* had a significant positive impact on realized volatility in Models 2, 4, and 5. I therefore find evidence to support H_{1b}.

Furthermore, *EPU* demonstrated a high level of statistical significance in the presence of *PCI* and other control variables. The variable *PCI* had a statistically significant negative impact on realized volatility in Models 3, 4, and 5. I therefore find evidence to support H_{2b}. Once again, *PCI* was significant in the presence of *EPU* and other control variables (at the 1% level), and the magnitude of the *PCI* coefficient increased with the addition of *EPU* (from -0.001 to -0.002) and the control variables (-0.002 to -0.003). As with implied volatility, the results in Table 4 show that the presidential party has no impact on volatility, unlike previous studies have suggested. Consistent with Beyer et al. (2006, 2015), I found that the impact of political gridlock is significantly positive (at the 1% level). Once again, consistent with the relationship proposed in Beyer et al. (2006), the impact of political gridlock on volatility was positive (at a 1% level of significance). In line with previous studies (Schwert, 1989), corporate bond spread and industrial production growth were positive and significant (at the 10% level), and default yield spread was positive and significant (at the 1% level). Term spread was negative and significant (5% level), consistent with Paye (2012). I did not find evidence that inflation growth is significantly correlated to realized volatility. Once again, the *F* statistic revealed that each model tested was significant. Of note is the fact that the adjusted R^2 value was highest for the unrestricted Model 5. Moreover, the adjusted R^2 value was higher for models containing both *EPU* and *PCI* than for models containing one variable or the other. These results suggest that together, economic policy uncertainty and partisan conflict provide additional explanatory power about market volatility when added to well-established macroeconomic variables. The finding is robust after controlling for volatility persistence through *LLRV*.

Table 3

Ordinary Least Squares Regressions of Market Volatility on Economic Policy Uncertainty and Partisan Conflict: Implied Volatility

	Models				
	(1)	(2)	(3)	(4)	(5)
Variable	Lag	+ EPU	+ PCI	+ EPU and PCI	Unrestricted
LLVIX	0.841***	0.810***	0.821***	0.751***	0.656***
	(29.09)	(28.05)	(26.36)	(22.02)	(14.45)
EPU		0.001*		0.001***	0.001**
		(1.88)		(2.67)	(2.31)
PCI			-0.001**	-0.001***	-0.002***
			(-2.25)	(-3.32)	(-4.34)
PP					-0.026
					(-1.26)
PG					0.088***
					(3.37)
CBS					0.022
					(0.47)
DYS					0.072**
					(2.45)
IPG					0.005**
					(2.04)
PPIG					0.108
					(0.09)
TS					-0.013
					(-1.49)
Constant	0.461***	0.486***	0.591***	0.732***	0.896***
	(5.55)	(6.01)	(5.58)	(6.89)	(7.42)
Observations	374	373	373	373	373
Adjusted R^2	0.707	0.711	0.711	0.721	0.733
F-statistic	846.1	445.1	447.5	304.9	113.2

Note. This table reports the log of monthly implied volatility returns (*LVIX*) on economic and political measures. Model 5 is the unrestricted model that regresses *LVIX* on *PCI*, *EPU*, and all the control variables. *LLVIX* is the log of VIX lagged one period. *EPU* represents Baker et al.'s (2012, 2016) economic policy uncertainty index. *PCI* represents Azzimonti's (2018) partisan conflict index. *PP* stands for party of the president, *PG* represents periods of political gridlock versus harmony, *CBS* stands for corporate bond spread, or the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. All data measures collected are monthly between January 1985 and April 2021. The *t*-statistics based on robust standard errors are reported in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 4

Ordinary Least Squares Regressions of Market Volatility on Economic Policy Uncertainty and Partisan Conflict: Realized Volatility

	Models				
Variable	(1) Lag	(2) +EPU	(3) +PCI	(4) +EPU and PCI	(5) Unrestricted
LLRV	0.648***	0.588***	0.630***	0.535***	0.350***
	(17.45)	(15.25)	(16.72)	(12.61)	(7.51)
EPU		0.002***		0.003***	0.002**
		(3.00)		(3.33)	(2.22)
PCI			-0.001*	-0.002***	-0.003***
			(-1.96)	(-3.22)	(-4.75)
PP					-0.004
					(-0.13)
PG					0.138***
					(3.31)
CBS					0.135*
					(1.79)
DYS					0.283***
					(5.86)
IPG					0.0018*
					(1.87)
PPIG					0.567
					(0.48)
TS					-0.037**
					(-2.22)
Constant	0.472***	0.326***	0.613***	0.552***	0.452***
	(9.23)	(4.38)	(7.32)	(6.78)	(5.24)
Observations	434	434	434	434	433
Adjusted R^2	0.418	0.440	0.423	0.458	0.510
F-statistic	304.4	149	150.7	94.14	51.84

Note. This table reports the log of monthly realized volatility returns (*LRV*) regressed on economic and political measures. Model 5 is the unrestricted model that regresses *LRV* on *PCI*, *EPU*, and all the control variables. Realized volatility is calculated from the sum of the daily squared S&P 500 returns after subtracting the calculated average daily return in that month. *LLRV* is the log of realized volatility lagged one period. *EPU* represents Baker et al.'s (2012, 2016) economic policy uncertainty index. *PCI* represents Azzimonti's (2018) partisan conflict index. *PP* stands for party of the president, *PG* represents periods of political gridlock versus harmony, *CBS* stands for corporate bond spread, the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, the yield difference between BAA-rated corporate bonds versus long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. All data measures collected are monthly between January 1985 and April 2021. The *t*-statistics based on robust standard errors are reported in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

The Effects of Political Gridlock on Economic Policy Uncertainty and Partisan Conflict

I performed a series of regressions in order to isolate the effects of political gridlock versus harmony and to assess their potentially separate impacts on economic policy uncertainty, partisan conflict, and measures of market risk. I executed this analysis in a method somewhat akin to that employed by Adjei and Adjei (2017), where the authors isolated and regressed political effects (party and year of a presidency) to test the relationship between political cycles and their impact on investor sentiment. I established four different models. In the first model, I regressed monthly measures of volatility on both *EPU* and *PCI* without accounting for periods of gridlock. In the second model, I tested for the impact of economic policy uncertainty and partisan conflict on market volatility by regressing volatility on both *EPU* and *PCI* during periods of political harmony. In the third model, I tested to see whether the risk impacts of economic policy uncertainty and partisan conflict differ during periods of political gridlock. To examine these effects, I then regressed volatility on *EPU* and *PCI* during months in which there was political gridlock at the federal level. Finally, in Model 4, I tested the interaction effects of political gridlock on both *EPU* and *PCI* while including all control variables in the analysis.

Table 5 reports the effects that periods of political harmony versus gridlock have on monthly measures of the log of implied volatility as measured by the VIX index (*LVIX*). As expected, the findings showed that *LLVIX* remained positive and significant (at 1%) in all models. In restricted Model 1, where *LVIX* was regressed on *LLVIX*, *EPU*, and *PCI*, I noted that, as already reported in Tables 3 and 4, *EPU* and *PCI* were positively and negatively significant, respectively (at the 1% level). Model 2 reports that during periods of political harmony, *EPU* remained positive and significant (at 1%), whereas *PCI* remained negative but became insignificant. During periods of political gridlock, Model 3, *EPU* remained positive and significant (at 5%); *PCI* remained negative and became highly significant (at 1%). I thereby find initial evidence to support H_{4a}. Partisan conflict significantly impacts volatility during periods of gridlock, but not during periods of harmony.

Model 4 reports the regression results for *LVIX* regressed on *LLVIX*, *EPU*, *PCI*, political gridlock (*PG*), and the intersections between *EPU* and political gridlock (*EPU* x *PG*) and between *PCI* and political gridlock (*PCI* x *PG*). I noted that *EPU* remained positive and significant (at 1%), and *PCI* remained negative but once again became insignificant. Political gridlock was positive and significant (at 1%). The finding that political gridlock is positively correlated to stock market volatility is consistent with the relationship suggested in Beyer et al. (2006). The inverse impact shown between partisan conflict and political gridlock also confirms the uniqueness of each measure. The interaction term of *EPU* x *PG* was negative and significant (at the 1% level), suggesting that economic policy uncertainty's impact on implied volatility is decreased during periods of political gridlock. Although there was a significant impact, this impact was negative instead of positive, thus H_{3a} is not supported. The interaction *PCI* x *PG* was negative but not significant, thus H_{4a} is not supported. However, when I restricted my models to periods of harmony versus gridlock (in Models 2 and 3) and allowed for the slopes to be different, *PCI* had a statistically significant negative impact on implied volatility during periods of political gridlock (at the 1% level) but not during periods of political harmony. Furthermore, the magnitude of the impact increased to -0.002. Consistent with the literature (Schwert, 1989), default yield spread and industrial production growth were positive and significant (at the 1% and 5% levels, respectively). Term spread was negative and significant (1% level), consistent with Paye (2012). I found no evidence that corporate bond spread or inflation growth are significantly correlated to implied volatility. The *F* statistics indicated that all models are significant.

Table 6 reports the effects that periods of political harmony versus gridlock have on monthly measures of the log of realized volatility (*LRV*) as calculated in this study. Once again, as expected, I found that the lagged log of realized volatility (*LLRV*) remained positive and significant (at the 1% level) in all models. The *F* statistic indicated that all models are significant. In restricted Model 1, where *LRV* was regressed on *LLRV*, *EPU*, and *PCI*, as already reported in Table 4, *EPU* and *PCI* were both highly significant at 1%. Model 2 reports that during periods of political harmony, *EPU* remained positive and significant (at the 1% level), whereas *PCI* remained negative but became insignificant. During a state of political gridlock, as depicted in Model 3, *EPU* remained positive and significant (at the 5% level). As with respect to implied volatility, in this model, *PCI* also remained negative and became significant at the 1% level during periods of gridlock. Additionally, the magnitude of *PCI* increased to -0.003 during gridlock.

Model 4 reports the regression results for *LRV* regressed on *LLRV*, *EPU*, *PCI*, political gridlock, the intersections between *EPU* and political gridlock (*EPU* x *PG*) and between *PCI* and political gridlock (*PCI* x *PG*), and all the control variables. I noted that *EPU* remained positive and significant at the 1% level while *PCI* remained negative but became insignificant. As with implied volatility, I found that political gridlock was positive and significant (at the 1% level), once again consistent with the relationship suggested in Beyer et al. (2006). Unlike the regression with implied volatility, there was no significant interaction effect on realized volatility between *EPU* and *PG*. Therefore, H_{3b} is not supported. Although the coefficient was negative, as hypothesized, there was no significant interaction effect on realized volatility between *PCI* and *PG*, which means I find no support for H_{4b}. However, once again, when the models were restricted to periods of gridlock versus harmony (in Models 2 and 3), allowing for the slopes to be different, *PCI* had a statistically significant negative impact on realized volatility during periods of political gridlock (at the 1% level), but not during periods of political harmony. The variable *EPU* remained positively and significantly correlated (at the 5% and 1% levels, respectively) to realized volatility. Consistent with the literature (Schwert, 1989), corporate bond spread, default yield spread, and industrial production growth were positive and significant (at the 10%, 1%, and 10% levels, respectively). Once again, term spread was negative and significant (5% level), consistent with Paye (2012). I found no evidence that inflation growth is significantly correlated to realized volatility. The *F* statistics indicated that all models were significant.

The results of Table 5 and 6 suggest that partisan conflict impacts implied and realized volatility only during periods of political gridlock. This makes sense given the higher level of partisan conflict that occurs during periods of gridlock versus harmony. Notably, the significant and negative interaction effect between *EPU* and *PG* (at the 1% level) using implied volatility as the dependent variable suggests that economic policy uncertainty becomes less of a factor in driving implied market volatility when the government is in a state of political gridlock. This result suggests that when gridlock exists at the federal level, investors find there is less chance for change in economic policies and by extension, less risk of economic policy uncertainty.

Table 5

Ordinary Least Squares Regressions of Market Volatility on Economic Policy Uncertainty and Partisan Conflict: Gridlock versus Harmony, Implied Volatility

	Models			
	(1)	(2)	(3)	(4)
Variable	Restricted	Harmony	Gridlock	Full Sample
LLVIX	0.751***	0.696***	0.672***	0.603***
	(22.02)	(12.38)	(13.76)	(12.79)
EPU	0.001***	0.003***	0.001**	0.003***
	(2.67)	(3.85)	(2.35)	(4.19)
PCI	-0.001***	-0.001	-0.002***	-0.001
	(-3.32)	(-1.46)	(-4.47)	(-1.10)
PP				0.001
				(0.17)
PG				0.431***
				(3.89)
EPU x PG				-0.002***
				(-2.99)
PCI x PG				-0.001
				(-1.09)
CBS				0.032
				(0.68)
DYS				0.057***
				(3.05)
IPG				0.006**
				(2.37)
PPIG				-0.489
				(-0.43)
TS				-0.018***
				(-2.08)
Constant	0.732***	0.659***	1.068***	0.766***
	(6.89)	(4.48)	(6.57)	(6.01)
Observations	373	105	268	373
Adjusted R^2	0.721	0.839	0.682	0.742
F-statistic	304.9	217.3	175.5	118.1

Note. This table reports the results of regressing the log of monthly implied volatility returns (*LVIX*) on the lagged log of the volatility index (*LLVIX*) and economic and political measures. Model 1 regresses *LVIX* on *LLVIX*, *EPU*, and *PCI* during the full sample time frame. Models 2 and 3 divide the sample time frame into periods of harmony and gridlock, respectively. Model 4 regresses *LVIX* on all variables during the full sample time frame. Economic policy uncertainty (*EPU*) is measured by the Baker et al. (2012, 2016) EPU index. Partisan conflict (*PCI*) is measured by the Azzimonti (2018) PCI index. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony (all majority parties are the same). *PP* denotes party of the president. *CBS* stands for corporate bond spread, or the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. All data measures collected are monthly between January 1985 and April 2021. The *t*-statistics based on robust standard errors are reported in parentheses.

$^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6

Ordinary Least Squares Regressions of Market Volatility on Economic Policy Uncertainty and Partisan Conflict: Gridlock versus Harmony, Realized Volatility

	Models			
Variable	(1) Restricted	(2) Harmony	(3) Gridlock	(4) Full Sample
LLRV	0.535***	0.594***	0.489***	0.340***
	(12.61)	(10.35)	(9.44)	(7.25)
EPU	0.003***	0.004***	0.002**	0.003***
	(3.33)	(4.19)	(2.74)	(2.67)
PCI	-0.002***	-0.002	-0.003***	-0.001
	(-3.32)	(-1.02)	(-3.77)	(-0.51)
PP				0.020
				(0.50)
PG				0.530***
				(3.24)
EPU x PG				-0.001
				(-1.07)
PCI x PG				-0.003
				(-1.63)
CBS				0.153*
				(2.01)
DYS				0.291***
				(5.91)
IPG				0.008*
				(1.75)
PPIG				-0.009
				(-0.00)
TS				-0.042**
				(-2.50)
Constant	0.732***	0.659***	1.068***	0.127
	(6.89)	(4.48)	(6.57)	(0.83)
Observations	373	104	330	433
Adjusted R^2	0.458	0.674	0.409	0.513
F-statistic	94.14	87.54	56.76	51.95

Note. This table reports the log of monthly realized volatility (*LRV*) on the lagged log of realized volatility (*LLRV*) and economic and political measures. Model 1 regresses *LRV* on *LLRV*, *EPU*, and *PCI* during the full sample time frame. Models 2 and 3 divide the sample time frame into periods of harmony and gridlock, respectively. Model 4 regresses *LRV* on all variables during the full sample time frame. Economic policy uncertainty (*EPU*) is measured by the Baker et al. (2012, 2016) EPU index. Partisan conflict (*PCI*) is measured by the Azzimonti (2018) PCI index.

Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony (all majority parties are the same). *PP* denotes party of the president. *CBS* stands for corporate bond spread, or the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. All data measures collected are monthly between January 1985 and April 2021. The *t*-statistics based on robust standard errors are reported in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

The Effects of High Levels of Partisan Conflict on Economic Policy Uncertainty

My final analysis in this study was to examine the impact of high levels of partisan conflict on economic policy uncertainty, based on theories of their interactive effects forwarded by past research (Füss & Bechtel, 2008; Gupta et al., 2018; Jia et al., 2021; Jiang & Shi, 2020; Pham, 2019). I tested the effects of the interaction between high levels of partisan conflict and economic policy uncertainty on both measures of volatility, implied and realized. Table 7 reports the results of this analysis.

In Table 7, Model 1, *LVIX* was regressed on *LLVIX*, on *EPU*, on *HighPCI*, and on the interaction between *EPU* and *HighPCI*. As expected, *LLVIX* was significant at 1%, and *EPU* was significant at 10%. Both *HighPCI* and the interaction term were insignificant. Model 2 regressed *LVIX* on the previously mentioned variables as well as on all the control variables. When combined with the other variables, *EPU* became insignificant; *HighPCI* and the interaction term remained insignificant. I therefore find no evidence to support $H_{5a.}$ In other words, economic policy uncertainty's impact on implied volatility does not significantly change during periods of higher partisan conflict. Once again, the results do not suggest that the presidential party impacts implied volatility. Political gridlock, however, was positive and significant at the 5% level. Default yield spread (*DYS*), consistent with Schwert (1989) was positive and significant (10% level). I did not find evidence that any of the remaining control variables were significant.

In Table 7, Model 3, *LRV* was regressed on *LLRV*, on *EPU*, on *HighPCI*, and on the interaction between *HighPCI* and *EPU*. As expected, *LLRV* was significant at 1%, and *EPU* was positive and significant at the 5% level; *HighPCI* and the interaction term were both insignificant. Model 4 regressed *LRV* on the previously mentioned variables as well as on all the control variables. When combined with the other variables in Model 4, *EPU* became insignificant; *HighPCI* and the interaction term remained insignificant. I find no evidence to support $H_{5b.}$ The impact of economic policy uncertainty on realized volatility does not significantly change during periods of higher partisan conflict. Once again, the results did not suggest that presidential party impacts realized volatility. Political gridlock, however, remained positive and significant at the 5% level. Default yield spread (*DYS*), consistent with Schwert (1989) was positive and significant (1% level). I did not find evidence that any of the remaining control variables were significant, as was the case in Model 3.

Regardless of the volatility measured employed (implied or realized), the results were similar. As seen in Table 7, the analyses failed to reject the null hypothesis and show any significant interaction effect between high levels of partisan conflict and economic policy uncertainty. I therefore find no evidence that higher versus lower levels of partisan conflict change the impact economic policy uncertainty has on volatility. This finding reflects the low correlation between the *PCI* and *EPU* (0.2319) measures and supports the idea that there is no clear relationship between these variables (Azzimonti, 2018). Both the *EPU* and *PCI* measures affect volatility independently of each other. The rest of the control variables perform similarly to previous models in this study.

Table 7

Ordinary Least Squares Regressions of Market Volatility on High/Low Levels of Partisan Conflict and Economic Policy Uncertainty

	Models			
	(1)	(2)	(3)	(4)
Variables	*LVIX*	*LVIX*	*LRV*	*LRV*
LLVIX	0.76500***	0.69700***		
	(23.66)	(16.66)		
LLRV			0.54200***	0.39700***
			(12.79)	(8.70)
EPU	0.00093*	0.00078	0.00255**	0.00130
	(1.87)	(1.39)	(2.23)	(1.18)
HighPCI	-0.06860	-0.10600	-0.14100	-0.22600
	(-0.97)	(-1.48)	(-0.98)	(-1.63)
EPU x HighPCI	0.00002	0.00013	0.00006	0.00056
	(0.04)	(0.19)	(0.05)	(0.44)
PP		-0.01780		0.00018
		(-0.91)		(0.01)
PG		0.05290**		0.08450**
		(2.37)		(2.34)
CBS		-0.00614		0.05880
		(-0.13)		(0.80)
DYS		0.05080*		0.22100***
		(1.77)		(4.79)
IPG		1.58500		-0.40600
		(1.29)		(-0.19)
PPIG		-0.50200		0.24200
		(-0.46)		(0.13)
TS		-0.01070		-0.02810
		(-1.20)		(-1.60)
Constant	0.61100***	0.70000***	0.39200***	0.26500***
	(6.92)	(6.98)	(3.81)	(2.93)
Observations	373	373	434	433
Adjusted R^2	0.717	0.724	0.455	0.491
F-statistic	229.2	102.1	77.3	47.67

Note. Table 7, Models 1 and 2 report the log of monthly implied volatility returns (*LVIX*) regressed on economic and political measures, including high and low levels of partisan conflict, defined by the median data point. *LLVIX* is the log of the volatility index lagged one period. Models 3 and 4 report the log of monthly realized volatility returns (*LRV*) regressed on these same measures. *LLRV* is the log of *LRV* lagged one period. Economic policy uncertainty (*EPU*) is measured by the Baker et al. (2012, 2016) index. High partisan conflict (*HighPCI)* includes any data point above the median value of 99.3899 from the partisan conflict index (*PCI*) developed by Azzimonti (2018). *EPU x HighPCI* is the interaction between *HighPCI* and *EPU*. *PP* stands for party of the president where a value of 1 represents a Republican in office and 0 a Democrat. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony (all majority parties are the same). *CBS* stands for corporate bond spread, or the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. All data measures collected are monthly between January 1985 and April 2021. The *t*-statistics based on robust standard errors are reported in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Discussion

Analysts focus on prevailing economic policy uncertainty and an increasing divide in U.S. partisan ideologies now more than ever (McCoy & Press, 2022). Given the timeliness of the topic, this study investigated the impact of both economic policy uncertainty and partisan conflict on different measures of stock market risk: implied and realized volatility. I examined the joint effect that each factor, economic policy uncertainty and partisan conflict, has on both implied and realized volatility, while controlling for political conditions and established volatility predictors. My findings showed that economic policy determinations and political conflict represent separate, key factors impacting market volatility. The results indicated that economic policy uncertainty and partisan conflict contemporaneously affect market volatility, and that the significant impact of each variable is distinct from the other. My analyses suggest that economic policy uncertainty as proxied by the *EPU* index has a positively significant impact on both forward and backward-looking measures of market volatility. In other words, increased economic policy uncertainty at the federal level has a heightening effect on stock market volatility. This result suggests that investors become anxious in an uncertain climate and the market reacts accordingly.

On the other hand, my findings provide evidence that partisan conflict, as proxied by the *PCI*, has a negative impact on both forward- and backward-looking measures of market volatility. Contrary to economic policy uncertainty, therefore, partisan conflict has a dampening effect on stock market volatility. This impact was statistically strengthened (both in level and in magnitude) with the inclusion of *EPU* and other variables in the model. This result suggests that heightened conflict stalls decision-making processes at the federal level, causing fewer policies to be changed or enacted, thereby reducing investor angst and the volatility of market returns. An important finding of this study is that the statistically significant impact of both the *EPU* and *PCI* measures on market volatility when considered together demonstrates the importance of their inclusion in any study examining risk in the markets.

Finally, given the pervasive state of political gridlock in the United States during the past 50 years, I also examined the effects of economic policy uncertainty and partisan conflict during periods of political gridlock versus harmony. Specifically, when I restricted my models to evaluate each period individually, I found that partisan conflict has a statistically significant negative impact on both measures of volatility during periods of political gridlock but not during periods of political harmony. Furthermore, the impact under gridlock is greater in magnitude (as captured by the coefficient). This outcome suggests that investors can expect partisan conflict to have an increased dampening effect on volatility during times of political gridlock. In the last analysis, I investigated whether the impact of economic policy uncertainty on volatility is affected by higher levels of partisan conflict. My results indicate that economic policy uncertainty is not significantly affected by high levels of partisan conflict, providing further testament to the idea that these two variables capture different, and important, impacts in the macroeconomy.

The findings associated with the presidential party and political gridlock variables are noteworthy as well. Whereas past research has shown that party of the president affects stock market returns, the results of this study indicate that presidential party was not a statistically significant factor in any of the models. These findings suggest that the impact of presidential party does not extend in a meaningful way to a market's volatility for the examined sample period. That being said, there is still a potential impact on volatility when controlling for election or mid-election years. This hypothesis should be tested in a future study. The idea that a state of political gridlock could impact market volatility is an interesting one as well. This effect could potentially be due to greater inaction on the part of lawmakers. Considering the prevalent state of gridlock in the U.S. government, future studies should explore its effect in greater depth and with greater precision.

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Appendix A

Variable Definitions

- ***LVOL*** = Monthly measure of the natural logarithm of stock market volatility. The measures of volatility include:

  1. ***LVIX*** = Implied volatility, or a measure of the anticipated volatility for the S&P 500 index over the next 30-day period (Yahoo! Finance, *CBOE Volatility Index*, 2021)

  2. ***LRV*** = Realized volatility, calculated as the square root of the sum of the daily squared S&P 500 returns that occur within each month period. (French, n.d.)

- $LVOL_{t-1}$ = One-period lagged value of each of the monthly measures detailed above.
- ***PCI*** = Partisan Conflict Index. Monthly measure of the level of partisan conflict between Democrats and Republicans as measured by newspaper articles conveying political disagreement at the national level. (Federal Reserve Bank of Philadelphia, *Partisan conflict index*, 2021).
- ***HighPCI*** = High Partisan Conflict: a dummy variable whose value is equal to 1 when *PCI* data points are greater than or equal to the median (99.3899) and 0 otherwise.
- ***EPU*** = Economic Policy Uncertainty Index (Baker et al., 2016): Monthly measure based on newspaper articles referencing “economic,” “policy,” and “uncertainty,” and other related terms; federal tax code provisions; and professional forecaster disagreement over future inflation and government expenditures. (*Economic policy uncertainty index*, n.d.)
- ***PP*** = Party of President: A dummy variable measuring party of the current president. A value of 1 represents a Republican in office; 0 represents a Democrat. (*Political parties of the presidents*, n.d.)

- ***PG*** = Political Gridlock: The period during which the majority party in the White House, the Senate, and the House of Representatives are not all the same. The dummy variable has a value of 1 during gridlock periods and a value of 0 during non-gridlock (harmony) periods. (United States House of Representatives, n.d.; United States Senate, n.d.)
- ***CBS*** = Corporate Bond Spread: This spread is the difference between the yield on AAA-rated (Federal Reserve Bank of St. Louis, *Moody's seasoned Aaa corporate bond yield,* 2021*)* versus BAA-rated corporate bonds (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield*, 2021*)*
- ***DYS*** = Default Yield Spread: This spread represents the difference between the monthly yield on BAA-rated corporate bonds versus the yield on long-term government bonds. (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield relative to yield on 10-year treasury constant maturity*, 2021)
- ***IPG*** = Industrial Production Growth: A monthly numeric measure of the change in industrial production from one month to the next. (Federal Reserve Bank of St. Louis, *Industrial production: total index*, 2021)
- ***PPIG*** = Inflation Growth: A monthly measure calculated as the change in producer price index (PPI) from one month to the next. (Federal Reserve Bank of St. Louis, *Producer price index by commodity: All commodities*, 2021)
- ***TS*** = Term Spread: This monthly variable represents the difference between the long-term yield on government bonds and the three month-Treasury bill rate. (Federal Reserve Bank of St. Louis, *10-year treasury constant maturity minus 3-month treasury constant maturity*, 2021)

Appendix B

Variance Inflation Factor Test for Multicollinearity for the Main Models

Table B1

Implied Volatility

Variable	VIF	1/VIF
DYS	5.65	0.176873
CBS	4.61	0.216876
LLVIX	2.32	0.431049
PCI	1.71	0.585233
EPU	1.69	0.591350
PG	1.31	0.764160
TS	1.30	0.768571
PP	1.20	0.830233
IPG	1.18	0.845873
PPIG	1.15	0.871138
Mean VIF	2.21	

Note. VIF = variance inflation factor. Variables with values lower than 10 satisfy conditions of low collinearity (Hair et al., 1995). *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *CBS* stands for corporate bond spread, or the difference between AAA and BAA corporate bond yields. *LLVIX* is the log of VIX lagged one period. Partisan conflict (*PCI*) is measured by the Azzimonti (2018) PCI index. Economic policy uncertainty (*EPU*) is measured by the Baker et al. (2012, 2016) EPU index. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony (all majority parties are the same). *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. *PP* denotes party of the president, where a value of 1 signifies a Republican in the White House, 0 for a Democrat. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. All data measures collected are monthly between January 1985 and April 2021.

Table B2

Realized Volatility

Variable	VIF	1/VIF
DYS	4.96	0.201439
CBS	3.78	0.264225
LLRV	1.93	0.518909
EPU	1.52	0.656014
PCI	1.48	0.674118
PP	1.31	0.764316
TS	1.28	0.784236
PG	1.23	0.812469
IPG	1.16	0.860271
PPIG	1.14	0.879269
Mean VIF	1.98	

Note. VIF = variance inflation factor. Variables with values lower than 10 satisfy conditions of low collinearity (Hair et al., 1995). *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *CBS* stands for corporate bond spread, or the difference between AAA and BAA corporate bond yields. *LLRV* is the lagged log of realized volatility. Economic policy uncertainty (*EPU*) is measured by the Baker et al. (2012, 2016) EPU index. Partisan conflict (*PCI*) is measured by the Azzimonti (2018) PCI index. *PP* denotes party of the president where a value of 1 signifies a Republican in the White House, 0 for a Democrat. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony (all majority parties are the same). *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. All data measures collected are monthly between January 1985 and April 2021.

ESSAY 2: CALMING MARKETS THROUGH CONFLICT: THE IMPACT OF PARTISAN CONFLICT ON POLITICALLY SENSITIVE INDUSTRY VOLATILITY

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ABSTRACT

Partisan conflict resulting from disagreement over federal policies has far-reaching implications for financial markets. The impact of partisan conflict on industry volatility, in particular on high politically sensitive industries such as healthcare and defense, however, remains largely unexplored in the literature. Using the partisan conflict index (PCI) created by Azzimonti (2018), this study fills that gap by examining the effects of partisan conflict on industry-level realized volatility and idiosyncratic risk through three separate measures of politically sensitive industries identified in the literature. The results show that higher levels of partisan conflict dampen volatility at the industry level, high politically sensitive industries have higher volatility than low politically sensitive ones, and partisan conflict reduces the volatility of high politically sensitive industries more than that of low politically sensitive industries. However, these findings do not persist across all measures of industry political sensitivity, which suggests that the political sensitivity of an industry is dynamic over time.

Keywords: volatility, partisan conflict, political sensitivity, uncertainty, industry

Essay 2: Calming markets through conflict: The impact of partisan conflict on politically sensitive industry volatility

Understanding the role that political conflict plays with respect to financial markets proves increasingly essential in our current world. Past research has examined the way in which partisan ideologies have become more polarized in U.S. politics since the early 1960s (Baker et al., 2014). Political polarization is a term used to describe the shifting of party ideologies and the extent to which Republican and Democratic beliefs differ (Jones, 2001). This polarization affects government decision-making (Hare & Poole, 2014) by impeding or prolonging the process (Rigby & Wright, 2015; Weber et al., 2021). Partisan conflict, due in part to this polarization (Azzimonti, 2018), has popularized the use of filibusters (Lee, 2015), which has served to aggravate policy gridlock even further (Binder, 1999). Polarizing partisan views result in greater legislative gridlock with fewer policy changes being made (Binder, 1999; Jones, 2001; Theriault, 2008), thereby promoting increased policy stability (Tsebelis, 1995). The deepened division between ideologies in the political realm is what Stanford political scientist Fiorina called "partisan polarization," (De Witte, 2020), a term attributed specifically to governing political bodies. No matter how you describe the phenomenon, it is unsurprising that separation in party ideology and uncertainty related to policy changes would ultimately impact equity markets, including volatility in those markets (Pástor & Veronesi, 2017; Tiwari et al., 2019).

A recent content-based measure, the partisan conflict index (PCI) was developed by Azzimonti (2018) to measure the degree of federal-level political discord spurred on by polarization. Since then, research has used this index to study a variety of factors, such as its impact on the equity premium (Gupta, Mwamba, et al., 2018), foreign direct investment (Azzimonti, 2019), oil and gold prices (Apergis et al., 2021; Jiang et al., 2020), high-yield exchange rates (Jia et al., 2021), and even Bitcoin (Su et al., 2021). Whereas PCI has been shown to predict lower market-level volatility (Gupta, Pierdzioch, et al., 2018), little is known about its effects on volatility at the industry level, particularly among those industries that are more susceptible to politics. For example, politically contentious industry-specific issues such as gun control and healthcare remain largely unresolved and slow to change under a polarized political system. This study thus fills a gap in the literature by examining the effects of partisan conflict on industry-level volatility, both overall and as it specifically relates to politically sensitive industries.

Literature has explored the sensitivity of certain industries to changes in the political arena due to a variety of factors. These factors include presidential cycles and election outcomes (Bradley et al., 2021; Herron et al., 1999; Julio & Yook, 2012), government spending or exposure (Agrawal & Knoebel, 2001; Atanassov et al., 2015; Baker et al., 2016; Pham, 2019), socially responsible versus irresponsible (“sin”) stocks (Bonaparte et al., 2017; Hong & Kostovetsky, 2012; Wang et al., 2022), political contributions and party in power (Addoum & Kumar, 2016; Cooper et al., 2010; Hill, 2013; Huang & Wang, 2018; Wellman, 2017), and political connections (Chen et al., 2010; Faccio, 2006; Hong & Kostovetsky, 2012; Kostovetsky, 2015).

Due to varying degrees of governmental exposure in certain industries, it follows that the market value and volatility of firms in politically sensitive industries would also be affected differently by federal-level partisan conflict than non-sensitive ones. In other words, these industries risk larger financial impact due to a changing political environment. While an increasingly pervasive phenomenon in U.S. government, partisan conflict remains relatively unexplored for its impact on industries. Nonetheless, a precedent for industry-level impact exists in the literature. In particular, partisan polarization has been shown to affect industries such as healthcare (Pacheco et al., 2020; Peterson, 2011), gun control (Patterson & Eakins, 1998; Ryan et al., 2020), and oil and gold (Jiang et al., 2020; Apergis et al., 2021). Government policy-makers, portfolio managers, and investors looking to diversify can benefit from information concerning factors that may influence politically sensitive industries differently.

For the purposes of this study, I employed three separate well-established classifications for politically sensitive industries. The first measure, that of Addoum and Kumar (2016), includes industries that were the most politically sensitive during a prolonged period of time under both Republican and Democratic presidencies. The second measure, that of Hong and Kostovetsky (2012), largely equates politically sensitive industries with sin stocks that are politically-charged. Sin firms are exposed to the risk of regulatory government intervention (Hong & Kostovetsky, 2012), making them particularly vulnerable to changes in policy. Lastly, the political sensitivity measure of Herron et al. (1999) and Julio and Yook (2012) centers around sensitivity to presidential election outcomes.

This study is novel in its exploration of the impact of partisan conflict on return volatility at the industry level, using two separate volatility measures, realized volatility and idiosyncratic risk. Examining industry-specific risk allows for a more in-depth study of those industries that serve as leading indicators of overall market volatility (Cheong et al. 2011). The literature also has noted the importance of considering both measures of volatility. In their study on the correlation between PCI and oil prices, Apergis et al. (2021) found that U.S. partisan conflict can represent both a systemic and an industry-specific risk in the market. In a more general sense, measures of industry-level volatilities are of particular interest to those investors who are not well diversified in their portfolios (Campbell et al., 2001). Bekaert et al. (2012) discussed the value of examining idiosyncratic volatility when considering the benefits of portfolio diversification. Since industry-level idiosyncratic volatility can impact investors as much as systematic volatility, idiosyncratic risk becomes an important measure to consider for the additional information it may provide. Furthermore, idiosyncratic volatility affects the risk level of arbitrageurs who employ trading strategies aimed at exploiting mispricing of individual stocks (Stambaugh & Yuan, 2017).

The results of my analysis revealed interesting findings at the industry level. These findings provide evidence that partisan conflict has a significant and negative impact on industry-level volatility. With respect to the first two industry politically sensitive measures, high politically sensitive industries across Republican and Democratic presidencies (Addoum & Kumar, 2016) and traditional sin stock industries (Hong & Kostovetsky, 2012), the regression analyses reported that PCI has a statistically significant negative correlation with both realized volatility and idiosyncratic risk. These high politically sensitive and sin stock industries have a significantly higher industry-level volatility. Moreover, my analyses revealed that PCI has a greater dampening effect on the volatility of these high politically sensitive and sin stock industries than it does on other industries, regardless of the volatility measure used. These findings support the idea that fewer policy decisions are made and less gets changed at the federal level under periods of partisan conflict. Correspondingly, markets calm down and display lower volatility. These results are robust after including industry dummies in the regression. When using the set of politically sensitive industries related to more individual presidential election outcomes (Herron et al., 1999; Julio & Yook, 2012), however, PCI was not shown to have additional impact on this classification of industries. This last finding suggests that political sensitivity is dynamic and that certain industries are susceptible to change due to different political events. Future studies on this topic are warranted.

Literature Review and Hypothesis Development

Politics and Partisan Conflict

Prior to the creation of the PCI, a broad body of literature studied the impact of political polarization and ensuing partisan conflict on government policy changes. The divided government hypothesis forwards the idea that increased polarization of political ideologies spurs higher levels of partisan conflict that can ultimately impact policy gridlock. In support of this hypothesis, Kelly (1993) showed how a divided government results in fewer policies being enacted. Edwards et al. (1997) found a greater percentage of important legislation failed to pass under a divided versus unified government. Similarly, Sojli and Tham (2015) found that divided governments negatively impact economic policy enactment. The party polarization hypothesis goes a step further to argue that higher party polarization becomes a more important factor (over divided governing majorities) when it comes to policy enactment. Under this hypothesis, Jones (2001) showed how greater political polarization drives legislative gridlock. Binder (2003, 2014) also attributed increased political polarization and gridlock at the federal level with increased instances of stalled policy implementation. McCarty (2011) found that a divided political stance makes policy enactment more difficult. McCarty et al. (2016) reported how delayed government policymaking is a by-product of growing political polarization at the federal level. Given this information, it follows that higher levels of partisan conflict mean less policy enactment and hence more policy stability (Tsebelis, 1995), resulting in less volatility in equity markets.

The effects of partisan conflict, however, are not equally distributed across industries. Partisan control and divergent ideologies can impact industries differently, depending on their political sensitivity (Herron et al., 1999). Despite the lack of literature focused specifically on partisan conflict's impact on politically sensitive industries, previous studies have considered the uneven role that politics plays among various industry factors. Political connections at the industry-level can affect such aspects as earnings forecasts and corruption by making firm disclosures more obscure (Chen et al., 2010). Political connections also help firms get information about legislative changes, helping their investment outcomes (Wellman, 2017). Political contributions by firms have been positively associated with future abnormal returns (Cooper et al., 2010), while political uncertainty has been linked to increased research and development efforts (Atanassov et al., 2015) and firm risk-taking and performance (Akey & Lewellen, 2016). Addoum and Kumar (2016) identified politically sensitivity industries whose stock returns are affected by changes in presidency. Yu et al. (2018) reported economic policy uncertainty (EPU), as a proxy for political uncertainty, was a driver in industry-level volatility.

My research uses the PCI developed by Azzimonti (2018) to measure political conflict. My choice to use the PCI was inspired by the prolific use of content-based analysis in academic research in recent years, especially with respect to gauging political uncertainty and risk, and the novelty of this particular measure. Given that the research in this area is in its nascent stage, few studies on this topic already exist. To my knowledge, no study has yet examined the effects of political conflict using PCI on industry-level volatility. While political polarization is not directly measured by PCI, it constitutes a large determinant of the index (Azzimonti, 2018). Previous literature has shown how PCI is associated with lower levels of corporate investment (Azzimonti, 2018). Huang and Wang (2018) found that PCI has predictive power for market returns in certain government-regulated industries. Qin et al. (2020) studied the relationship between PCI and gold and found that higher PCI leads to higher gold prices. Jiang et al. (2020) studied PCI and the oil and gold industries. Apergis et al. (2021) examined the relationship between PCI and international oil prices, claiming that investors in the oil industry and other sectors may change investment strategies as a result of increasing political polarization; their results reported a positive correlation between PCI and oil prices. Whereas PCI has been linked to industry-specific returns for individual industries such as oil and gold, the effects of PCI on politically sensitive market volatility and on the volatility of sin stocks remain a mystery.

Politically Sensitive Industries

For the purpose of this study, I considered three established definitions of politically sensitive industry based on the literature: that of Addoum and Kumar (2016), that of Hong and Kostovetsky (2012), and that of Herron et al. (1999) and Julio and Yook (2012). Although previously discussed studies taken together categorize a fair number of industries as being potentially influenced by politics, one study in particular stands out for its measure of political sensitivity over a prolonged period of time and under both Republican and Democratic presidencies. Addoum and Kumar (2016) categorized the industries most impacted over time by a change in the political climate, both positively and negatively. Moreover, Addoum and Kumar (2016) employed the same Fama and French 48-industry classification (French, n.d.) in their study as I use here, allowing for greater consistency in industry definitions. Following the classification from this study, therefore, of the 48 Fama and French industries, 19 are politically sensitive: Guns (Defense), Healthcare, Smoke (Tobacco), Oil, Soda, Lab Equipment, Boxes, Food, Construction, Real Estate, Gold (Precious Metals), Textiles, Chips, Books, Finance, Paper (Business Supplies), Aero (Aircraft), Computers, Beer (Alcohol).

The second seminal study used in this analysis, Hong and Kostovetsky (2012), explored the politically charged sin stocks in terms of political contributions and socially responsible investing. Three industries in this category are categorized by the Fama and French 48: Guns (Defense), Smoke (Tobacco), and Beer (Alcohol). Furthermore, these same industries appeared the most often over time in all the politically sensitive industry groupings in Addoum and Kumar (2016), adding support to their inclusion as a measure.

The final industry classification, that of Herron et al. (1999), originally stemmed from an analysis of those sectors of the economy most impacted by the 1992 presidential election. More specifically, Herron et al. (1999) examined the policy preferences of the three 1992 presidential candidates to discern their impact on the profits of different economic sectors. Notably, their results confirmed political sensitivity to 1992 presidential platforms in 15 out of 74 sectors (Herron et al., 1999). Furthermore, the authors attributed political sensitivity to a divergence of political ideology in the presidential platforms. Their findings suggested that partisan conflict, in a more general sense, could impact politically sensitive industries through policy disagreement. Although sectors are categorized differently than industries, Julio and Yook (2012) subsequently established a list of industries based on the Herron et al. (1999) study. The popularity of the industry measure in literature led me to include it here as one of my politically sensitive groupings. There are seven Julio and Yook (2012) politically sensitive industries: Drugs, Guns, Healthcare, Smoke, Oil, Telecommunications, and Transportation.

Industry-Level Realized Volatility and Idiosyncratic Risk

Measures of industry-level volatilities are of particular interest to those investors who are not as well diversified in their portfolios as financial theory suggests they should be (Campbell et al., 2001). Campbell et al. (2001) claimed that changes in idiosyncratic volatility at the industry level impacts under-diversified investors as much as systematic market volatility, making both measures important to consider. Malkiel and Xu (2002) also argued that idiosyncratic risk provides a useful measure for those investors that do not hold a diversified market portfolio. In addition, industry-level volatility affects the risk level of arbitrageurs who employ trading strategies that exploit the mispricing of individual stocks (Stambaugh & Yuan, 2017). Goyal and Santa-Clara (2003) claimed that idiosyncratic, not systematic, risk was a driving force in determining average stock risk. Boutchkova et al. (2012) considered both systematic volatility and idiosyncratic risk in their examination of political risks affecting the volatility of industry returns on a global level. Finally, examining industry-specific risk allows for a more in-depth study of those industries that serve as lead indicators of overall market volatility (Cheong et al. 2011). Given the prevalence of political conflict at the federal level, its impact on policy enactment, and the importance of evaluating forces that affect industry-level risk, this study provides timely information on this topic by examining the effects of partisan conflict on high politically sensitive industries.

Hypotheses

My hypotheses focus on the effects of partisan conflict on volatility at the industry level, particularly with respect to politically sensitive industries. At the industry level, higher partisan conflict leads to less decision-making, which means fewer changes to enacted policies that could affect industry, and by extension, less return volatility. Therefore, I expect that partisan conflict has a negative impact on industry-level volatility.

H_1: Partisan conflict is negatively associated with industry-level volatility.

H_{1a}: Partisan conflict is negatively associated with industry-level realized volatility.

H_{1b}: Partisan conflict is negatively associated with industry-level idiosyncratic risk.

More specifically, I expect a stronger negative impact on industry-specific volatility for politically sensitive industries that are affected to a greater extent by the political arena and policymaking. I thereby propose the following hypotheses:

H_2: Partisan conflict has a greater negative impact on industry-level volatility for high politically sensitive industries.

H_{2a}: Partisan conflict has a greater negative impact on industry-level realized volatility for high politically sensitive industries.

H_{2b}: Partisan conflict has a greater negative impact on industry-level idiosyncratic risk for high politically sensitive industries.

Data

The sample period for this study extends from January 1985 to March 2021 to capture key variables that are not available prior to January 1985. The PCI by Azzimonti (2018) is the main variable used in this study; it is a recent content-based measure that calculates its index from a semantic search of newspaper articles. The goal of the PCI is to identify situations of political discord by quantifying the frequency of articles that contain keywords of political disagreement among lawmakers on government policies. These expressions of disagreement occur at the federal level and ultimately signal varying levels of partisan conflict. While PCI does not directly represent a political polarization measure per se, polarization of political ideologies is a major contributing factor to the index's performance (Azzimonti, 2018). In other words, increased political polarization should naturally translate into a higher level of partisan conflict as differing ideologies create roadblocks to efficient decision-making. The article search for this index was performed in Factiva, which is a digitized platform containing all major newspapers. I retrieved this index from the Federal Reserve Bank of Philadelphia website (*Partisan conflict index*, 2021).

Control Variables

The first control variable I included is the monthly Baker et al. (2012, 2016) three-component EPU index. This index has been shown to impact market- and industry-level volatility (Chowdhury et al., 2022; Liu & Zhang, 2015; Li et al, 2019). The first component of this index is a news-based measure of 10 leading U.S. newspapers. This component tracks words related to "economic," "policy," and "uncertainty" used together in the same article. Baker et al. (2012) then constructed a normalized index based on these articles. The second component of the index includes temporary tax code provision lists at the federal level, collected by the Congressional Budget Office (CBO) for the purpose of constructing annual dollar-weighted numbers of those provisions that are due to expire 10 years hence. Baker et al. (2012) measured the level of uncertainty by the direction of the future federal tax code. The final component of the EPU measure surveys disagreement among economic forecasters based on information taken from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The disagreements examined are based on future inflation gauged by the consumer price index and future government expenditures. To form the overall EPU three-component index, 50% weight is devoted to the newspaper-based measure, and the remaining 50% is split equally between expiring tax code provisions and the disagreement among economic forecasters. The EPU index has undergone numerous robustness checks to assure the reliability of the measure (Baker et al., 2012, 2016). EPU data comes from the "Economic Policy Uncertainty" (n.d.) website. In addition to EPU, I controlled for two political variables shown to have an effect on volatility measures. Given past research that has shown how presidential party affects stock market returns and volatility (e.g., Leblang & Mukherjee, 2005; Pástor & Veronesi, 2020; Santa-Clara & Valkanov, 2003; Sy & Al Zaman, 2011), I included a dummy variable to represent party of the president in office during the sample period (*Political parties of the presidents*, n.d). Similarly, a state of political gridlock versus harmony in Washington has also been shown to have effects on stock market performance (Beyer et al., 2006, 2015; Huang & Wang, 2018; Lobão & Guimarães, 2019). Political gridlock is defined as a state in which the party in the White House and the controlling parties in both the Senate and the House of Representatives are not all the same (Beyer et al., 2006). In a state of political harmony, all controlling parties are the same. Therefore, political gridlock versus harmony is also a dummy variable, where a value of 1 represents periods of political gridlock and a value of 0 represents political harmony. I found information for the majority party in both the U.S. House of Representatives (United States House of Representatives, n.d.) and the U.S. Senate (United States Senate, n.d.). From this information I noted the periods during which political gridlock occurred (all controlling parties at the federal level were not the same).

Lastly, following the literature (e.g., Christiansen et al., 2012; Engle et al., 2013; Paye, 2012; Schwert, 1989), I included other macroeconomic measures related to market volatility. All data for the following control variables were collected from the Federal Reserve of St. Louis website (Federal Reserve Bank of St. Louis, 2021). The first measure, corporate bond spread (*CBS*), represents the difference in yields between the AAA (Federal Reserve Bank of St. Louis, *Moody's seasoned Aaa corporate bond yield*, 2021) and the BAA-rated corporate bonds (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield*, 2021). Default yield spread (*DYS*) measures the difference between the yield on BAA-rated corporate bonds and the yield on long-term government bonds (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield relative to yield on 10-year treasury constant maturity,* 2021). Industrial production growth (*IPG*) measures the change in the total output manufactured in utility, mining, and manufacturing from one month to the next (Federal Reserve Bank of St. Louis, *Industrial production: total index*, 2021). Inflation growth (*PPIG*) is calculated using monthly Producer Price Index data (Federal Reserve Bank of St. Louis, *Producer price index by commodity: All commodities*, 2021); it represents the change in inflation from one period to the next. Finally, term spread (*TS*) is a measure of the difference between the long-term yield on government bonds and the 3-month Treasury bill rate (Federal Reserve Bank of St. Louis, *10-year treasury constant maturity minus 3-month treasury constant maturity*, 2021). Data for all control variables are monthly and span the dates of the study: January 1985 to April 2021.[1]

Following Boutchkova et al. (2012) and Chen et al. (2010), I also controlled for industry-level characteristics when investigating the effects of partisan conflict on industry-level volatility measures (realized volatility and idiosyncratic risk). These variables include the lag of the respective volatility measure used, in this case realized and idiosyncratic volatility (*LLRVInd* and *LIdioR*), logged industry size (*Lsize)*, and leverage (*Lev*). Industry size is calculated as the sum of the total assets of all firms in each industry. Industry leverage is the weighted average ratio of long-term debt over the total assets of all firms in each industry. Firm-level data was obtained from Compustat through the University of Pennsylvania Wharton Research Data Services

[1] Additional variables were initially included in this analysis, such as inflation as measured by the consumer price index and earnings (Shiller, 2000), but due to concerns over multicollinearity in the data, these variables were subsequently eliminated.

website (2021). I used Standard Industrial Classification codes to identify the firms in each of the Fama and French 48 industries (French, n.d.).

Methodology

Impact of Partisan Conflict on Industry-Level Realized Volatility and Idiosyncratic Risk

I first examined the impact of partisan conflict on industry-level volatility. To test hypotheses H_{1a} and H_{1b}, I employed ordinary least squares (OLS) regression with robust standard errors. I regressed the volatility measure (log of realized volatility and idiosyncratic risk, respectively) on its one-period lag, on PCI, and on a vector of macro-level and industry-level control variables. My regression model is represented by the following equation:

$$VOL_{i,t} = \alpha + \rho VOL_{i,t-1} + \beta PCI_t + \gamma X_{i,t} + \Theta Y_{i,t} + \varepsilon_{i,t} \quad (1)$$

Following Christiansen et al. (2012), Paye (2012), and Nonejad (2017), I used the natural logarithm of realized volatility. The first $VOL_{i,t}$ measure used $LRVInd_{i,t}$ denoting the natural logarithm of industry-level realized volatility for industry *i* in period *t*. Using the natural log of volatility serves to normalize the data for this regression. Several seminal studies found realized volatility to be an accurate measure of actual volatility (Andersen & Bollerslev, 1998; Andersen et al., 2000, 2001; Barndorff-Nielsen & Shephard, 2002; Schwert, 1989). Daily realized volatility is derived from realized variance and is calculated using the sum of intraday squared returns. I calculated the values for realized volatility at the industry level. I calculated industry-specific volatility using returns from the Fama and French 48 industry portfolios. I obtained daily industry returns from the Kenneth R. French website using the Fama and French 48 industry classification (French, n.d.). I calculated industry-level monthly realized volatility by summing the daily squared industry returns. I estimated volatility in the following manner (Schwert, 1989):

$$\sigma_{i,t}^2 = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{2}$$

where N_t represents the number of days in month t and $r_{i,t}$ is the daily return of industry i in month t. Industry-level realized volatility is then measured as the square root of $\sigma_{i,t}^2$.

$$RVInd_{i,t} = \sqrt{\sigma_{i,t}^2} \tag{3}$$

The second volatility measure, $IdioR_{i,t}$, represents idiosyncratic risk. Industry-specific idiosyncratic risk is calculated in relation to systematic stock returns. Consistent with Campbell et al. (2001), Rahman (2009), and Cheong et al. (2011), I determined the industry-specific residual by regressing daily industry returns ($r_{i,t}$) on the daily market risk premium ($r_{m,t}$). I ran the following regression on each industry return of the Fama and French 48 industry portfolio:

$$r_{i,t} = \alpha_i + \beta_i * (r_{m,t}) + \varepsilon_{i,t} \tag{4}$$

I captured the monthly idiosyncratic risk ($IdioR_{i,t}$) as the standard deviation of daily residuals within the month. In other words, the idiosyncratic risk of industry i is equal to the standard deviation of the residuals. I performed all analyses in Stata.

Consistent with past studies (Goodell & Vähämaa, 2013; Paye, 2012), I included the lagged values of volatility ($LLRVInd_{i,t}$ and $LIdioR_{i,t}$) in my models as controls for the previous month's volatility effect. My main independent variable is the partisan conflict index (PCI_t) from Azzimonti (2018). The efficient market hypothesis (Fama, 1970) forwards the idea that effects on markets will be quickly accounted for in terms of market risk and return. Thus, given the frequency of my measures, I used concurrent versus lagged variables for PCI to examine its contemporaneous effect. In Equation 1, $\gamma X_{i,t}$ represents a vector of macro-level control variables. The first control variable, *EPU*, represents the level of economic policy uncertainty as captured by the Baker et al. (2012, 2016) index. I also included the dummy variable *PP* to reflect party of the president (Belo et al., 2013; Blinder & Watson, 2016; Pástor & Veronesi, 2012, 2013, 2107; Santa-Clara & Valkanov, 2003; Sy & Al Zaman, 2011). A value of 1 represents a Republican president whereas a value of 0 represents a Democrat in office. In addition, based on previous findings regarding the links between political gridlock or a divided government on market returns and volatility (Beyer et al., 2015; Binder, 2003; Füss & Bechtel, 2008; Sojli & Tham, 2015), I included the dummy variable *PG* for periods of political gridlock. A value of 1 signifies months of gridlock and a value of 0 represents months of political harmony. The remaining control variables employed for the macroeconomy are those suggested from prior literature (Engle et al. 2013; Paye, 2012; Schwert, 1989) and detailed previously, namely corporate bond spread (*CBS*), default yield spread (*DYS*), industrial production growth (*IPG*), inflation growth (*PPIG*), and term spread (*TS*). Finally, $\Theta Y_{i,t}$ represents industry-level control variables. I employed logged industry size (*Lsize)*, and leverage (*Lev*) following Boutchkova et al. (2012) and Chen et al. (2010). Industry size represents the sum of the total assets of all firms in each industry. Industry leverage is calculated as the weighted average ratio of long-term debt over the total assets of all firms in each industry.

To test the effects of partisan conflict on high politically sensitive industry volatility (H_2), the regression model is represented by the following equation:

$$VOL_{i,t} = \alpha + \rho VOL_{i,t-1} + \beta_1 PCI_t + \beta_2 HPS_t + \beta_3 HPS_t \, x \, PCI_t + \gamma X_{i,t} + \Theta Y_{i,t} + \varepsilon_{i,t} \qquad (5)$$

where $VOL_{i,t}$ represents the volatility measures detailed previously ($LLRVInd_{i,t}$ and $LIdioR_{i,t}$). I regressed both $VOL_{i,t}$ measures on a one-period lag, on PCI_t, on the high politically sensitive industry dummy (HPS_t), on the interaction of HPS and PCI ($HPS_t \ x \ PCI_t$), and on a vector of macro-level ($\gamma X_{i,t}$) and industry-level ($\Theta_{i,t}$) control variables.

I categorized industries from the Fama and French 48 industry portfolio (French, n.d.) into high politically sensitive versus low politically sensitive industries. For the purpose of this study, I considered three established definitions from the literature for high politically sensitive industry: that of Addoum and Kumar (2016), that of Hong and Kostovetsky (2012), and that of Herron et al. (1999) and Julio and Yook (2012). I created a dummy variable for each of these classifications, *HPS1*, *HPS2*, and *HPS3*, respectively. In each case, the dummy variable assumes a value of 1 for each high politically sensitive industry and a value of 0 for the rest. Following Addoum and Kumar (2016), of the 48 Fama and French industries, 19 are politically sensitive: Guns (Defense), Healthcare, Smoke (Tobacco), Oil, Soda, Lab Equipment, Boxes, Food, Construction, Real Estate, Gold (Precious Metals), Textiles, Chips, Books, Finance, Paper (Business Supplies), Aero (Aircraft), Computers, Beer (Alcohol). Following Hong and Kostovetsky (2012), three industries are politically sensitive: Guns (Defense), Beer (Alcohol), and Smoke (Tobacco). Finally, following Herron et al. (1999) and Julio and Yook (2012), seven industries are considered politically sensitive: Drugs, Guns, Healthcare, Smoke, Oil, Telecommunications, and Transportation. I created an interaction variable between each of the three industry classifications and *PCI* (*PCIxHPS1*, *PCIxHPS2*, *PCIxHPS3*, respectively) to test their interactive effect on the industry-level volatility measures. The vector of macro- and industry-level control variables used in Equation 5 are the same as those detailed in Equation 1. In all regressions, I tested the robustness of the models using the Huber/White sandwich estimator of variance to correct heteroscedasticity. I added industry dummies to control for time-invariant heterogeneity between industries.

Results

Appendix A presents variable definitions for the main variables used in this study. Table 1 shows the summary statistics for the key variables used. The number of observations changes according to the frequency of the measure. Note that in the case of the presidential party dummy variables, the mean is 0.55172. Recalling that a value of 1 refers to a Republican president, therefore, we can see that there was a Republican in office approximately 55% of the time during the sample period. Note that the mean for the political gridlock (*PG*) variable is 0.75862. Recalling that a value of 1 indicates political gridlock, we see that about 76% of the time frame used in this study existed under a period of political gridlock.

Table 1

Descriptive Statistics of the Main Variables

Variable	Obs.	*M*	*SD*	Min.	Max.
LRVInd	20,880	1.64254	0.49275	-0.0302	3.9315
LLRVInd	20,880	1.64095	0.49254	-0.0302	3.9315
IdioR	20,880	0.83999	0.56052	0.10896	7.21355
LIdioR	20,880	0.83833	0.55996	0.09286	7.21355
PCI	435	110.095	34.4151	34.74	271.29
EPU	435	113.275	39.6669	57.2026	350.46
PP	435	0.55172	0.49733	0	1
PG	435	0.75862	0.42793	0	1
Lev	20,880	0.25595	0.10331	0.02804	0.68063
Lsize	20,880	12.0175	1.78724	7.99019	18.0513
CBS	435	-0.9885	0.37049	-3.38	-0.55
DYS	435	2.33053	0.70057	1.29	6.01
IPG	434	0.00141	0.00998	-0.1359	0.06196
PPIG	434	0.00174	0.00974	-0.0533	0.02986
TS	435	1.70349	1.12307	-0.7	3.69

Note. This table reports the descriptive statistics for the key variables used in this study. Obs. = observations; M = mean; SD = standard deviation; Min. = minimum value; Max. = maximum value. *LRVInd* represents the log of monthly market-level realized volatility. *LLRVInd* is the log of *LRVInd* lagged one period. *IdioR* represents idiosyncratic risk, and the lag of idiosyncratic risk is denoted by *LIdioR*. *PCI* is measured by the Azzimonti (2018) partisan conflict index. *EPU* is measured by the Baker et al. (2012, 2016) economic policy uncertainty index. Presidential party (*PP*) is a dummy variable where 1 = a Republican in office and 0 = a Democrat. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony. Industry leverage (*Lev*) is the weighted average ratio of long-term debt over the total assets of all firms in each industry. Log of industry size *(Lsize)* is the logarithm of the sum of the total assets of all firms in each industry. *CBS* represents corporate bond spread, the difference between AAA and BAA corporate bond yields. *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate.

To address concerns of multicollinearity, Table 2 displays the correlation coefficient matrix between measures. The correlation between the log of realized volatility (*LRVInd*) and its lagged measure (*LLRVInd*) was high at 0.7107, as expected, as was the correlation between idiosyncratic risk (*IdioR*) and its lag (*LIdioR*) at 0.7501. The remaining correlations were low enough to not cause concern. Correlations between *PCI* and all volatility measures were significant at a level of 5%. There was significant correlation between *EPU* and *PCI*, but the correlation was low at 0.2322. In addition, *PCI* was significantly correlated with both presidential party (*PP*) and with political gridlock (*PG*), both at low levels (-0.1695 and 0.2463, respectively). As a robustness check, Appendix B contains a variance inflation factor test that also satisfies the condition of no multicollinearity.

Next, I moved to the industry-level analysis. Table 3 reports the summary statistics for the Fama and French 48 industry portfolios. These statistics display the mean and standard deviation of the log of realized volatility for each industry (*LRVInd*), the log of size (*Lsize*), and leverage (*Lev*). The Political Sensitivity column reflects classifications into high or low levels of industry political sensitivity based on Addoum and Kumar’s (2016) work (*HPS1*), Hong and Kostovetsky’s (2012) work (*HPS2*), and finally the works of Herron et al. (1999) and Julio and Yook (2012), which are noted as *HPS3*.

Table 2

Correlation Matrix of the Main Variables

	LRVInd	*LLRVInd*	*IdioR*	*LIdioR*	*PCI*	*EPU*	*PP*	*PG*	*Lev*	*Lsize*	*CBS*	*DYS*	*IPG*	*PPIG*	*TS*
LRVInd	1.0000														
LLRVInd	0.7107*	1.0000													
IdioR	0.7514*	0.5863*	1.0000												
LIdioR	0.5852*	0.7517*	0.7501*	1.0000											
PCI	-0.1447*	-0.1505*	-0.1457*	-0.1567*	1.0000										
EPU	0.3294*	0.3103*	0.1588*	0.1411*	0.2322*	1.0000									
PP	-0.0299*	-0.0330*	-0.0397*	-0.0400*	-0.1695*	0.0662*	1.0000								
PG	0.0182*	-0.0082	0.0165*	-0.0055	0.2463*	0.0787*	0.0480*	1.0000							
Lev	-0.0161*	-0.0159*	0.0289*	0.0303*	0.0465*	0.0437*	0.0020	0.0356*	1.0000						
Lsize	-0.0488*	-0.0493*	-0.1947*	-0.1957*	0.1664*	0.1041*	-0.0853*	-0.0364*	-0.2322*	1.0000					
CBS	-0.3599*	-0.3946*	-0.1768*	-0.1932*	0.1015*	-0.4169*	-0.1943*	-0.0044	0.0245*	-0.0080	1.0000				
DYS	0.4630*	0.4877*	0.2735*	0.2849*	0.0791*	0.5109*	-0.0945*	-0.0344*	0.0148*	0.1476*	-0.7968*	1.0000			
IPG	-0.1555*	-0.1758*	-0.1296*	-0.1504*	0.0594*	-0.1238*	-0.0836*	-0.0336*	-0.0149*	-0.0341*	0.2772*	-0.2701*	1.0000		
PPIG	-0.1193*	-0.1416*	-0.0800*	-0.0863*	0.0221*	-0.0832*	0.0054	-0.1466*	0.0038	0.0068	0.2422*	-0.2223*	0.2585*	1.0000	
TS	0.0030	0.0164*	-0.0780*	-0.0649*	0.0768*	0.1333*	-0.0885*	-0.2566*	-0.0517*	-0.0511*	-0.2427*	0.3106*	0.0458*	-0.0004	1.0000

Note: LRVInd is the log of the monthly realized volatility for each industry. *LLRVInd* is the one period lag of *LRVInd*. *IdioR* is industry-level idiosyncratic risk. *LIdioR* is the one period lag of *IdioR*. Partisan conflict is measured by the Azzimonti (2018) partisan conflict index (*PCI*). Economic policy uncertainty is measured by the Baker et al. (2012, 2016) *EPU* index. *PP* represents presidential party, where 1 = Republican and 0 = Democrat in office. *PG* stands for political gridlock, where 1 = gridlock and 0 = harmony. Leverage (*Lev*) is the total long-term debt over total assets aggregated at industry level. *Lsize* is the logarithm of industry size (total assets). *CBS* is the corporate bond spread between AAA versus BAA-rated corporate bond yields. *DYS* is the return spread between long-term corporate bonds and long-term government bond yields. *IPG* is the industry production growth. *PPIG* is the inflation (producer price index) growth rate. *TS* is the term spread represented by the difference between the long-term yield on government bonds and the Treasury bill rate.

*$p < 0.05$.

Table 3

Summary Statistics of Industry-Level Variables

Industry	*LRVInd*		*Lsize*		*Lev*		Political Sensitivity		
	M	*SD*	*M*	*SD*	*M*	*SD*	HPS1	HPS2	HPS3
Aero	1.65	0.43	11.97	0.88	0.20	0.04	High	Low	Low
Agric	1.66	0.46	9.62	1.02	0.21	0.08	Low	Low	Low
Autos	1.80	0.42	13.69	1.08	0.27	0.09	Low	Low	Low
Banks	1.60	0.51	16.40	1.47	0.16	0.07	Low	Low	Low
Beer	1.49	0.42	11.40	1.09	0.25	0.05	High	High	Low
BldMt	1.54	0.45	11.85	0.74	0.27	0.03	Low	Low	Low
Books	1.51	0.46	10.57	0.71	0.29	0.09	High	Low	Low
Boxes	1.62	0.40	10.54	0.68	0.38	0.08	High	Low	Low
BusSv	1.60	0.45	13.12	1.28	0.19	0.04	Low	Low	Low
Chems	1.56	0.45	12.73	0.75	0.23	0.03	Low	Low	Low
Chips	1.80	0.46	12.66	1.32	0.15	0.04	High	Low	Low
Clths	1.61	0.43	10.80	0.97	0.20	0.05	Low	Low	Low
Cnstr	1.79	0.46	11.09	0.82	0.30	0.05	High	Low	Low
Coal	2.17	0.53	9.54	1.17	0.33	0.08	Low	Low	Low
Comps	1.80	0.45	12.49	0.93	0.15	0.05	High	Low	Low
Drugs	1.50	0.39	12.82	1.30	0.16	0.06	Low	Low	High
ElcEq	1.71	0.40	12.10	0.95	0.14	0.03	Low	Low	Low
FabPr	1.77	0.49	8.73	0.45	0.26	0.06	Low	Low	Low
Fin	1.59	0.58	14.57	1.61	0.16	0.06	High	Low	Low
Food	1.31	0.38	12.39	0.74	0.24	0.04	High	Low	Low
Fun	1.79	0.45	11.39	0.96	0.44	0.09	Low	Low	Low
Gold	2.27	0.37	10.69	1.49	0.16	0.04	High	Low	Low
Guns	1.67	0.40	10.14	0.76	0.22	0.06	High	High	High
Hlth	1.64	0.40	11.43	1.13	0.39	0.06	High	Low	High
Hshld	1.38	0.40	11.99	0.98	0.20	0.05	Low	Low	Low
Insur	1.42	0.48	14.90	1.34	0.05	0.02	Low	Low	Low
LabEq	1.64	0.45	11.01	1.07	0.17	0.05	High	Low	Low
Mach	1.60	0.48	12.41	0.81	0.22	0.04	Low	Low	Low
Meals	1.50	0.39	11.44	0.90	0.38	0.09	Low	Low	Low
MedEq	1.54	0.37	11.51	1.30	0.18	0.05	Low	Low	Low
Mines	1.83	0.48	11.25	1.71	0.21	0.04	Low	Low	Low
Oil	1.70	0.45	14.26	1.05	0.18	0.04	High	Low	High
Other	1.56	0.48	11.19	1.42	0.42	0.08	Low	Low	Low
Paper	1.46	0.41	12.04	0.72	0.29	0.04	High	Low	Low
PerSv	1.59	0.40	10.97	0.99	0.37	0.06	Low	Low	Low
RlEst	1.51	0.52	10.96	1.04	0.41	0.10	High	Low	Low
Rtail	1.51	0.42	13.31	0.89	0.24	0.03	Low	Low	Low
Rubbr	1.48	0.41	10.05	0.75	0.38	0.08	Low	Low	Low

Industry	LRVInd		Lsize		Lev		Political Sensitivity		
	M	*SD*	*M*	*SD*	*M*	*SD*	HPS1	HPS2	HPS3
Ships	1.83	0.39	9.53	0.79	0.26	0.08	Low	Low	Low
Smoke	1.70	0.43	11.25	0.85	0.30	0.11	High	High	High
Soda	1.69	0.44	10.88	1.11	0.25	0.05	High	Low	Low
Steel	1.82	0.51	12.17	0.86	0.21	0.03	Low	Low	Low
Telcm	1.46	0.44	14.30	0.94	0.32	0.28	Low	Low	High
Toys	1.80	0.40	10.49	0.77	0.16	0.05	Low	Low	Low
Trans	1.58	0.40	13.20	0.92	0.28	0.03	Low	Low	High
Txtls	1.64	0.53	9.70	0.31	0.28	0.08	High	Low	Low
Util	1.19	0.47	14.48	0.78	0.34	0.02	Low	Low	Low
Whlsl	1.39	0.43	12.37	0.85	0.26	0.03	Low	Low	Low

Note. This table presents the summary statistics of the industry level variables. The Fama and French 48 industry portfolio (French, n.d.) is listed in alphabetical order by industry, which includes aircraft (Aero), agriculture (Agric), automobiles and trucks (Auto), banking (Banks), beer & liquor (Beer), construction materials (BldMt), printing and publishing (Books), shipping containers (Boxes), business services (BusSv), chemicals (Chems), electronic equipment (Chips), apparel (Clths), construction (Cnstr), coal (Coal), computers (Comps), pharmaceutical products (Drugs), electrical equipment (ElcEq), fabricated products (FabPr), trading (Fin), food products (Food), entertainment (Fun), precious metals (Gold), defense (Guns), healthcare (Hlth), consumer goods (Hshld), insurance (Insur), measuring and control equipment (LabEq), machinery (Mach), restaurants, hotels, motels (Meals), medical equipment (MedEq), non-metallic and industrial metal mining (Mines), petroleum and natural gas (Oil), almost nothing (Other), business supplies (Paper), personal services (PerSv), real estate (RlEst), retail (Rtail), rubber and plastic products (Rubbr), shipbuilding, railroad equipment (Ships), tobacco products (Smoke), candy & soda (Soda), steel works, etc. (Steel), communication (Telcm), recreation (Toys), transportation (Trans), textiles (Txtls), utilities (Util), wholesale (Whlsl). *LRVInd* is the log of the monthly realized volatility for each industry. *Lsize* is the logarithm of industry size (total assets). *Lev* is the total long-term debt over total assets aggregated at industry level. *HPS1* represents high politically sensitive industries identified by Addoum and Kumar (2016). *HPS2* represents high politically sensitive sin stock industries identified by Hong and Kostovetsky (2012). *HPS3* represents high politically sensitive industries identified by Herron et al. (1999) and Julio and Yook (2012).

My first analysis tests the impact of partisan conflict on industry volatility overall, both realized and idiosyncratic. I expected that, similar to its effect on market-level volatility, partisan conflict would have a negative (dampening) impact on these measures of volatility. Tables 4 and 5 report the results of this analysis. Table 4 regresses the log of industry-level volatility (*LRVInd*) on *PCI* and the other variables, while Table 5 uses idiosyncratic risk (*IdioR*) as the response variable. Models 2 and 4 in both panels use industry dummies. Table 4 shows that the lagged measure of industry-level realized volatility was positive and significant (at the 1% level) in all models, as expected. All models showed that partisan conflict has a significant and negative impact on volatility at the 1% level, even after controlling for lagged volatility, all control variables, and industry dummies. This finding is in support of H_{1a}. In Models 3 and 4, *EPU* was significant and positive (at the 1% level), and the negative impact of *PCI* on volatility was higher than the positive impact of *EPU*, as measured by the magnitude of the coefficients (-0.0015 versus 0.0013 and -0.0021 versus 0.0014, respectively). There was no significant effect of presidential party in any of the models. Political gridlock showed a significant and positive correlation (at the 1% level). Consistent with previous literature (Boutchkova, 2012; Chen, 2010), there was a significant size effect at the 1% level in Models 3 and 4. Using industry dummies made the leverage effect (*Lev*) insignificant and changed the logged size variable (*Lsize*) coefficient from a significantly negative to a significantly positive value. Also consistent with the literature, corporate bond spread and default yield spread were significant and positive (at the 1% level) in Models 3 and 4. Term spread was negative and significant (at the 1% level). Industrial production and inflation growth, however, did not represent significant factors impacting realized volatility.

Table 5 reports that the lagged measure of idiosyncratic risk was positive and significant (at the 1% level) in all models, as expected. In addition, after controlling for lagged volatility, all control variables, and industry dummies in all models, *PCI* had a significant and negative impact on volatility at the 1% level. This result supports H_{1b}. In Models 3 and 4, *EPU* was significant and positive (at the 1% level). Once again, a noteworthy finding is that the negative impact of partisan conflict on idiosyncratic risk was greater than the positive impact of economic policy uncertainty, as measured by the magnitude of the coefficients in Models 3 and 4 (-0.0010 versus 0.0007 and -0.0018 versus 0.0007, respectively). There was no significant presidential party effect in any of the models. Political gridlock showed a significant and positive correlation (at the 1% level). Consistent with previous literature (Boutchkova, 2012; Chen, 2010), there was a significant leverage and size effect at the 1% level in Model 3, but these effects became insignificant with the inclusion of industry dummies in Model 4. Furthermore, the use of industry dummies in Model 4 changed the size coefficient from a negative to a positive value. Consistent with the literature, corporate bond spread and default yield spread were both significant and positive (at the 1% level) in both Models 3 and 4. Term spread was negative and significant (at the 1% level). As in Table 4, in Table 5 industrial production and inflation growth did not represent significant factors impacting idiosyncratic risk.

Table 4

Impact of Partisan Conflict on Industry-Level Volatility: Realized Volatility

Variable	Model 1	Model 2	Model 3	Model 4
LLRVInd	0.7050***	0.6548***	0.5810***	0.4840***
	(141.43)	(121.24)	(97.12)	(76.42)
PCI	-0.0006***	-0.0007***	-0.0015***	-0.0021***
	(-7.84)	(-9.57)	(-17.03)	(-22.92)
Lev			-0.1480***	-0.0343
			(-6.27)	(-0.79)
Lsize			-0.0163***	0.0184***
			(-11.29)	(4.75)
EPU			0.0013***	0.0014***
			(12.86)	(14.65)
PP			-0.0018	-0.0062
			(-0.35)	(-1.28)
PG			0.0409***	0.0574***
			(7.38)	(10.33)
CBS			0.1450***	0.1130***
			(11.63)	(8.95)
DYS			0.1800***	0.1820***
			(24.48)	(23.48)
IPG			0.1600	0.1580
			(0.50)	(0.52)
PPIG			0.4270	0.2110
			(1.57)	(0.79)
TS			-0.0267***	-0.0235***
			(-11.32)	(-9.84)
Constant	0.5468***	0.6421***	0.6850***	0.3930***
	(45.66)	(31.85)	(29.57)	(8.56)
Industry Dummies	No	Yes	No	Yes
Adjusted R^2	0.506	0.527	0.543	0.570
F-statistic	10,242	470.3	2,010.9	480.4

Note. This table reports the results of regressing the log of industry-level realized volatility (*LRVInd*) on *PCI* (partisan conflict index) and the other variables. All models have 20,880 observations. Models 1 and 3 use an overall measure of industry-level realized volatility, while Models 2 and 4 additionally use industry dummies. Leverage (*Lev*) is the total long-term debt over total assets aggregated at industry level. *Lsize* is the logarithm of industry size (total assets). *EPU* is the economic policy uncertainty index. *PP* represents presidential party, where 1 = Republican and 0 = Democrat in office. *PG* stands for political gridlock, where 1 = gridlock and 0 = harmony. *CBS* is the corporate bond spread between AAA versus BAA-rated corporate bond yields. *DYS* is the return spread between long-term corporate bonds and long-term government bond yields. *IPG* is the industry production growth. *PPIG* is the inflation (producer price index) growth rate. *TS* is the term spread represented by the difference between the long-term yield on government bonds and the Treasury bill rate. Robust *t*-statistics are reported in parentheses.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 5

Impact of Partisan Conflict on Industry-Level Volatility: Idiosyncratic Risk

Variable	Model 1	Model 2	Model 3	Model 4
LIdioR	0.7454***	0.6256***	0.6810***	0.5350***
	(72.72)	(56.90)	(62.01)	(45.54)
PCI	-0.0005***	-0.0008***	-0.0010***	-0.0018***
	(-6.33)	(-10.66)	(-9.45)	(-16.13)
Lev			-0.1180***	-0.0387
			(-4.26)	(-0.69)
Lsize			-0.0285***	0.0025
			(-16.92)	(0.60)
EPU			0.0007***	0.0007***
			(5.33)	(6.23)
PP			-0.0009	-0.0048
			(-0.15)	(-0.84)
PG			0.0250***	0.0422***
			(3.99)	(6.72)
CBS			0.1690***	0.1750***
			(9.56)	(9.94)
DYS			0.1490***	0.1740***
			(16.49)	(18.32)
IPG			0.0598	-0.3210
			(0.13)	(-0.76)
PPIG			0.0468	-0.1070
			(0.12)	(-0.29)
TS			-0.0337***	-0.0367***
			(-12.96)	(-13.72)
Constant	0.2678***	0.3904***	0.5330***	0.2650***
	(21.61)	(17.58)	(18.55)	(5.20)
Industry Dummies	No	Yes	No	Yes
Adjusted R^2	0.562	0.592	0.580	0.615
F-statistic	2,831.3	217.5	635.6	211.5

Note. This table reports the results of regressing industry-level idiosyncratic risk (*IdioR)* on *PCI* (partisan conflict index) and the other variables. All models have 20,880 observations. Models 1 and 3 use an overall measure of industry-level idiosyncratic risk, while Models 2 and 4 additionally use industry dummies. Leverage (*Lev*) is the total long-term debt over total assets aggregated at industry level. *Lsize* is the logarithm of industry size (total assets). *EPU* is the economic policy uncertainty index. *PP* represents presidential party, where 1 = Republican and 0 = Democrat in office. *PG* stands for political gridlock, where 1 = gridlock and 0 = harmony. *CBS* is the corporate bond spread between AAA versus BAA-rated corporate bond yields. *DYS* is the return spread between long-term corporate bonds and long-term government bond yields. *IPG* is the industry production growth. *PPIG* is the inflation (producer price index) growth rate. *TS* is the term spread represented by the difference between the long-term yield on government bonds and the Treasury bill rate. Robust *t*-statistics are reported in parentheses.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

My second analysis tested the impact of partisan conflict on the realized and idiosyncratic volatility of high politically sensitive industries. I expected that partisan conflict would have a greater impact on politically sensitive industries since these industries are more sensitive to changes in economic policies. For example, the ongoing healthcare and gun control debates should have a higher impact on the healthcare and defense industries. Tables 6-8 report the results of this analysis. Tables 6, 7, and 8 report on each of the three measures of high political sensitivity. Table 6 employs the high politically sensitive industry dummy (*HPS1*) constructed in line with Addoum and Kumar (2016). The high politically sensitive industry dummy (*HPS2*) in Table 8 was calculated based on the Hong and Kostovetsky (2012) sin stock industries. Lastly, in Table 9, the high politically sensitive industry dummy (*HPS3*) was calculated based on the Herron et al. (1999) and Julio and Yook (2012) industry classifications. In their respective tables, each high politically sensitive industry dummy was then interacted with *PCI* to test *PCI*'s effects on the volatility of these industries compared with that of non-sensitive industries. In each table, Models 1 and 2 report the results from regressing the log of industry-level realized volatility (*LRVInd*) on its lagged value, *PCI*, the high politically sensitive industry dummy (*HPS1*, *HPS2*, *HPS3*, respectively), and the interaction between *PCI* and this dummy (*PCI x HPS1*, *PCI x HPS2*, *PCI x HPS3*). Model 2 additionally used industry dummies. Models 3 and 4 regressed *LRVInd* on the aforementioned variables as well as on the other macro- (*EPU, PP, PG, CBS, DYS, IPG, PPIG, TS*) and industry-level variables (*Lev, Lsize*). Model 4 also used industry dummies. Models 5 through 8 of all tables regressed idiosyncratic risk (*IdioR*) on the same variable combinations listed in Models 1 through 4. Models 6 and 8 controlled for industry dummies.

The results from all models in Table 6 show that the respective lagged measure of volatility was positive and significant (at the 1% level), as expected. In addition, these models show that, even after controlling for lagged volatility, key macro- and industry-level variables, and industry dummies, partisan conflict had a significant and negative impact on volatility at the 1% level. This impact, as measured by the coefficient, was greater for models that included industry dummies, all else equal.

In addition, all models in Table 6 supported H_{2a} and H_{2b}. The results report that partisan conflict has a stronger negative impact on both realized volatility and idiosyncratic risk for high politically sensitive industries (*HPS1*) than for low politically sensitive industries. In other words, partisan conflict significantly reduces the volatility of high politically sensitive industries more than with other industries. This impact is shown through the significant negative interaction effects (*PCI x HPS1*) at the 5% level in Models 1, 2, and 5 and at the 1% level in the remaining models. Moreover, this impact is greater for models that controlled for industry dummies, all else equal. Table 6 also provides evidence that the grouping of 19 high politically sensitive industries (*HPS1*) has significantly higher realized and idiosyncratic volatility (at the 1% level in all models). In other words, these industries have higher volatility than the remaining industries.

Tables 6-8 all report similar effects from the key macro- and industry-level variables. The variable *EPU* was significant and positive (at the 1% level). There was no evidence that presidential party has a significant effect in any of the models. Political gridlock showed a significant and positive correlation (at the 1% level). Consistent with previous literature (Boutchkova, 2012; Chen, 2010), there was a significant and negative leverage effect (at the 1% level), but only in Models 3 and 7, which did not control for industry dummies. Size effect was significant (at the 1% level) in Models 3, 4, and 7. Controlling for industry dummies changed the size effect coefficient from a negative to a positive value. Of the remaining macro-level control variables and consistent with the literature, corporate bond spread and default yield spread were both significant and positive (at the 1% level) in all models. Term spread was negative and significant (at the 1% level). Industrial production and inflation growth did not represent significant factors in this analysis.

The results from all models in Table 7 also show that the lagged measure of volatility was positive and significant (at the 1% level). In addition, after controlling for lagged volatility, key macro- and industry-level variables, and industry dummies, these models show that *PCI* had a significant and negative impact on volatility at the 1% level. Once again, this impact was greater for models that controlled for industry dummies, all else equal.

All models in Table 7 also support H_{2a} and H_{2b}. Through the interaction variable (*PCI x HPS2*), partisan conflict had a significantly greater negative impact on realized and idiosyncratic volatility for politically sensitive industries (*HPS2*) than for non-politically sensitive industries. This effect was significant at the 10% level in Model 5, at the 5% level in Models 1 and 7, and at the 1% level in Models 2, 3, 4, 6, and 8. In other words, partisan conflict significantly dampens the volatility of high politically sensitive industries more than with other industries. As measured by the coefficient, this interactive effect became greater in magnitude when controlling for industry dummies. Table 7 also provides evidence that high politically sensitive sin stock industries (*HPS2*) have significantly higher realized and idiosyncratic volatility in all models. In other words, these industries have higher volatility than the remaining industries, with the effect becoming greater in magnitude when controlling for industry dummies.

In Table 8, the lagged measure of volatility was positive and significant (at the 1% level) in all models, as expected. In addition, all models showed that, after controlling for lagged volatility returns, *EPU*, key industry- and macro-level variables, *PCI* also had a negative and significant effect on volatility (at the 1% level). As already demonstrated in Tables 6 and 7, the effect's magnitude became greater when controlling for industry dummies, all else equal. Furthermore, of important note, when *EPU* and *PCI* were both included in the models in Tables 6, 7, and 8, the negative impact of *PCI* on volatility was higher than the positive impact of *EPU*, as shown in each case through the magnitude of the coefficient. This finding suggests that partisan conflict may impact industry volatility to a greater degree than does economic policy uncertainty.

None of the models in Table 8 provide evidence in support of H_{2a} or $H_{2b.}$ When using the Herron et al. (1999) and Julio and Yook (2012) definition of high politically sensitive industry, the interaction between *PCI* and *HPS3* was insignificant. This finding suggests that with respect to these industries (or at least this combination of industries), partisan conflict does not significantly reduce their volatility more than with other industries. Moreover, as indicated by the insignificant coefficient, *HPS3* does not have a higher level of realized or idiosyncratic volatility than the less-sensitive industries.

Table 6

Regression Analysis of Partisan Conflict and High Politically Sensitive Industries as defined by Addoum and Kumar (2016)

	Models							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	*LRVInd*	*LRVInd*	*LRVInd*	*LRVInd*	*IdioR*	*IdioR*	*IdioR*	*IdioR*
LLRVInd	0.7040***	0.6540***	0.5800***	0.4830***				
	(140.99)	(121.06)	(96.80)	(76.26)				
LIdioR					0.7420***	0.6250***	0.6790***	0.5330***
					(72.06)	(56.79)	(61.52)	(45.39)
PCI	-0.0004***	-0.0005***	-0.0014***	-0.0020***	-0.0004***	-0.0006***	-0.0008***	-0.0015***
	(-4.85)	(-5.98)	(-13.12)	(-18.34)	(-3.73)	(-6.50)	(-7.19)	(-12.87)
HPS1	0.0437***	0.1310***	0.0536***	0.1970***	0.0658***	0.1850***	0.0712***	0.2280***
	(2.61)	(4.64)	(3.34)	(7.54)	(3.37)	(6.71)	(3.74)	(8.52)
PCI x HPS1	-0.0003**	-0.0003**	-0.0004***	-0.0005***	-0.0003**	-0.0005***	-0.0004***	-0.0006***
	(-1.96)	(-2.29)	(-2.78)	(-3.39)	(-2.15)	(-3.27)	(-2.79)	(-4.16)
EPU			0.0013***	0.0014***			0.0007***	0.0007***
			(12.87)	(14.66)			(5.34)	(6.24)
PP			-0.0018	-0.0063			-0.0010	-0.0048
			(-0.36)	(-1.29)			(-0.17)	(-0.85)
PG			0.0411***	0.0574***			0.0254***	0.0421***
			(7.41)	(10.32)			(4.05)	(6.72)
Lev			-0.1460***	-0.0319			-0.1140***	-0.0354
			(-6.18)	(-0.73)			(-4.14)	(-0.63)
Lsize			-0.0159***	0.0182***			-0.0278***	0.0023
			(-10.94)	(4.71)			(-16.38)	(0.54)
CBS			0.1450***	0.1130***			0.1690***	0.1760***
			(11.60)	(8.96)			(9.56)	(9.97)
DYS			0.1810***	0.1830***			0.1500***	0.1750***
			(24.60)	(23.53)			(16.52)	(18.39)
IPG			0.1610	0.1580			0.0540	-0.3250
			(0.50)	(0.52)			(0.12)	(-0.77)
PPIG			0.4240	0.2100			0.0435	-0.1070
			(1.56)	(0.79)			(0.11)	(-0.29)
TS			-0.0267***	-0.0236***			-0.0337***	-0.0368***
			(-11.31)	(-9.87)			(-12.96)	(-13.77)
Constant	0.5310***	0.5340***	0.6600***	0.2280***	0.2450***	0.2390***	0.4980***	0.0798***
	(39.13)	(25.41)	(27.41)	(4.75)	(17.59)	(15.67)	(17.16)	(1.58)
Industry Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.507	0.520	0.543	0.570	0.563	0.591	0.580	0.615
F-statistic	5124.3	461.8	1724.6	472.3	1450.7	214.4	557.2	209.1

Note. This table reports the regression results of partisan conflict's impact on high politically sensitive industry volatility, where high political sensitivity of an industry follows Addoum and Kumar (2016). All models have 20,880 observations. Models 1 and 2 report the results from regressing the log of industry-level realized volatility (*LRVInd*) on its lagged value (*LLRVInd*), *PCI*, the high politically sensitive industry dummy (*HPS1*), and the interaction between *PCI* and *HPS1* (*PCI x HPS1*). Model 2 additionally includes industry dummies. Models 3 and 4 regressed *LRVInd* on the aforementioned variables as well as on the control variables. Model 4 additionally includes industry dummies. Models 5 through 8 regressed idiosyncratic risk (*IdioR*) on its lagged value (*LIdioR*) and on the same variable combinations listed in Models 1 through 4. Models 6 and 8 controlled for industry dummies. *PCI* is the partisan conflict index (Azzimonti, 2018). High politically sensitive industries (*HPS1*) have a value of 1; other industries have a value of 0. *PCI x HPS1* is the interaction term between *HPS1* and *PCI*. *EPU* is the economic policy uncertainty index by Baker et al. (2016). *PP* represents presidential party, where 1 = Republican and 0 = Democrat in office. *PG* stands for political gridlock, where 1 = gridlock and 0 = harmony. Leverage (*Lev*) is the total long-term debt over total assets aggregated at industry level. *Lsize* is the logarithm of industry size (total assets). *CBS* is the corporate bond spread between AAA versus BAA-rated corporate bond yields. *DYS* is the return spread between long-term corporate bonds and long-term government bond yields. *IPG* is the industry production growth. *PPIG* is the inflation (producer price index) growth rate. *TS* is the term spread represented by the difference between the long-term yield on government bonds and the Treasury bill rate. Robust *t*-statistics are reported in parentheses.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7

Regression Analysis of Partisan Conflict and High Politically Sensitive Industries as defined by Hong and Kostovetsky (2012)

	Models							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	*LRVInd*	*LRVInd*	*LRVInd*	*LRVInd*	*IdioR*	*IdioR*	*IdioR*	*IdioR*
LLRVInd	0.7050***	0.6540***	0.5790***	0.4820***				
	(141.11)	(120.85)	(96.82)	(76.07)				
LIdioR					0.7440***	0.6250***	0.6800***	0.5330***
					(72.06)	(56.74)	(61.61)	(45.32)
PCI	-0.0005***	-0.0006***	-0.0015***	-0.0021***	-0.0005***	-0.0007***	-0.0009***	-0.0017***
	(-7.12)	(-8.69)	(-16.24)	(-21.99)	(-5.76)	(-9.68)	(-9.04)	(-15.48)
HPS2	0.0572*	0.1030**	0.0640**	0.1750***	0.1060**	0.2250***	0.1040**	0.2870***
	(1.72)	(2.58)	(1.96)	(4.47)	(2.46)	(4.48)	(2.49)	(5.87)
PCI x HPS2	-0.0006**	-0.0007***	-0.0008***	-0.0011***	-0.0006*	-0.0009***	-0.0007**	-0.0012***
	(-2.01)	(-2.48)	(-2.84)	(-3.93)	(-1.71)	(-2.86)	(-2.15)	(-3.69)
EPU			0.0013***	0.0014***			0.0007***	0.0007***
			(12.88)	(14.65)			(5.33)	(6.23)
PP			-0.0018	-0.0063			-0.0010	-0.0049
			(-0.35)	(-1.31)			(-0.16)	(-0.87)
PG			0.0408***	0.0573***			0.0252***	0.0420***
			(7.36)	(10.3)			(4.03)	(6.70)
Lev			-0.1460***	-0.0155			-0.1130***	-0.0183
			(-6.17)	(-0.35)			(-4.08)	(-0.32)
Lsize			-0.0167***	0.0181***			-0.0280***	0.0022
			(-11.45)	(4.68)			(-16.44)	(0.52)
CBS			0.1460***	0.1130***			0.1690***	0.1750***
			(11.67)	(8.94)			(9.55)	(9.95)
DYS			0.1810***	0.1830***			0.1490***	0.1750***
			(24.57)	(23.56)			(16.49)	(18.38)
IPG			0.1590	0.1590			0.0577	-0.3240
			(0.50)	(0.52)			(0.13)	(-0.77)
PPIG			0.4260	0.2090			0.0444	-0.1080
			(1.57)	(0.79)			(0.12)	(-0.30)
TS			-0.0269***	-0.0236***			-0.0336***	-0.0368***
			(-11.39)	(-9.86)			(-12.93)	(-13.75)
Constant	0.5440***	0.6380***	0.6860***	0.3870***	0.2630***	0.3850***	0.5200***	0.2570***
	(44.95)	(31.57)	(29.18)	(8.42)	(21.15)	(17.29)	(18.07)	(5.06)
Industry Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.506	0.520	0.543	0.570	0.563	0.591	0.580	0.615
F-statistic	5124.7	462.0	1726.2	472.1	1452.7	213.4	553.5	208.4

Note. This table reports the regression results of partisan conflict's impact on high politically sensitive industry volatility, where high political sensitivity of an industry follows Hong and Kostovetsky (2012). All models have 20,880 observations. Models 1 and 2 report the results from regressing the log of industry-level realized volatility (*LRVInd*) on its lagged value (*LLRVInd*), *PCI*, the high politically sensitive industry dummy (*HPS2*), and the interaction between *PCI* and *HPS2* (*PCI x HPS2*). Model 2 additionally includes industry dummies. Models 3 and 4 regressed *LRVInd* on the aforementioned variables as well as on the control variables. Model 4 additionally includes industry dummies. Models 5 through 8 regressed idiosyncratic risk (*IdioR*) on its lagged value (*LIdioR*) and on the same variable combinations listed in Models 1 through 4. Models 6 and 8 controlled for industry dummies. *PCI* is the partisan conflict index (Azzimonti, 2018). High politically sensitive industries (*HPS2*) have a value of 1; other industries have a value of 0. *PCI x HPS2* is the interaction term between *HPS2* and *PCI*. *EPU* is the economic policy uncertainty index by Baker et al. (2016). *PP* represents presidential party, where 1 = Republican and 0 = Democrat in office. *PG* stands for political gridlock, where 1 = gridlock and 0 = harmony. Leverage (*Lev*) is the total long-term debt over total assets aggregated at industry level. *Lsize* is the logarithm of industry size (total assets). *CBS* is the corporate bond spread between AAA versus BAA-rated corporate bond yields. *DYS* is the return spread between long-term corporate bonds and long-term government bond yields. *IPG* is the industry production growth. *PPIG* is the inflation (producer price index) growth rate. *TS* is the term spread represented by the difference between the long-term yield on government bonds and the Treasury bill rate. Robust *t*-statistics are reported in parentheses.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8

Regression Analysis of Partisan Conflict and High Politically Sensitive Industries as defined by Herron et al. (1999) and Julio and Yook (2012)

	Models							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	*LRVInd*	*LRVInd*	*LRVInd*	*LRVInd*	*IdioR*	*IdioR*	*IdioR*	*IdioR*
LLRVInd	0.7050***	0.6550***	0.5800***	0.4830***				
	(141.28)	(121.13)	(97.08)	(76.32)				
LIdioR					0.7450***	0.6250***	0.6800***	0.5350***
					(72.71)	(56.86)	(61.76)	(45.49)
PCI	-0.0005***	-0.0006***	-0.0015***	-0.0021***	-0.0005***	-0.0008***	-0.0010***	-0.0017***
	(-7.11)	(-8.63)	(-16.16)	(-21.73)	(-5.69)	(-9.52)	(-9.01)	(-15.38)
HPS3	-0.0038	-0.0097	0.0044	-0.0261	0.0082	-0.0359	0.0264	-0.0430
	(-0.16)	(-0.30)	(0.20)	(-0.87)	(0.31)	(-1.11)	(1.04)	(-1.37)
PCI x HPS3	-0.0001	-0.0001	-0.0001	-0.0003	-0.0001	-0.0002	-0.00004	-0.0003
	(-0.38)	(-0.61)	(-0.42)	(-1.40)	(-0.39)	(-0.96)	(-0.22)	(-1.31)
EPU			0.0013***	0.0014***			0.0007***	0.0007***
			(12.86)	(14.65)			(5.34)	(6.23)
PP			-0.0018	-0.0063			-0.0009	-0.0049
			(-0.35)	(-1.30)			(-0.14)	(-0.85)
PG			0.0410***	0.0574***			0.0247***	0.0421***
			(7.39)	(10.33)			(3.94)	(6.72)
Lev			-0.1460***	-0.0258			-0.1220***	-0.0303
			(-6.17)	(-0.58)			(-4.39)	(-0.53)
Lsize			-0.0161***	0.0184***			-0.0293***	0.0025
			(-11.01)	(4.75)			(-17.04)	(0.60)
CBS			0.1450***	0.1120***			0.1700***	0.1750***
			(11.61)	(8.93)			(9.61)	(9.93)
DYS			0.1800***	0.1820***			0.1510***	0.1740***
			(24.45)	(23.48)			(16.55)	(18.33)
IPG			0.1610	0.1590			0.0556	-0.3210
			(0.50)	(0.52)			(0.12)	(-0.76)
PPIG			0.4260	0.2100			0.0492	-0.1080
			(1.57)	(0.79)			(0.13)	(-0.29)
TS			-0.0267***	-0.0236***			-0.0337***	-0.0368***
			(-11.31)	(-9.87)			(-12.96)	(-13.77)
Constant	0.5480***	0.6400***	0.6820***	0.3880***	0.2670***	0.3870***	0.5390***	0.2590***
	(44.19)	(31.43)	(28.99)	(8.40)	(20.79)	(17.22)	(18.48)	(5.08)
Industry Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.506	0.520	0.543	0.570	0.562	0.591	0.580	0.615
F-statistic	5128.5	461.8	1723.9	472.2	1421.1	213.1	550.5	208.0

Note. This table reports the regression results of partisan conflict's impact on high politically sensitive industry volatility, where high political sensitivity of an industry follows Hong and Kostovetsky (2012). All models have 20,880 observations. Models 1 and 2 report the results from regressing the log of industry-level realized volatility *(LRVInd*) on its lagged value (*LLRVInd), PCI*, the high politically sensitive industry dummy (*HPS3*), and the interaction between *PCI* and *HPS3* (*PCI x HPS3*). Model 2 additionally includes industry dummies. Models 3 and 4 regressed *LRVInd* on the aforementioned variables as well as on the control variables. Model 4 additionally includes industry dummies. Models 5 through 8 regressed idiosyncratic risk (*IdioR*) on its lagged value (*LIdioR*) and on the same variable combinations listed in Models 1 through 4. Models 6 and 8 controlled for industry dummies. *PCI* is the partisan conflict index (Azzimonti, 2018). High politically sensitive industries (*HPS3*) have a value of 1; other industries have a value of 0. *PCI x HPS3* is the interaction term between *HP3 and PCI*. *EPU* is the economic policy uncertainty index by Baker et al. (2016). *PP* represents presidential party, where 1 = Republican and 0 = Democrat in office. *PG* stands for political gridlock, where 1 = gridlock and 0 = harmony. Leverage (*Lev*) is the total long-term debt over total assets aggregated at industry level. *Lsize* is the logarithm of industry size (total assets). *CBS* is the corporate bond spread between AAA versus BAA-rated corporate bond yields. *DYS* is the return spread between long-term corporate bonds and long-term government bond yields. *IPG* is the industry production growth. *PPIG* is the inflation (producer price index) growth rate. *TS* is the term spread represented by the difference between the long-term yield on government bonds and the Treasury bill rate. Robust t-statistics are reported in parentheses.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Discussion

In a society rife with uncertainty and increasing concerns over the effects of political polarization, my study investigating the effects of partisan conflict on industry-level volatility is a timely one. The purpose of this essay was to investigate the effects of partisan conflict on high politically sensitive industry volatility in particular. My analyses revealed interesting findings that suggest that political polarization is not necessarily all bad, especially when it comes to volatility in equity markets. I found a statistically significant negative correlation between partisan conflict and industry-level volatility using two distinct measures of volatility. Moreover, my results showed that the impact of partisan conflict on volatility was greater than the impact of economic policy uncertainty, as evidenced by the magnitude of the coefficients.

Using politically sensitive industry classifications from Addoum and Kumar (2016) and Hong and Kostovetsky (2012), I also found evidence that high levels of partisan conflict can help reduce volatility for politically sensitive industries more so than for other industries. These findings were based on measures of political sensitivity shown to be persistent over a prolonged period of time. These results support the argument that increased political conflict serves to hinder potential policy changes, as the enactment of new policies becomes stalled in attempts to pass them into legislation.

With respect to my final measure of political sensitivity, including industries suggested in Herron et al. (1999) and Julio and Yook (2012), there was no evidence of additional impact on volatility as a result of higher partisan conflict. These seemingly conflicting results lead me to two conclusions. First, the discrepancy in findings supports the idea forwarded in Herron et al. (1999) that political sensitivity of an industry may shift as presidential platforms change and as the level of polarization evolves over time. Thus, the measure based on Herron et al. (1999) and

Julio and Yook (2012) did not necessarily reflect political sensitivity over time. The other two measures, based on more prolonged periods, however, presumably provide a more accurate account of industries that remain politically sensitive as a result of higher regulatory environments and more political controversy surrounding them (as with sin stocks). My second conclusion is that more research needs to be done to ascertain the persistence of political sensitivity over time and industry. This study forms the foundation for such an examination.

Political polarization, especially in recent times, is not viewed in a favorable light; it is instead blamed for many of society's woes. In particular, stalled decision-making on Capitol Hill, as witnessed by government shutdowns and the recent proliferation of filibusters, can be attributed in no small part to polarized political ideologies (Binder, 2014). Certain industries, namely those the most susceptible to changes in government policy, are undoubtedly more affected by political conflict. The analyses in this study suggest one advantage stemming from higher levels of partisan conflict: its calming effect on volatility, both at the market and industry levels. Analysts and investors can use the information in this study to help gauge market risk and its impact on investments.

As partisan polarization increasingly defines government and society as a whole, further studies should continue to examine the effects of partisan conflict on financial markets. In particular, future research could investigate individual firm impacts within each politically sensitive industry and across time to gain a deeper understanding of the ways in which political conflict affects the operations of these firms.

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Appendix A

Variable Definitions

- ***LRVInd*** = Log of Industry-level Realized Volatility. Monthly measure of the natural logarithm of industry-level realized volatility. Monthly realized volatility is calculated by taking the square root of the sum of the daily squared industry returns. Daily returns used are based on the Fama and French 48 industries. (French, n.d.)
- ***LLRVInd*** = Lagged Log of Industry-level Realized Volatility. One-period lagged value of the log of industry-level realized volatility.
- ***IdioR*** = Idiosyncratic Risk. Industry-specific residual is calculated by regressing daily industry returns (ri) on the daily market risk premium (rm). The idiosyncratic risk of industry i is equal to the standard deviation of the residuals. (French, n.d.)
- ***LIdioR*** = Lag of Idiosyncratic Risk. One-period lagged value of idiosyncratic risk measure.
- ***PCI*** = Partisan Conflict Index. Monthly measure of the level of partisan conflict between Democrats and Republicans as measured by newspaper articles conveying political disagreement at the national level. (Federal Reserve Bank of Philadelphia, *Partisan conflict index*, 2021).
- ***EPU*** = Economic Policy Uncertainty Index (Baker et al., 2016): Monthly measure based on newspaper articles referencing "economic," "policy," and "uncertainty," and other related terms; federal tax code provisions; and professional forecaster disagreement over future inflation and government expenditures. (*Economic policy uncertainty index*, n.d.)
- ***PP*** = Party of President: A dummy variable measuring party of the current president. A value of 1 represents a Republican in office; 0 represents a Democrat. (*Political parties of the presidents*, n.d.)

- ***PG*** = Political Gridlock: The period during which the majority party in the White House, the Senate, and the House of Representatives are not all the same. The dummy variable has a value of 1 during gridlock periods and a value of 0 during non-gridlock (harmony) periods. (United States House of Representatives, n.d.; United States Senate, n.d.)
- ***Lev*** = Industry Leverage. Industry leverage is calculated as the weighted average ratio of long-term debt over the total assets of all firms in each industry. Firm-level data obtained from Compustat (University of Pennsylvania Wharton Research Data Services, 2021).
- ***Lsize*** = Log of Industry Size. Industry size is calculated as the sum of the total assets of all firms in each industry. Firm-level data obtained from Compustat (University of Pennsylvania Wharton Research Data Services, 2021).
- ***CBS*** = Corporate Bond Spread: This spread is the difference between the yield on AAA-rated (Federal Reserve Bank of St. Louis, *Moody's seasoned Aaa corporate bond yield,* 2021*)* versus BAA-rated corporate bonds (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield*, 2021*)*
- ***DYS*** = Default Yield Spread: This spread represents the difference between the monthly yield on BAA-rated corporate bonds versus the yield on long-term government bonds. (Federal Reserve Bank of St. Louis, *Moody's seasoned Baa corporate bond yield relative to yield on 10-year treasury constant maturity*, 2021)
- ***IPG*** = Industrial Production Growth: A monthly numeric measure of the change in industrial production from one month to the next. (Federal Reserve Bank of St. Louis, *Industrial production: total index*, 2021)

- ***PPIG*** = Inflation Growth: A monthly measure calculated as the change in producer price index (PPI) from one month to the next. (Federal Reserve Bank of St. Louis, *Producer price index by commodity: All commodities*, 2021)
- ***TS*** = Term Spread: This monthly variable represents the difference between the long-term yield on government bonds and the three month-Treasury bill rate. (Federal Reserve Bank of St. Louis, *10-year treasury constant maturity minus 3-month treasury constant maturity*, 2021)

Appendix B

Variance Inflation Factor Test for Multicollinearity for the Main Models

Table B1

Realized Volatility

Variable	VIF	1/VIF
DYS	4.85	0.20601
CBS	3.89	0.256865
EPU	1.51	0.661432
LLRVInd	1.49	0.672525
PCI	1.37	0.730785
PP	1.31	0.760976
TS	1.3	0.769893
PG	1.22	0.816653
Lsize	1.21	0.825418
IPG	1.17	0.856743
PPIG	1.14	0.875129
Lev	1.1	0.912445
Mean VIF	1.8	

Note. VIF = variance inflation factor. Variables with values lower than 10 satisfy conditions of low collinearity (Hair et al., 1995). *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *CBS* represents corporate bond spread, the difference between AAA and BAA corporate bond yields. *EPU* is measured by the Baker et al. (2012, 2016) economic policy uncertainty index. *LLRVInd* is the log of *LRVInd* lagged one period. *PCI* is measured by the Azzimonti (2018) partisan conflict index. Presidential party (*PP*) is a dummy variable where 1 = a Republican in office and 0 = a Democrat. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony. *(Lsize)* is the logarithm of the sum of the total assets of all firms in each industry. Log of industry size *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. Industry leverage (*Lev*) is the weighted average ratio of long-term debt over the total assets of all firms in each industry.

Table B2

Idiosyncratic Risk

Variable	VIF	1/VIF
DYS	4.76	0.210003
CBS	3.97	0.252146
EPU	1.48	0.673848
PCI	1.34	0.745418
PP	1.31	0.761365
TS	1.31	0.762601
LIdioR	1.29	0.77819
Lsize	1.28	0.779457
PG	1.22	0.81682
IPG	1.17	0.854015
PPIG	1.14	0.875523
Lev	1.09	0.914503
Mean VIF	1.78	

Note. VIF = variance inflation factor. Variables with values lower than 10 satisfy conditions of low collinearity (Hair et al., 2015). *DYS* stands for default yield spread, or the difference between the yield on BAA-rated corporate bonds versus the yield on long-term government bonds. *CBS* represents corporate bond spread, the difference between AAA and BAA corporate bond yields. *EPU* is measured by the Baker et al. (2012, 2016) economic policy uncertainty index. *PCI* is measured by the Azzimonti (2018) partisan conflict index. Presidential party (*PP*) is a dummy variable where 1 = a Republican in office and 0 = a Democrat. *TS*, or term spread, represents the difference between the long-term yield on government bonds and the 3-month Treasury bill rate. *LIdioR is* the lag of idiosyncratic risk. Log of industry size *(Lsize)* is the logarithm of the sum of the total assets of all firms in each industry. Political gridlock (*PG*) is the state in which the party in the White House, the majority party in the House of Representatives, and the majority party in the Senate are not all the same. A value of 1 denotes a state of political gridlock; a value of 0 represents a state of political harmony. *IPG*, or industrial production growth, is calculated from the industrial production measure. *PPIG*, or inflation growth rate, is calculated from the producer price index. Industry leverage (*Lev*) is the weighted average ratio of long-term debt over the total assets of all firms in each industry.

VITA

Deborah Berg Beyer was raised in Waukesha, Wisconsin. She completed her undergraduate degree in French and Mathematics from St. Olaf College in 1988. She completed an MA (1990) and PhD (1995) in French Literature from the University of Wisconsin – Madison. She taught French for a number of years at Western Illinois University, where she received tenure. She then decided to pursue a career teaching Finance. She completed her MBA from Florida State University in 2016 and began teaching undergraduate and MBA-level business courses at the University of Wisconsin Oshkosh. Deborah is currently employed as an Assistant Professor of Finance at the University of Wisconsin – Stevens Point.