An Investigative Analysis of the Effect of Economic policy Uncertainty upon Stock Market Returns on Industry Portfolios

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Abstract

This paper examines whether the returns on 13 industry portfolio returns are significantly exposed to the United States economic policy uncertainty index whilst controlling for industry specific risk factors. The paper finds that the US EPU is statistically significant in estimating the volatility of 12 industry portfolios. The EPU is found to be most effective at predicting the returns of industries that involve heavy manufacturing and export dependent industries. Economic policy uncertainty is found to have an intertemporal significant effect upon industry returns. Econometric analysis index is used to test the predictive capacity of the economic policy uncertainty in forecasting future industry portfolio volatility with results implying that the macroeconomic variable has acute predictive capacity.

Keywords: Economic Policy Uncertainty, Industry Portfolios, Asset Pricing

1 Introduction

1.1 The Profile of Uncertainty

According to Campbell and MacKinlay's *The Econometrics of Financial Markets* [, 1] "the starting point of every financial model is the uncertainty facing investors, and, the substance of every financial model involves the impact of uncertainty on the behavior of investors and, ultimately, on market prices". Through the fundamental economic assumptions of diminishing marginal utility, individuals exhibit aversion to risk, which arises from uncertainty, and therefore have concave utility functions. This preference among individuals of disliking uncertainty is manifested in the pricing of assets because individuals are less willing to exchange for a good associated with greater risk. Furthermore, individual's utility preferences indicate a desire for smooth consumption patterns across time, which are threatened by the presence of uncertainty, are illustrative of the rationale creating an incentive for individuals to insure against uncertainty and risk. Indeed, a fundamental insight into asset pricing[27] illustrates that the key to the pricing of an asset is quantifying how much it increases or diminishes the certainty of potential outcomes. Aversion to risk drives individuals to outweigh negative outcomes and under-weigh good outcomes. Therefore, disliking uncertainty and the desire for smooth consumption means that for risk averse individuals, the most valuable assets are those providing income when wealth is lowest (i.e., in the worst cases)[20]. Consequently, there exists substantial research into the effects of uncertainty upon individual's choices; notably among the research is the 1954 axiom of rational theory of decision known as the sure-thing principle.

The sure-thing principle, whilst appearing tautological, provides significant insight into the decision-making process of individuals facing uncertainty and dictates that a decision that is deemed preferable in both the case and the negation of an event occurring is optimal and should be taken regardless of the probability of the event occurring[2]. However, alternative evidence provides contradictory insight into individual's rationale amid uncertainty. The disjunction effect postulates that while an individual's decision may be the same across multiple mutually-exclusive scenarios, rationally indicating that the decision is preferred and should be taken regardless of which of the mutually-exclusive scenarios is indeed realized, individuals may, in the presence of uncertainty, be reluctant to processing the implications of each scenario and may violate the sure-thing principle[3]. The disjunction effect indicates that individuals may exhibit a loss of acuity that is induced by uncertainty, provided that reasoning differs across mutually exclusive scenarios for taking the same decision.

On the other hand, research of financial securities prices has developed the idea that market prices fully reflect all available information, known as the efficient market hypothesis. Despite being widely accepted following the paper by Eugen Fama in 1970[4], the theory has also sparked immense criticism [29] following suggestions that the underlying principles, of investor rationality, embedded within efficient market hypothesis are incorrect. Further investigation into the models of human behavior has prompted alternative interpretations of behavioral finance. Criticism of the efficient market hypothesis often indicates patterns in investor behavior that are the result of beliefs held without reasonable evidence or, similarly, investors exhibit waves of optimism and pessimism that cause prices to deviate systematically from their fundamental values[4]. Indeed, these studies are consistent with the research of Tversky, A. and Shafir [3]. Consequently, the disjunction effect may be informative of the volatility in speculative asset prices following revelations of information. By understanding the effect of investor uncertainty upon the price of financial securities, it may be feasible to estimate stock market patterns through modelling of investor uncertainty. However, imperatively, the understanding of investor uncertainty requires an appreciation of where investors' uncertainty arises from.

This dissertation aims to examine the causative nature of economic policy uncertainty upon investor behavior by investigating the extent to which changes in the economic policy uncertainty index affect the volatility of industry categorized portfolios. In doing so, the estimation may provide an insightful explanation of the fluctuations in industry portfolio returns using a known macroeconomic risk factor. The motivation for this dissertation involves contributing to the asset pricing literature by providing evidence of the effect of an observed macroeconomic variable upon the realized variability of industry stocks. In doing so, the results will offer intuition to industry professionals and highlight a precautionary measure to be more vigilant of for improved growth. The present dissertation is formatted with six subsequent sections. The literature review provides scope of the existing literature surrounding this dissertation topic. The data section outlines the data used in the methodology, provided in section four. Results are discussed in section five with the conclusion and final remarks in section six and seven respectively. Tables and bibliography are provided after the final remarks.

2 Literature Review

2.1 The Nexus of Uncertainty

Analysis of investment under uncertainty has demonstrated that interest rates have significant impact upon investment decisions. Primarily, the unpredictability of interest rate patterns can increase the expected value of a future payoff from investment[29], increasing the attractiveness of investment amid interest rate volatility. However, uncertainty over interest rate patterns can also decrease the attractiveness of investment[20] through the increase in expected value that results from waiting to see whether interest rates increase or decrease. Indeed, the stability of interest rates may be more important than the level of interest rates for stimulating investment. This analysis coincides with a model was developed by Blanchard in 1981 [5], who concluded that the effect of a change in monetary policy is a discrete change in asset market returns, resulting from the anticipated sequence of profits and real interest rates. However, the empirical evidence suggested that while monetary policy has significant effect on stock market returns, individual's anticipation of the policies can be more important. Blanchard remarked that announcements generally lead to a change in expected profits and discount rates, two factors involved in the above equation. Further, Blanchard's evidence suggested that while the effect on the stock market precedes the policy change, the actual causation is a result of the policy announcement; policy implementation may have an insignificant effect. Blanchard considered it plausible that the announcement would generate the expected effect of the policy intervention before the implementation itself. The findings from Blanchard's paper suggest that the effects of changes in investor expectations may be more causative than realized changes in interest rates.

The contradictory effects of interest rate uncertainty have intuitive implications that are inherent in other instruments of government policy. Governments implement policies that have significant impact upon of consumers and firms, which often have unintended side effects, that can reduce or enhance uncertainty [24]. It is feasible to consider that government policy decisions are most influential to individual levels of uncertainty, particularly when considering the whole economy. Empirical evidence suggests that uncertainty about the enactment of stimulus policies is likely to have a detrimental effect on investment. Furthermore, Metcalf and Hasset [**?**] developed a model investigating the effect of policy uncertainty upon firm investment levels, with their results illustrating that it raises the threshold at which a firm invests whilst simultaneously lowering the scale of its investment.

Building upon Metcalf and Hasset's research [24], the present dissertation intends to model uncertainty that arises from government policies upon the stock market volatility of firms. Critically, the model will categorize firms by industry in order to distinguish between industries that are more susceptible to policy uncertainty. Investigating the effect of economic policy uncertainty has its practicability constraints. It is difficult to model the effect of an unobserved variable upon asset market return. Therefore, it is necessary to construct an index for policy-related economic uncertainty; conveniently, this has been developed by Baker, Bloom and Davis in 2016[7]. Their work quantifies uncertainty within an economy using three variables. It combines the provision of news media coverage with the number of federal tax code provisions expiring in the following years as well as the disparity in forecasts of macroeconomic variables. The availability of this index has made possible the development of the model estimating the effect of uncertainty upon stock market returns.

Examination of the trend of economic policy data support the evidence that crises often coincide with low levels of investment and economic growth. Therefore, there is significant motivation to extend research of the economic policy uncertainty index(hereafter EPU), focusing on the effect of EPU upon stock prices. Moreover, investigation of this effect could be expanded to examine the effect of EPU upon stock prices of portfolios categorized by industry.

The motivation for categorizing portfolios by industry subsists in the estimation of the effect of EPU upon specific industries, which would provide powerful insight for policy makers and investors to predetermine how susceptible particular industries are to the changes implemented by the government. This examination may highlight vulnerabilities to policy decisions, that may affect certain industries, which could prove incredibly useful for devising measures to improve stability within the sector. Moreover, analysis of the effect of policy uncertainty upon industry portfolios may provide insight into how the general economy is affected by government decisions. Analysis of the general economy may fail to highlight latent patterns in the data, therefore by categorizing the portfolios according to industry, a more coherent explanation may be provided through the evidence.

2.2 Economic Policy Uncertainty

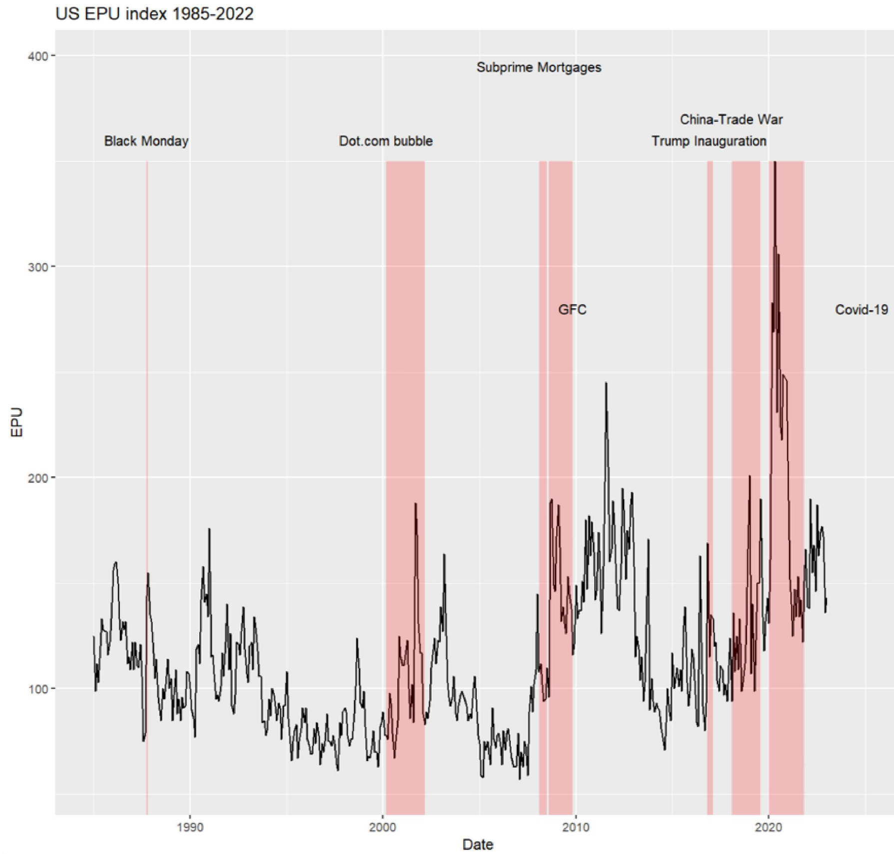
The present dissertation intends to implement a model estimating the effect of United States EPU upon industry portfolios. While uncertainty can arise from a myriad of factors within an economy, this dissertation focuses upon uncertainty through three factors that are comprised within the EPU index. The first factor used to construct the EPU index reflects the frequency of articles in US newspapers that contain the combination of the following words: "economic" or "economy"; "uncertain" or "uncertainty"; "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House"[1]. This factor benefits from the use of a popularized text search method, using newspaper archives to effectively measure uncertainty induced by government decisions. The potency of media coverage in conveying information to instigate hysteria has been noted by financial researchers. Evidence highlights the profound effects of financial media coverage in generating distrust and uncertainty in financial institutions, causing significant panic, as exemplified by the "perfect storm" following the Lehman Brothers collapse[29].

Consequently, this evidence suggests that newspaper text searches provide an effective proxy for uncertainty surrounding economic policy conditions over time. However, it must be considered that much of press coverage concerns negative or pessimistic information, providing a distorted representation of true events. Moreover, it is also appropriate to scrutinize this factor due to the presence of inaccuracies in media coverage, whereby press information may, intentionally or not, cause an increase in individual's uncertainty on false pretenses, thus generating a latent pattern of uncertainty driven through press coverage rather than economic policy decisions. Similarly, there is a possibility that, given a political slant, a newspaper's financial coverage provides exaggerated or misrepresented information causing a bias in EPU index. Therefore, to ensure the robustness of this measure, the EPU is constructed using two other factors and, imperatively, evaluated to examine the consistency with other measures of economic policy uncertainty. The index incorporates the number of federal tax code provisions set to expire within the next ten years. Therefore the EPU index measures the uncertainty prognosis concerning the path that the federal tax code will take in the future. The final component comprises uncertainty through the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters[7], calculating the difference between forecasters' predictions about policy-related macroeconomic variables.

The EPU index evaluation process involves using an extensive audit of articles of 12,000 randomly selected articles drawn from US newspapers, with auditors assessing whether an article discusses economic policy uncertainty based on the outlined criteria. When compared to the computer-automated methods, there exists a strong correlation with the human generated indices (0.86 from 1985 to 2012 and 0.93 from 1900 to 2010)[1]. This process indicates that rigorous evaluation of the efficacy of the automated search process is a sufficiently high to be considered a useful explanatory variable. Furthermore, the relationship between the EPU index and other measures of policy uncertainty is explored to examine the correlation in trend patterns across historic periods of crisis or volatility[7].

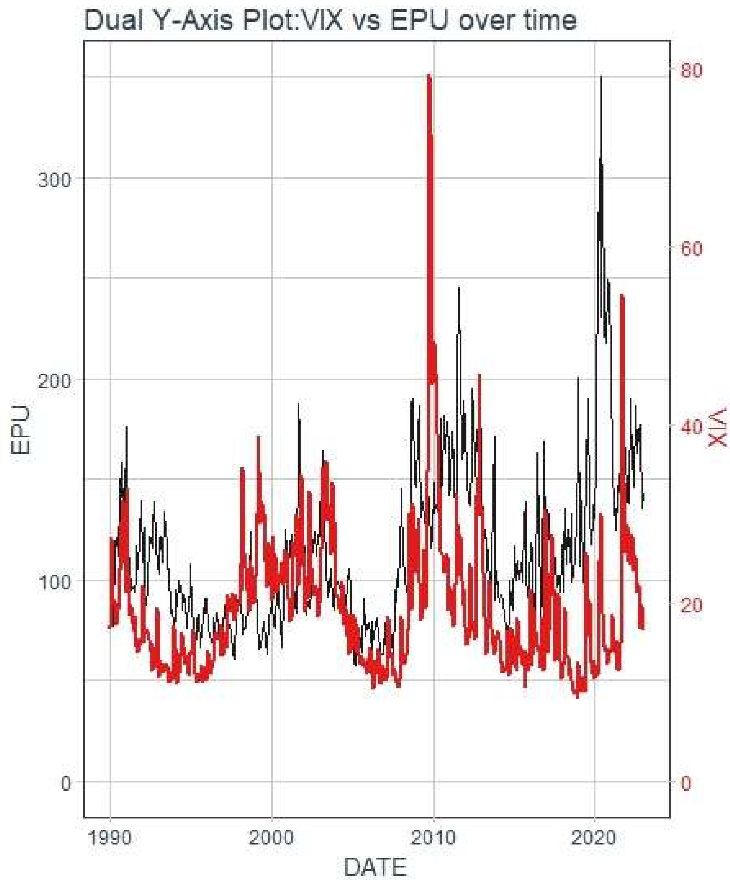
The purpose of the figures shown below is to demonstrate the sophistication of the EPU, highlighting the coordination of uncertainty with levels of low economic growth, and increased volatility of the stock market. Examination of the figures below provides explanation of the motivations for interpreting the effect of EPU upon industry categorized stock market portfolios, with significant correlation between stock market volatility and EPU as well as strong negative covariance between economic growth and EPU. The joint variability is indicative of the effect of uncertainty upon investment habits, and ponders the direct causative relation between EPU and stock market values. Figure 1 presents the time profile of US EPU, illustrating the trends over periods of significant uncertainty such as Black Monday, the global financial crisis, the inauguration of President Trump and the COVID-19 pandemic. There is an unequivocal upward trend after the EPU hits its lowest level throughout three decades at 59 in 2005 and peaks at 350 in May 2020. Moreover, there is an observable increase in volatility after the global financial crisis and persistently throughout the Trump presidency (0.99 percentage point increase in EPU from May to June 2016). Figure 2 provides a comparative picture of an additional measure of volatility (the CBoE volatility index). There is noticeable consistency in the pattern of the variables, with both measures rising from 1999-2002, 2008-2010 and 2019-2021. Figure 3 illustrates the slightly weak negative correlation between the volume of trades in the US and the EPU index. As EPU decreases from 1985 to 2000, there is a steady upward trend in volume of trades, followed by a decrease in sales over the next two years as EPU increases. Similarly, the increase in EPU from 2019 to 2021 coincides with the decrease in trade volume illustrating negative correlation between the variables. This figure further attests the inexorable relationship between uncertainty and investment habits, even though for some periods the connection has not been smooth.

Figure 1: Economic Policy Uncertainty 1985-2022



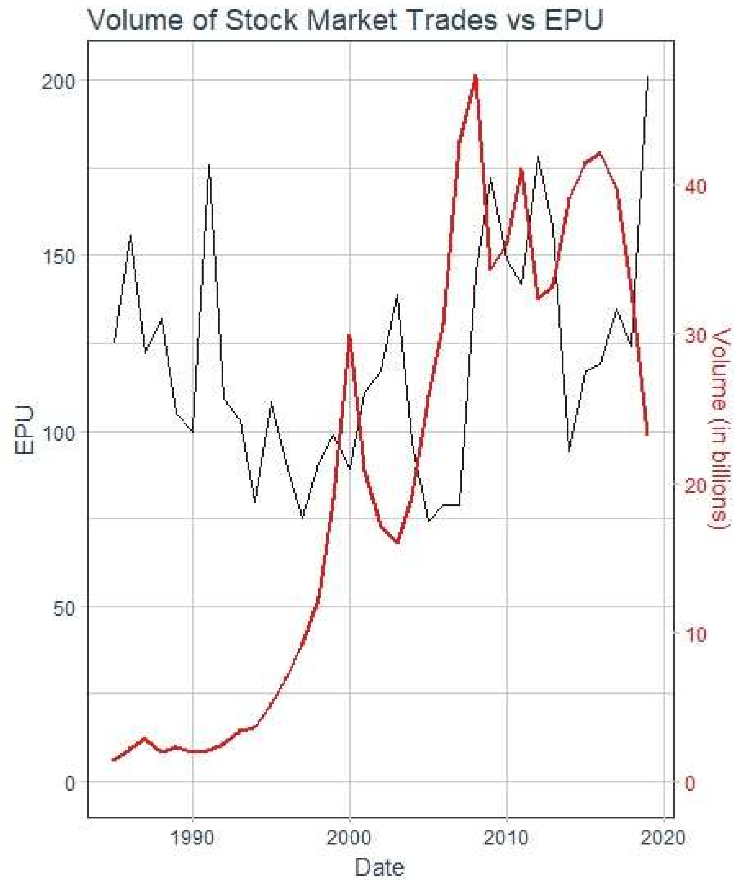
[7]

Figure 2: Volatility Index vs Economic Policy Uncertainty



Source: Baker, Bloom and Davis (2022)[7]

Figure 3: United States GDP vs EPU



Source: Baker, Bloom and Davis (2022)[7]

2.1 EPU Index Literature

Unanticipated government decisions surrounding monetary policy pose significant impact on the world economy which may, in turn, influence asset prices. These asset market changes stem from three main factors. Primarily, policy uncertainty affects factors surrounding investors' earnings forecasts [26]. Secondly, evidence suggests that changes in policy uncertainty alter individuals' consumption, investment and saving habits [19]. In addition, government's decisions change firms' propensity for investment [21].

The uncertainty surrounding monetary decisions enhances the magnitude of the endogenous shock upon the asset market due to the preferences of consumers and firms. Risk aversion causes investors to dislike uncertainty which, in the presence of these unexpected changes, significantly alters the asset price market; these changes affect individuals' preferences surrounding compensation for risk. Higher levels of uncertainty about future income require a higher risk premium [20], meaning that unanticipated government decision may play a pivotal role in the return of assets.

There exists significant research suggesting the strong impact of economic policy uncertainty upon market returns. Pástor Veronesi's 2013 paper [26] formulated a general equilibrium model illustrating the causation between unanticipated policy announcements and lower stock prices. Similarly, their model illustrates that in times of lower economic growth, EPU leads to higher risk premia. Empirical evidence suggests that investors hedge against economic policy uncertainty [23]. Consequently, economic policy uncertainty should be used as a relevant risk factor in the pricing of capital markets.

2.2 Alternative Approaches

There exists overwhelming empirical evidence, using EPU as a predictor variable, which suggests that policy uncertainty is priced in capital markets. For example, analysis by Bali et al. [10] indicates that a portfolio of stocks with the lowest uncertainty beta yields 6 percent risk-adjusted return. One of the most prominently referenced papers in asset pricing literature involving EPU is from Baker et al [17], which estimates the influence of policy uncertainty on the volatility of returns in an industry specific model.

In addition, more recent empirical evidence has built upon the models previously mentioned, estimating specific asset returns of multiple industries using the EPU index. For example, Azimli [16] uses a model controlling for industry-specific and firm-specific risk. This intuitive approach enables the author to evaluate the effect on individual industries of the EPU facilitating an analysis of which industries are most susceptible to changes in economic policy and uncertainty. The paper's model provides evidence that the returns of export reliant industries are more sensitive to government decisions. Azimli makes the claim that this is a result of their dependence on government export subsidies[16]. The approach in this paper is indeed intuitive, involving the estimation of returns by arranging industry portfolios based on estimates of their uncertainty beta. These estimates are generated by a three-year rolling window regression. The use of the uncertainty beta variable enables the author to take account for industry specific risk. This approach also includes a benchmark asset pricing model, without consideration of the EPU, of which Azimli's model is compared against. The use of this control pricing model strengthens the evidence given in this paper by comparing forecasts using both methods and concluding which is more accurate.

The paper closest to the present dissertation is Azimli (2022)[16]; it models the effect of US EPU on industry portfolio returns. The paper does not comment on why other macroeconomic variables are implemented in the regression, and it only compares the performance of the model relative to four-factor model approaches and estimated GMM models which adds a momentum factor. Azimli's paper is more restricted than the present dissertation and does not consider the performance of alternative methodologies, including the most popularized GARCH-MIDAS model, and the impact of the value weighted portfolio in creating a bias towards bigger stocks. More importantly, Azimli's paper does not consider alternative macroeconomic variables meaning that there is a lack of confidence in the results due to the omitted variable bias[16]. The paper is instead primarily concerned with explaining the effect of EPU upon portfolios whilst controlling for the impact of the value weighted portfolio in creating a bias towards bigger stocks which is a necessary precaution but is overstated, with other important control measures instead being overlooked. The present dissertation provides controls for the bias created by value weighted portfolios whilst also incorporating influential macroeconomic variables that impact upon stock market returns so simultaneously rectifying some of the omitted variable bias issues of Azmili's paper.

Another intriguing approach amongst the EPU asset pricing literature has involved examining the influence of the EPU in different countries upon asset market returns. For example, Hu et al. [**?** , 22]xamined the responsiveness of the Chinese market to EPU shocks in the United States. The methodology in this paper involves estimating the effects of US EPU using a combination of two modelling techniques. An ARMA (1,1) process is used to extract shocks from US EPU coupled with a GARCH (1,1) model. An ARMA (1,1) process combines autoregressive models with moving average processes.

2.3 The GARCH Approach

GARCH models are widely used for financial data, building upon the autoregressive conditional heteroskedasticity model introduced by Engle in 1982[**?** , 14] The parsimonious approach is useful for modelling and forecasting volatility in asset returns and does not require a high number of parameters. Using the GARCH model, current volatility is a weighted sum of the most recent shock and the lagged volatility. The beta term is representative of news, indicating the cumulative information about volatility.

The use of the GARCH method does, however, encounter some issues. The dataset in Su, Fang and Yin [26] encountered a common issue in macroeconomic analysis whereby two variables do not share the same data frequency. In order to solve this problem, they used a component model utilized in a paper by Engle, Ghysels and Sohn [26]. The GARCH-MIDAS model incorporates two volatility components. By accounting for both short- and long-term volatility, the GARCH MIDAS model holds, even in the presence of unbalanced data. The versatility of this type of modelling has made it very popular in macroeconomic empirical analysis. In the bivariate GARCH-MIDAS model used in this paper, the long-term volatility is estimated using the weighted average of

US economic policy uncertainty index combined with a global uncertainty variable. Their findings indicate that EPU, which is the most popular uncertainty index of the three variables they used, was positively associated with stock market volatility.

The presence of the GARCH method in the model is helpful in resolving an issue presented by the financial data; it controls for the business cycle using term and credit spread in China. Controlling for business conditions reduces the model's risk of being subject to selection bias, eliminating the presence of an exogenous shock influencing market returns outside of the endogenous factor variables. Moreover, the GARCH (1,1) model is applied to correct the autoregressive conditional heteroskedasticity in the error term from an OLS regression model. This approach uses the same inference applied by Bali [10], using a GARCH model to estimate a portfolio's conditional covariance with the market and testing whether the conditional covariance predicts the time-variation in the portfolio. This process was found to be robust to variation in macroeconomic variables, increasing the strength of the evidence. The findings of Hu et al. [22] indicate that there is a significant negative relationship between EPU shock in the United States and the returns on assets in the Chinese market, with most prominent responsiveness to shocks coming from manufacturing and media industries.

The dissertation builds upon the model used in the Su, Fang and Yin paper [26], using similar techniques to the GARCH-MIDAS model to estimate the effect of EPU on volatility. The dissertation, however, will incorporate some new variables that were not used in the model. Firstly, the model will use data from the global economic policy uncertainty index, which conveniently establishes a good proxy for the worldwide EPU. Using this variable, the model will be more effective in accounting for the idiosyncratic, economy specific uncertainty, estimating its effect on the industry portfolio return data. Furthermore, this dissertation will attempt to adopt a similar variable as used in Azimli [16], using an industry-specific uncertainty beta, thus allowing for more in-depth analysis of EPU on stock market returns. This will involve obtaining rolling window regressions This can be performed using OLS estimators for fixed "window sizes" and examining the stability of the estimators. Portfolios can then be constructed based on their industry-specific uncertainty beta.

3 Data

3.1 Industry Portfolios

The dataset used in the dissertation comprises of stock market returns assigned from the NYSE, AMEX, and the NASDAQ to an industry portfolio based on its four-digit SIC code at that time. This method uses Compustat SIC codes for the fiscal year ending in the previous calendar year. Returns are then computed from July of the previous year to the current year. The dissertation uses two methods to form portfolios of industry stocks that have differing interpretative consequences. First, a portfolio based on equal-weighted returns is formed which is more affected by lower value stocks. Second, a value-weighted portfolio that is influenced by larger stocks. These two approaches for representing the behavior of industry stock returns can therefore provide a convenient means for examining the returns of an industry stock as a function of firm size. Empirical analysis of firm size has proven that it has a significant effect upon expected stock returns [32]. Moreover, there exists extensive evidence that the size of a stock is correlated to the pattern of average returns with size being used as a factor in French and Fama's three factor asset pricing method [32]. Therefore, incorporating both methods to the dissertation's approach has clear benefits in that it will provide insightful evidence upon whether economic policy uncertainty has greater impact upon smaller or larger stocks. Moreover, the advantage of including two constructions of industry portfolios is that it allows more specifications to be run, making significant results more robust if they can be reproduced. The return data has been made available through the convenient provision of stock market data through researcher Kenneth French who has used data obtained through an equivalent approach to examine the effect of business conditions upon expected stock returns.

3.1.1 Economic Policy Uncertainty Index

The index for economic policy uncertainty has been obtained through researchers Baker, Bloom and Davis [7] whose methodology for quantifying uncertainty concerning economic policy has been approved for market-use validation, with the index being carried by commercial data providers such as Bloomberg and Reuters [7]. The approach to reliably measure economic policy uncertainty is formulated based upon news media coverage of uncertainty, the probability of change in tax codes and the disagreement of analysts surrounding future fiscal and monetary policies. The approach used for construction of the index means that it captures uncertainty concerning who will make policy decisions, what policy actions will be undertaken and when and the effects of policies that are undertaken. Therefore, the index captures uncertainties that are the indirect ramification of non-economic related policy matters [7]. Usage of this method is advantageous when compared to other variables that capture uncertainty, but without consideration of non-economic matters, such as the Cboe Volatility Index. The availability of this data at monthly periods requires the methodology to incorporate a suitable way to accommodate data of differing intervals.

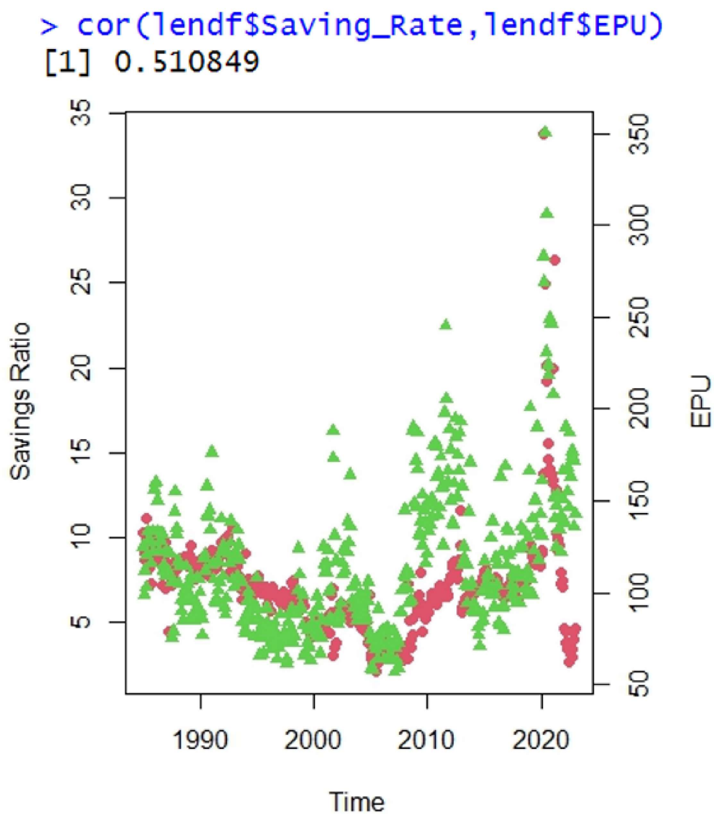
The availability of the EPU index from 1985 to 2022 provides a substantial period in which to analyze this relationship. However, given the extent of technological advancement during this 37-year period, it is likely that there will exist some structural breaks in the dataset which may need to be addressed in the methodology. For example, during the period after the 9/11 terror attack, there is an abrupt negative exposure of returns of the aircraft industry portfolio. These industry specific shocks will pose credibility threats to a GARCH model which is generally assumed to be stationary, rendering the model invalid and distorting the forecasting capabilities. To remedy this issue, it is possible to include a dummy variable in the presence of breaks in the data set which can be implemented into the GARCH-models as external regressors in the mean model. The discussion of implementing the dummy variables to account for structural breaks in the data set is elaborated upon in the methodology specifications (Section 4.2).

3.1.2 Eliminating Omitted Variable Bias

The data set makes use of two different variables affecting investor behavior. The inclusion of these measures in the model in the context of the GARCH model is significant, such that it considers the role that other exogenous factors have upon stock market volatility. Indeed, conclusions from the five factor asset pricing model have illustrated the significance of the relation of investment levels to patterns of average returns [33]. Therefore, it is imperative to include a variable accounting for investment levels in the model so that it increases confidence of the results. This is because it eliminates omitted variable bias, whereby the estimates of the parameters in a regression analysis are unreliable because the assumed specification fails to consider an independent variable that is a determinant of the dependent variable and correlated with one of the included variables. In the context of this dissertation, failing to include a measure to account for investment levels could deceptively provide a statistically biased result that overestimates the significance of EPU in predicting industry portfolio returns.

The present dissertation includes two variables to model for investment levels. Financial theory indicates that the provision of credit from financial institutions facilitates leveraged investment which increases total investment in the economy[29]. Consumption smoothing is a common feature of inter-temporal asset pricing models. Evidence suggests [2] that due to the risk averse nature of investors, the preference for smooth consumption patterns means that investors want to save less when income is temporarily low, and without an offsetting reduction in capital-investment opportunities, lower desired savings tend to push expected returns up. Furthermore, this risk-aversion preference also means that in periods of higher policy uncertainty, investors will save more. Consequently, to avoid correlation between the error term and an independent variable in the regression model, I must control for the saving's ratio. The saving's ratio data is provided on a monthly basis by the federal reserve bank of St Louis. The personal saving is calculated as a percentage of disposable personal income and is equal to personal income less personal outlays and taxes.

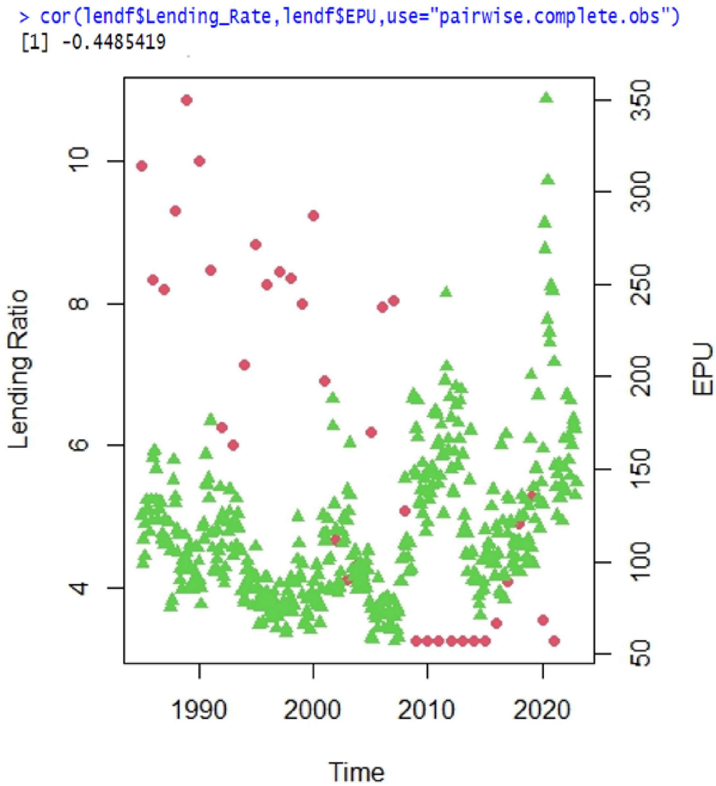
Figure 4: Personal Savings Rate Correlation with Economic Policy Uncertainty



FRED® [39]

Similarly, a variable that is also correlated with EPU, and existentially impacts the volatility of stock market returns is financial leverage [**?**][29]. In times of uncertainty, banks, through regulations or through their own decision making, have lower propensity to provide credit to the private sector, meaning that investments and stock market returns are linked. This alludes me to including a variable that captures financial leverage suitably: the lending ratio. The figure below illustrates the negative correlation between the lending ratio and the EPU index, highlighting the inverse relationship between uncertainty and investment therefore indicating the need to include the lending ratio as an independent variable in the regression model. The lending ratio data has been provided by the World Bank at monthly intervals and is defined as the bank rate that usually meets the short- and medium-term financing needs of the private sector.

Figure 5: Lending Rate Correlation with Economic Policy Uncertainty



Source:FRED®[34]

4 Methodology

4.1 The GARCH-MIDAS Approach

This paper adds to the expanding literature featuring applications of generalized autoregressive conditional heteroskedasticity studies to examine industry portfolio dynamics. The methodology pursued in this dissertation is inspired by two papers. Primarily, the model implemented by Engle and Rangel [34] which incorporates a spline-GARCH model where the daily equity volatility is a outcome of a slowly varying deterministic component and a mean reverting unit GARCH. This model differentiates itself from conventional stochastic volatility models by permitting fluctuations in unconditional volatility over time. Engle and Rangel's model is applied to fifty years of equity market data [34], finding that volatility in macroeconomic factors, including GDP growth and inflation, are explanatory variables. Similarly, the GARCH-MIDAS approach has been explored to model the relation of stock market data, observed daily, with macroeconomic variables that are observed on a monthly basis. The present dissertation adopts a rigorous framework that is designed to combine data sampled at different frequencies, incorporating the mean reverting daily GARCH process and a MIDAS polynomial applied to monthly financial macroeconomic variables, thus facilitating examination of the macrovolatility links. Furthermore, the GARCH-MIDAS approach separates the variance into long term and short term components improving the prediction accuracy.

This versatile methodology is increasingly popular amongst researchers investigating the effect of macroeconomic variables upon stock market returns and is notably prevalent among EPU index studies. While there is some flexibility among the dynamics of EPU index as an explanatory variable, this methodology is implemented upon the assumption of efficient markets, such that prices of securitized financial instruments are a true reflection of all relevant and available information. However, the model framework is subject to particular constrains, most prevalently during the period following the 2008 great financial crisis. This results from changes in liquidity availability and subsequent alterations in consumer behavior that have a tangible bearing upon stock market activity distinct from those resulting from the uncertainty surrounding economic policy or government decisions. Instead, there is evidence to suggest that the increase in stock market volatility were more likely due to a pessimistic outlook on the real economy and damaged perception of retail banking credibility rather than uncertainty amidst economic policy. However, throughout the examined period changes in stock market returns are more likely to be reflective of fluctuations in economic policy certainty. Moreover, confidence persists in the methodology due to the interconnection of retail bank credibility and economic policy, with government policies aimed, particularly during periods of crisis, at the behest of banking sector credibility and the smooth pattern of credit provision in the economy.

The GARCH-MIDAS approach is favorable but does have shortcomings. Predominantly, it may be difficult to identify the causal effect which economic policy uncertainty has upon industry portfolio returns through the concurrence of other influential macroeconomic variables. The presence of latent variables in the model will distort the credibility of empirical analysis. A proposed resolution to this issue for the present dissertation is to control for three additional variables impacting the stock market returns in a corresponding way to economic policy uncertainty: saving's ratio and leverage ratio (and market concentration). This is an effective means for discerning the effect of economic policy uncertainty which has profound implications on the provision of credit to investors and therefore the propensity of individuals to invest in securitized assets, with stock market trends are fundamental reflections of investment capacities, as the impact of individuals' availability of leveraging their investment is controlled for. Furthermore, appropriate control measures to remedy the identification issue also include individual saving's ratio, which, as identified by researchers, has profound effects upon the valuation of investments and their potential payoffs. By controlling for these measures influencing stock market returns and investor habits, the dissertation's approach effectively isolates the effect of economic policy uncertainty.

There exists a double-edged sword in the use of industry portfolio stock market returns that avoiding biases through weighting is difficult. French and Fama's analysis[31] on industry portfolios used value and equal weighted portfolios of NYSE stocks to represent the behavior of stock returns. The value weighted portfolio is weighted toward large stocks while equal -weighted returns are affected more by small stocks. While the two portfolios provide a means to examine the behaviour of stock returns as a function of firm size, a dimension which is known to be important in describing the cross section of expected stock returns [32].

4.2 Specifications

To explore the relationship between US EPU index to the long-term volatility of daily returns of industry portfolios, this dissertation implements an approach following the framework outlined by Engle et al.[30]. The model is outlined as follows:

$r_{i,t,j} = \mu + \sqrt{l_t s_{i,t,j} \epsilon_{i,t,j}} \forall i = 1, \ldots, N_t$ (1)

$\sigma^2_{i,t,j} = l_t s_{i,t,j}$ (2)

Where $r_(i,t,j)$ refers to the return on portfolio j on day i of month t, and μ is the unconditional return mean. N_t subsequently refers to the number of days in a month and $\epsilon_{i,t,j}|\Phi_{i-1,t} \sim N(0,1)$, given the information set $\Phi_{i-1,t}$ existing until day $(i-1)$ of month t, the GARCH model error term is normally distributed. Equation 2 indicates the division of the conditional variance of the daily return, defined as total conditional variance $\sigma^2_{i,t,j}$, into two coexisting components: short-term $s_{i,t,j}$ and long-term l_t. The short-run volatility component, $s_{i,t,j}$, is consistent with traditional GARCH(1,1) processes as shown below:// $s_{i,t,j} = (1-\alpha-\beta) + \alpha \frac{(r_{i,t,j}-\mu)^2}{l_t} + \beta s_{i-1,t,j}$ (3)// Where α and β are the parameters to be estimated for the GARCH components. For the model to function, both parameters must be greater than zero but must not be cumulatively greater than one (i.e., $\alpha > 0$, $\beta > 0, \alpha + \beta < 1$). Following the framework of Engle et al. [, 30] it is necessary to use the logarithmic form of the growth rate of the EPU index because the changes in the macroeconomic variable can be negative. Therefore, we model the long term volatility component as follows:

$\log(l_t) = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}$ (4)

Here, m is the intercept and θ represents the weighted gradient effect of the lagged EPU variable X_{t-k} upon the long-term volatility of the industry portfolio returns. The summation to K values refers to the maximum lag order of smooth volatility in MIDAS filtering. Through this model, it has been shown that the marginal effect upon the long-term volatility component is dependent on the weighting and the gradient terms . Moreover, the weighting scheme of beta weights $\varphi_k\left(\omega_1, \omega_1, \omega_2\right)$ with the independent variables (ω_1, ω_2) are formulated accordingly:

$$\varphi_k\left(\omega_1, \omega_2\right) = \frac{\frac{(k}{K)}^{\omega_1 - 1} \frac{(1-k}{K)}^{\omega_2 - 1}}{\sum_K^k \frac{(k}{K)}^{\omega_1 - 1} (1 - \frac{j}{K})^{\omega_2 - 1}} \ (5)$$

$$\varphi_k\left(1, \omega_2\right) = \frac{\frac{(1-k}{K)}^{\omega_2 - 1}}{\sum_K^k (1 - \frac{j}{K})^{omega_2 - 1}} \ (6)$$

Equation 5 formulates the weighting scheme that represents the attenuated weight distributions. However, equation 6 can be obtained through implementing the constraint of $\omega_1 = 1$ to obtain the restricted weight function. The framework of Engle et al.[30] indicates that for GARCH-MIDAS models with RV, it is optimal to set $\omega_1 = 1$ such that the weights are monotonically decreasing over the lags. Hence, for the GARCH-MIDAS models with RV, we set $\omega_1 = 1$ such that the resulting beta lag structure involves a single parameter. Subsequently, equation 6 is the restricted weighting function that generates an attenuated weight distribution, with the attenuation rate is determined by the parameters ω_2; the larger the value of ω_2, the faster the decay rate. Both the beta weighting functions, equation 5 and 6, can therefore be applied to the GARCH-MIDAS model estimation. The equations 1,3,4 and 6 forma a GARCH-MIDAS model based on the EPU exponential change rate. Additionally, quasi- maximum likelihood estimation (QMLE) was adopted to estimate the parameter space $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega\}$.

Following GARCH model fundamental framework analysis of Conrad and Schienle [**?**], it is necessary to provide rigorous misspecification testing in the form of an omitted multiplicative long-term component. Consequently, the dissertation methodology includes the regression-based test proposed by Conrad and Schienle [30] as a preliminary check before estimating the GARCH-MIDAS model. The regression is considered in logarithmic form:

$$\ln\left(\overline{RV_t}\right) = c + \omega_0 X_0 + v_t \ (7)$$

$$\overline{RV_t} = \sum_{i=1}^{M} \frac{r_{i,t,j}}{\hat{\sigma}^2_{i,t,j}} \ (8)$$

Here, X_0 represents the EPU explanatory variables and the parameter v_t is included to ensure the regression meets the independent and identical distribution requirements. Furthermore, $|hat\sigma^2_{i,t,j}$ is the estimated variance from the model under the null hypothesis of the simple GARCH model. As outlined previously, $r_{i,t,j}$ refers to the logarithmic return on portfolio j on day i of month t, and μ is the unconditional return mean and RV_t is defined as the sum of volatility-adjusted squared daily returns within each month. The regression-based test checks whether the null hypothesis $(H_0 : \omega_0 = 0)$ that the single component GARCH is correctly specified can be rejected upon using economic policy uncertainty as an explanatory variable. If the null hypothesis is not rejected in this case, it is possible to consider an alternative approach that would use the unrestrictive weighting scheme. This would not be optimal, however would be necessary in the case that we fail to reject the null hypothesis. This would incorporate a two-component GARCH which would be generated in the following way:

$\ln\left(\overline{RV_t}\right) = c + \omega_0 X_0 + \omega_1 X_1 + v_t$ (9)

With equation 8 remaining the same, this alternative approach would incorporate additional, control variables in the form of a vector comprised of measures for savings ratio and leverage ratio. This approach would serve as an appropriate alternative to the single component GARCH model, by accounting for measures that have plausible and empirically evidenced impacts upon stock market volatility, therefore preventing the presence of latent, influencing variables in the GARCH model.

Finally, using a data set with over three decades of returns can lead to issues of credibility of the necessary assumptions for the GARCH model. While the presence of structural breaks in the data set poses an issue to the stationarity of data, there is a means of remedying this issue that can preserve the robustness of the GARCH modelling process. This incorporates using dummy variables to delineate between the breaks in the data. The dummy variables, denoted D_i, will be indicators of the series of returns having shifted to a more volatile state. Through this methodology, two mutually exclusive states can be estimated using the same model approach, with D_i=1, denoting the period of higher volatility and more rapid movements in the stock market and D_i=0 denoting the period of lower fluctuations. This methodology has disadvantages as it does not consider whether the periods of higher volatility are a result of endogenous variables in the specified model, i.e. correlated with any of the explanatory variables in the model. Indeed, structural breaks whether they are the result of financial crises or are industry specific shocks are modelled in an inconveniently identical way, as periods of increased volatility. For the GARCH-MIDAS (1,1) approach the specification is as follows:

$s_{i,t,j} = (1 - \alpha_2 - \beta) + \alpha_1 D_{i,t,j} + \alpha_0 \frac{(r_{i,t,j} - \mu)^2}{l_t} + \beta s_{i-1,t,j}$ (10)

$\alpha_2 = \alpha_1 + \alpha_0$ (11)

Assessing the predictive power of the model involves comparing the accuracies of the different models by using loss functions. This assessment follows the functions employed by Hansen et al. (2011) [36] , evaluating the predictive capacity of the GARCH-MIDAS models using loss function shown below:

$\text{MSE} = \frac{1}{T}\sum_{i=1}^{T}(\sigma_{i,}^2 - \bar{\sigma}_{i,}^2)^2$ (11)

Research suggests that greater use of criteria indicates more effective analysis [38] . To generate the respective loss values, the methodology uses the square value of daily return as an estimative tool to represent the daily fluctuation level [37] . Subsequently, the loss values are tested for statistical significance using model confidence set tests to evaluate the precision of the model. The MCS tests, implemented by Hansen et al. [36], are analogous to obtaining confidence intervals for the estimated parameters. The MCS is regarded as significantly robust given that it is useful in acknowledging limitations to the dataset. The MCS tests are conducted using continuous significance tests and the most insignificant model is eliminated. By setting a confidence level α, if the p value is larger than the confidence level then there is significant indication that the model has predictive capacity. A model with a greater p value is indicative of greater predictive ability.

5 Results

5.1 Industry Portfolio Return Results

As shown in the table, the industry portfolio returns have a greater standard deviation than their mean illustrating the high level of volatility. The suitability of the industry portfolio returns for GARCH modelling must be tested in order to determine the procedures of the model and the possibility of necessary adjustments. First, this involves taking Chow tests of the returns to detect structural breaks which, if detected, would require a modification of the standard GARCH model. The length of the time series data means that there may be periods of prolonged variation in the data that is not consistent with the general pattern of the returns. However, the conducted Chow tests were unable to detect structural breaks throughout the time series(as shown in figure 6), meaning that the standard GARCH model would not require adjustments. Secondly, examination of the returns illustrates the high volatility of the returns with the industries relating to natural resources (precious metals and steel), real estate and automobile manufacturing exhibiting the highest standard deviation of returns. Conversely, and perhaps unsurprisingly, pharmaceutical industry returns were least subject to deviation across the sample, perhaps as a result of the consistent need for these products reducing the volatility in demand. Moreover, theindustry portfolios illustrate evidence of fat tails since the kurtosis exceeds the value of the normal distribution, with most notable evidence of negative skewness in the real estate industry portfolio, indicating that the left tail is extreme. Moreover, the portfolios illustrate evidence of ARCH effects as shown by the autocorrelations of the squared residuals which gradually decline over time. Indeed, an implication of the GARCH (1,1) model is that the autocorrelations are all positive, which is generally uncommon for financial time series data [35], Therefore, there is indication of the suitability of the GARCH model for the industry portfolio returns. (Pattern/Trend Analysis of EPU vs Return)

5.2 Empirical Results

In this section, regression tests are conducted to examine the appropriateness of the standard GARCH model in predicting the long term average variance, and perhaps whether the presence of a long term component improves the predictive capacity. The subsequent models and their estimated parameters are then scrutinized according to significance tests to indicate their accuracy. The results (shown in table 1 in section 8) for the parameter ω_0 are positive at the 1% significance level, indicating the significance of the relation between the EPU index and monthly realized volatility of the industry portfolios. The results also indicate that the model including the long term component is significant under the F-statistic test. Consequently, the null hypothesis (the significance of the one-component GARCH model) can be rejected. This result provides evidence to incorporate the EPU index as a component of the GARCH-MIDAS model to predict industry returns.

5.3 Model Estimation

Parameter estimations are performed to examine the appropriateness of the GARCH-MIDAS model in forecasting industry return volatility. The maximum lag order K is determined using the information criterion (Conrad et al. 2015), therefore the lag order is chosen according to Bayesian information criterion. This measure indicates the number of periods over which the influence of the EPU index is persistent in the volatility of industry returns. (The parameter results are shown in the table). The significance of the parameters μ, α, β is illustrated by two facets: the parameters are positive and their sum(alpha +beta) is close to, but not greater than, one. These parameters are not large but they are very significant, with the evidence indicating that the short-term volatility components of the industry returns are indicative of a GARCH(1,1) effect. Moreover, the significance of the θ components at the 5% confidence level illustrate that EPU has significant correlation with the long-term volatility component of the industry returns. The effect of this correlation implies that increases in US EPU are correspondent with increased volatility of industry returns, (most notably among heavy manufacturing industries) illustrating evidence to suggest that increased policy uncertainty increases the volatility of industry portfolio returns. This process is repeated with a model that incorporates control measures including the savings rate and the lending rate. The second estimation model increases the significance of the results with the θ components accepted at the 1% confidence level. Notably, however, the correlation between the independent variables and the industry returns is strongest for the EPU index, perhaps illustrating greater influence upon the industry market volatility.

The distribution of the beta weights illustrate the decay rate of the lagged variables. The distribution indicates that the correlation components of the EPU (and control variables) decrease as the number of lags increases which means that more recent volatility in the macroeconomic variables is more strongly correlated with increased volatility in the industry returns. Therefore, only one lagged variable is used in the estimation.(The rate of decay is strongest for the model that includes control variables given that the estimated ω parameter is higher.) Moreover, the long term volatility component is compared with the overall return variance in figure 7. The figure shows the similarity in trends of the two volatility measures, with the long term volatility component having a smoother trend over time. The blue line is total volatility while the black line is the long term volatility estimate. The observed relationship between the long-term volatility component and the total volatility of the industry portfolios is evidence of the effect of US EPU upon the industry returns. (Significant trend patterns are shown in section 9).

5.4 Evaluation of forecast performance

Whilst the statistical significance of a model is generally perceived as useful, particularly when it is useful to determine the variation of the dependent variable [19], there is often more focus designated to the predictive ability of the model. This section of the dissertation is devoted to empirically testing the predictive power of the EPU index. This involves dividing the dataset into two subgroups, with the in-sample data used for estimating the parameters and the out-of-sample data used for forecasting. The method for obtaining predictions involves rolling window forecasting, meaning that the sample is broken into periods of the given "window" length over which the data are cultivated to forecast the volatility for the next period. The two subsequent GARCH-MIDAS models (with one including further control variables) are compared to a standard GARCH model, as a benchmark upon which to gauge the accuracy of the GARCH-MIDAS forecasting. Once the predictions are obtained, MCS tests are carried out to determine the statistical significance of the loss differences produced by the models. Following the MCS test framework outline by [36]., the control parameters are set accordingly: K=2 (bootstrap length); number of simulations B=10000; confidence level α=0.1. An observed p value greater than the confidence level will indicate significant predictive power.

Table 2 shows the MCS test result of the models. While the confidence level is not particularly rigorous, the results show that the presence of EPU in the forecasting model improves the accuracy of predictions. The GARCH-MIDAS models have a higher forecasting accuracy, prompting evidence to suggest that US EPU index has some validity in predicting the volatility of industry portfolio returns. Moreover, the presence of further control variables is shown to also increase the accuracy of the forecasting, with the p values indicating that the second GARCH-MIDAS is more useful at predicting the fluctuations of the industry portfolios. This illustrates that for the out-of-sample prediction window, the US EPU index and included control variables are effective at increasing the precision of the forecasts. However, neither of the models included is deemed significant when increasing the rigidity of the confidence intervals. Indeed, the MCS tests reject the models at the 0.5 confidence interval, perhaps illustrating that the estimations of the model are subject to noise. The forecast error is seen to increase as the number of future periods increases. The presence of noise in the forecasting procedure may be the result of hidden structural breaks. Perhaps, the forecasting could be improved by implementing the Hatemi-J test [36] because it is possible to detect structural breaks even at an unknown period. Moreover, the estimation methods for the long-term volatility component could be improved by decreasing the window size for the rolling window estimates, as the decaying effect of the lagged macroeconomic variables may distort the predictive capacity of the GARCH-MIDAS model. Whilst the results have shown the statistical significance of the EPU index in explaining, the variation in industry returns, there remains a motivation for refinement of the model to improve the forecasting capacity and to offer market participants an insight into the future trend pattern of returns.

6 Conclusion

The parameter estimates shown in the tables (1) through (4) illustrate convincing evidence that economic policy uncertainty fluctuations are an explanatory variable in the volatility of industry returns. The most important facets of the findings from this paper are the results that suggest explanatory evidence of historic industry returns. The improvement in the estimation capacity of the GARCH model by incorporating macroeconomic variables acts as potential evidence of the causative effect of EPU upon investor behavior. This section includes a discussion of the economic intuition of the results and the ways to build upon the findings. Whilst there were insignificant results for candy and soda markets, precious metals and pharmaceuticals, the remaining industries that were examined illustrated a positive correlation between their respective volatilities. Most notably, the real estate industry returns were most strongly correlated with US economic policy uncertainty. Monetary policy has a contribution to the housing cycle [29] This result is indicative of the influence of monetary policy upon real estate investment, with interest rates altering the cost of borrowing for consumers investing in real estate. Moreover, with mortgages often charging borrowers variable rates, the uncertainty surrounding potential movement in the policy rate, which is represented through the EPU index, is shown to have a significant effect upon real estate industry returns. The results obtained in this paper may indicate that the uncertainty effect, that results from policy adjustments, has a deleterious effect upon real estate market returns. Furthermore, the results also provide evidence to suggest a causative relationship between EPU volatility and building material industry return fluctuations. The derived demand effect that links real estate market returns and demand for building materials is supportive of the contribution that EPU has upon the housing cycle.

Additionally, the results suggest that the aircraft industry return volatility had a strong significant relation with the volatility of EPU. This evidence is analogous with that of Azimli [16] whose research indicated a strong EPU-return relationship, most notably from 1998 to 2005. Azimli's approach involved a generalized method of moments estimation to obtain their results. The cohesion with the results obtained in this paper adds evidence to support the notion that EPU is an explanatory variable in aircraft returns. In addition, further evidence from the findings in this paper also corresponds with the results found by Bali et al. [10]. There is evidence suggesting that the EPU index holds the most significant relation with portfolios of industries that are related to heavy manufacturing. The intuition for this relation is that manufacturing industries have a greater capital intensity and consequently are more susceptible to growth trends. Similarly, research suggests that the EPU index has negative correlation with capital investment [24] and increases the cost of capital [26] . The resultant effect, following the evidence suggested by these papers, would be of reduced returns, following a decreased perception of investment attractiveness. The results from the dissertation also suggest a strong relationship between the volatility of the EPU index with automobile industry fluctuations. Following evidence from Pastor and Varonesi [24], this may be the result of the higher sensitivity of export subsidization to government policy decisions. The automobile industry has an exposure to export subsidization and therefore in periods of greater uncertainty, in which subsidization is lower, the attractiveness of investment is deemed worse and the productive capacity of automobile firms is depleted. [35]. Moreover, the findings illustrate a somewhat strong relation between EPU volatility and the return volatility of the financial sector. Whilst there may be some significance to this result, it may highlight a shortcoming of the estimation procedure of this paper. There is a possibility that the model suffers from endogeneity due to the data in this dissertation, which may cause unreliable estimates. Given that the measure for EPU is calculated using media provision, which may be reactionary to the economic cycle, there is possibility that the uncertainty index is correlated with latent variables that are existent in the error term. Furthermore, the findings from the methodology are inaccurate if, persistently, the EPU index changes are tangential to the other factors affecting the dependent variable. This paper's empirical approach does include measures to reduce the effect of endogeneity in the results by controlling for the savings rate and lending rate. Although, this process could be enhanced by the inclusion of a vector autoregression to capture the effect of the uncertainty to a better extent. Contrastingly, the testing procedures in the evaluation of the GARCH-MIDAS model show that inclusion of US EPU does not provide an effective forecasting tool. This is perhaps a result of the noise generated by the estimations of the long-term volatility component. The econometric analysis from Engle et al. [35] of the estimation methods argues that the measurement error involving the long-term volatility component will deteriorate the fit of the equation (9), therefore diluting the inference with respect to the correlation coefficient. Moreover, the measurement error generates a bias estimate which indicates that not filtering the long-term volatility component corrupts the analysis of the causal patterns. Indeed, the econometric analysis from Engle et al.[35] also indicates that replacing the long-term volatility component with a sample estimate will also induce a measurement error that will lead to incohesive estimation. Resultantly, this dissertation could be improved by using a rolling window specification for the MIDAS filter, such that both the long term and short term volatility components change at the same frequency, which has been shown to be superior for estimating procedures [35]. Upon implementing the necessary refinement of the estimation tools, it is feasible that the US EPU index could be used as a forecast for future returns of industry portfolios, with greater precision than what has been achieved in this dissertation. Nonetheless, the incentive for estimating industry returns persists due to the significance of the results obtained through the GARCH-MIDAS model and the explanatory power that this model generates. Indeed, the improvement from the standard GARCH model is indicative of this incentive. Consequently, this econometric exercise should be repeated for other countries, such as the United Kingdom, where the effects of uncertainty generated by policies or political decisions may have unanticipated effects upon industry portfolio returns.

7 Final Remarks

This paper contributes to the asset pricing literature by analyzing the efficacy of risk-based factors to capture industry portfolio returns. Economic policies pose unexpected effects upon investor behavior which create pecuniary implications that are specific to industries. This paper has demonstrated the effects of US policy implementation on industry returns, whilst controlling for other macroeconomic variables affecting the stock market returns. The GARCH-MIDAS model reveals that economic policy uncertainty has a small but statistically significant effect upon industry portfolio volatility. There are three reasons for these results. Primarily, the negative relationship between uncertainty and investor confidence as well as the disjunction effect of uncertain outcomes. Moreover, the negative nature of the reactions to economic policy may be evidence of investor risk aversion.

8 Tables

Table 1 In-sample estimates of GARCH−MIDAS models for stock market volatility.

Industry	μ	ω	α	β
Candy & Soda	0.96367	1.69818	0.12702	0.83847
Pharmaceuticals	1.11555	0.65626	0.04501	0.92614
Textiles	1.01248	5.01884	0.19418	0.73584
Building Materials	1.15290	1.57400	0.11107	0.86066
Steel Works	1.12830	2.56919	0.13690	0.83985
Automobiles & Trucks	0.97846	1.92611	0.18737	0.81059
Aircraft	1.54493	1.65041	0.21885	0.77441
Precious Metals	0.88502	18.37793	0.16719	0.68324
Petroleum & Natural Gas	1.14090	1.63136	0.13497	0.83238
Wholesale	1.24501	15.74599	0.32542	0.08374
Real Estate	0.74050	2.40387	0.21482	0.76411
Finance Trading	1.35881	2.22315	0.12326	0.83052

Note: This table shows the in-sample estimation of GARCH-MIDAS models with three specifications by maximum likelihood estimation (QMLE).The estimation results of GARCH-MIDAS-RV model are shown above. The last column of each panel corresponds to the values of log-likelihood function (LLF). μ) is the constant intercept term. α) is the coefficient to the squared residuals in the GARCH equation and β) is the coefficient of lagged variance.

Table 2 MCS tests and t-statistics of the loss functions generated by the following model approches

Industry	GARCH	GARCH-MIDAS(1)	GARCH-MID
Candy & Soda	0.001	0.001	0.001
Pharmaceuticals	0.001	0.003	0.002
Textiles	0.003	0.006	0.009
Building Materials	0.003	0.011	0.017
Steel Works	0.004	0.006	0.002
Automobiles & Trucks	0.001	0.011	0.021
Aircraft	0.001	0.007	0.01
Precious Metals	0.0001	0.0004	0.0009
Petroleum & Natural Gas	0.001	0.004	0.05
Wholesale	0.002	0.046	0.050
Real Estate	0.003	0.075	0.108
Finance Trading	0.001	0.07	0.045

Note: Values greater than 0.1 indicate significant results at the 0.1 confidence level.

[1]***denotes significance at 1% level.

Table 3 Descriptive Statistics of Transformed Data

Industry	Mean	Standard Deviation	Kurtosis
Candy & Soda	1.189	6.5633	3.8787
Pharmaceuticals	1.197987	4.79085	4.2843
Textiles	0.954551	8.1713	8.218285
Building Materials	1.12024	6.451974	4.257372
Steel Works	0.947834	8.561673	4.584825
Automobiles & Trucks	1.109387	8.66074	5.700348
Aircraft	1.145952	6.497125	5.096653
Precious Metals	0.793414	10.82381	6.20667
Petroleum & Natural Gas	1.0272144	6.376534	4.4989
Wholesale	0.937065	5.05013	3.61017
Real Estate	0.6287074	7.282176	17.12997
Finance Trading	1.207593	6.60947	1.388335

Table 4 In-sample estimates of GARCH−MIDAS models for stock market volatility.

Industry	μ	ω	α	β
Candy & Soda	0.96367	1.69818	0.12702	0.83847
Pharmaceuticals	1.11555	0.65626	0.04501	0.92614
Textiles	1.01248	5.01884	0.19418	0.73584
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Real Estate	0.74050	2.40387	0.21482	0.76411
Finance Trading	1.35881	2.22315	0.12326	0.83052

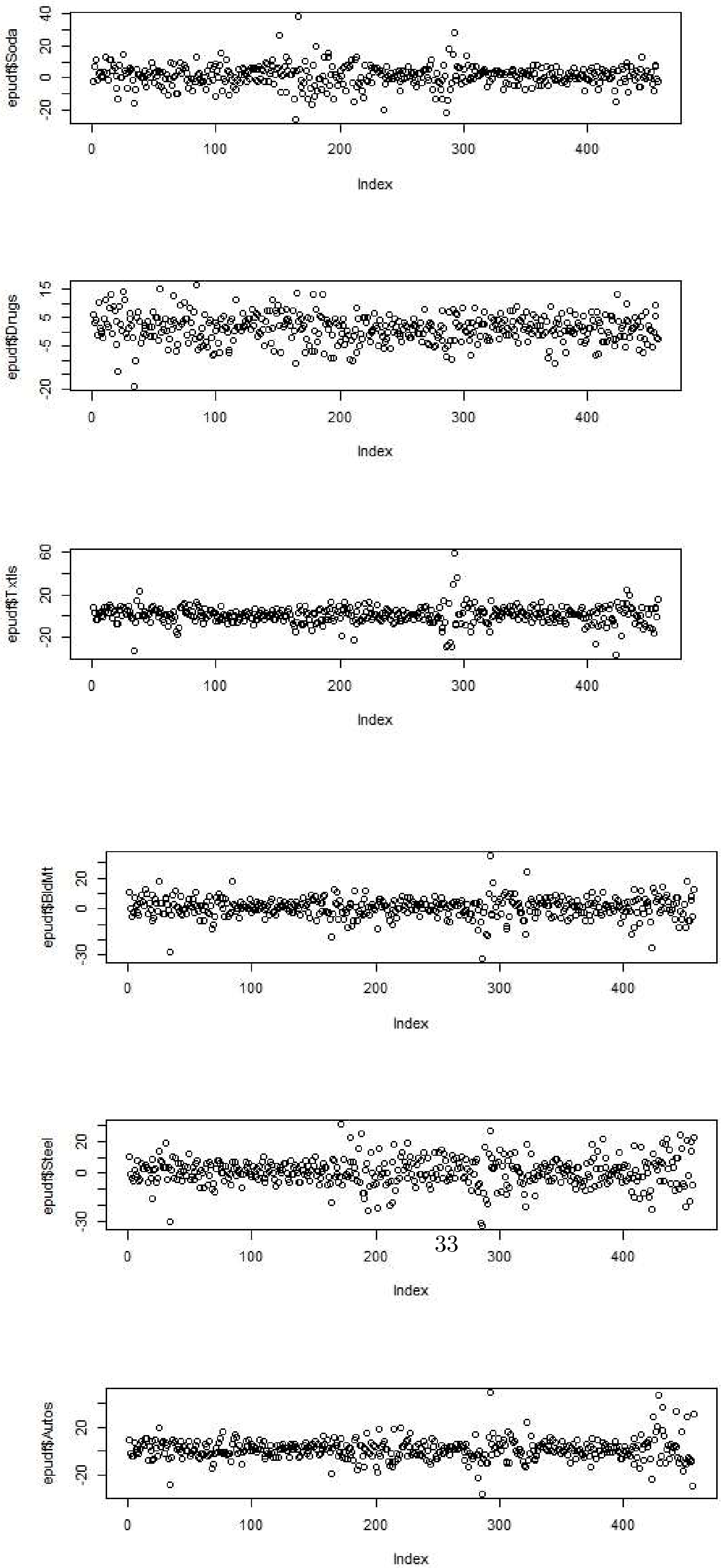
Note: This table shows the in-sample estimation of GARCH-MIDAS models with three specifications by maximum likelihood estimation (QMLE).The estimation results of GARCH-MIDAS-RV model are shown above. The last column of each panel corresponds to the values of log-likelihood function (LLF). μ) is the constant intercept term. α) is the coefficient to the squared residuals in the GARCH equation and β) is the coefficient of lagged variance.

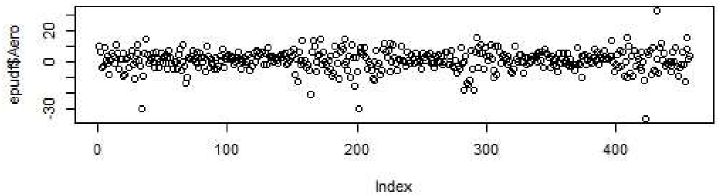
[1]***denotes significance at 1% level.

[2]Example for a second table footnote.

9 Figures

Figure 6: Chow Test Plots

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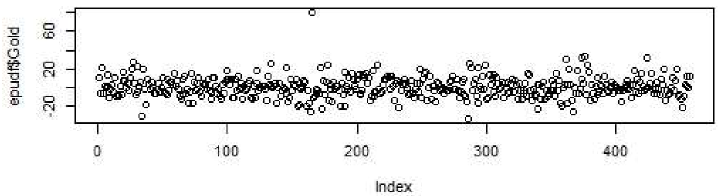
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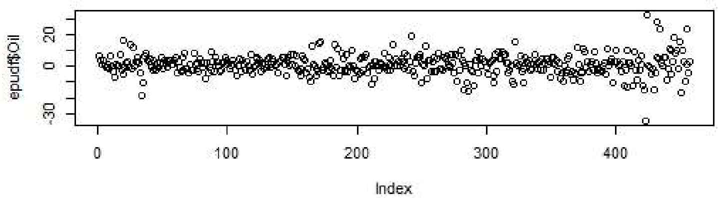
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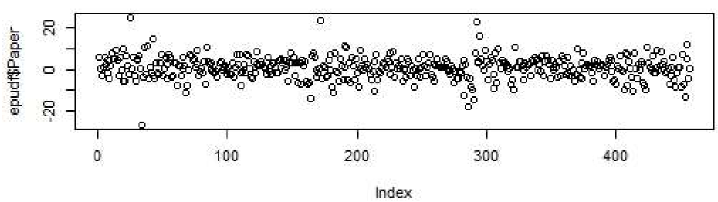
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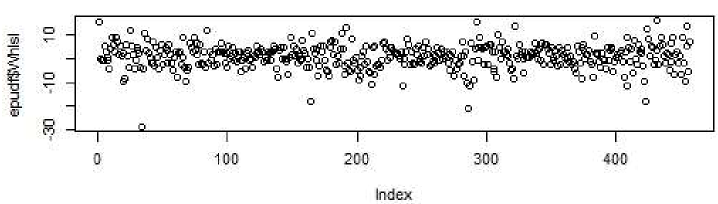
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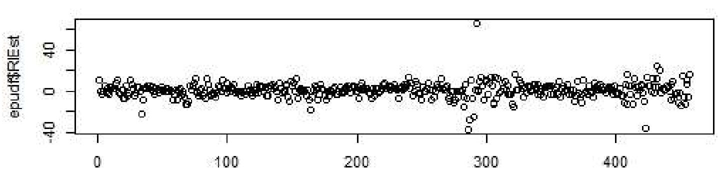
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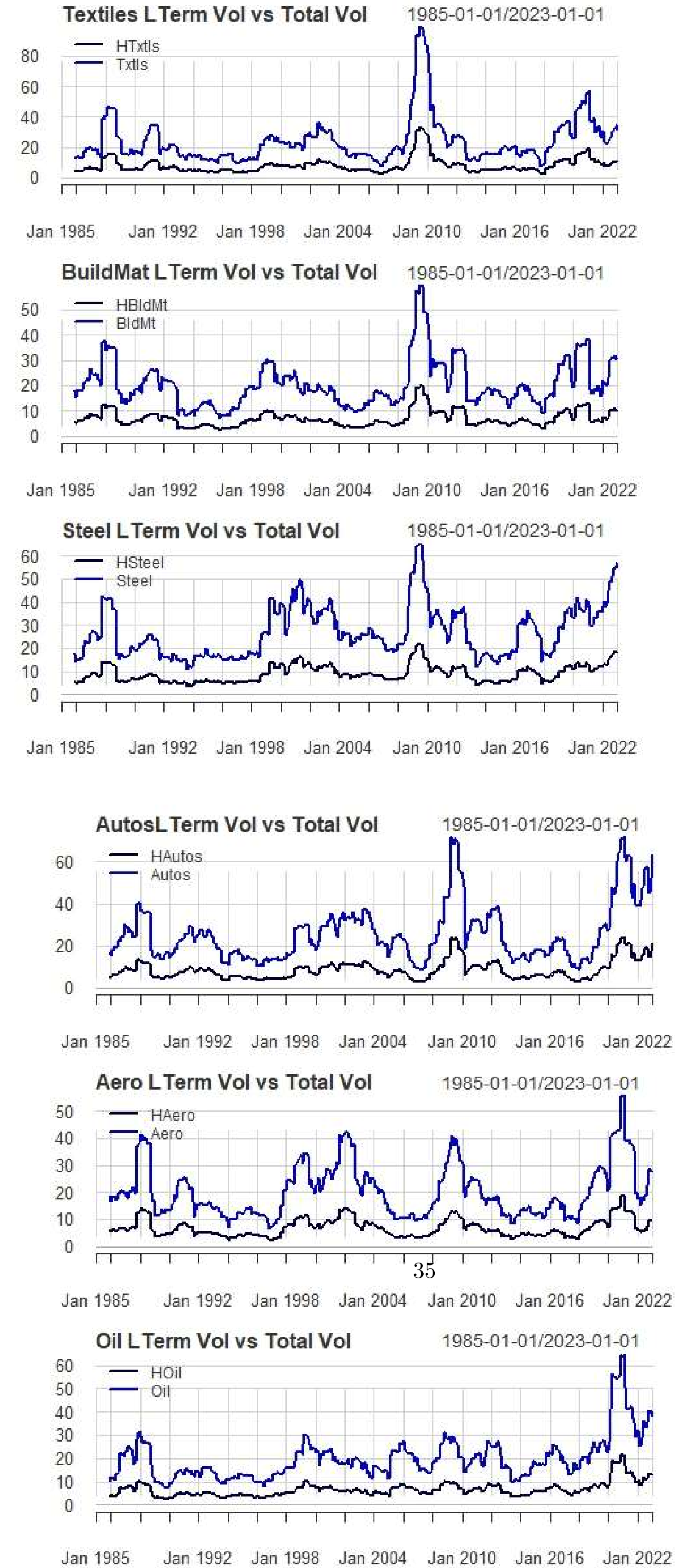
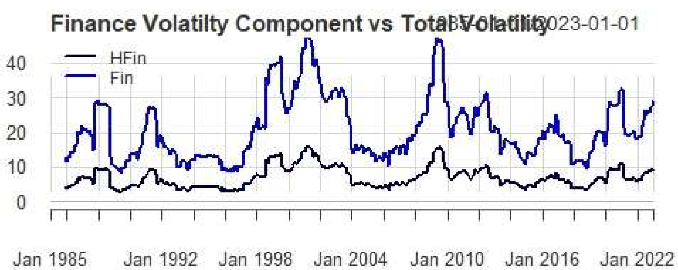
Figure 6:Significant Long Term Volatility Component vs Total Volatility




Wholesale LTerm Vol vs Total Vol
1985-01-01/2023-01-01
HWhlsl
Whlsl
30
20
10
0
Jan 1985
Jan 1992
Jan 1998
Jan 2004
Jan 2010
Jan 2016
Jan 2022


Rl Estate LTerm Vol vs Total Vol
1985-01-01/2023-01-01
HRlEst
RlEst
80
60
40
20
0
Jan 1985
Jan 1992
Jan 1998
Jan 2004
Jan 2010
Jan 2016
Jan 2022


Finance Volatilty Component vs Total Volatility
HFin
Fin
40
30
20
10
0
Jan 1985
Jan 1992
Jan 1998
Jan 2004
Jan 2010
Jan 2016
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