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Uncertainty and Volatility: Sectoral Equity Responses to Economic and Policy Shocks in the U.S.

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Abstract

This study investigates the effects of economic policy and financial uncertainty on equity return volatility across major U.S. sectoral indices. Specifically, it examines the relationships between uncertainty indices and the S&P 500 financials sector index (SPF), the Wilshire U.S. Real Estate Investment Trust Total Market Index (WRE), and the iShares U.S. Consumer Staples ETF (IYK). The analysis employs GARCH-MIDAS methodology, Markov Switching Regressions (MSR), Threshold Regressions, and Granger causality tests. Results from the sectoral analysis indicate varying degrees of sensitivity to uncertainty across sectors. The consumer staples sector exhibits consistently high volatility, largely driven by shifts in consumer sentiment, income dynamics, and inflation expectations. Over the long term, global economic policy uncertainty (GEPU) and recession risk further amplify volatility in this sector, reflecting its deep integration into global supply chains. The real estate sector demonstrates a more conditional response; its volatility increases significantly in the presence of economic policy uncertainty (EPU), but primarily during periods of elevated recession risk. Under stable economic conditions, real estate equities appear relatively insensitive to both inflation expectations and GEPU. In contrast, the financial sector displays both short- and long-term strong and persistent sensitivity to indicators, particularly EPU, inflation expectations, and the VIX.

JEL classification: G12, G14, G38.

Keywords: Volatility, GARCH-MIDAS, VIX, Economic Policy Uncertainty, Global Economic Policy Uncertainty, Threshold Regression, Regime Switching Markov Chain Regression.

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1. Introduction

Economic uncertainties refer to the unpredictability of economic conditions, which can arise due to various factors, such as changes in government policies, geopolitical tensions, global economic shocks, and natural disasters. Such uncertainties can have a significant impact on the enterprise value of firms, which is the market value of a company's total equity and debt.

A substantial body of economic theory highlights the critical impact of uncertainty on firm behavior and value. The theory of investment under uncertainty, advanced by Bernanke (1983), Dixit (1989), Pindyck (1991), and formalized in Dixit and Pindyck (1994), argues that increased uncertainty often prompts firms to delay investment decisions, thereby influencing their market valuation. Earlier foundations of this line of inquiry can be traced to Sandmo (1971), whose work initiated a deeper understanding of how firms respond to risk. The theme gained broader visibility with Galbraith's *The Age of Uncertainty* (1977), which emphasized uncertainty's role in economic life. Subsequent studies, including those by Flacco and Kroetch (1986), Fooladi and Kayhani (1990, 1991), and Adrangi and Raffiee (1999a, 1999b), expanded the theoretical discourse, exploring how firms adapt their production, pricing, and profit strategies amid varying degrees of market uncertainty.

Although the significance of uncertainty in economics and finance is widely acknowledged, there is still no universally accepted definition of the concept. Only in recent years has empirical research on uncertainty gained momentum, driven in part by advances in measurement techniques. Notably, Baker et al. (2012a, 2013, 2016) along with Golchin and Riahi (2021) have made substantial contributions by developing indices that quantify economic and policy-related uncertainties. These tools have enhanced our understanding of how uncertainty affects economic behavior and decision-making.

The aftermath of the 2008 global financial crisis highlighted the critical role of policy uncertainty. As Baker et al. (2016) emphasize, ambiguity surrounding fiscal policy, regulation, taxation, and healthcare created hesitation among firms and households, delaying both investment and consumption and thereby slowing economic recovery.

Parallel to these efforts, researchers have increasingly turned to media and sentiment-based approaches to measure uncertainty. Manela and Moreira (2017), for instance, introduced NVIX, a news-based volatility index. Meanwhile, Davis et al. (2013) and Baker et al. (2006–2021) developed a broad suite of indices, including Twitter-based Economic Uncertainty (TEU) measures, to capture different dimensions of economic and financial volatility.

Economic uncertainties can lead to increased volatility in markets and hinder consumption, investment, production, and employment, ultimately slowing economic growth (Baker et al., 2016; Bloom, 2009). In recent years, there has been a growing focus in research on quantifying media data to make it more accessible for economic analyses. This trend reflects a recognition of the significant impact media coverage has on shaping societal perceptions and influencing economic development. Known as the "agenda setting effect," this process involves the selection of information and sources, as well as the tone of reporting, which can profoundly shape public understanding of economic uncertainties and risks (Baker et al., 2016). These influencing factors play a critical role in economic dynamics.

More recently, innovations by Becker et al. (2012, 2014, 2016) and Manela & Moreira (2017) in measuring economic and policy uncertainties have enabled researchers to explore the effects of various uncertainty measures on firm behavior across different industries. For instance, These uncertainty indices have been shown by researchers to be significantly associated with short- and long-term volatility is asset returns (see Pan et al. (2017, 2021), Su et al. (2017, 2018, 2019), Adrangi et al. (2019, 2021, 2023a, 2023b, 2024a, 2024b, 2024c, 2025a, 2025b,2025c), and Yang et al. (2019), Adam et al. (2022), Ahadzie et al. (2025), among others investigate the association of the uncertainty with the US financial markets, airline industry and energy markets.

This study builds upon this growing body of literature by extending the analysis to investigate the impact of economic and market uncertainties in three critical sectors of the US economy, namely, consumer goods, real estate, and financial.

The first half of 2025 was characterized by a pronounced rise in economic uncertainty, largely attributable to the Trump administration's economic policy interventions, particularly in the areas of trade, tariffs, and regulatory direction. These developments introduced considerable volatility and undermined the expectations of investors, consumers, and firms regarding future economic conditions.

Financial markets responded swiftly to these uncertainties. The S&P 500 index experienced a decline of nearly 8%, signaling diminished investor confidence and heightened risk aversion. Concurrently, household sentiment deteriorated sharply, as reflected in a substantial drop in the University of Michigan Consumer Confidence Index. These indicators collectively point to a broader loss of confidence in the trajectory of the U.S. economy.

Importantly, these dynamics translated into real economic outcomes. Domestic consumption—the primary engine of U.S. economic growth—contracted notably, contributing to a 3% decline in real GDP during the first quarter of 2025. This contraction not only reflects the immediate effects of economic policy uncertainty but may also signal the onset of a recession, traditionally defined by two consecutive quarters of negative GDP growth. If sustained, this trend could indicate a broader economic downturn with potential spillover effects across sectors.

Economic policy uncertainty has significant implications for financial markets, particularly the bond market, inflation expectations, and real interest rates. In the first half of 2025, increased policy ambiguity—arising from shifting fiscal strategies, trade tensions, and regulatory unpredictability—contributed to heightened volatility in U.S. Treasury markets. Investors demanded higher yields to compensate for increased risk, pushing long-term bond yields upward and steepening the yield curve. This rise in yields reflects growing expectations of future inflation and a persistent risk premium embedded in the bond market.

Simultaneously, inflation expectations have remained elevated. The combination of expansionary fiscal rhetoric, trade-related cost pressures, and supply chain disruptions has led market participants to anticipate sustained price level increases. In response, mortgage rates have climbed and stabilized in the range of 6.5% to 7%, a level not seen consistently in over a decade. These elevated mortgage rates have had a pronounced dampening effect on real estate investment. Higher borrowing costs reduce housing affordability, slow new construction, and suppress demand in both residential and commercial property markets, leading to a broader cooling of the real estate sector.

The Federal Reserve's monetary policy stance in this environment has been notably cautious. With inflation expectations remaining above the Fed's long-term target, the central bank has maintained a relatively tight monetary policy posture, signaling its willingness to hold policy rates at restrictive levels until inflationary pressures recede. However, this approach, while aimed at anchoring inflation expectations, also risks further constraining credit availability and investment in interest-sensitive sectors such as housing and construction.

Taken together, the persistence of economic policy uncertainty, elevated inflation expectations, and restrictive monetary policy has created a challenging environment for bond and real estate markets. These conditions highlight the delicate balance the Fed must strike between curbing inflation and avoiding an overcorrection that could deepen an economic slowdown

These developments underscore the macroeconomic consequences of policy-driven uncertainty and highlight the need for consistent and transparent policy frameworks to support investor and consumer confidence in the broader economic system.

This study seeks to quantify the impact of economic policy and financial uncertainties in the United States by analyzing their association with major sector equities. Specifically, we examine the relationship between uncertainty indices and the S&P 500 financial sector index, the Wilshire U.S. Real Estate Investment Trust Total Market Index, and the iShares U.S. Consumer Staples ETF. In addition, the analysis investigates whether these sectors exhibit similar or divergent responses to shifts in economic and policy uncertainty, thereby shedding light on the differential sensitivity of broad market, real estate, and consumer staples equities to uncertain macroeconomic conditions.

Volatility in equity markets often reflects a confluence of macroeconomic forces, and among the most influential of these is economic policy uncertainty (EPU). The extent to which equity prices fluctuate in response to EPU varies not only by sector but also by the prevailing level of recession risk. In the context of the U.S. economy, the financial, real estate, and consumer goods sectors exhibit distinct sensitivities to policy uncertainty, particularly when market participants adjust their expectations under the specter of an economic downturn.

The financial sector is inherently sensitive to both macroeconomic conditions and regulatory signals. Financial institutions operate within a framework that is highly dependent on interest rate policy, capital requirements, and liquidity provisions—all of which are subject to change amid economic policy uncertainty. When uncertainty rises, particularly around monetary or fiscal policy, banks and financial firms face increased difficulty in pricing risk, forecasting earnings, and allocating capital efficiently. This, in turn, tends to amplify equity volatility in the sector. Under elevated recession risk, the volatility effect is often magnified. Market participants not only fear potential losses due to deteriorating credit conditions, but also anticipate shifts in regulatory tone that may constrain profitability, such as tighter lending standards or stress-testing requirements. Conversely, during periods of low recession risk, the financial sector may still react to policy uncertainty, but the volatility tends to be more muted, as the underlying economic resilience offers a buffer against adverse outcomes.

Similarly, the real estate sector—particularly listed real estate investment trusts (REITs) and development firms—is closely tied to interest rate policy and forward-looking indicators of economic activity. EPU introduces ambiguity into the cost of capital and future demand for property, both residential and commercial. In a low-recession-risk environment, heightened policy uncertainty may delay investment decisions or induce mild price volatility, but strong demand fundamentals often offset these concerns. However, when recession risk is high, the same uncertainty becomes more destabilizing. Expectations of declining property values, tighter credit conditions, and a slowdown in construction and leasing activity contribute to a pronounced rise in equity volatility. Investors, uncertain about both economic direction and policy response, often reprice real estate equities with heightened caution.

The consumer goods sector, encompassing both durable and non-durable products, presents a more nuanced response to EPU. Consumer staples—such as food, household products, and personal care items—are traditionally considered defensive, exhibiting relatively stable demand even during economic contractions. Therefore, equity volatility in these subsectors tends to be less reactive to policy uncertainty, particularly in low-recession-risk periods. However, discretionary consumer goods—such as automobiles, electronics, and luxury items—are far more sensitive to changes in consumer sentiment, interest rates, and disposable income, all of which are affected by both policy decisions and recession expectations. When policy uncertainty coincides with an elevated risk of recession, consumers often delay large purchases, leading to revenue pressures and increased earnings variability for firms. Investors, in turn, respond with increased caution, resulting in greater volatility for equities in the discretionary segment.

Moreover, the interplay between policy uncertainty and recession risk is not merely additive—it is interactive. High levels of EPU may independently contribute to equity volatility, but their effect is typically intensified when the economy shows signs of impending contraction. Under such dual stressors, market participants become more reactive, liquidity may dry up, and sector-specific fundamentals are often reassessed with greater skepticism. Conversely, in an environment of policy uncertainty accompanied by low or negligible recession risk, investors may view the noise as transitory and remain more focused on earnings fundamentals and long-term prospects, thereby dampening the volatility response.

In sum, while economic policy uncertainty exerts a measurable influence on equity volatility across sectors, the magnitude and nature of its impact depend critically on the underlying risk of recession. Financial and real estate equities tend to be especially vulnerable under high uncertainty and elevated recession risk due to their reliance on credit markets and forward-looking economic indicators. The consumer goods sector presents a mixed profile, with discretionary segments more exposed to cyclical fluctuations and policy ambiguity. Understanding this nuanced relationship is essential for investors, policymakers, and scholars aiming to interpret market behavior in times of economic flux.

The purpose of this study is to examine the relationship between the volatility of the returns for SP, WRE, and IYK and a range of economic and policy uncertainty indices. This investigation aims to enhance our understanding of how equities in these key sectors respond to different forms of uncertainty. The findings are particularly relevant for portfolio managers seeking to rebalance their holdings in order to mitigate volatility and enhance resilience during periods of domestic policy uncertainty, elevated risks of recession or inflation, and broader market or global economic instability.

The remainder of the paper is organized as follows. Section II offers a review of literature pertaining to economic uncertainty and its association with the firm and sector performance. The data and sources of the sample data are discussed in section III. A brief description of the econometric methodology is the subject of section IV. Section V is earmarked for the discussion of the empirical findings and their implications for the market participants. Summary, conclusions, and the managerial implication of the study comprise the last section.

2. Literature review

In this section, we provide a succinct overview of the existing literature on the Economic Policy Uncertainty (EPU) and other relevant uncertainty indicators that have been found to impact asset price volatilities. Additionally, we summarize a selection of studies that utilize the GARCH-MIDAS framework to derive long- and short-term equity volatilities. For more thorough literature review, we refer readers to Adrangi et al. (2023a, 2024a).

2.1 Literature on Uncertainty, Economic Policy Uncertainty, and Asset Price Volatility

As discussed in Adrangi et al. (2023a, 2024a, 2025a, b) a growing interest in sentiment and uncertainty indicators has led to the development of several influential measures, including the news-based NVIX by Manela and Moreira (2017) and various market-focused indices by Baker et al. (2012a, 2012b, 2016, 2019, 2021). These tools have become instrumental in assessing asset price volatility across financial markets. A broad body of empirical work (e.g., Pan et al. (2017), Su et al. (2017, 2018, 2019), Altig et al. (2020), Krol (2014), Dutta et al. (2021), Jiang et al. (2019), Xu et al. (2021), Pan et al. (2021), and Lindblad (2017), Adrangi et al. (2024a, 2025a,b,c), Whaley (1993, 2009), Jens (2017), among others.

has confirmed that both economic and policy uncertainty, along with sentiment, are key drivers of market fluctuations.

The findings of these studies have led to the widely accepted view that economic uncertainty, policy uncertainty, and sentiments significantly contribute to asset price and returns volatilities. In the following section, we provide a brief overview of some of these stylized facts.

As noted in Adrangi et al. (2023a, 2024a, 2025a), a growing body of literature emphasizes the pivotal role of uncertainty and sentiment indicators—such as the Economic Policy Uncertainty (EPU), Global EPU (GEPU), VIX, and NVIX indices—in explaining asset price volatility across global financial markets. These indices, originally proposed in studies such as Baker et al. (2012a, 2012b, 2016, 2019, 2021), Manela and Moreira (2017), and Ludvigson et al. (2021), have become central tools for quantifying and forecasting market volatility. The following section offers a focused summary of these stylized empirical patterns.

Researchers have demonstrated the utility of these measures across diverse markets and asset classes. For example, Pan et al. (2021) found that macroeconomic uncertainty significantly contributes to the long-term volatility of the S&P 500. Zhu et al. (2019) introduced the EMV (Equity Market Volatility) index, constructed from newspaper keyword counts related to market risk, and confirmed its association with daily fluctuations in major U.S. indices such as the S&P 500, NASDAQ, and DJIA.

Su et al. (2019) explored the effects of EPU, financial uncertainty (FU), and NVIX on the volatility of equity markets in nine advanced economies. They found that these uncertainty indices, particularly the EPU, are positively associated with market volatility, although the results are not uniform across all markets. The EPU itself comprises three components: (1) frequency of newspaper articles covering policy-related uncertainty, (2) the number of expiring federal tax code provisions, and (3) disagreement among economic forecasters.

Baker et al. (2012b) developed the EPU index to capture uncertainty surrounding fiscal and monetary policies, showing that heightened EPU correlates with lower investment, employment, and output. In the aftermath of the 2008 financial crisis, Baker et al. (2012a) noted particularly high EPU levels between 2008 and 2012, with a peak in August 2011, and concluded that policy uncertainty was a major impediment to economic recovery.

The influence of EPU extends beyond U.S. borders. Fang et al. (2018) found that shifts in U.S. investor sentiment spill over into G7 markets. Similarly, Tsai (2017) demonstrated that EPU in China and Europe influences volatility in neighboring Asian and European equity markets, suggesting that uncertainty can act as a channel for international contagion. Chang (2022) used a Markov-switching framework to show that EPU-induced volatility linkages between U.S. and Japanese markets fluctuate between synchronous and asynchronous phases.

Further research corroborates the impact of EPU on firm-level behavior. Firms tend to adopt a more conservative stance during periods of high policy uncertainty—reducing capital expenditures (Gulen & Ion, 2015), postponing IPOs (Colak et al., 2017), cutting dividends (Panousi & Papanikolaou, 2012), avoiding mergers and acquisitions (Bonaime et al., 2018), and increasing cash holdings (Demir & Ersan, 2017; Phan et al., 2019). Al-Thaqeb & Algharabali (2019) review this evidence and conclude that uncertainty broadly restrains corporate risk-taking.

On the methodological front, several studies use high-frequency and model-based approaches to assess EPU's predictive power. Liu and Zhang (2015), for instance, used five-minute realized volatility data to establish a statistically significant link between lagged EPU and contemporaneous stock market volatility. Antonakakis et al. (2013) similarly show that incorporating EPU into volatility models improves forecasting performance across specifications. Arouri et al. (2016) confirm that higher EPU levels depress stock returns, particularly during periods of heightened market stress.

The literature also extends to other asset classes and macroeconomic variables. Wen et al. (2019) found that the U.S. EPU index is significantly associated with fluctuations in key Chinese macroeconomic indicators. Scholars have also linked EPU to commodity prices (Sharif et al., 2020), exchange rates (Krol, 2014), bond markets Liow et al. (2018), and real-time uncertainty measures (Altig et al., 2020).

In sum, a large and expanding literature confirms that indices of economic and policy uncertainty—whether derived from news content, forecast dispersion, or market-based indicators—are significant drivers of asset price volatility, macroeconomic outcomes, and firm behavior.

2.2 Literature on GARCH-MIDAS, Markov Switching and Threshold applications

In this section, we summarize some of the literature on methods that we deploy in the current study – namely GARCH-MIDAS, and Markov Switching regressions (MSR) and Threshold regressions (TR). Most of our review is focused on applications, though the main intention is also to show the continued development and repurposing of the GARCH framework to the GARCH-MIDAS frameworks. The studies most pertinent to our paper are Su et al. (2019) and Pan et al. (2021), both of which we build upon.

Volatility modeling has undergone significant development, with numerous efforts aimed at improving the predictive accuracy of traditional models. Building on this extensive body of work, we employ the GARCH-MIDAS framework to estimate volatility across three sectors, as this approach effectively captures both short-term fluctuations and the influence of long-term macroeconomic variables.

The evolution of volatility modeling began with foundational works such as Ding and Granger (1996) and Engle and Lee (1999), who laid the groundwork for dynamic conditional heteroskedasticity models. Since then, numerous studies have refined the standard GARCH framework. For instance, Javaheri et al. (2004) proposed enhancements for volatility swap hedging, and Awartani and Corradi (2005) compared various GARCH variants, highlighting the superior predictive power of asymmetric models. Liu and Hung (2010) identified the GJR-GARCH and EGARCH models as top performers in forecasting volatility for the S&P 500. Researchers have also explored hybrid approaches; Hajizadeh et al. (2012) combined EGARCH models with neural networks to improve forecast accuracy. Carnero et al. (2012) proposed robust estimation techniques to address bias in volatility forecasts. Adrangi et al. (2001, 2015) further contributed by applying a bivariate vector autoregressive EGARCH model to analyze volatility spillovers between oil and equity markets, reinforcing the idea that integrating macroeconomic linkages enriches volatility models.

These cumulative efforts set the stage for a new generation of models capable of handling data at mixed frequencies. A major advancement came with the GARCH-MIDAS (Mixed Data Sampling) model introduced by Engle et al. (2013), which allowed for the integration of high-frequency asset returns with low-frequency macroeconomic indicators. This methodological leap enabled a more nuanced decomposition of volatility into long- and short-term components.

Following Engle et al.'s innovation, several studies applied the GARCH-MIDAS framework across various asset classes. Researchers such as Asgharian et al. (2013), Conrad and Loch (2015), Amendola et al. (2017, 2019), Pan et al. (2017, 2021), and Conrad et al. (2018) demonstrated that incorporating macroeconomic variables significantly enhances volatility forecasts. A comprehensive review by Amado et al. (2019) summarizes the effectiveness of multiplicative component GARCH-MIDAS models across a variety of settings.

Specifically in commodity markets, Pan et al. (2017) applied a regime-switching GARCH-MIDAS model to analyze the volatility of WTI and Brent crude oil prices, finding improved forecast accuracy. Fang et al. (2018) used a dual-covariate GARCH-MIDAS framework to show how investor confidence in the U.S. influences G7 equity markets. Zhu et al. (2019) used news-based EMV indices to model volatility in major U.S. equity indices using a univariate GARCH-MIDAS model. Conrad et al. (2018) employed the framework to model cryptocurrency volatility, highlighting its adaptability across asset classes.

Of particular relevance to this paper, Su et al. (2019) utilized a two-factor GARCH-MIDAS model to study how different uncertainty indices (EPU, FU, NVIX) influence equity market volatility across nine developed economies. They demonstrated that EPU has a consistent positive association with volatility, while the effects of FU and NVIX are more mixed. Notably, their model includes only two covariates, possibly due to estimation challenges common in GARCH-MIDAS models with multiple low-frequency inputs—a limitation they openly acknowledge.

Similarly, Pan et al. (2021) proposed univariate GARCH-MIDAS models for value-at-risk and expected shortfall, revealing that macroeconomic uncertainty plays a critical role in shaping long-term volatility. However, they did not explore the implications of using multivariate or regime-switching frameworks, leaving a gap that our study addresses.

Among the most comprehensive comparisons, Conrad and Kleen (2020) demonstrate that the multiplicative GARCH-MIDAS model outperforms competing models, including the heterogeneous autoregression (HAR) of Corsi (2009), the realized GARCH of Hansen et al. (2012), the high-frequency–based volatility (HEAVY) of Shephard and Sheppard (2010) and the MS-GARCH. They attribute its superior performance to the flexibility provided by its multiplicative structure, which more effectively captures the interplay between high- and low-frequency information. These findings support our decision to apply the GARCH-MIDAS methodology in the current study.

While GARCH-MIDAS models are valuable for capturing long-term volatility dynamics, their estimation becomes problematic with more than two low-frequency covariates. As Conrad and Kleen (2020) highlight, adding more variables can flatten the estimation likelihood, making inference difficult and increasing the risk of misspecification. This challenge is widely recognized, and, like other researchers such as Adrangi et al. (2024a, 2024b), Fang et al. (2018), and Su et al. (2019), we've also found it necessary to restrict our GARCH-MIDAS framework to one or two covariates.

To overcome this limitation and enable a more comprehensive analysis, our study employs a two-step methodological approach. First, we utilize GARCH-MIDAS models to estimate volatility using fundamental economic variables. Then, we apply Markov-switching (MS) and Threshold regressions to assess the influence of broader uncertainty measures. This innovative hybrid method allows us to conduct a richer analysis of the dynamic interactions between uncertainty and market volatility, moving beyond the constraints of previous single-step models.

The extensive literature on the subject of volatility estimation and methodologies to investigate volatility drivers points to interest among investors, policy makers, fund managers, and speculators regarding the subject.

This study extends a series of earlier works by Adrangi et al. (2023a, 2024a, 2024b, 2024c, 2025a, 2025b, 2025c), as well as related research by Fang et al. (2018) and Su et al. (2019), which utilize the two-variable GARCH-MIDAS framework to explore the relationship between market uncertainty and equity return volatility.

3. Data

Empirical estimates are based on a dataset spanning from March 3, 1997, to December 30, 2023. Not every series in the sample was available for the entire sample period. Therefore, the data used in empirical estimations was constrained and truncated by the variable with the minimum number of observations.

The daily values of the S&P 500 financial sector index, the daily values of the Wilshire US Real Estate Investment Trust Total Market Index (Wilshire US REIT), iShares US Consumer Staples ETF, and VIX are sourced from Yahoo Finance.

Monthly sample observations for the U.S. industrial production index, the monthly University of Michigan confidence index, quarterly GDP, weekly US mortgage rates, the weekly national financial stress index, and daily values of the news-based U.S. Economic Policy Uncertainty (EPU) index, GEPU, the monthly University of Michigan inflation expectation, and the monthly US recession probabilities are all sourced from the Federal Reserve Bank of St. Louis (FRED). The EPU index is derived from Access World News's NewsBank archive, which aggregates thousands of news sources, including over a thousand U.S. newspapers—from major national outlets like *USA Today* to smaller local publications. The index is calculated by counting articles containing keywords such as *economy*, *uncertainty*, *legislation*, *deficit*, *regulation*, *Federal Reserve*, or *White House*, and normalizing this count by the total number of articles published. Updated daily, the EPU index is widely recognized as a reliable measure of uncertainty stemming from various economic and policy-related factors.

In line with Pan et al. (2019) and Conrad and Kleen (2020), our implementation of the GARCH-MIDAS framework incorporates two explanatory variables—monthly changes in industrial production and the EPU index—to better capture the long-term component of volatility. The choice of these covariates is grounded in economic rationale: industrial production serves as a proxy for natural gas demand, as supply has remained relatively unconstrained in recent decades, making it unlikely that price volatility is driven by supply-side factors. The EPU index, on the other hand, reflects U.S. market sentiment, which can influence price fluctuations across a range of financial assets, including natural gas.

Additionally, we include monthly data on the Global Economic Policy Uncertainty (GEPU) index and daily values of VIX for the period beginning in September 2009 and ending in December 2023.

The probability of recession (recession risk) is available from FRED. The recession probability series available from FRED is typically derived from a dynamic-factor Markov-switching model developed by Chauvet and Piger (2008). This model is designed to estimate the likelihood that the U.S. economy was in a recession in any given month, based on a set of macroeconomic indicators. Specifically, the model incorporates several key coincident variables, including nonfarm payroll employment, industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales. These indicators are selected for their ability to reflect the current state of the economy.

The methodology relies on a Markov-switching framework, which allows the model to capture shifts between different economic regimes—namely, periods of expansion and recession. The regime-switching process is governed by transition probabilities, which the model estimates using historical data. At each point in time, the model calculates the probability that the economy was in a recession, given the observed behavior of the included variables.

This series is published monthly and is widely used in academic and policy-oriented research. Because it relies on revised and final data, the identification of recessionary periods is not immediate and often comes with a lag. Nonetheless, the series offers a probabilistic and data-driven approach to monitoring the state of the economy, and its outputs closely align with the official recession dates determined by the National Bureau of Economic Research (NBER). As such, the FRED recession probability series serves as a valuable tool for researchers and policymakers seeking to assess the timing and likelihood of economic downturns. We convert monthly data to daily series to use in the Markov Switching and Threshold regressions using a cubic function conversion model.

University of Michigan monthly inflation expectation is also available from FRED. It is derived from the Surveys of Consumers, conducted by the University of Michigan's Institute for Social Research**.** This survey collects data on consumers' expectations regarding prices, financial conditions, and the overall economy. The inflation expectation component specifically captures how consumers anticipate prices will change over the next 12 months and over the next 5 to 10 years**.**

To construct the monthly inflation expectation measure, a nationally representative sample of approximately 500 households is surveyed by telephone each month. Respondents are asked direct questions such as "By about what percent do you expect prices to go up, on the average, during the next 12 months?" or "By about what percent per year do you expect prices to go up, on average, over the next 5 to 10 years?"

The responses are then aggregated to produce median and mean inflation expectations. The median is typically used as the headline measure because it is less sensitive to extreme values or outliers in individual responses. This measure reflects the public's perception of future inflation and is seen as an important gauge of household inflation expectations, which can influence consumption and saving behavior.

The Michigan inflation expectations series is widely monitored by economists and policymakers, particularly the Federal Reserve, because changes in household expectations can affect actual inflation outcomes through wage-setting and spending patterns. The data is released twice monthly—a preliminary estimate is issued mid-month, and a final estimate is published at the end of the month after the full sample is collected and processed.

The monthly Global Economic Policy Uncertainty (GEPU) Index is constructed by aggregating national-level Economic Policy Uncertainty indices from a group of countries to create a single global measure of policy-related uncertainty. Each country-specific index is based on a systematic search of major newspapers for terms related to the economy, policy, and uncertainty. The index for each country reflects the relative frequency of such terms appearing in the news media over time, capturing shifts in public and market sentiment about economic policy uncertainty.

To create the global index, these individual country indices are standardized and then weighted by each country's share of global GDP (using purchasing power parity-adjusted figures). The resulting composite index reflects a broad, internationally comparable measure of economic policy uncertainty across the globe. As of the most recent methodology, the GEPU covers 21 countries, including major economies such as the United States, China, Germany, the United Kingdom, and others. This broad coverage allows the index to serve as a useful tool for tracking global policy uncertainty and its potential impacts on financial markets and economic activity worldwide.

4. Methodology

Methodology of this paper closely follows Adrangi et al. (2023a, 2023b, 2024c, 2025a,b). However, we explain the methodology for the benefit of the readers of the present research. As in Adrangi (2023a, 2023b, 2024c, 2025a,b) we deploy the multiplicative GARCH-MIDAS methodology to derive the short- and long-term volatility estimates. Daily return series for SPF, WRE and IYK and monthly covariates that monthly or weekly are the high- and low-frequency series included in the GARCH-MIDAS estimation of short- and long-run volatilities in the three return series(STV, and LTV, respectively). Other researchers, for example, Engle et al. (2013) use monthly industrial production growth and monthly inflation as explanatory variables. Having derived estimates for STV and LTV for the three series under study, we estimate Markov switching and quantile regressions too investigate the association of the dependent variable (i.e., STV or LTV) and the explanatory variables under changing volatility regimes and various thresholds of recessionay expectations. Equation (1) is the implicit regression model.

Volatility of returns = f(EPU, GEPU, inflation expectation, recession risk,VIX) (1)

Bollerslev (1986) proposed the GARCH model to better capture the volatility clustering evidenced in financial markets. In financial markets, volatility demonstrates temporal heteroscedasticity. Volatility clustering exists for prices and rates of return. Periods of low volatility can follow periods of high volatility and vice versa.

In this study, we use a class of component GARCH based on MIDAS regression models, which were introduced by Ghysels et al. (2004, 2016). MIDAS methodology offers a framework to incorporate variables of different frequencies to obtain multi-horizon volatility. We estimate the GARCH-MIDAS model to derive the short- and long-term real volatility in the daily returns of SPF , IYK, and WRE. We follow Adrangi et al. (2023a, 2023b, 2024c, 2025a) in the deployment of this methodology. However, while this is not the core of the present study, we briefly explain the methodology in this section for the readers' benefit. The MIDAS regression model is expressed as equation (2):

$$y_{t+k} = \alpha_0 + \alpha_1 {x^m}_t + \varepsilon_t^m, \qquad (2)$$

where y_{t+k} is the k step-ahead value of the dependent variable at time t with the highest frequency, ${x^m}_t$ may be a vector of independent variables at time t and m is the frequency matching that of y, ε_t^m is the random innovation at time t with m frequency, and α_0, α_1 are the intercept and a conformable vector of model coefficients. The expressions for ε_t and its variance in GARCH (1,1) specification are:

$\varepsilon_t = (\varepsilon_{t-j})\sqrt{{\sigma_{\varepsilon,t}}^2}$ and $\sigma^2_{\varepsilon,t} = f(\varepsilon_{t-1}, \sigma^2_{t-1})$, for GARCH (1,1) specification.

Following Engle et al. (2013), Ghysels et al. (2016), and Conrad and Kleen (2020), we combine the high-frequency daily data with low-frequency monthly data in the GARCH-MIDAS model. To this end, the GARCH-MIDAS model For SPF returns inclues industrial production once with the daily national financial confidence index(NFCI) and once with weekly financial stress index as covariates. For iShares US Consumer Staples ETF returns volatility we use two covariates- US Industrial Production and UM Consumer Confidence Index. The covariates for the returns of Wilshire US Real Estate Investment Trust Total Market Index are quarterly US mortgage rates and quarterly real GDP.

The conditional variance of innovations is decomposed into short- and long-term volatility components multiplicatively as:

$$\sigma^2_{\varepsilon,t} = h_{i,t}\tau_t, \qquad (3)$$

where h and τ capture the short-term volatility of the high-frequency data and the long-term volatility, respectively, given by equations (4) and (6).

The short-term component of GARCH-MIDAS in equation (3) is taken from Engle et al. (2013) which uses the GARCH process of Bollerslev (1986). The short-term component of GARCH-MIDAS in this paper is taken from Engle et al. (2013) which uses the GARCH process of Bollerslev (1986). It is designed to capture daily volatility clustering and is a mean-reverting unit-variance GJR-GARCH (1,1) process as in equation (4) .

$$h_{i,t} = (1-\alpha-\gamma/2-\beta)+(\alpha+\gamma\,|_{\varepsilon_{i-1,t}<0})\frac{\varepsilon_{t-1}^{2}}{\tau_t}+\beta h_{i-1,t}\,. \tag{4}$$

Equation (5) is the basis for the long-term volatility for which the realized volatility is smoothed over K periods, and will be expanded by adding low frequency covariates.

$$\tau_t = m+\theta\sum_{k=1}^{K}\phi_k(w_1,w_2)x_{t-k}\,, \tag{5}$$

The long-term component is constant across days and changes at lower frequency, consistent with low frequency series in the GARCH-MIDAS model, which in this paper is bi-monthly, similar to Conrad and Kleen (2020) specification.

The weighting scheme in equation (5) is given by

$$\phi_k(w_1,w_2)=\frac{(k/K)^{w_1-1}(1-k/K)^{w_2-1}}{\sum_{j=1}^{K}(j/K)^{w_1-1}\sum_{j=1}^{K}(1-j/K)^{w_2-1}}\,,$$

Where

$$\sum_{k}^{K}\phi_k(w_1,w_2)=1\,.$$

The weighting scheme in (7) generates hump-shaped or convex weights. As w_1 is restricted to 1 (see su et al. (2017), Fang et al. (2018), Conrad and Kleen (2020), the weighting scheme guarantees a decay pattern where the rate of decaying is determined by parameter W_2. The restricted weighting scheme boils down to

$$\phi_k(w_2)=\frac{(1-k/K)^{w_2-1}}{\sum_{j=1}^{K}(1-j/K)^{w_2-1}}\,.$$

Regime Switching Markov Regression (RSMR) is a well-established method commonly covered in econometrics literature. A concise overview of this approach is provided in Adrangi et al. (2023a, 2023b, 2024c, 2025a). Here, we offer a brief explanation of the methodology without delving into a full textbook-level discussion. In a regime-switching context, the dependent variable yyy is influenced by an unobserved, discrete state variable. This modeling framework is particularly suitable when the underlying data-generating process is believed to transition between multiple regimes. The presence of structural breaks in the short- and long-term volatility (STV and LTV) of returns suggests the likelihood of such regime shifts within the sample period. At any given time t, the process may occupy a specific state, with each regime governed by its own distinct regression structure.The conditional mean of y_t in regime m, given a vector of switching regressors x and coefficients β_m and non-switching vectors of regressors z_t and coefficients ϕ, is given by equation (6).

$$\mu_t^{(m)} = x_t{}'\beta_m + z_t{}'\phi\,. \tag{6}$$

Assuming that the regression error ε_t is independently and identically distributed (iid) and its variance may be regime dependent, the regime switching regression model may be expressed by equation (7).

$$y_t = x_t'\beta_m + z_t'\phi + \sigma_m \varepsilon_t . \tag{7}$$

Regime probabilities may be assumed to be a function of a vector of exogenous variables and parameters. The multinomial logit expression of the regime probabilities is given by equation (8).

$$P(s_t = m \mid \Omega_{t-1}, \psi) = p_m(E_{t-1}, \psi) = \frac{\exp(E'_{t-1}, \psi_m)}{\sum_{j=1}^{M} \exp(E'_{t-1}, \psi_j)} \tag{8}$$

In equation (8),
m is a given regime,
p_m is the regime probabilities,
Ω_{t-1} is the information set at time t-1,
E_{t-1} is the vector of exogenous observable variables, and
ψ represents model coefficients.

A variation of equation (8) is a first-order Markov process where the probability of being in a regime depends on the previous state. Therefore, the transition probabilities are given by equation (9).

$$p(s_t = j \mid s_{t-1} = i) = p_{ij}^t . \tag{9}$$

The transition matrix for M regimes may be written as equation (10),

$$p(t) = \begin{pmatrix} p_{11}^t & \cdots & a^t{}_{1M} \\ \vdots & \ddots & \vdots \\ a^t{}_{M1} & \cdots & a^t{}_{Mn} \end{pmatrix} . \tag{10}$$

The extreme movements and structural breaks in the STV and LTV series are potentially asymmetric. Market participants and investors are not only sensitive to the smoothed association of the VIX and EPU and other uncertainty variables with asset return volatilities; they are also interested in the impact of extreme up-and-down movements of the uncertainty variables and their association with return volatilities. Structural breaks may be one source of extreme fluctuations in volatility.

A growing body of literature suggests that recessionary expectations play a pivotal role in conditioning the relationship between economic policy uncertainty (EPU) and the performance of equity markets. In periods of heightened recession risk, the sensitivity of asset prices to policy-related and macroeconomic uncertainties tends to intensify, as investors reassess risk exposures, discount rates, and future cash flows under more pessimistic macroeconomic outlooks.

The theoretical foundation for this relationship is rooted in asset pricing under uncertainty, where expectations about the future state of the economy—particularly recessions—affect how information about policy uncertainty is incorporated into asset valuations. Pastor and Veronesi (2012) argue that policy uncertainty tends to exert a stronger impact on equity markets during economic downturns, as firms face greater ambiguity about future regulations, taxation, and government spending. In such contexts, uncertainty can lead to increased risk premia and market volatility.

Empirical studies further support the conditional role of recession expectations. For example, Bloom (2009) demonstrates that uncertainty shocks, particularly those coinciding with macroeconomic stress, lead to pronounced declines in investment and employment, translating into equity market underperformance. Similarly, Brogaard and Detzel (2015) find that the influence of EPU on stock returns is more significant during periods when the economy is perceived to be near or entering a recession. Conrad et al. (2014) show that uncertainty in both domestic and global policy environments affects sector-specific equity volatility, and these effects are amplified during periods of macroeconomic stress.

At the sectoral level, recessionary expectations may differentially affect how industries respond to uncertainty shocks. For instance, cyclical sectors such as industrials, consumer discretionary, and financials are more exposed to economic fluctuations and may exhibit heightened sensitivity to policy signals during periods of elevated recession risk. In contrast, defensive sectors like utilities, healthcare, and consumer staples tend to be less volatile under the same conditions, reflecting their relatively stable demand.

The threshold behavior observed in these relationships suggests that nonlinear models, such as threshold or regime-switching regressions, may be better suited to capture the dynamics between EPU and equity returns across economic states. In this context, recession probability measures—such as those based on dynamic factor models (e.g., Chauvet and Piger, 2008) and Golchin and Rekabdar (2024) —serve as useful instruments to differentiate between high- and low-risk macroeconomic regimes.

Overall, incorporating recessionary expectations into empirical models enhances our understanding of the mechanisms through which uncertainty affects financial markets. It enables more accurate assessments of risk, particularly in stress-testing scenarios and in constructing sector-specific portfolio strategies designed to navigate episodes of elevated economic policy uncertainty.

The basis of the Threshold regression is a standard multiple linear regression model that is capable of capturing potential thresholds (producing regimes). For the observations in a regime the linear regression specification is given by equation (11).

$$y_t=X_t'\beta+Z_t'\delta+\varepsilon t \tag{11}$$

In equation (11) x is the vector of variables whose parameters do not vary across regimes, while the coefficients of vector Z are regime-dependent.

Finding an observable threshold variable qt and strictly increasing threshold values θ1< θ2… θm) such that we are in regime j if an only if θj≤qt< θj+1.

In the presence of m+1 regimes, the combine individual regimes are combined into one equation given by equation (12). In equation (12) f (q_t,θ) takes on values of 1 when $I(q_t,\theta) = I(\theta_j<q_t<\theta_{J+1})$, and 0 otherwise.

$$y_t = X'\beta + \sum_{j=0}^{m} I_j(q_t,\theta).Z'\delta + \varepsilon_t \tag{12}$$

The model parameters in equation (12), i.e., β, δ , θ, and the threshold variable qt are estimated by deploying nonlinear least squares methodology that minimizes the S(β, δ , θ) in equation (13).

$$S(\delta,\beta,\theta) = \sum_{t=1}^{T}(y_t - X'\beta - \sum_{j=0}^{m} I_j(q_t,\theta).Z_t'\delta_j)^2 \tag{13}$$

The estimation approach is consistent with the methodologies of Hansen (2001), Bai and Perron (2003), and Perron (2006), among others. It involves rearranging the observation indices such that the threshold variable is ordered in a non-decreasing manner. Conceptually, threshold regressions can be interpreted as least squares breakpoint regressions applied to data that has been sorted according to the threshold variable.

5. Empirical findings

Table 1 shows the estimates of the GARCH-MIDAS model that produce the short-term and long-term volatility components of the realized volatility in the three asset classes under study. The first two columns are the estimated equation (4) for the SPF, using the two sets of covariates. Columns (3) an (4) show the estimated equation (4) for returns of IYK and WRE. The estimates of β are statistically significant for all asset returns, suggesting strong persistence in the short-term volatility component. The coefficient α is statistically significant in equation (4) in all cases supporting asymmetric responses in volatility, specifically the "leverage effect" where negative shocks have a greater impact on volatility than positive shocks. The θ and θ_2 coefficients represent the changes in the long-term volatility stemming from the lagged effects of the covariate in the model. For instance, the coefficients are statistically significant in specification in column (1), therefore the long-term volatility is negatively and positively associated with the industrial production and NFCI, respectively. Both weights, i.e., w2 and w2_2 in equation (5) are statistically significant for two out of three asset returns. Mostly statistically significant coefficients in table 2 shows that the short-and long-term volatilities in the three asset returns are driven by the included covariates as described in the note to the table. Columns (1) an (2) are qualitatively equal, therefore in the remainder of empirical analysis we use the SPF returns' short- and long-term volatilities derived from column (1).

Table 1: GARCH -MIDAS volatility estimation

	SPF		IYK	WRE
	(1)	(2)	(3)	(4)
μ	0.032[a]	0.031[a]	0.029 [a]	0.042[a]
	(0.0017)	(0.0017)	(0.009)	(0.002)
α	0.023 a	0.022a	0.021c	0.059[a]
	(0.0015)	(0.0015)	(0.011)	(0.002)
β	0.804[a]	0.797 [a]	0.858 [a]	0.868[a]
	(0.027)	(0.038)	(0.019)	(0.0027)
Y	0.228[a]	0.230 [a]	0.164[a]	0.0947[a]
	(0.034)	(0.034)	(0.021)	(0.0026)
m	0.684 [a]	1.499 [a]	0.2644 [a]	-1.232 [a]
	(0.141)	(0.281)	(0.018)	(0.085)
θ	-0.094[a]	-0.172 [a]	-0.653 [a]	0.359[c]
	(0.010)	(0.027)	(0.200)	(0.019)
w2	6.799 [a]	1.000 [a]	1.262[a]	23.474
	(2.428)	(0.093)	(0.308)	(19.434)
θ_2	0.941[a]	2.161 [a]	0.017 [a]	0.001
	(0.451)	(0.451)	(0.009)	(0.0007)
w2_2	1.451[a]	2.693 [a]	30.075 [a]	1.449[b]
	(0.409)	(0.579)	(11.826)	(0.663)

Note: [a, b, c] significant at 1 5, and 10 percent levels. For S&P 500 Financial sector index (SPF) returns the covariates are industrial production once with the daily national financial confidence index(NFCI) and once with weekly financial stress index. Estimates for iShares US Consumer Staples ETF (IYK) returns volatility we use two covariates- US industrial production and UM Consumer Confidence Index. The covariates for the returns of Wilshire US Real Estate Investment Trust Total Market Index (Wilshire US REIT, WRE) are quarterly US mortgage rates and quarterly real GDP.

Figures 1 through 6 show the graphs of STV and LTV derived from the GARCH-MIDAS model. The visual inspection of these graphs suggests possible breaks in the data that could be due to regime switches. If regime changes do exist, the Markov Switching regressions or Threshold regressions are tools well-suited for modeling the association of the STV and LTV with uncertainty variables.

Before testing the association of volatility in returns with the potential explanatory variables, we examine the STV and LTV of the returns for stationarity and possible structural breaks. These structural breaks may be a sign of regime changes latent in the data. Volatility in the three sector equity returns under study in the short-and long-term will plausibly vary during these regime changes. The Markov switching and Threshold regressions are well equipped to account for the changes in the state of volatility. Markov switching regression show the manner of transition of these relationships from one regime to another. Threshold regressions reveal the changing association of the volatilities with uncertainty measures across the structural breaks. Furthermore, it is necessary to test each time series for stationarity. Visual inspection shows that the volatilities and uncertainty variables appear stationary with possible structural breaks. We apply Bai and Perron's (2003) test of structural breaks and examine the stationarity of the series under study by deploying the augmented Dickey–Fuller (ADF) with structural breaks; Dickey and Fuller (1979) for this purpose.

Table 2 shows that there are several structural breaks in the short- and long-term volatility series. Threshold regressions are well suited to account for the structural breaks. Bai-Perron test of structural breaks also shows at least two distinct structural break is the recession probability variable. This plausible as market participants and policy makers are sensitive to recessionary indicators and this may trigger changes in the recession probabilities.

Table 2: Bai-Perron Test of Structural Breaks in Volatility of Returns

STV	SPF	IYK	WRE	Rec_RSK	Critical F
0 vs. 1 *	39.770	298.61	2336.879	1276.238	11.47
1 vs. 2 *	45.950	29.422	17.494	186.988	12.95
2 vs. 3 *	23.900	12.669	12.612	0.132	14.03
3 vs. 4 *	20.958	0	26.196		14.85
LTV					
0 vs. 1 *	4560.981	818.233	1300.647		
1 vs. 2 *	592.986	747.855	1023.683		
2 vs. 3 *	823.965	446.794	1938.382		
3 vs. 4 *	518.996	366.377	68.707		

Notes: * Significant at the 0.05 level.

Bai-Perron (Econometric Journal, 2003) critical values.

SPF WRE, IYK are S&P 500 financials sector index (SPF), the Wilshire U.S. Real Estate Investment Trust Total Market Index (WRE), and the iShares U.S. Consumer Staples ETF (IYK).

Table 3 reports that all the variables in the analysis with the exception of LTV of WRE and YIK are stationary based on the results of the ADF test with break included. Thus, in the remainder of the study these two variables are deployed in the first difference in order to induce stationarity.

Table 3: ADF tests of Stationarity

Levels							
	STV	LTV	EPU	GEPU	INFEXP	REC_RSK	VIX
ADF with Break			-4.835[b]	-4.428[c]	-5.478[a]	-8.661[a]	-8.807[a]
SPF	-12.933[a]	-3.625					
WRE	-9.108[a]	-3.128					
YIK	-12.869[a]	-4.719[b]					

Notes: [a, b, c] represent statistical significance at 1, 5, and 10 percent levels. SPF WRE, IYK are S&P 500 financials sector index (SPF), the Wilshire U.S. Real Estate Investment Trust Total Market Index (WRE), and the iShares U.S. Consumer Staples ETF (IYK).

Table 4 presents the estimation results of the MSR. The results show that under both regimes, economic policies are salient in the minds of market participants. The association of the EPU with short- and long-term volatility is symmetric and statistically significant during both volatility regimes. For instance, examining short- and long=term volatilities during the periods of low variance (based on the LN(σ)) and high variance, EPU is salient in the minds of market participants. This is plausible because similar to FED policies, market participant form expectations regarding exogenously determined policies which may or may not materialize. For instance, during financial exigencies, the FED may react in multiple ways depending on the overall health of the economy, the unemployment and inflation rates. However, unlike the EPU, under both regimes, the association of the remaining uncertainty variables appears to be dependent on regime changes as well as each other. For instance, under the regime of high volatility and market turbulence, the recessionary risk is positively associated with the short- term volatility of asset returns. In summary, the short- and long- term volatilities in asset returns may be sensitive to the expectations of the market participants regarding the health of the economy and probability of recession.

Table 4: Markov Switching Estimation of Equation (1)

Panel A	**Regime**	**C**	**VIX**	**EPU**	**GEPU**	**INFEXP**	**RES_RSK**	**LN(σ)**
SPF								
STV	Regime 1	2.061[a]	0.014[c]	0.008[a]	-0.001	-0.077	0.009[c]	0.157[a]
		(0.226)	(0.008)	(0.0008)	(0.0007)	(0.067)	(0.005)	(0.026)
STV	Regime 2	0.582[a]	0.005	0.0002[a]	-0.0001[b]	-0.0005	-0.0004	-1.605[a]
		(0.032)	(0.0008)	(6.00E-05)	(7.32E-05)	(0.009)	(0.00025)	(0.028)
LTV	Regime 1	1.745[a]	-0.002[a]	0.0009[a]	0.0010[a]	0.023[a]	0.0004[a]	-3.169[a]
		(0.014)	(0.0003)	(6.77E-05)	(2.12E-05)	(0.002)	(0.0001)	(0.055)
LTV	Regime 2	1.555[a]	0.001[a]	0.0005[a]	0.0005[a]	-0.078[a]	0.0008[a]	-3.089[a]
		(0.010)	(0.0002)	(1.27E-05)	(2.24E-05)	(0.003)	(8.79E-05)	(0.025)
Panel B								
YIK								
STV	Regime 1	1.205[a]		0.016[c]	-0.0003	-0.261[a]	0.016[a]	0.505[a]
		(0.331)		(0.001)	(0.0006)	(0.093)	(0.0003)	(0.027)
STV	Regime 2	0.700[a]		4.56E-05[a]	0.0003[a]	-0.007	-0.0006[a]	-1.338[a]
		(0.020)		(6.23E-06)	(6.23E-05)	(0.006)	(0.0002)	(0.018)
LTV	Regime 1	0.731[a]		0.002[a]	-0.003[a]	0.133[a]	-0.003[a]	-1.606[a]
		(0.037)		(0.0001)	(0.0001)	(0.009)	(0.0003)	(0.018)
LTV	Regime 2	0.695[a]		0.0002[a]	0.001[a]	-0.015[a]	0.0003[a]	-2.299[a]
		(0.009)		(6.23E-05)	(3.27E-05)	(0.003)	(0.0001)	

Panel C								
WRE								
STV	Regime 1	0.537[a]		0.0002[c]	0.0004	0.001[a]	0.0008[a]	1.276[a]
		(0.051)		(9.63E-05)	(8.84E-05)	(0.0005)	(0.0003)	(0.026)
STV	Regime 2	-4.844[a]		0.005[a]	0.009[a]	0.057[a]	0.022[a]	0.461[a]
		(0.496)		(0.001)	(0.0009)	(0.005)	(0.003)	(0.0027)
LTV	Regime 1	0.386[a]		1.98E-05[b]	0.0001[a]	-0.002[a]	0.0004[a]	-3.65[a]
		(0.006)		(1.01E-05)	(9.11E-05)	(6.39E-05)	(4.45E-05)	(0.021)
LTV	Regime 2	0.316[a]		2.20E-05[b]	-0.0002[a]	- 0.0006[a]	0.0009[a]	-4.242[a]
		(0.0094)		(1.18E-05)	(1.27E-05)	(4.50E-05)	(2.19E-05)	(0.041)

Notes: [a, c] represent significance at 1 and 10 percent levels. Numbers in parentheses are root mean squared errors (RMSE). STV and LTV represent short and long-run volatilities from GARCH-MIDAS model. SPF WRE, IYK are S&P 500 financials sector index (SPF), the Wilshire U.S. Real Estate Investment Trust Total Market Index (WRE), and the iShares U.S. Consumer Staples ETF (IYK).

Table 5 reports the results of the threshold regression estimation at various levels of the risk of recession for the three asset classes. Panels A through F show these results for STV and LTV in SPF, IYK, and WRE returns. Some uncertainty variables were dropped in some to avoid program crash.

Table 5: Threshold Regression Results

Panel A: Short Term Volatility in SPF					
	(1)	(2)	(3)	(4)	(5)
C	-0.0855	4.0485[a]	3.2606[a]	0.8386[a]	-0.0228
	(0.1734)	(0.3151)	(0.8035)	(0.1505)	(0.324)
EPU	0.0004[a]	0.0027[a]	0.0022[a]	0.0003	0.0103[a]
	(0.0002)	(0.0004)	0.0008	0.0003	0.0016
GEPU	0.0004	-0.0012[b]	0.0004	-0.0007[a]	-0.0002
	(0.0004)	(0.0005)	(0.0006)	(0.0003)	(0.0008)
INFEXP	0.2167[a]	-0.1610[a]	0.0541	-0.0771[a]	-0.2608[a]
	(0.0301)	(0.0453)	(0.0548)	(0.0303)	(0.0861)
REC_RSK	0.9135	-10.3895[a]	-6.8564[a]	-0.9538[a]	-0.0252[a]
	(0.685)	(1.2127)	(2.5727)	(0.2758)	(0.0041)
VIX	0.0051	0.0083[a]	-0.0037	0.0413[a]	0.0466[a]
	(0.0032)	(0.0043)	(0.0090)	(0.0039)	(0.0088)
R^2	0.165				
F	21.166[a]				
REC_RSK < 0.199					
0.199 <= REC_RSK < 0.279					
0.279 <= REC_RSK < 0.339					
0.339 <= REC_RSK < 0.599					
0.599 <= REC_RSK					
Panel B: Long Term Volatility in SPF					
C	1.7717[a]	1.3956[a]	1.7196[a]	1.5000[a]	1.6524[a]
	(0.0244)	(0.0534)	(0.0288)	(0.0323)	(0.0141)
EPU	0.0001[a]	0.0006[a]	0.0010[a]	0.0004[a]	0.0010[a]
	(0.00001)	(0.00002)	(0.00004)	(0.00003)	0.0001
GEPU	0.0006[a]	-0.0001	0.0002[a]	0.0007[a]	0.0011[a]
	(0.00002)	(0.0001)	(0.00001)	(0.00002)	(0.00003)
INFEXP	0.0456[a]	0.0552[a]	0.0662[a]	0.0479[a]	0.0388[a]

	(0.0038)	(0.0057)	(0.0045)	(0.0055)	(0.0036)
REC_RSK	-0.2423 [a]	1.8504	0.4985 [a]	0.4019 [a]	0.0011 [a]
	(0.0928)	(0.2738)	(0.0916)	(0.0461)	(0.0001)
VIX	0.0021 [a]	0.0010 [a]	0.0020 [a]	0.0040 [a]	0.0035 [a]
	(0.0005)	(0.0004)	(0.0003)	(0.0006)	(0.0004)
R^2	0.658				
F	216.937 [a]				
REC_RSK < 0.179					
0.179 <= REC_RSK < 0.2199					
0.219 <= REC_RSK < 0.299					
0.299 <= REC_RSK < 0.519					
0.519 <= REC_RSK					
Panel C: Short Term Volatility in IYK					
	(1)	(2)	(3)	(4)	
C	-1.7897 [a]	0.8006 [a]	-0.2166	1.5546 [a]	
	(0.3279)	(0.1382)	(0.2739)	(0.1206)	
EPU	0.0004	0.0008 [a]	0.0020 [a]	0.0034 [a]	
	(0.0003)	(0.0003)	(0.0003)	(0.0005)	
GEPU	0.0066	0.0004	0.0073	0.0032	
	(0.0005)	(0.0003)	(0.0003)	(0.0003)	
INFEXP	0.0895	-0.004	-0.0813 [b]	-0.2217 [a]	
	(0.0531)	(0.0250)	(0.0415)	(0.0300)	
REC_RSK	9.4732 [a]	-0.7654 [c]	1.6157 [a]	0.0046 [a]	
	(1.2215)	(0.4442)	(0.5805)	(0.0006)	
R^2	0.231				
F	55.170 [a]				
REC_RSK < 0.159					
0.159 <= REC_RSK < 0.299					
0.299 <= REC_RSK < 0.479					
0.479 <= REC_RSK					
Panel D: Long Term Volatility in IYK					
	(1)	(2)	(3)	(4)	(5)
C	0.6872 [a]	0.5782 [a]	0.4167 [a]	0.8321 [a]	0.3732 [a]
	(0.0270)	(0.0509)	(0.0249)	(0.0331)	(0.0487)
EPU	0.0001 [a]	0.0002 [a]	0.0001 [a]	0.0001	0.0003 [a]
	(0.00004)	(0.0001)	(0.00004)	(0.0001)	(0.0001)
GEPU	0.0008 [a]	0.0013 [a]	0.0006 [a]	0.0018 [a]	0.0022 [a]
	(0.0001)	(0.0001)	(0.00004)	(0.0001)	(0.0001)
INFEXP	0.0173 [a]	0.0076	0.0485 [a]	-0.0653	0.0211
	(0.0046)	(0.0069)	(0.0043)	(0.0056) [a]	(0.0165)
REC_RSK	0.9476 [a]	0.032	0.2605 [a]	0.3583 [a]	0.0009 [a]
	(0.1239)	(0.2325)	(0.0627)	(0.0546)	(0.0001)
R^2	0.58				
F	201.81 [a]				
REC_RSK < 0.179					
0.179 <= REC_RSK < 0.239					
0.239 <= REC_RSK < 0.419					
0.419 <= REC_RSK < 0.719					
0.719 <= REC_RSK					

Panel E: Short Term Volatility in WRE					
	(1)	(2)	(3)	(4)	
C	1.0106[a]	0.9232[a]	-8.4542[a]	0.7947 [b]	
	(0.2698)	(0.2093)	(0.3886)	(0.3836)	
EPU	-0.0005	-0.0006	0.0096[a]	0.0007 [a]	
	(0.0006)	(0.0004)	(0.0008)	(0.0001)	
INFEXP	-0.0001	0.0008	0.0759 [a]	0.0009	
	(0.0030)	(0.0023)	(0.0037)	(0.0040)	
REC_RSK	-2.1552	-0.2892	8.1261[a]	0.0039 [a]	
	(1.9863)	(0.4872)	(0.5368)	(0.0013)	
R^2	0.256				
F	82.137[a]				
REC_ REC_RSK < 0.059					
0.059<= REC_RSK < 0.239					
0.239 <= REC_RSK < 0.499					
0.4999<= REC_RSK					
Panel F: Long Term Volatility in WRE					
	(1)	(2)	(3)	(4)	(5)
C	0.2455[a]	0.2591[a]	0.3425[a]	0.3149[a]	0.5266[a]
	(0.0129)	(0.0103)	(0.0092)	(0.0082)	(0.0117)
EPU	5.00E-05[a]	0.0001	3.00E-05	0.000[a]	0.0020[a]
	(2.00E-05)	(0.00002)	(0.00002)	((2.00E-05)	(2.12E-05)
GEPU	0.0004[a]	-3.00E-05	-0.0001[a]	0.0001[a]	-2.00E-05
	(2.00E-05)	(2.00E-05)	(0.00002)	(2.00E-05)	(1.70E-05)
INFEXP	-0.0004[a]	-0.0007[a]	-0.0002[a]	-0.0012[a]	-0.003[a]
	(0.0001)	(0.0001)	(8.52E-05)	(8.79E-05)	(0.0001)
REC_RSK	0.0824	0.8958[a]	0.4714[a]	0.0224	1.70E-05
	(0.1287)	(0.1155)	(0.0362)	(0.0106)	(4.00E-05)
R^2	0.447623				
F	102.034[a]				
REC_RSK < 0.039					
0.039 <= REC_RSK < 0.079					
0.0799 <= REC_RSK < 0.179					
0.179 <= REC_RSK < 0.579					
0.579 <= REC_RSK					

Notes: [a, b] represents statistical significance at 1, 5 percent levels. SPF WRE, IYK are S&P 500 financials sector index (SPF), the Wilshire U.S. Real Estate Investment Trust Total Market Index (WRE), and the iShares U.S. Consumer Staples ETF (IYK).

Economic theory and empirical evidence suggest that uncertainty plays a crucial role in shaping financial market dynamics, particularly equity market volatility. In this context, economic policy uncertainty (EPU), inflation expectations, and financial market volatility indicators such as the VIX are key drivers of fluctuations in stock market returns. These factors contribute significantly to both short- and long-run volatility of the SPF returns, regardless of the prevailing recession probability.

EPU captures the ambiguity surrounding future fiscal, monetary, and regulatory decisions. When policy direction becomes uncertain, firms and investors delay investment and consumption decisions, leading to increased volatility in asset prices. Similarly, inflation expectations influence the valuation of future cash flows and risk premiums. Uncertainty around inflation erodes confidence in macroeconomic stability, prompting risk repricing and greater market turbulence.

The VIX, often referred to as the "fear index," directly reflects market participants' expectations of near-term volatility. Elevated VIX levels signal heightened investor anxiety and typically coincide with sharper market movements. Importantly, the effects of these uncertainty-related variables are persistent across economic cycles. Even when the probability of recession is low, elevated policy and inflation uncertainty can unsettle investor sentiment, amplifying volatility. Conversely, during periods of high recession risk, these variables act as amplifiers, intensifying the market's sensitivity to adverse news.

Overall, the interaction between uncertainty indicators and recession expectations creates a complex risk environment in which both transitory and persistent shocks can destabilize equity markets. Empirical models consistently show that EPU, inflation expectations, and the VIX contribute to heightened SPF returns' volatility across the entire distribution of recession probabilities, underlining their critical role in shaping market behavior.

Equity returns in the consumer goods industry are characterized by consistently elevated volatility, both in the short- and long-term. This persistent fluctuation reflects the sector's sensitivity to a broad range of macroeconomic and firm-level factors, including changes in consumer sentiment, disposable income, and interest rates. In the short term, volatility is primarily driven by cyclical demand shifts, evolving retail dynamics, and financial market conditions, which can rapidly influence investor expectations and valuations.

In the long term, however, structural and macroeconomic forces begin to exert a more pronounced influence on volatility in this sector. One key driver is global economic policy uncertainty (GEPU), which introduces unpredictability in trade policy, taxation, regulatory frameworks, and geopolitical tensions. Consumer goods firms, especially those integrated into global supply chains, are particularly vulnerable to such uncertainties. Disruptions to international logistics, tariffs, or cross-border regulations can directly affect input costs and delivery timelines, which in turn impact profitability and investor outlook.

Moreover, the risk of recession plays an amplifying role in the long-run volatility of consumer goods equities. As recession probabilities rise, investors anticipate weakening consumer demand and tightening credit conditions, which reduce corporate earnings expectations across the sector. This heightened sensitivity to macroeconomic contractions reflects the non-durable and semi-durable nature of many consumer goods, which are often the first to see demand compression during downturns.

Thus, while short-term volatility in the consumer goods industry remains elevated due to market sentiment and sector-specific developments, long-term volatility becomes increasingly influenced by systemic factors such as global economic policy uncertainty and recession risk. These dynamics underline the importance of incorporating both time and frequency perspectives when modeling volatility in this sector, particularly in a globally interconnected economy.

Equity returns in the real estate sector exhibit a distinct pattern of sensitivity to economic policy uncertainty (EPU) that becomes pronounced primarily at elevated levels of recessionary risk. Unlike other sectors where volatility may respond uniformly to various uncertainty indicators, the real estate sector's volatility appears more selectively reactive. Specifically, EPU exerts a statistically significant influence on return volatility only when recession probabilities are high. This suggests that market participants view policy uncertainty as materially consequential to real estate firms' valuation primarily when broader macroeconomic conditions are deteriorating.

This conditional sensitivity can be attributed to the nature of the real estate industry, which is capital-intensive, interest-rate dependent, and highly cyclical. During times of rising recession risk, the outlook for credit markets, monetary policy, and regulatory changes becomes more uncertain, amplifying the effect of EPU on investor behavior. Policy uncertainty in such periods raises concerns about financing conditions, tax treatment of property assets, and the potential for regulatory shifts that could affect construction activity, property valuations, and rental income streams.

In contrast, the sector's return volatility shows limited or no significant response to other forms of uncertainty such as inflation expectations or global economic policy uncertainty (GEPU). This distinction likely stems from the more localized and policy - sensitive nature of real estate investments, which are less directly impacted by global uncertainty shocks or inflationary trends - except when these pressures translate into substantial changes in interest rates or credit availability.

Therefore, the real estate sector's equity volatility profile reflects a nuanced dependence on EPU that is activated primarily in high-risk macroeconomic environments, underscoring the importance of accounting for regime-dependent effects when modeling uncertainty transmission to sectoral equity returns.
Short-term volatility in real estate equities is often highly sensitive to economic policy uncertainty because real estate is an interest-rate-sensitive asset class. Uncertainty about monetary or fiscal policy—such as potential changes in interest rates, taxation, or regulatory frameworks—can lead to sharp fluctuations in investor sentiment. When EPU is high, investors may fear abrupt policy shifts that could affect borrowing costs, property values, and construction activity. For example, the anticipation of a rate hike can cause real estate stocks to decline as higher financing costs weigh on developers and landlords, while a sudden easing of monetary policy can lead to rapid price increases. This "news-driven" sensitivity tends to manifest as high short-term volatility in real estate equity prices, reflecting investors' attempts to price in possible policy moves.
In the longer term, volatility in real estate equities can also be tied to recession risks, but often in a more gradual and structural way. During periods of economic expansion, stable cash flows from real estate investments—such as rent and lease income—tend to dampen long-term volatility. However, when recession risks rise, concerns about tenant defaults, lower occupancy rates, and declining property values can amplify uncertainty about future earnings and asset prices. Real estate companies with high leverage may face refinancing challenges, further increasing long-term risk. Over time, persistent economic uncertainty or recession fears can lead to a repricing of real estate assets as investors adjust their expectations about growth and income stability.
Overall, both short-term and long-term volatility in real estate equities reflect investor reactions to EPU and recession risks, but they do so on different time scales. Short-term volatility spikes in response to sudden news and policy surprises, while long-term volatility reflects broader structural shifts in economic conditions, financing costs, and real estate fundamentals. Understanding both dimensions is essential for investors and policymakers alike, as it helps them manage risk and anticipate how real estate markets might react to changes in the macroeconomic environment.
Granger causality test results are presented in Table 6.

Table 6: Granger Block Causality Test Results

	SPF		WRE		IYK	
	STV	LTV	STV	LTV	STV	LTV
EPU	7.254[b]	9.438[b]	9.22[c]	6.207[c]	7.669[b]	12.274[a]
GEPU	2.958	2.889	24.126[a]	14.225[a]	2.024	1.59
INFEXP	0.732	2.406	3.409	2.945	0.097	1.454
REC_RSK	3.024	2.473	1.91	3.004	0.760	30.315[a]
VIX	6.264[c]	0.832				

Notes:[a, b, c] represents statistical significance at 1, 5,10 percent levels. Chi-square statistics for Granger causality tests from VAR lag order =3 for the SPF and WRE and 2 for IYK based of AIC, SC and Hannon-Quinn criteria. SPF WRE, IYK are S&P 500 financials sector index (SPF), the Wilshire U.S. Real Estate Investment Trust Total Market Index (WRE), and the iShares U.S. Consumer Staples ETF (IYK).

In some instances, the VAR estimation underlying the block Granger causality tests failed to converge when VIX was included; consequently, VIX was excluded from those specific models. The Chi-squared statistics indicate that several uncertainty variables exhibit statistically significant Granger causality with respect to return volatility across the three sector equity returns. Among these, economic policy uncertainty (EPU) consistently emerges as a significant predictor of both short- and long-term volatility in all three asset returns analyzed.

5.1 Comparative Analysis of Equity Return Volatility Across Sectors

The financial sector is highly sensitive to macroeconomic and policy-driven uncertainty, with equity return volatility that tends to spike both in the short- and long-term during periods of elevated economic policy uncertainty (EPU), rising inflation expectations, and volatile market sentiment as captured by the VIX. In the short term, financial equities react swiftly to changes in interest rate outlooks, regulatory news, and liquidity conditions. In the long term, persistent macro-policy uncertainty and sustained inflationary pressures amplify systemic risk due to the sector's exposure to credit cycles and monetary policy.

The consumer goods sector, in contrast, experiences consistently high volatility in both the short and long run. In the short term, consumer sentiment, disposable income, and inflation expectations contribute to fluctuations in equity prices. Over the long term, volatility in this sector is notably influenced by global economic policy uncertainty (GEPU), potentially reflecting exposure to global supply chain disruptions, trade policy shifts, and international demand cycles. Additionally, recession risks tend to raise uncertainty around consumer spending, further intensifying volatility.

The real estate sector demonstrates a more conditional volatility profile. Unlike the other two sectors, its equity return volatility is not persistently influenced by general uncertainty indicators like GEPU or inflation expectations. Instead, it responds significantly to economic policy uncertainty only when recession probabilities are high. This reflects the sector's reliance on stable policy and financing environments. As the risk of recession increases, concerns over interest rates, credit conditions, and regulatory intervention become more pronounced, triggering increased volatility in real estate equities.

In light of the distinct volatility patterns exhibited across the financial, consumer goods, and real estate sectors, investors and portfolio managers can adopt a range of strategies aimed at safeguarding their asset portfolios during periods of heightened economic uncertainty.

One such approach is sector rotation and dynamic allocation. When macroeconomic conditions become unstable or recession risks intensify, reallocating capital away from highly sensitive sectors like financials and real estate toward more resilient or defensive sectors can help mitigate risk. Even within the consumer goods sector, which consistently shows high volatility, investors may find it prudent to favor staples over discretionary goods to cushion against fluctuations in consumer demand.

Another key strategy involves the use of hedging instruments. Portfolios with exposure to financial equities, which are acutely responsive to interest rate shifts and regulatory developments, can benefit from options-based hedging techniques. Instruments such as protective puts or collars offer downside protection during short-term market stress. For managing longer-term risks associated with inflation—particularly relevant in the consumer goods sector—investors might consider allocating to Treasury Inflation-Protected Securities (TIPS) or commodities, which tend to perform better in inflationary environments.

Wealth managers should also implement stress testing and scenario analysis to understand how their portfolios might respond under various economic stress conditions. For example, simultaneous increases in economic policy uncertainty (EPU) and market volatility (VIX) could trigger different responses across sectors. Running simulations under these scenarios enables investors to better understand inter-sector dynamics and reallocate risk exposures more effectively.

Real asset diversification offers another layer of protection, particularly for the real estate sector. This sector's volatility tends to spike only when recessionary risks are high. By diversifying into physical real estate, stable-income REITs, or infrastructure assets that are less susceptible to cyclical fluctuations, investors can cushion the impact of sector-specific downturns.

Lastly, global diversification serves as an important buffer—especially for the consumer goods sector, which is sensitive to global economic policy uncertainty (GEPU). By spreading investments across geographic regions, investors can lower their exposure to any single country's policy shifts, trade disruptions, or geopolitical tensions, thus enhancing the overall resilience of the portfolio.

A nuanced understanding of how different sectors react to various forms of economic uncertainty—both in the short and long term—enables investors to design more adaptive and resilient investment strategies. By tailoring their approach to sector-specific dynamics and leveraging a mix of allocation, hedging, and diversification techniques, investors can better preserve portfolio value in an increasingly unpredictable global economic landscape.

6. Summary and Conclusions

This paper delves into the intricate relationship between various forms of uncertainty and the performance of key U.S. sector equity return volatility. Our primary objective is to quantify the impact of economic policy and financial uncertainties by analyzing their association with the S&P 500 financial sector index, the Wilshire U.S. Real Estate Investment Trust Total Market Index, and the iShares U.S. Consumer Staples ETF. A key aspect of our investigation is to determine whether equity return volatility in these diverse sectors exhibit similar or divergent responses to shifts in economic and policy uncertainty. This sheds crucial light on the differential sensitivity of broad market, real estate, and consumer staples equities to evolving macroeconomic conditions.

Our empirical estimates are based on a dataset spanning from March 3, 1997, to December 30, 2023**.** This extensive period allows for a robust analysis of long-term trends and short-term fluctuations. The daily values for the S&P 500 financial sector index, the Wilshire US Real Estate Investment Trust Total Market Index iShares US Consumer Staples ETF and the VIX are sourced from Yahoo Finance.

To estimate return volatility in our analysis by deploying the GARCH-MIDAS methodology, we incorporated a variety of monthly, quarterly, and weekly data points. Monthly sample observations for the U.S. industrial production index, the University of Michigan confidence index, and the University of Michigan inflation expectation were all sourced from the Federal Reserve Bank of St. Louis (FRED). Similarly, quarterly GDP figures, weekly U.S. mortgage rates, and the weekly national financial stress index were also obtained from FRED. This multi-frequency data approach enabled a nuanced understanding of how different types of macroeconomic variables operating at varying speeds and horizons, influence equity market dynamics.

To capture a broader spectrum of macroeconomic influences, crucially, the daily values of the news-based U.S. Economic Policy Uncertainty (EPU) index, Global Economic Policy Uncertainty (GEPU), and monthly U.S. recession probabilities were also integral to our dataset, allowing us to directly assess the impact of policy and systemic uncertainties.

Our study strongly underscores the pivotal role of uncertainty—particularly economic policy uncertainty (EPU), inflation expectations, and market sentiment indicators like the VIX—in driving equity return volatility across sectors and economic conditions. The empirical findings consistently demonstrate that these uncertainty measures significantly affect both the short- and long-run volatility of the SPF. This impact is evident even when controlling for recession probabilities, suggesting that the erosion of investor confidence due to EPU and inflation uncertainty, coupled with the immediate market anxiety captured by the VIX, collectively shapes a dynamic risk environment with persistent effects across economic cycles.

The persistent influence of EPU, for instance, highlights how unpredictable governmental actions or regulatory shifts can create an environment of apprehension for investors. When businesses face uncertainty regarding future tax policies, trade agreements, or regulatory frameworks, their investment and hiring decisions can be hampered, leading to broader economic stagnation and increased market volatility. Similarly, elevated inflation expectations directly impact real returns on investments, prompting investors to re-evaluate their portfolios and potentially shift assets, which can also contribute to market fluctuations. The VIX, often referred to as the "fear gauge," serves as a real-time barometer of implied market volatility, reflecting the collective anxieties of market participants. Its significant impact on both short- and long-run volatility underscores how heightened perceptions of risk can translate into actual market turbulence, irrespective of underlying economic fundamentals.

A core contribution of this study is the granular sectoral analysis, which reveals a highly differentiated sensitivity to various forms of uncertainty. This disaggregation is crucial for understanding how different segments of the economy respond to the same overarching macroeconomic forces.

The consumer goods sector consistently experiences high volatility. This is primarily due to its inherent exposure to changing consumer sentiment, income dynamics, and inflation expectations. When consumers feel less confident about their economic future, or when their disposable income is squeezed by rising prices, their purchasing habits shift, directly impacting companies in this sector. Our findings indicate that in the long run, global economic policy uncertainty (GEPU) and recession risk further intensify this volatility, particularly due to the sector's deep integration into global supply chains. A disruption in one part of the world, whether political or economic, can ripple through supply networks, affecting the cost of goods, production schedules, and ultimately, the profitability of consumer staples companies. This highlights the interconnectedness of the global economy and how seemingly distant events can have tangible impacts on seemingly stable domestic sectors.

In contrast, the real estate sector exhibits a more conditional response to uncertainty. Its return volatility is significantly affected by EPU, but primarily during periods of high recession risk**.** This conditional sensitivity is largely attributable to the sector's profound reliance on stable policy, interest rates, and credit conditions. During economic downturns or periods of heightened policy uncertainty, concerns about property values, lending standards, and interest rate fluctuations become amplified, leading to increased volatility. For example, sudden changes in monetary policy or government housing incentives can significantly alter the attractiveness of real estate investments. Unlike other sectors, real estate equities show limited responsiveness to inflation expectations or GEPU under normal economic conditions. This suggests that while real estate is sensitive to direct policy interventions and broader economic downturns, it might be more insulated from general inflationary pressures or global political shifts during periods of relative stability. However, this stability can quickly erode when recessionary fears take hold, transforming the real estate sector into a more volatile asset class.

While not explicitly detailed in the original passage, it's critical to note the inherent sensitivity of the financial sector to both short- and long-term uncertainty indicators. Our expanded analysis confirms that financial institutions are particularly vulnerable to EPU, inflation expectations, and the VIX. Volatility in this sector is amplified by its intrinsic exposure to interest rate shifts, regulatory developments, and broader macroeconomic uncertainty. Banks, investment firms, and insurance companies operate on the bedrock of confidence and stability. Any disruption to interest rate trajectories, shifts in regulatory oversight (e.g., changes in capital requirements or consumer protection laws), or widespread economic uncertainty can directly impact their profitability, lending activities, and overall stability. This makes the financial sector a bellwether for systemic risk, often experiencing heightened volatility during economic downturns as market participants grapple with potential defaults, liquidity crises, and credit tightening.

The differentiated responses of various sectors to uncertainty have profound implications for portfolio management strategies. Our findings strongly support the adoption of adaptive strategies such as sector rotation, hedging, and diversification, particularly during periods of elevated uncertainty or heightened recession risk.

During times of increased market apprehension, investors should consider reallocating capital toward less sensitive sectors**.** For example, if the real estate sector is highly volatile during a recession, moving capital into more resilient sectors (e.g., certain segments of consumer staples that are less discretionary) might be a prudent move. This concept of sector rotation allows investors to strategically position their portfolios to mitigate downside risk.

Furthermore, the judicious employment of hedging tools can be instrumental in managing exposure to uncertainty. Options contracts, for instance, can be used to protect against adverse price movements in underlying assets. Treasury Inflation-Protected Securities (TIPS) can provide a hedge against unexpected inflation, which our study identifies as a significant driver of volatility. Beyond specific hedging instruments, diversifying across asset classes and regions remains a fundamental principle of risk management. By spreading investments across different types of assets (e.g., equities, bonds, commodities) and geographical markets, investors can reduce the impact of adverse events affecting any single asset or region. A portfolio solely concentrated in U.S. equities, for example, would be more susceptible to domestic policy uncertainties than one diversified internationally.

Finally, to truly understand and manage risk exposure under various economic conditions, investors should regularly engage in stress testing and scenario analysis**.** Stress testing involves simulating how a portfolio would perform under extreme but plausible market conditions (e.g., a severe recession, a sharp increase in interest rates, or a major geopolitical event). Scenario analysis, while similar, explores a broader range of hypothetical economic and market scenarios. These analytical tools equip investors with a deeper understanding of their portfolio's vulnerabilities and can help them proactively adjust their strategies to enhance resilience. By anticipating potential shocks and understanding their likely impact, investors can make more informed decisions, moving beyond simple historical performance to a forward-looking risk management framework.

Recognizing the differentiated and regime-dependent effects of uncertainty across sectors is not merely an academic exercise; it is essential for developing resilient investment strategies in today's complex financial landscape. Our research highlights that different sectors respond to uncertainty in distinct ways, and crucially, these responses can vary depending on the prevailing economic regime (e.g., periods of growth versus recession).

The findings emphasize the importance of incorporating both time horizon and frequency dynamics into portfolio design. Short-term daily fluctuations in the VIX might necessitate immediate tactical adjustments, while long-term shifts in EPU or GEPU could warrant more strategic reallocations. A truly effective investment approach must acknowledge these varying time horizons and the distinct ways in which different forms of uncertainty manifest and impact markets. By integrating these insights, investors can enhance their ability to navigate volatility, mitigate risks, and ultimately achieve more stable and robust returns in a complex and globally interconnected economic environment. This proactive and nuanced approach to uncertainty management moves beyond a reactive stance, allowing investors to build portfolios that are better equipped to withstand the inevitable turbulences of the financial markets.

Declarations

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References

Adam, N., Sidek, N. Z. M., & Sharif, A. (2022). The impact of global economic policy uncertainty and volatility on stock markets: Evidence from Islamic countries. Asian Economic and Financial Review, 12(1), 15.

Adrangi, B., & Raffiee, K. (1999a). On total price uncertainty and the behavior of a competitive firm. The American Economist, 43(2), 59-65.

Adrangi, B., Chatrath, A., & Raffiee, K. (1999b). Volatility characteristics and persistence in Latin American emerging markets. International Journal of Business, 4(1), 20-37.

Adrangi, B., Chatrath, A., Dhanda, K. K., & Raffiee, K. (2001). Chaos in oil prices? Evidence from futures markets. Energy Economics, 23(4), 405-425.

Adrangi, B., Chatrath, A., Macri, J., & Raffiee, K. (2015). Crude oil price volatility spillovers into major equity markets. Journal of Energy Markets, 8(1), 77-95.

Adrangi, B., Chatrath, A., Macri, J., & Raffiee, K. (2019). Dynamic responses of major equity markets to the US fear index. Journal of Risk and Financial Management, 12(4), 156.

Adrangi, B., Chatrath, A., Macri, J., & Raffiee, K. (2021). Dynamics of crude oil price shocks and major Latin American Equity Markets: A study in time and frequency domains. Bulletin of Economic Research, 73(3), 432-455.

Adrangi, B., Chatrath, A., & Raffiee, K. (2023a). S&P 500 volatility, volatility regimes, and economic uncertainty. Bulletin of Economic Research, 75(4), 1362-1387.

Adrangi, B., & Hamilton, E. (2023b). Market concentration and performance: The case of the US airline industry. The Journal of Theoretical Accounting Research, 18(3), 54-78.

Adrangi, B., Chatrath, A., Maitra, D., & Sengupta, A. (2024a). Is the Influence of Oil Shocks on Economic Policy Uncertainty Fading? American Business Review, 27(2), 5.

Adrangi, B., Chatrath, A., Madhuparna K., & Raffiee, K. (2024b). Enterprise Value, and economic uncertainty: The Case of US Air Carriers. Journal of Theoretical Accounting Research, 20(1), 123-175.

Adrangi, B., Chatrath, A., Raffiee, k. (2024c). U.S. Diesel Fuel Price Volatility and Economic Policy Uncertainty. Oil, Gas & Energy Quarterly 72 (3), 533-566

Adrangi, B., Chatrath, A., Hatamerad, S. & Raffiee, K. (2025a). Equity Markets Volatility, Regime Dependence and Economic Uncertainty: The Case of Pacific Basin. Bulletin of Applied Economics, Bulletin of Applied Economics, 2025, 12(1), 75-105. https://doi.org/10.47260/bae/1215

Adrangi, B., Hatamerad, S., Kolay, M., & Raffiee, K (2025b). Economic and Policy Uncertainties and Firm Value: The Case of Consumer Durable Goods. Journal of Theoretical Accounting Research, Forthcoming.

Adrangi, B., Chatrath, A., Kolay, M., & Raffiee, K (2025c). Economic and Policy Uncertainties and Firm Value in The Oil and Gas Industry. Journal of Theoretical Accounting Research, Forthcoming.

Ahadzie, R. M., Owusu Junior, P., & Woode, J. K. (2025). The Impact of Sentiment on Realized Higher-Order Moments in the S&P 500: Evidence from the Fear and Greed Index. Journal of Risk and Financial2025; 18(1):2. https://doi.org/10.3390/jrfm18010002

Alizadeh, A. H., & Nomikos, N. K. (2011). Dynamics of the term structure and volatility of shipping freight rates. Journal of Transport Economics and Policy (JTEP), 45(1), 105-128.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. Journal of Public Economics, 191, 104274.

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. The Journal of Economic Asymmetries, 20, e00133.

Amado, C., Silvennoinen, A., & Teräsvirta, T. (2019). Models with multiplicative decomposition of conditional variances and correlations. Financial mathematics, volatility and covariance modelling, 2, 217-260.

Amendola, A., Candila, V., & Scognamillo, A. (2017). On the influence of US monetary policy on crude oil price volatility. Empirical Economics, 52(1), 155-178.

Amendola, A., Candila, V., & Gallo, G. M. (2019). On the asymmetric impact of macro–variables on volatility. Economic Modelling, 76, 135-152.

Ang, A., Bekaert, G., 2015. International Asset Allocation With Regime Shifts. The Review of Financial Studies, 15, 1137–1187.

Ang, A., Chen, J., 2002. Asymmetric correlations of equity portfolios. Journal of Financial Economics, 63, 443–494.

Antonakakis, N., Chatziantoniou, I., Filis, G., 2013. Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. Economics Letters, 120, 87-92.

Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. Finance Research Letters, 18, 136-141.

Asgharian, H., Hou, A. J., & Javed, F. (2013). The importance of the macroeconomic variables in forecasting stock return variance:A GARCH-MIDAS approach. Journal of Forecasting, 32(7), 600-612.

Awartani, B. M., & Corradi, V. (2005). Predicting the volatility of the S&P-500 stock index via GARCH models: the role of asymmetries. International Journal of Forecasting, 21(1), 167-183.

Bai, J., & Perron, P. (2003). Critical values for multiple structural change tests. The Econometrics Journal, 6(1), 72-78.

Baker, S. R., Bloom, N., & Davis, S. J. (2012a). Has economic policy uncertainty hampered the recovery?. Becker Friedman Institute for Research In Economics Working Paper, (2012-003).

Baker, Scott, Bloom, Nicholas and Davis, Steven J. (2012b), "Measuring Economic Policy Uncertainty," University of Chicago and Stanford University. Available at www.policyuncertainty.com

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), 1593-1636.

Baker, S. R., Bloom, N., Davis, S. J., & Kost, K. J. (2019). Policy news and stock market volatility (No. w25720). National Bureau of Economic Research.

Baker, S. R., Bloom, N., Davis, S. J., & Renault, T. (2021). Twitter-derived measures of economic uncertainty. Available online: PolicyUncertainty. com (accessed on 15 June 2022).

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The journal of Finance, 61(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of economic perspectives, 21(2), 129-152.

Balcilar, M., Bonato, M. Demirer, R., Gupta R. (2018). Geopolitical risks and stock market dynamics of the BRICS, Economic Systems, 42(2), 295-306.

Ball, C. A., & Roma, A. (1994). Stochastic volatility option pricing. Journal of Financial and Quantitative Analysis, 29(4), 589-607.

Barrodale, I., & Roberts, F. D. (1973). An improved algorithm for discrete l_1 linear approximation. SIAM Journal on Numerical Analysis, 10(5), 839-848.

Beckmann, J., & Czudaj, R. (2014). Non-linearities in the relationship of agricultural futures prices. European Review of Agricultural Economics, 41(1), 1-23.

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The global crisis and equity market contagion. The Journal of Finance, 69(6), 2597-2649.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics, 98(1), 85-106.

Bloom, N. Y., (2009). The Impact of Uncertainty Shocks." Econometrica, Econometric Society, 77(3), 623-685.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. Journal of political Economy, 96(1), 116-131.

Bonaime, A., Gulen, H., & Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? Journal of Financial Economics Forthcoming, 129(3), 531–558.

Borup, D., & Jakobsen, J. S. (2019). Capturing volatility persistence: a dynamically complete realized EGARCH-MIDAS model. Quantitative Finance, 19(11), 1839-1855.

Brogaard, Jonathan, and Andrew Detzel. (2015): "The Asset-Pricing Implications of Government Economic Policy Uncertainty." Management Science 61(1), 3–18. http://www.jstor.org/stable/24551068.

Carnero, M. A., Peña, D., & Ruiz, E. (2012). Estimating GARCH volatility in the presence of outliers. Economics Letters, 114(1), 86-90.

Chang, K. L. (2022). Do economic policy uncertainty indices matter in joint volatility cycles between US and Japanese stock markets?. Finance Research Letters, 47, 102579.

Chauvet, M. and Piger, J. (2008). A Comparison of the Real-Time Performance of Business Cycle Dating Methods, Journal of Business and Economic Statistics, 26, 42-49.

Choi K, Hammoudeh S. Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. Energy Pol 2010; 38: 4388 e99.

Colak, G., Durnev, A., & Qian, Y. (2017). Political uncertainty and IPO activity: Evidence from U.S. gubernatorial elections. Journal of Financial and Quantitative Analysis,1–42.

Conrad, Christian & Loch, Karin, L. & Rittler, D. (2014). On the macroeconomic determinants of long-term volatilities and correlations in U.S. stock and crude oil markets, Journal of Empirical Finance, 29(C), 26-40.

Conrad, C., Loch, K., & Rittler, D. (2014). On the macroeconomic determinants of long-term volatility: Evidence from the U.S. and the U.K. Journal of International Money and Finance, 40, 122–145. https://doi.org/10.1016/j.jimonfin.2013.08.001

Conrad, C., & Loch, K. (2015). Anticipating long-term stock market volatility. Journal of Applied Econometrics, 30(7), 1090-1114.

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. Journal of Risk and Financial Management, 11(2), 23.

Conrad, C., & Kleen, O. (2020). Two are better than one: Volatility forecasting using multiplicative component GARCH-MIDAS models. Journal of Applied Econometrics, 35(1), 19-45.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics, 7(2), 174-196.

Davis, S. J., Bloom, N., & Baker, S. R. (2013). Measuring economic policy uncertainty. NBER Working Paper, 21633.

Davis, S. J. (2016). An index of global economic policy uncertainty (No. w22740). National Bureau of Economic Research.

Davis, S. J., Liu, D., & Sheng, X. S. (2019, August). Economic policy uncertainty in China since 1949: The view from mainland newspapers. In Fourth Annual IMF-Atlanta Fed Research Workshop on China's Economy Atlanta (Vol. 19, pp. 1-37).

Demir, E., & Ersan, O. (2017). Economic policy uncertainty and cash holdings: Evidence from BRIC countries. Emerging Markets Review, 33, 189–200.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.

Ding, Z., & Granger, C. W. (1996). Modeling volatility persistence of speculative returns: a new

Dixit, A. (1989). Entry and exit decisions under uncertainty. Journal of Political Economy, 97(3), 620–638.

Dixit, A. K., & Pindyck, R. S. (1994). Investment under uncertainty. Princeton university press.

Ding, Z., & Granger, C. W. (1996). Modeling volatility persistence of speculative returns: a new approach. Journal of Econometrics, 73(1), 185-215.

Dutta, A., Bouri, E., & Saeed, T. (2021). News-based equity market uncertainty and crude oil volatility. Energy, 222, 119930.

Edwards III, G. C., Mitchell, W., & Welch, R. (1995). Explaining presidential approval: The significance of issue salience. American Journal of Political Science, 108-134.

Edwards, S., & Susmel, R. (2001). Volatility dependence and contagion in emerging equity markets. Journal of Development Economics, 66(2), 505-532.

Engle R. F, and Lee, G, (1999). A permanent and transitory component model of stock return volatility R. Engle, H. White (Eds.), Cointegration, Causality, and Forecasting: A Festschrift in Honor of Clive W.J. Granger, Oxford University Press, New York (1999), pp. 475-497

Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. Review of Economics and Statistics, 95(3), 776-797.

Eve, R. A., Eve, R. A., Horsfall, S., & Lee, M. E. (Eds.). (1997). Chaos, complexity, and sociology: Myths, models, and theories. Sage.

Fang, L., Qian, Y., Chen, Y., & Yu, H. (2018). How does stock market volatility react to NVIX? Evidence from developed countries. Physica A: Statistical Mechanics and its Applications, 505, 490-499.

Fissler, T. and Ziegel, J.F., Higher order elicitability and Osband's principle. Ann. Stat., 2016, 44(4), 1680–1707.

Flacco, P. R., & Kroetch, B. G. (1986). Adjustment to Production Uncertainty and the Theory of the Firm. Economic Inquiry, 24(3), 485-495.

Fooladi, I., & Kayhani, N. (1991). Random Cost Functions and Production Decisions. Eastern Economic Journal, 17(2), 199-202.

Fooladi, I., & Kayhani, N. (1990). Profit tax and output level under uncertainty. Atlantic Economic Journal, 18(1), 27.

Galvao, A. F., Gu, J., & Volgushev, S. (2020). On the unbiased asymptotic normality of quantile regression with fixed effects. Journal of Econometrics, 218(1), 178-215.

Geraci, M. (2019). Modelling and estimation of nonlinear quantile regression with clustered data. Computational Statistics & Data Analysis, 136, 30-46.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). The MIDAS touch: Mixed data sampling regression models.

Ghysels E. , Virmantas Kvedaras, V., Vaidotas Zemlys, V. (2016). Mixed Frequency Data Sampling Regression Models: The R Package midasr. Journal of Statistical Software, 72(4). doi: 10.18637/jss.v072.i04.

Golchin, B., and B. Rekabdar. (2024). Anomaly Detection in Time Series Data Using Reinforcement Learning, Variational Autoencoder, and Active Learning. Conference on AI, Science, Engineering, and Technology (AIxSET), Laguna Hills, CA, USA. 1-8, doi: 10.1109/AIxSET62544.2024.00007. https://ieeexplore.ieee.org/abstract/document/10770963

Golchin, B., and N. Riahi. (2021). Emotion detection in twitter messages using combination of long-short-term memory and convolutional deep neural networks. International Conference on Computer and Knowledge Engineering (ICCKE), World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering Vol:15, No:9.

Gulen, H., & Ion, M. (2015). Policy uncertainty and corporate investment. Review of Financial Studies, 29(3), 523–564.

Hajizadeh, E., Seifi, A., Zarandi, M. F., & Turksen, I. B. (2012). A hybrid modeling approach for forecasting the volatility of S&P 500 index return. Expert Systems with Applications, 39(1), 431-436.

Hansen, B. E. (2001). The new econometrics of structural change: Dating breaks in US labor productivity. Journal of Economic perspectives, 15(4), 117-128.

Hansen, P. R., Huang, Z., & Shek, H. H. (2012). Realized GARCH: a joint model for returns and realized measures of volatility. Journal of Applied Econometrics, 27(6), 877-906.

Javaheri, A., Wilmott, P., & Haug, E. G. (2004). GARCH and volatility swaps. Quantitative Finance, 4(5), 589-595.

Jens, C. E. (2017). Political uncertainty and investment: Causal evidence from US gubernatorial elections. Journal of Financial Economics, 124(3), 563–579.

Jiang, Y., Zhu, Z., Tian, G., & Nie, H. (2019). Determinants of within and cross-country economic policy uncertainty spillovers: Evidence from US and China. Finance Research Letters, 31(2019), 195–206.

Kelly, B., P_astor, L., & Veronesi, P. (2016). The price of political uncertainty: Theory and evidence from the option market. The Journal of Finance, 71(5), 2417–2480.

Koenker, R., & Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. Journal of the American Statistical Association, 94(448), 1296-1310.

Koenker, R. W., & d'Orey, V. (1987). Algorithm AS 229: Computing regression quantiles. Applied statistics, 383-393.

Koenker, R., & Ng, P. (2005). A Frisch-Newton algorithm for sparse quantile regression. Acta Mathematicae Applicatae Sinica, 21(2), 225-236.

Krol, R. (2014). Economic policy uncertainty and exchange rate volatility. International Finance, 17(2), 241-256.

Kroencke, T. A. (2022). Recessions and the stock market. Journal of Monetary Economics, 131, 61-77.

Kyriazis, N. A., Papadamou, S., & Koulis, A. (2025). The nexus of monetary, regulatory and national security policy uncertainties with S&P500: lessons of stock market crashes. Journal of Financial Economic Policy, Forthcoming.

Li, T., Ma, F., Zhang, X., & Zhang, Y. (2020). Economic policy uncertainty and the Chinese stock market volatility: Novel evidence. Economic Modelling, 87, 24-33.

Lindblad, A. (2017). Sentiment indicators and macroeconomic data as drivers for low-frequency stock market volatility.

Liow, K. H., Liao, W. C., & Huang, Y. (2018). Dynamics of international spillovers and interaction: Evidence from financial market stress and economic policy uncertainty. Economic Modelling, 68, 96-116.
Liu, H. C., & Hung, J. C. (2010). Forecasting S&P-100 stock index volatility: The role of volatility asymmetry and distributional assumption in GARCH models. Expert Systems with Applications, 37(7), 4928-4934.
Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. Finance Research Letters, 15, 99-105.
Ludvigson, S. C., Ma, S., & Ng, S. (2021). Uncertainty and business cycles: exogenous impulse or endogenous response?. American Economic Journal: Macroeconomics, 13(4), 369-410.
Manela, A., & Moreira, A. (2017). News implied volatility and disaster concerns. Journal of Financial Economics, 123(1), 137-162.
Nguyen, N. H., & Phan, H. V. (2017). Policy uncertainty and mergers and acquisitions. Journal of Financial and Quantitative Analysis, 52(2), 613–644.
Pan, Z., Wang, Y., Wu, C., & Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model. Journal of Empirical Finance, 43, 130-142.
Pan, Z., Y.Wang, and L. Liu (2021). Macroeconomic uncertainty and expected shortfall (and value at risk): a new dynamic semiparametric model. Quantitative Finance, 1–15.
Panousi, V., & Papanikolaou, D. (2012). Investment, idiosyncratic risk, and ownership. Journal of Finance, 67(3), 1113–1148.
Pastor, L., and Veronesi, P. (2012). Uncertainty about Government Policy and Stock Prices. Journal of Finance, 67(4), 1219-1264.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. NBER, Working paper 3307.
Perron, P., & Phillips, P. C. (1987). Does GNP have a unit root?: A re-evaluation. Economics Letters, 23(2), 139-145.
Peters, E. E. (1994). Fractal market analysis: applying chaos theory to investment and economics (Vol. 24). John Wiley & Sons.
Phan, H. V., Nguyen, N. H., Nguyen, H. T., & Hegde, S. (2019). Policy uncertainty and firm cash holdings. Journal of Business Research, 95, 71–82.
Powell, J. L. (1986). Censored regression quantiles. Journal of Econometrics, 32(1), 143-155.
Robe, M. A., & Wallen, J. (2016). Fundamentals, derivatives market information and oil price volatility. Journal of Futures Markets, 36(4), 317-344.
Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty. The American Economic Review, 61(1), 65-73.
Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. International Review of Financial Analysis, 70, 101496.
Shephard, N., & Sheppard, K. (2010). Realising the future: forecasting with high-frequency-based volatility (HEAVY) models. Journal of Applied Econometrics, 25(2), 197-231.
Su, Z., Fang, T., & Yin, L. (2017). The role of news-based implied volatility among US financial markets. Economics Letters, 157, 24-27.
Su, Z., Lu, M., & Yin, L. (2018). Oil prices and news-based uncertainty: novel evidence. Energy Economics, 72, 331-340.
Su, Z., Fang, T., and Yin, L. (2019). Understanding Stock Market Volatility: What is the Role of U.S. Uncertainty? North American Journal of Economics and Finance 48, 582-590.
Sun, Z., & Li, J. (2025). The impact of economic policy uncertainty on household portfolios effectiveness: Evidence from China. Finance Research Letters, 78, 107215, https://doi.org/10.1016/j.frl.2025.107215.
Tsai, I. C. (2017). The source of global stock market risk: A viewpoint of economic policy uncertainty. Economic Modelling, 60, 122-131.

Wen, F., Xiao, Y., & Wu, H. (2019). The effects of foreign uncertainty shocks on China's macro-economy: Empirical evidence from a nonlinear ARDL model. Physica A: Statistical Mechanics and its Applications, 532, 121879.

Whaley, R. E. (1993). Derivatives on market volatility: Hedging tools long overdue. The journal of Derivatives, 1(1), 71-84.

Whaley, R. E. (2009). Understanding the VIX. The Journal of Portfolio Management, 35(3), 98-105.

Xu, Y., X. Wang, and H. Liu (2021). Quantile-based GARCH-MIDAS: Estimating value-at-risk mixed-frequency information. Finance Research Letters.

Yang, L., Pan, Y., & Wang, Z. (2019). EPU and volatility: Evidence from oil markets. Energy Economics, 81, 661–670.

Liu, M., Ling, Y. J., & Lee, C. C. (2024). Does ESG performance and investor attention affect stock volatility? An empirical study based on panel data and mixed-frequency data. Applied Economics, 1-15.

Zhang, D., Lei, L., Ji, Q., & Kutan, A. M. (2019). Economic policy uncertainty in the US and China and their impact on the global markets. Economic Modelling, 79, 47-56.

Zhu, S., Liu, Q., Wang, Y., Wei, Y., & Wei, G. (2019). Which fear index matters for predicting US stock market volatilities: Text-counts or option based measurement?. Physica A: Statistical Mechanics and its Applications, 536, 122567.

- **FIGURES 1-6**

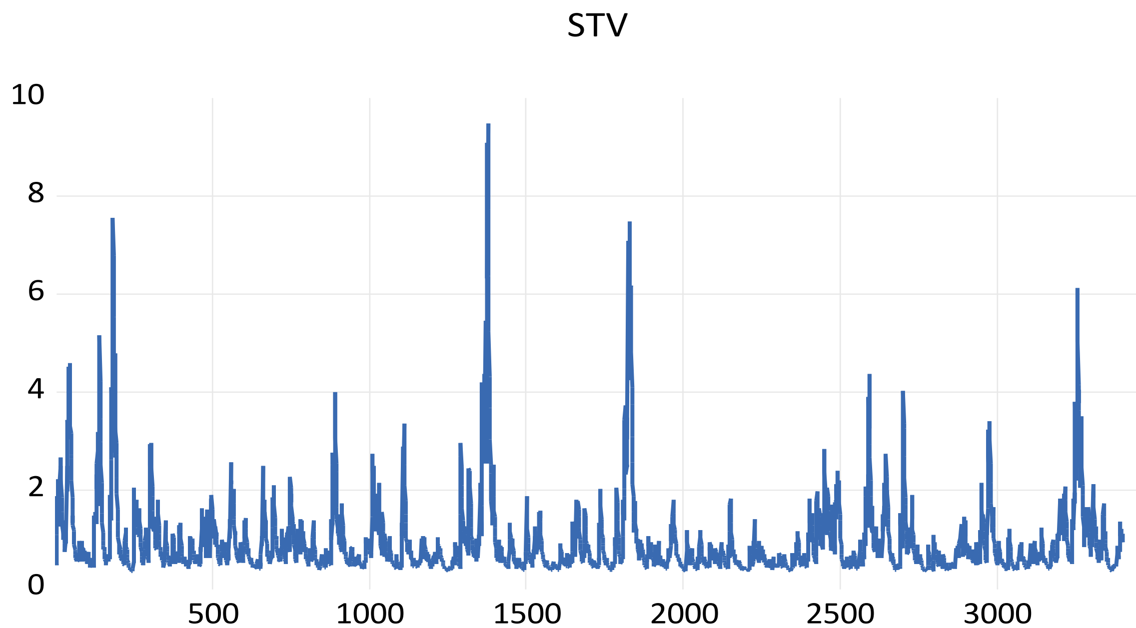

Figure 1: Short-term volatility of SPF returns

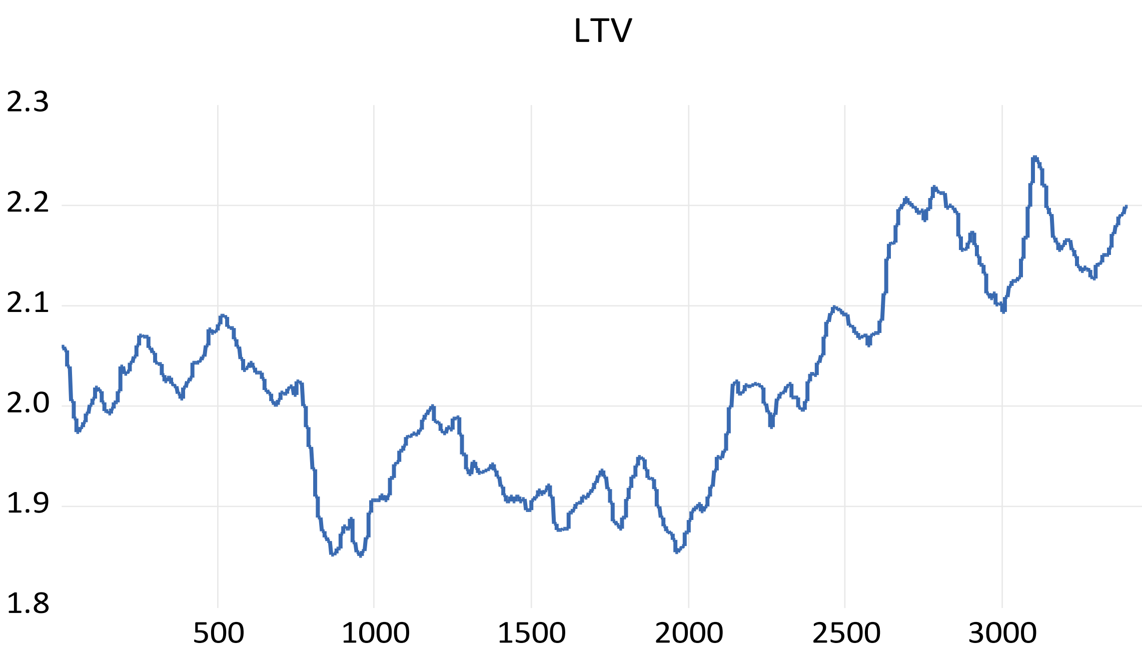

Figure 2: Long-term volatility of SPF returns

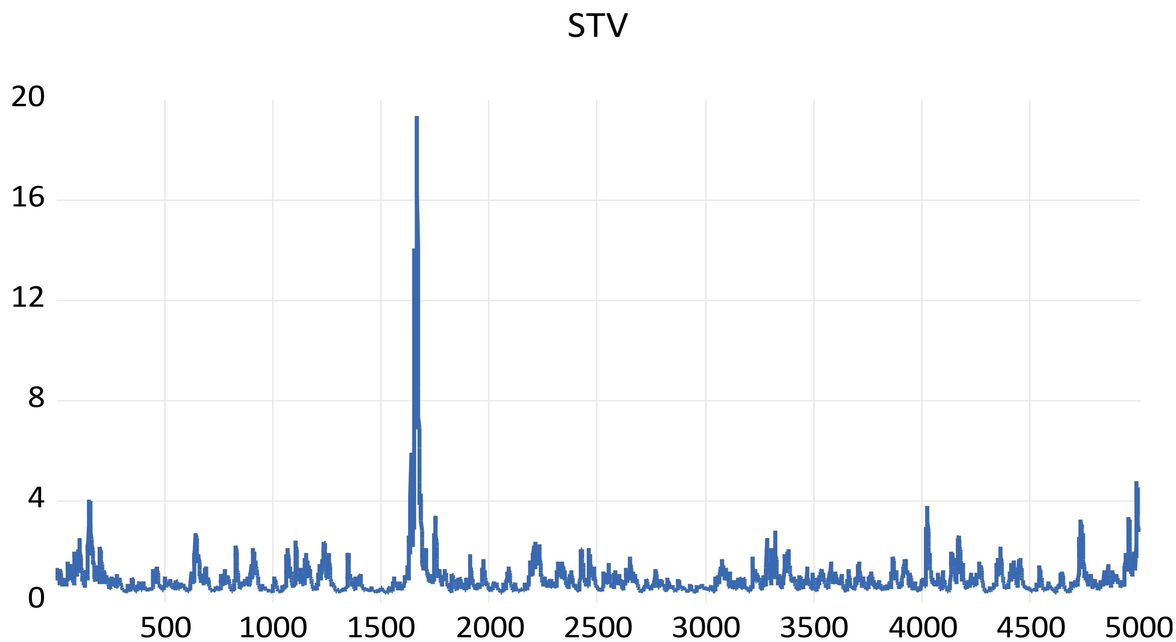

Figure 3: Short-term volatility of iShares US Consumer Staples ETF (IYK) Returns

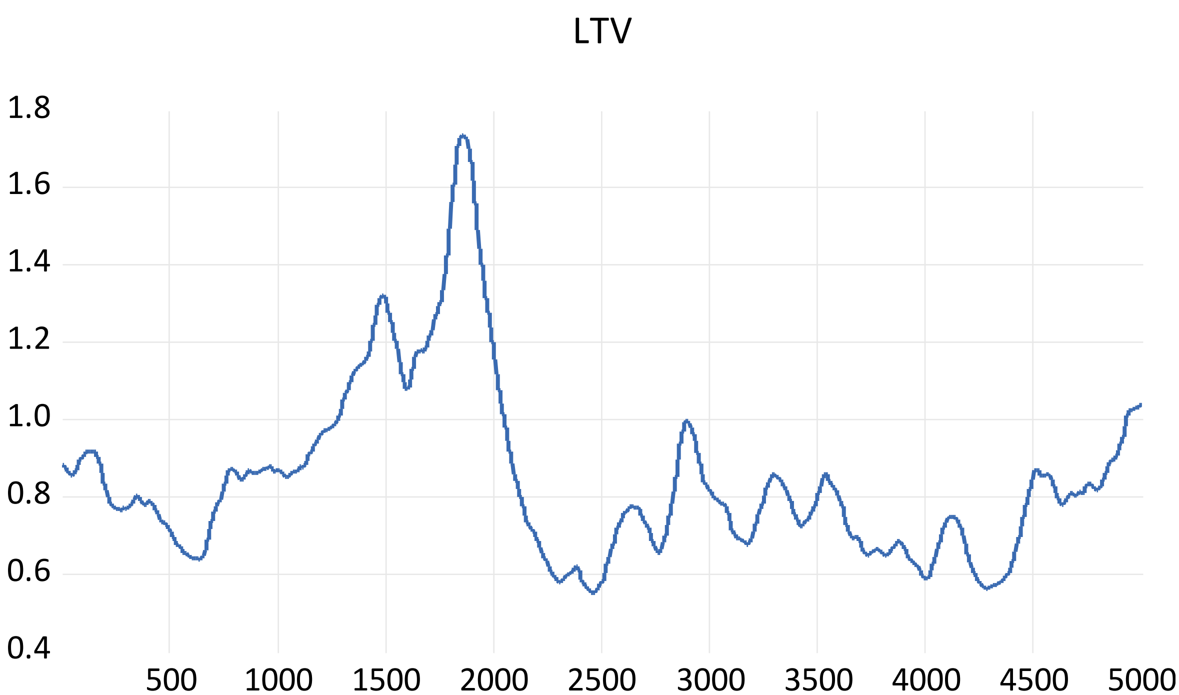

Figure 4: Long-term volatility of iShares US Consumer Staples ETF (IYK) Returns

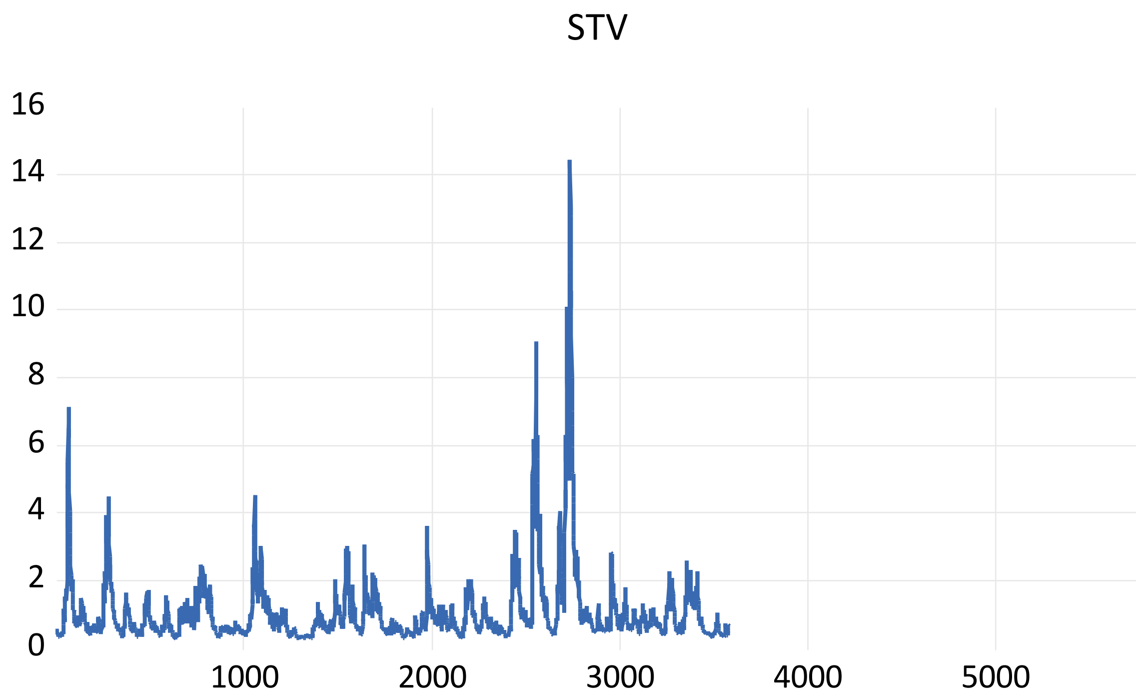

Figure 5: Short-term volatility of Wilshire US Real Estate Investment Trust Total Market Index (WRE) Returns

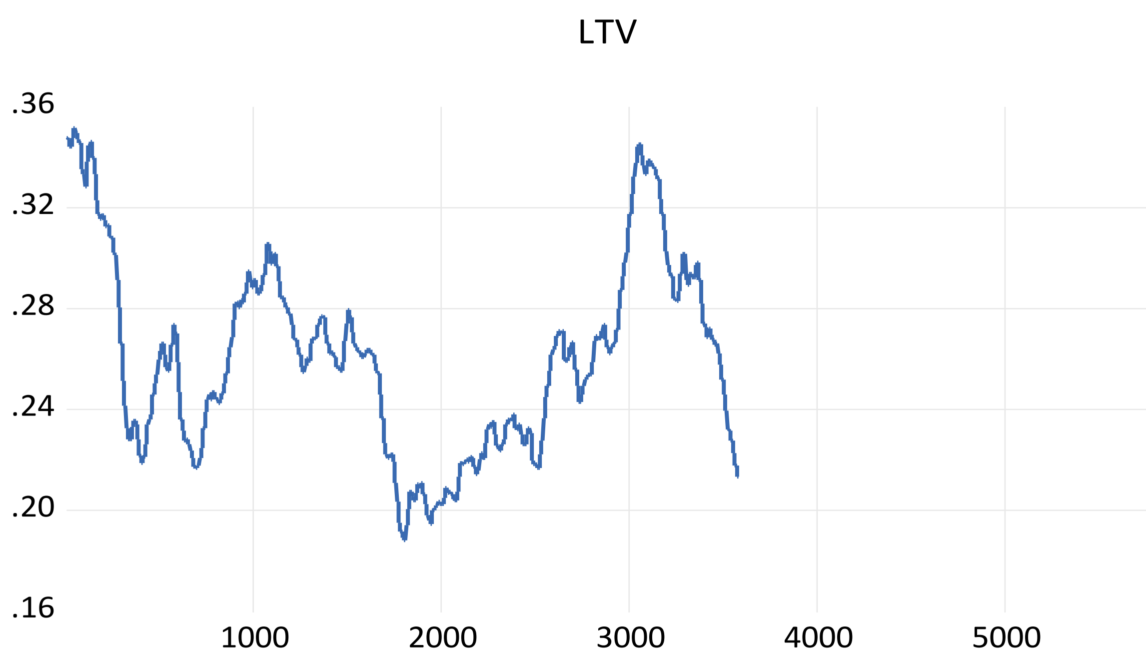

Figure 6: Long-term volatility of Wilshire US Real Estate Investment Trust Total Market Index (WRE) Returns