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Conditional Pricing of Macroeconomic Risk Factors using Attention

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Resume

Cet article examine l'applicabilité et la robustesse de la Théorie d'Arbitrage des Prix (TAP) avec des facteurs macroéconomiques pour expliquer les primes de risque dans le contexte des marchés financiers. Enracinée dans les travaux fondateurs de Chen, Roll, and Ross [1986] et Fisher, Martineau, and Sheng [2022], cette étude intègre le concept innovant de l'attention portée aux facteurs de risque macroéconomiques avec le cadre établi de la TAP. Les recherches précédentes n'ont pas réussi à démontrer que les facteurs de risque macroéconomiques sont valorisés, ce qui est un casse-tête. L'objectif principal de la recherche est de déterminer si les estimations des primes de risque pendant des périodes d'attention accrue des investisseurs peuvent être efficacement valorisées par les facteurs macroéconomiques. Cependant, les résultats sont en accord avec la littérature existante, démontrant une relation statistiquement insignifiante. Les résultats indiquent également le rôle de l'attention, et ces facteurs "pourraient" être valorisés lorsque l'attention est élevée (la valeur absolue moyenne de lambda augmente avec l'attention pour la plupart des facteurs de risque). Malgré un bruit considérable, l'étude tente de discerner des motifs et de tirer des enseignements significatifs, en particulier pendant les périodes d'attention accrue.

Mots-clés: Théorie d'arbitrage des prix, Indices d'attention macroéconomique, Charges factorielles, Primes de risque, Fenêtre glissante, Régression en deux étapes, Variables macroéconomiques, Inflation, Pétrole

Abstract

This paper examines the applicability and robustness of the Arbitrage Pricing Theory (APT) with macroeconomic factors in explicating risk premia in the context of financial markets. Grounded in the seminal works of Chen et al. [1986] and Fisher et al. [2022], this study integrates the innovative concept of attention to macroeconomic risk factors with the established APT framework. The prior literature has failed to find that macroeconomic risk factors are priced, which is a puzzle. The principal objective of the research is to ascertain whether risk premia estimations during heightened periods of investor attention can be effectively priced by macroeconomic factors. However, the findings align with existing literature, demonstrating a statistically insignificant relationship. The results also point to the role of attention, and those factors "might" be priced when attention is high (the average absolute lambda increases with attention for most risk factors). Despite considerable noise, the study attempts to discern patterns and derive meaningful insights, specifically during periods of heightened attention.

Keywords: Arbitrage pricing theory, Macroeconomic attention indices, Factor loadings, Risk premia, Rolling window, Two-stage regression, Macroeconomic variables, Inflation, Oil

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1 Introduction

The Arbitrage Pricing Theory (APT) is an effective framework for comprehending the complexities of financial markets and asset pricing, which economist Stephen Ross introduced in 1976. According to this theory, a number of macroeconomic variables may be stated linearly to represent the expected return on an asset. According to APT, it is possible to anticipate a financial asset's returns by concurrently taking into account a number of systematic risk variables. By allowing the addition of other risk categories, it differs from the conventional Capital Asset Pricing Model (CAPM), which considers market risk exclusively. Risk premia play a pivotal role within the APT framework as they denote the extra return investors demand accepting specific risks. The theory explains how these risk characteristics and the risk premia affect the predicted returns of various assets. As a result, the Arbitrage Pricing Theory (APT) is frequently used in finance-related studies.

Early tests of APT, such as those conducted by Roll and Ross [1980], involved estimating factor loadings (betas), followed by calculating the factor risk premia in a time-series regression. Subsequently, Chen et al. [1986] further enhanced the empirical testing of APT. However, much of the literature has reported insignificant risk premia for macroeconomic risk factors, suggesting that economic activities do not adequately explain stock returns, a puzzle that continues to perplex researchers.

In this thesis, the primary motivation for utilizing the Arbitrage Pricing Theory (APT) is to scrutinize its effectiveness in determining risk premia in financial markets.

Turning our focus to macroeconomic attention indices, Savor and Wilson [2013] studied the impact of macroeconomic announcements on asset prices. These are scheduled releases of economic data such as GDP growth rates, inflation data, and changes in interest rates. They found that these events significantly influence the prices of assets in financial markets. In other words, the stock market's reaction is more significant on days when such announcements are made. This is partly because these announcements provide new information about economic fundamentals, which investors then incorporate into their valuation of assets. Fisher et al. [2022] developed a novel empirical instrument for estimating the risk premiums associated with macroeconomic announcements.

The present research was inspired by the seminal work of Chen et al. [1986], who investigated the impact of economy state variables as systematic influences on stock market performance.

Furthermore, this study is also inspired by Fisher et al. [2022], who developed novel measures of attention towards various macroeconomic risks using news articles from renowned publications such as the New York Times (NYT) and the Wall Street Journal (WSJ). These metrics record variations in attention related to planned announcements and react to shifts in pertinent fundamental aspects. Importantly, our study confirms the effectiveness of the unique attention measurements employed by Fisher et al. [2022] across diverse categories of macroeconomic news. This essential finding has considerable implications for upcoming uses in finance and economics.

Using macroeconomic attention data in arbitrage pricing theory's framework enables us to estimate the risk premia, focusing on the times when attention to these macro factors is high. Through various experiments, we found that even if we narrow our focus on times when the investor's attention is high, again, these risk premia are not statistically significant, which is an even bigger puzzle. Therefore, our results are in line with the research that has come before. The relation between risk premia and attention does not follow the theories of endogenous attention. The price of risk, and economic uncertainty, is assumed to increase attention in these theories.

Similar macro variables were employed in this study, which can be found in Chen et al. [1986]. Industrial production, unexpected inflation, change in expected inflation, term premium, risk premium, and oil are the factors under consideration. Also, the Fisher et al. [2022]'s attention data for inflation and oil is used in this research.

To estimate risk factors, we used the Fama and MacBeth [1973] approach to estimate factor loading and risk premia for each macro variable both in the whole sample and in rolling windows. We also assess conditional and unconditional risk premia on attention on the full sample. Unconditional on attention, the findings demonstrate that macroeconomic factors are unable to account for stock returns. Although these macro factors should be priced conditional on attention, we found most are not statistically significant. To analyze the relation between attention and risk premia in depth, we conducted many tests on a rolling window of 5 years. We split the lambdas estimated from the rolling window into quartiles and calculate the average attention associated with each quartile. Conversely, we also split the attention into quartiles and calculate the average and absolute lambdas associated with each attention group. We did similar experiments only on the sample when the lambdas were statistically significant. We expect the patterns to be U-shaped or increasing. Although some patterns exist between attention and risk premia (the average absolute lambda increases with attention for most risk factors), they are not significant due to many reasons, like the outliers presented in box plots.

1.1 Literature Review

1.1.1 Capital Asset Pricing Model (CAPM) and its limitations

A well-known asset pricing model is the Capital Asset Pricing Model (CAPM), which was developed in the 1960s by Sharpe [1964], Lintner [1965] and Mossin [1966]. It establishes a connection between an asset's expected return and its systematic risk, symbolized by beta, as well as the market's expected return. The CAPM, built upon the foundation of the mean-variance portfolio optimization proposed by Markowitz [1952], was initially formulated as a "single-factor model." This model incorporated only one independent variable, the market risk premium, to explain asset returns based solely on their exposure to systematic risk within the market. However, as empirical research progressed, it became apparent that the CAPM had limited explanatory power regarding the cross-section of asset returns. So, the CAPM's single-factor method has since consistently being expanded. Researchers began discovering the existence of additional factors beyond market beta that had significant influence on asset prices. These factors included variables such as size, value, and profitability. It became clear that a single-factor model was insufficient to capture the complexity and variety of risk factors that affected asset returns. Banz [1981], Reinganum [1981], Gibbons [1982], Basu [1983] and Chan, Chen, and Hsieh [1985] provide empirical proof that refutes the static single-factor CAPM.

The limitations of the CAPM became more apparent as researchers delved deeper into asset pricing models. In the seminal work by Fama and French [1992], they put forth a three-factor model that challenged the CAPM by incorporating additional variables beyond market beta. According to their findings, size and book-to-market ratio emerged as crucial factors in predicting stock returns. Their research demonstrated that the CAPM alone was inadequate in accurately capturing the cross-section of stock returns. Building upon the three-factor model, Hou, Xue, and Zhang [2015] extended the CAPM by introducing a four-factor model. By adding a new element, their research aimed to improve our knowledge of asset pricing and improve the model's capacity to account for fluctuation in stock returns. In order to include a wider variety of risk factors impacting asset price, they attempted to increase the list of variables beyond market beta, size, and book-to-market ratio.

To capture the complexities of asset pricing, Fama and French [2015] introduced the five-factor model, representing a significant expansion of the CAPM. Their research sought to advance our understanding of asset pricing and enhance the model's ability to take stock return variation into account by introducing new components. They tried to expand the list of variables beyond market beta, size, and book-to-market ratio in order to account for a larger range of risk factors influencing asset price. In addition to market beta, size, and book-to-market ratio, the five-factor model put out by Fama and French [2015] also incorporates profitability and investment characteristics as additional drivers of asset returns.

The limitations of the CAPM prompted the development of more comprehensive asset pricing models known as "multi-factor models." These models aim to capture the factors influencing security market returns, offering a more nuanced approach to understanding asset pricing dynamics. There are three distinct types of multi-factor models: macroeconomic, fundamental, and statistical (Connor [1995]). In this study, the focus is on macroeconomic factor models.

1.1.2 Insights into Macroeconomic Factor Models, Arbitrage Pricing Theory (APT), and the Influence of Macroeconomic Risk on Asset Pricing

Macroeconomic factor models utilize observable economic time series as indicators of pervasive factors that drive security returns. These models recognize that macroeconomic conditions are vital in shaping risk perceptions and risk premia. Inflation, percentage changes in industrial production, the excess return on long-term government bonds, and the realised return premium on low-grade corporate bonds compared to high-grade bonds are all examples of macroeconomic indicators often employed in academic literature. The assumption of a linear relationship between the random return of a security and macroeconomic shocks is central to the framework of macroeconomic factor models. The model's premise is that changes in macroeconomic variables impact the expected returns and risk premia of securities systematically.

As an alternate asset pricing model, "Arbitrage Pricing Theory (APT)" is a multi-factor model created in response to the CAPM's drawbacks. It integrates multiple risk factors impacting asset returns. It was first presented by Stephen Ross in 1976. According to the CAPM, only one kind of non-diversifiable risk, referred to as market risk, influences security returns. On the other hand, APT acknowledges that several risks may influence predicted returns. Therefore, the APT model considers the possibility of numerous risks influencing expected returns, suggesting that investors confront a mix of risks rather than merely systematic risks.

The complex and multifaceted nature of risk, as emphasized by authors like Cochrane [2009], sets the foundation for our exploration of risk premia. Risk premia can be understood as the compensation investors demand bearing various risks associated with an investment. They represent the additional returns investors anticipate receiving as a reward for taking on a risk beyond what is inherent in a risk-free investment.

For a long time, the finance literature has attempted to link asset values to the macroeconomy. Whether macroeconomic risk matters for asset pricing has been the subject of extensive research, and the evidence regarding its significance is mixed. Some studies have found support for the impact of macroeconomic variables on asset pricing, while others have not. For instance, according to Brunnermeier, Farhi, Koijen, Krishnamurthy, Ludvigson, Lustig, Nagel, and Piazzesi [2021], the evidence on the significance of macroeconomic risk for asset pricing needs to be more conclusive. Various research studies have yielded conflicting results, with some indicating that macroeconomic variables play a role in determining asset prices, while others suggest limited or no impact. While economic variables have shown the ability to forecast stock returns, their associated risk premiums are statistically insignificant, as highlighted by Ferson and Harvey [1991]. This implies that although these variables may have predictive power, they do not consistently command additional returns as compensation for bearing their associated risks.

Similarly, studies conducted by Chen et al. [1986] have examined the risk premiums of economic variables such as industrial production, inflation, and the spread between long and short-term interest rates. Their findings suggest that the risk premiums associated with these variables are not always statistically significant. Furthermore, Kan, Robotti, and Shanken [2013] criticizes the standard methodology employed in asset pricing tests and argues that much of the evidence for risk premiums may be weak or spurious when subjected to appropriate analysis.

In the context of macroeconomic variables and the Capital Asset Pricing Model (CAPM), Jagannathan and Wang [1996] proposed a conditional version of the CAPM. However, their research indicates that the risk premium associated with macroeconomic variables, including the market risk premium, is statistically insignificant. The literature on risk premiums related to macroeconomic variables reveals a complex landscape with diverse findings. While some studies support the influence of macroeconomic risk on asset pricing, others find the relationship to be statistically insignificant or affected by methodological limitations.

Industrial production, term structure, expected inflation, and unexpected inflation are the five macroeconomic factors tested in reference French [2017], all of which have been hypothesised to affect stock returns. The variables' statistical significance is retested using four years of monthly current data for six countries (developed and developing). Term structure, predicted inflation and unexpected inflation are found to be insignificant in explaining domestic market returns, but risk premium and industrial production were significant across the sample.

The impact of macroeconomic factors on asset pricing extends to money supply, which has been recognized as a significant element. Studies by Homa and Jaffee [1971] and Hamburger and Kochin [1972] reveal a positive correlation between money supply and stock prices. These findings align with the theories put forth by real activity economists, who argue that an increase in money supply signifies rising money demand and, consequently, an upswing in economic activity.

In their article, Fama and Schwert [1977] examines the impact of inflation on various asset types, including stocks, bonds, and real estate. Using historical data from the United States, they analyze how changes in inflation rates affect asset returns. Their findings reveal interesting patterns: bond returns positively correlate with expected inflation, suggesting that bonds can hedge against inflation. They also identify real estate as a complete hedge against expected and unexpected inflation. However, the most intriguing result is that stock returns negatively correlate with expected and unexpected inflation. This finding diverges from the conclusions of Firth [1979], who found a positive relationship between stock returns and inflation in the UK.

According to Fama [1981], inflation and real economic activity are two crucial variables that influence stock returns. Positive stock returns tend to be associated with higher levels of real economic activity, indicating a positive link between economic growth and stock market performance. Conversely, negative stock returns are often linked to higher inflation rates, suggesting that inflation erodes the purchasing power of future cash flows and negatively affects stock prices. However, Fama [1981] concludes that limited evidence supports a significant direct correlation between stock returns and changes in the money supply. While the money supply is an important macroeconomic variable, Fama's research suggests that its impact on stock returns may not be as pronounced as the influence of inflation and real economic activity.

In their study, Geske and Roll [1983] explored the relationship between macroeconomic factors and stock returns. They found a negative empirical relationship between stock returns and inflation consistent with prior studies such as Fama and Schwert [1977] and Fama [1981]. This finding suggested that changes in inflation levels have a detrimental impact on stock market performance. To explain this phenomenon, Geske and Roll [1983] provided a compelling rationale supported by empirical evidence. They argued that unexpected inflation and changes in expected inflation lead to negative real shocks, resulting in increased unemployment and reduced corporate profitability. Consequently, corporate and personal tax revenues decline, causing a rise in the treasury's deficit. In response, the government needs to adjust its spending to compensate for the revenue changes, leading to increased borrowing from the public. To accommodate the increased treasury debt, the Federal Reserve System responds by increasing the growth rate of base money. Changes in the money base growth rate subsequently contribute to higher inflation.

Previous studies, such as Fama [1981] and Geske and Roll [1983], have primarily examined the individual links within the proposed causal chain between macroeconomic factors and stock returns. However, to provide a more comprehensive analysis, James, Koreisha, and Partch [1985] undertake a study investigating the simultaneous relations among stock returns, real activity, inflation, and changes in the money supply. A vector autoregressive moving average (VARMA) model is employed to achieve this. The results are consistent with the causality model proposed by Geske and Roll [1983].

In their study, Chen et al. [1986] (CRR) extend the Arbitrage Pricing Theory (APT) framework to examine the relationship between macroeconomic factors and stock returns. They aim to provide evidence supporting the APT and enhance our understanding of the economic forces influencing asset values. To evaluate their multi-factor model, CRR considers six macroeconomic variables. They find that expected and unexpected inflation, as well as oil prices, do not have a significant impact on stock market returns. However, they discover that the term structure spread (yield spread), default risk premium, and industrial production substantially influence stock returns. The most striking conclusion of the Chen et al. [1986] is that, even if a stock market index accounts for a sizeable amount of the time-series variability of stock returns, it has little impact on pricing when measured against indicators of the state of the economy. The multi-factor model proposed by Chen et al. [1986] serves as a template for numerous subsequent works in the field of asset pricing (Berry, Burmeister, and McElroy [1988], Connor [1995]).

After the influential study by Chen et al. [1986], the relationship between stock market movement and macroeconomic factors has garnered significant attention in the literature. One notable macroeconomic factor examined is the term structure of interest rates, as highlighted by Campbell [1987].

Campbell [1987]'s study found a correlation between stock returns and the steepness of the yield curve, represented by the yield spread between long-term and short-term interest rates. Specifically, greater future stock returns were associated with a steepening yield curve, while lower future stock returns were linked to a flattening yield curve. However, it is important to note that Campbell [1987] also discovered that the risk premiums associated with certain interest rate variables were not statistically significant. This implies that these variables did not consistently predict stock returns. The research conducted by Campbell [1987] and others shed light on the intricate dynamics between macroeconomic factors and stock returns.

Industrial production has been found to exhibit a significant positive relationship with stock returns during the period from 1926 to 1986, as highlighted by Cutler, Poterba, and Summers [1989] (CPS). However, when considering the sub-period from 1946 to 1985, which closely aligns with the sample period of Chen et al. [1986] (1958-1984), the correlation between stock returns and industrial production becomes less pronounced. In addition, CPS observes that stock returns do not exhibit a reliable correlation with inflation, money supply, or long-term interest rates. These findings suggest that the relationship between these macroeconomic variables and stock returns may not be consistent or statistically significant. While industrial production appears to have a more consistent relationship with stock returns, the associations between stock returns and other macroeconomic factors, such as inflation, money supply, and long-term interest rates, are less robust and may vary over different time periods.

In a study by Gjerde and Saettem [1999], the relationship between macroeconomic factors and stock performance in Norway is examined. Their research aims to understand how these variables interact and influence stock returns. Their findings indicate a favorable correlation between stock returns and real interest rates, as well as the price of oil. However, their research fails to demonstrate a meaningful connection between stock returns and inflation.

In their study, Doong, Yang, and Wang [2005] investigated the relationship between stocks and exchange rates in six Asian nations using the Granger causality test. Their findings show that, with the exception of one country, there is a significantly negative correlation between stock returns and changes in exchange rates.

In Shanken and Weinstein [2006], they have examined the relation between expected returns, and measures of systematic risk with respect to five macroeconomic factors studied in Chen et al. [1986]. They found that only the industrial production factor is significantly priced in the overall period of 1958–1983. Also, the premium of UPR is insignificantly negative for this period. They fail to find any evidence of factor pricing in the 1968–1977 subperiod.

Liu and Zhang [2008] contribute to the literature by examining the role of industrial production growth, a macroeconomic variable, in pricing the cross-section of momentum portfolios. They specifically focus on the relationship between past winners and losers in stock returns and their expected growth in cash flows. Building on this insight, the authors demonstrate that the expected-growth risk, representing the covariance between industrial production and the portion of the portfolio's return associated with its expected growth, progressively increases across the momentum deciles. They also found that the risk premia associated with macro variables are statistically insignificant.

1.1.3 The Impact of Macroeconomic News and Shocks on Stock Returns

Various studies have focused on understanding the relationship between stock returns and macroeconomic shocks. Schwert [1981] contributes to this understanding by investigating the daily returns of the Standard and Poor's composite portfolio around the announcement dates of the Consumer Price Index (C.P.I.) from 1953 to 1978. The study reveals an intriguing finding that the stock market shows a reaction to unexpected inflation coinciding with the C.P.I. announcement, while there appears to be no significant stock market response to unexpected inflation during the period preceding the announcement. Nevertheless, the reaction of stock returns to news about inflation is weak and slow.

From September 1977 to October 1982, daily stock prices responded to monetary information, but news about the consumer price index, unemployment, and industrial production had no discernible impact on prices (Pearce and Roley [1984]).

By taking into account a somewhat wider range of variables (15 relevant macroeconomic variables) up until August 1984, Hardouvelis [1987] comes to the conclusion that financial news has the biggest influence on stock prices.

In their study, Cutler et al. [1989] aimed to assess the impact of news on market returns. They found it difficult to identify consequential information to account for the market's largest price movements. In order to explore whether the stock market responds to information beyond their models, they examined market movements during significant political and global events. Surprisingly, they observed only minor market reactions to these events. Additionally, their research revealed that market movements often occur on days when there are no major news releases. These findings challenge the prevailing belief that changes in stock prices can be fully explained by considerations of future cash flows and discount rates.

Fundamental macroeconomic news has little impact on stock values, according to prior research (Schwert [1981], Pearce and Roley [1984]). Each of these studies assumes that investors' response to the news is the same over different stages of the business cycle. According to McQueen and Roley [1993], after allowing for different stages of the business cycle, a stronger relationship between stock prices and news is evident. Particularly, when the economy is already robust, news of higher-than-expected real activity causes stock prices to fall, whereas the same surprise in a poor economy causes stock prices to increase. This finding contributes to the explanation of why macroeconomic news, other than monetary information, was not given a lot of significance in earlier announcement studies.

Current studies show a strong correlation between stock market performance and economic fundamentals, and a model based on this link is necessary for forecasting future trajectories and trends (Morck, Yeung, and Yu [2000], Rapach, Wohar, and Rangvid [2005] and Ahn, Lee, Sohn, and Yang [2019]).

In the study conducted by Flannery and Protopapadakis [2002], the authors address the challenges associated with determining the impact of real macroeconomic factors on equity returns. A generalised autoregressive conditional heteroskedasticity (GARCH) model is used to determine which macroeconomic surprises (out of 17 choices) have an impact on realised equity returns or their conditional volatility. They identify three variables, CPI, PPI, and the monetary aggregate for which there is a relationship between surprises and returns, but only one of them (monetary aggregate) affects returns both directly and indirectly. By incorporating these factors into their model, Flannery and Protopapadakis [2002] aim to capture the nonlinear and time-varying nature of the impacts of macroeconomic variables on stock returns.

Gürkaynak, Sack, and Swanson [2005] conducted a study to investigate the relationship between long-term interest rates and economic news. Using empirical analysis, they examined the impact of economic indicators, policy announcements, and other economic news releases on long-term interest rates, revealing the sensitivity of these rates to information shocks.

In a recent study by Boyd, Hu, and Jagannathan [2005], the authors examine how security returns react to unemployment surprises. They find that during economic expansions, the stock market shows a positive response to news of rising unemployment, indicating a favorable reaction. Conversely, during economic contractions, the study reveals a negative stock market response to such news. These findings provide insights into the dynamic relationship between unemployment news and stock market behavior, revealing nuanced reactions in different economic conditions.

Using Federal funds futures data to determine policy expectations, Bernanke and Kuttner [2005] has shown that the stock market exhibits a rather strong and persistent reaction to unanticipated monetary policy measures.

Andersen, Bollerslev, Diebold, and Vega [2007] contribute to the literature by examining the stock market's response to macroeconomic news using a high-frequency futures data set. Their study reveals a similar result to previous research, suggesting that the stock market's reaction to macroeconomic news is contingent upon the prevailing economic conditions.

In their study, Savor and Wilson [2013] provide evidence of the significant influence that macroeconomic announcements have on asset prices. The authors demonstrate that scheduled economic announcements play a vital role in shaping investor sentiment and influencing market dynamics. In particular, they discover that average stock market returns are much greater on days when crucial macroeconomic news, such as inflation, unemployment, or interest rate announcements, are scheduled. Based on these results, it appears that more than 60% of the yearly equity risk premium is generated on the days of these announcements.

Ai and Bansal [2018]'s study examines the relationship between risk preferences and the premium associated with macroeconomic announcements. The stock market appears to react strongly to macroeconomic news. They conducted an empirical analysis that reveals how risk-averse investors exhibit a higher premium for holding risky assets when macroeconomic announcements are imminent.

Macroeconomic variables can be a useful source of information for predicting the future performance of the stock market, and macroeconomic fundamentals have concentrated effects during a bear market period, according to Liu and Kemp [2019] analysis of the forecasting accuracy of macroeconomic variables for predicting excess returns of the U.S. oil and gas industry stock index.

Economic uncertainty and risk aversion, which may be thought of as the price of risk, are shown to be positively correlated with endogenous attention in the studies of Bansal and Shaliastovich [2011] and Kacperczyk, Van Nieuwerburgh, and Veldkamp [2016]. These variables also serve as significant factors in determining macroeconomic announcement premia, as identified by Ai and Bansal [2018].

Bybee, Kelly, Manela, and Xiu [2020] analyze the structure of economic news using textual analysis of business news articles. They propose an alternative approach to understanding economic conditions by summarizing economic narratives in news texts. By employing a topic model and analyzing the content of the Wall Street Journal, they identify recurrent themes that reflect subjects of attention in financial markets and the broader economy. Their study shows that these themes closely align with numerical measures of economic activity and have incremental forecasting power for macroeconomic outcomes. Additionally, Bybee et al. [2020] propose a novel econometric perspective on shock identification, leveraging text corpora to isolate news-based narratives related to specific economic events.

In a related vein, Fisher et al. [2022] make a significant contribution to the literature by introducing the concept of "macroeconomic attention indices (MAI)." These indices are derived from news articles published in the New York Times and Wall Street Journal, providing new measures of market attention to specific macroeconomic fundamentals. The authors find that these attention indices are efficient predictors for announcement risk premia, indicating their value in understanding market reactions to macroeconomic news. Their study, Fisher et al. [2022], focuses on the relationship between macroeconomic attention and various macroeconomic risks, such as unemployment and monetary policy. They observe that attention to specific macroeconomic risks experiences significant spikes around scheduled announcements and responds to changes in related fundamentals. Notably, their research reveals that attention levels are higher for negative news compared to positive news. These findings enhance our understanding of market attention dynamics and their implications for macroeconomic factors.

Investors' judgments of macroeconomic risk are crucial to theoretical asset pricing, but they are difficult to evaluate experimentally, according to Bybee, Kelly, and Su [2022]. They put out a brand-new technique for calculating ICAPM state variables and asset price elements from Wall Street Journal business news articles. Their approach combines empirical asset pricing models with methods for natural language understanding. They see news articles as a valuable source of data for quantitative asset pricing models.

The studies conducted by Fisher et al. [2022], Bybee et al. [2020], and Bybee et al. [2022] make valuable contributions to the literature by shedding light on the role of news media in understanding market attention and its relationship to macroeconomic factors.

This paper is organized as follows. Section 2 describes the data, including economic variables, test assets, and macroeconomic attention indices. Section 3 describes the methodologies adopted in the present study, including two-stage regressions of FamaMacBeth, rolling window, and comprehensive investigation of risk factors. Section 4 details the empirical analysis. Section 5 concludes.

2 Data

This study aims to empirically examine the relation between industry portfolios and macro variables' risk premia conditional on the macroeconomic attention indices. We explain the selected macroeconomic variables in section 2.1, the test assets we used in section 2.2, and macroeconomic attention indices (MAI) in section 2.3.

2.1 Economic Variables

In this study, we employ six macroeconomic factors derived below and motivated by Chen et al. [1986].

Industrial Production (*IP*):The Federal Reserve Bank of St. Louis's FRED database has information on real production for all American manufacturing, mining, and electric and gas utilities measured by the monthly Industrial Production Index (INDPRO). The index is created each month to highlight short-term variations in industrial production. In addition to highlighting structural changes in the economy, it monitors changes in production output. MP_t is the industrial production growth rate for month t. Growth in the production index from month to month is an indicator of growth in the industry, which is defined as:

$$MP_t = \log_e IP_t - \log_e IP_{t-1}$$

Unexpected Inflation (*UI*): Unexpected inflation is when the actual inflation rate differs from what people expected. It can lead to redistributive effects, uncertainty in planning, resource misallocation, and reduced confidence. Unexpected inflation for month t is defined as:

$$UI_t = I_t - E\left[I_t \mid t-1\right]$$

where I_t is the realized monthly first difference Consumer Price Index, defined as:

$$I_t = \log CPISA_t - \log CPISA_{t-1}$$

$CPISA_t$ is the seasonal adjusted Consumer Price Index at time t from the FRED database at the Federal Reserve Bank of St. Louis. CPI tracks the average price changes of a basket of goods and services that represent the consumption patterns of households. "Inflation" is typically measured using various indices, with the Consumer Price Index (CPI) being a commonly used indicator.

Change in Expected Inflation (DEI): Expected inflation refers to the anticipated rate of inflation in the future. It influences economic behavior, interest rates, and wage bargaining. We can define the expected inflation as:

$$E\left[I_t \mid t-1\right] = r_{ft} - E\left[RHO_t \mid t-1\right]$$

where r_{ft} is the one-month treasury bill rate from the Center for Research in Securities Prices (CRSP). RHO_t is the ex post real return on treasury bills in month t as below:

$$RHO_t \equiv r_{ft} - I_t$$

To measure the ex ante real rate, $E\left[RHO_t \mid t-1\right]$, we use the Fama and Gibbons [1984] method. The difference between RHO_t and RHO_{t-1} is modeled as $RHO_t - RHO_{t-1} = u_t + \theta u_{t-1}$ such that $E\left[RHO_t \mid t-1\right] = \left(r_{ft-1} - I_{t-1}\right) - \hat{u}_t - \hat{\theta}\hat{u}_{t-1}$.

Then the formula for DEI would be:

$$DEI_t \equiv E\left[I_{t+1} \mid t\right] - E\left[I_t \mid t-1\right]$$

Term Premium (UTS): The difference in yield between long-term and 1-year treasuries is known as the term premium. It is the premium that bondholders seek to compensate for the higher interest rate risk and inflation expectations associated with owning longer-term notes. It can affect borrowing costs, so knowing what the market expects is crucial.

$$UTS_t = LGB_t - TB_{t-1}$$

LGB_t is the return on a portfolio of long-term government bonds obtained from Ibbotson and Sinquefield [1982] for the period 1953-78. From 1979 through 1983, LGB_t was obtained from the CRSP. TB_{t-1} denotes the treasury bill rate known at the end of period $t-1$ and applies to period t.

Risk Premium (UPR): The yield difference between corporate bonds with BAA and AAA ratings is what this variable, which comes from the FRED database at the Federal Reserve Bank of St. Louis, is defined as. Bonds rated BAA are low-grade bonds, and for AAA-rated bonds, we use the return on a portfolio of long-term government bonds (LGB). It represents the additional compensation investors demand for holding lower-rated bonds due to increased credit risk. It is an essential indicator for assessing credit market conditions and investor sentiment.

Oil: The spot crude oil price, as a macroeconomic variable, represents the current market value of oil for immediate delivery. It influences the performance of the energy sector, inflation, consumer spending, trade balances, and global economic growth and is influenced by geopolitical and supply factors. West Texas Intermediate (WTI) is a high-quality crude oil used as a benchmark for oil pricing in the United States and worldwide.

Table 1: Basic Macro Variable Definitions

Symbol	**Variable**	**Definition or Source**
I	Inflation	Log of Consumer Price Index of U.S. from FRED database
TB	Treasury bill rate	End-of-period return on 1-month bills from FRED database
LGB	Long-term government bonds	AAA-rated bonds from FRED database
IP	Industrial production	INDPRO series from FRED database
BAA	Low-grade bonds	from FRED database
OIL	Spot crude oil price	from FRED database

Table 2: Derived Variables

Symbol	**Variable**	**Definition**
MP_t	Monthly growth of industrial production	$\log_e IP_t - \log_e IP_{t-1}$
UI_t	Unexpected Inflation	$I_t - E\left[I_t \mid t-1\right]$
DEI_t	Change in Expected Inflation	$E\left[I_{t+1} \mid t\right] - E\left[I_t \mid t-1\right]$
UTS_t	Term Premium	$LGB_t - TB_{t-1}$
UPR_t	Risk Premium	$BAA_t - LGB_t$

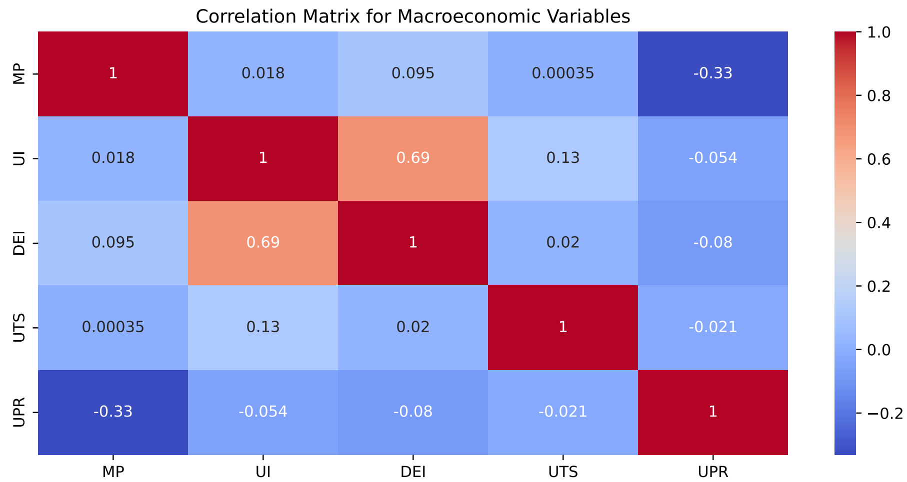
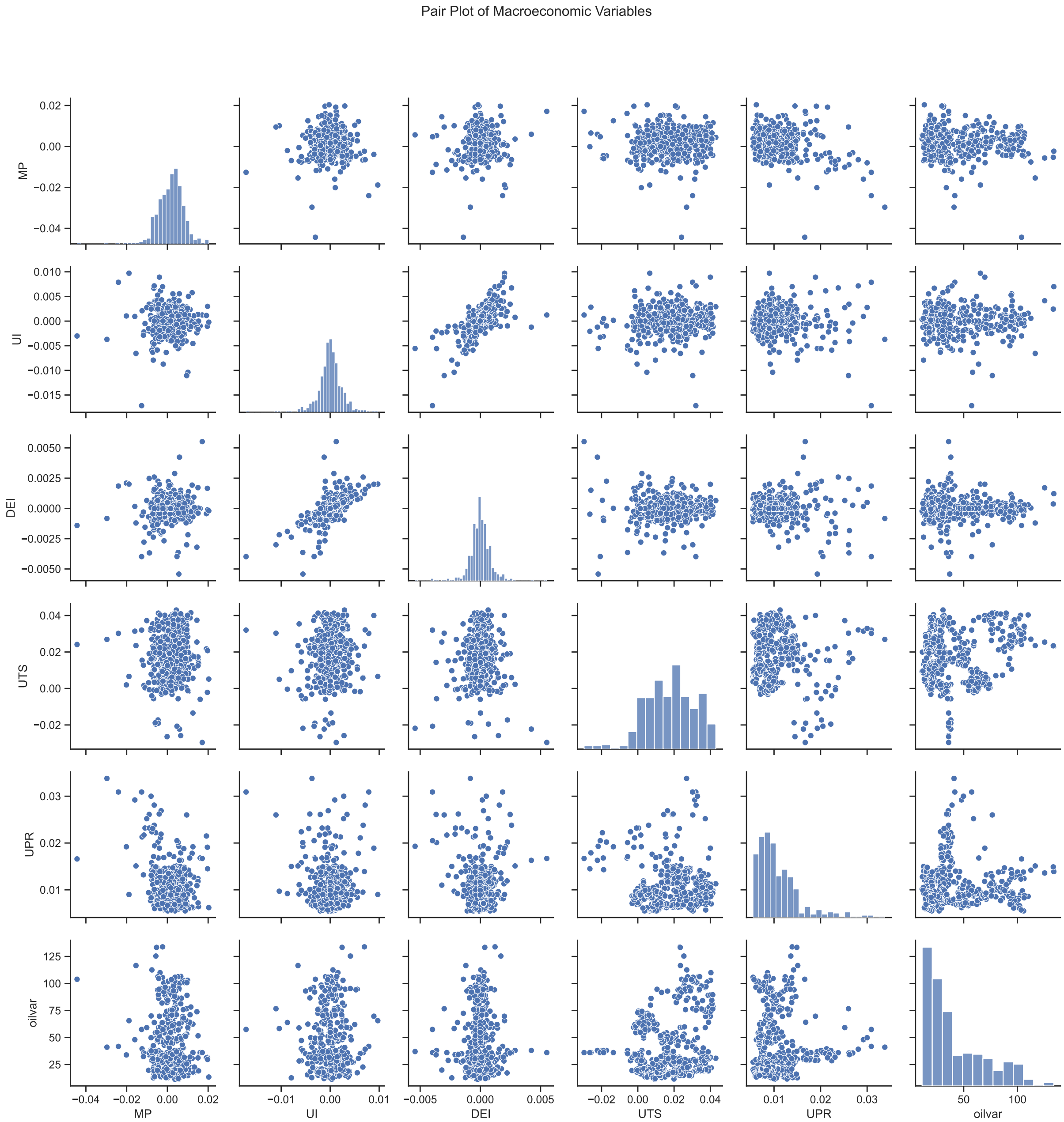


Figure 1: Correlation Heatmap of Macroeconomic Variables

Six macroeconomic factors are correlated in Figure 2.1. From 1980 to 2019, a complete sample is used to calculate this matrix. As can be seen in the figure, the unexpected inflation (UI) correlates closely with the change in expected inflation (DEI), with a correlation of 0.69. This is reasonable since they both contain the time series of $E\left[I_t \mid t-1\right]$.

Figure 2: Relationships Between Multiple Macro Variables and Their Distribution



2.2 Test Assets

We chose 49 monthly industry portfolio value-weighted returns from the FamaFrench website from 1980 to 2019 as our test assets for this section. Fama and French assigned each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit SIC code. Table 3 summarises the descriptive statistics for the six industry portfolios. To estimate the following statistics, 471 monthly data points are used.

Table 3: Summary Statistics of 6 Selected Industry Portfolios for 1980 to 2019

Industry	**Mean**	**Median**	**Std.Dev.**	**Min**	**Max**
Banking	1.12	1.52	6.00	-27.23	20.4
Insurance	1.12	1.57	5.21	-26.78	22.87
Real Estate	0.66	0.97	6.79	-37.51	66.02
Trading	1.21	1.65	6.34	-26.14	19.53
Agriculture	1.05	1.03	6.15	-29.04	28.88
Food	1.20	1.17	4.34	-17.86	19.61

2.3 Macroeconomic Attention Indices (MAI)

The attention data of this section is derived from Fisher et al. [2022]. The New York Times and Wall Street Journal's daily and monthly macroeconomic attention indicators were given by Fisher et al. [2022]. MAI is a novel empirical tool for measuring investors' risk premiums on macroeconomic announcements. Endogenous attention theories seek to explain why certain investors are prepared to incur more expenses or make extra efforts to acquire knowledge about fundamentals. Endogenous attention increases with economic uncertainty and the price of risk. Accordingly, we investigate the empirical connections between macroeconomic attention and fundamentals, by the links between theories of endogenous attention and announcement risk premia. Macroeconomic attention indices (MAI), new measures of attention to various macroeconomic variables, including employment and monetary policy and inflation, were developed by Fisher et al. [2022] to examine the attention to macroeconomic news. In this study, we particularly focus on unexpected inflation (UI) and change in expected inflation (DEI) and oil as macro variables; we use the indices of investor attention to the inflation and oil macroeconomic risk. Whether positive or negative, changes in the fundamentals of the economy tend to attract more attention, as suggested by Fisher et al. [2022]. According to theory, when risk premia increase, attention increases, making MAI a helpful empirical tool for our study.

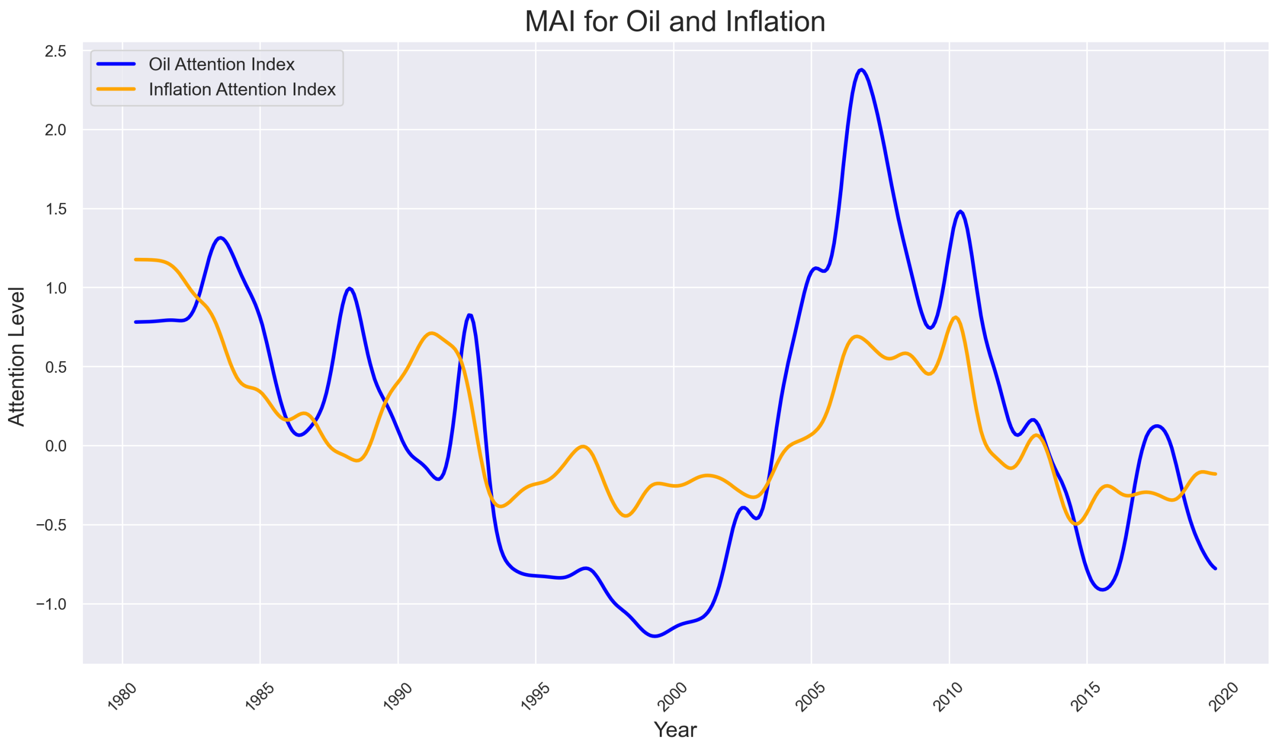


Figure 3: Visual Representation of the 6-Month Rolling Average for Oil and Inflation Macroeconomic Attention Indices Over Time

3 Methods

The main economic forces that systematically affect the pricing of all assets are captured by "factor models" (Sharpe, Alexander, and Bailey [1999]). When it comes to modeling equity returns, factor models are widely used and reliable because they provide a concise statistical explanation of the cross-sectional dependency structure of equity returns. The selection of risk factors typically focuses on those that seem significant, that is, those that worry investors enough to demand significant risk premiums to bear exposure to those sources of risk (Bodie, Kane, and Marcus [2005]). Under no-arbitrage conditions, Ross's (1976) arbitrage pricing theory (APT) established a solid economic connection between the factor structure in returns and risk premia. The APT was innovative without requiring a specific identification or economic interpretation for the components because it could speak directly to fundamental economic notions like risk exposures and risk premia. One of the most straightforward and understandable factor model is the "macroeconomic model." According to Connor [1995], these models use observable economic time series to measure the pervasive factors in security returns. The random return of each security is assumed to respond linearly to macroeconomic shocks. A security's linear sensitivities to the factors are called "factor betas" or "factor loadings." In the 1980s, macroeconomic factor models attracted the most attention, particularly with the publications of Chen et al. [1986]. Using the macroeconomic variables (section 2.1) implies that individual stock returns follow a factor model of the form (Chen et al. [1986]):

$$R_{it} = a_i + \beta_{iMP}MP_t + \beta_{iDEI}DEI_t + \beta_{iUI}UI_t + \beta_{iUPR}UPR_t + \beta_{iUTS}UTS_t + \beta_{iOIL}OIL_t + \epsilon_{it} \quad (1)$$

where βs are the factor loadings on macro variables, a_i is a constant term and ϵ_{it} is the idiosyncratic error term. This research employs a modified Fama and MacBeth [1973] two-stage regression approach, incorporated with a rolling window technique to analyze the data. The following outlines the detailed methodology.

3.1 Fama–MacBeth Regression

The two-stage Fama-MacBeth procedure is an instrumental methodology used in empirical finance to estimate factor loadings (betas) and risk premiums (lambdas). The method is particularly beneficial in evaluating a portfolio's exposure or discerning the extent to which a specific risk factor influences portfolio returns. It also helps determine the worth of the portfolio's exposure to a specific risk factor, given data on risk factors and portfolio returns. If the factor exposure is identified or computed, the corresponding risk premium can be leveraged to forecast the return for any portfolio with similar exposure. Formally, there will be $i = 1, \ldots, N$ asset or portfolio returns over $t = 1, \ldots, T$ periods, with the excess period return for each asset being indicated. The aim is to determine if the $j = 1, \ldots, M$ factors can adequately account for the excess returns and the risk premium related to each risk factor. In our instance, $N = 49$ industry portfolios and $M = 6$ risk factors. The essential assumptions of classical linear regression may not apply, leading to inference issues in such cross-sectional regressions. Potential violations include measurement errors, covariation of residuals due to heteroskedasticity and serial correlation, and multicollinearity.

Fama and MacBeth [1973] presented a two-stage approach for cross-sectional regression of returns on risk factors to solve the inference problem brought on by the correlation of the residuals. By regressing the time series of stock returns (TSR) on the macroeconomic variables, first-stage regressions investigate the relevance of factor sensitivities (betas, factor loadings). By regressing the cross-section of stock returns on the M estimates of factor sensitivity (betas) derived from the first-stage regressions on T cross-sections, the second-stage regressions investigate the importance of factor risk premiums.

3.2 First Stage Regression

We proceed by following approach, as recommended by Bai and Zhou [2015], which postulates that returns are driven by a model with M factors. By utilizing vector and matrix notation, this model can be represented as follows:

N time-series regression, one for each asset or test portfolio, of its excess returns on the factors to estimate the factor loadings. In matrix form, for each asset:

$$\underset{T\times 1}{\boldsymbol{r}_i} = \underset{T\times(M+1)}{\boldsymbol{F}} \underset{(M+1)\times 1}{\boldsymbol{\beta}_i} + \underset{T\times 1}{\boldsymbol{\epsilon}_i} \tag{2}$$

where $\boldsymbol{r}_i$ is the excess returns of test assets i (49 industry portfolios), $\boldsymbol{\beta}_i$ are the factor loadings, $\boldsymbol{F}$ is the observed macro factor innovation j (M total) and $\boldsymbol{\epsilon}_i$ is the idiosyncratic errors.

3.2.1 Estimating Factor Loadings

Take the model provided by equation 2. Asset-by-asset time series regressions (TSR) allow us to estimate factor exposures when we have knowledge of relevant factors:

$$\beta_i = \frac{\operatorname{cov}(\boldsymbol{r}_i, \boldsymbol{F})}{\operatorname{var}(\boldsymbol{F})} \tag{3}$$

In matrix form, it can be written as (Giglio, Kelly, and Xiu [2021]):

$$\widehat{\beta} = \bar{r}\bar{F}^{\top}\left(\bar{F}\bar{F}^{\top}\right)^{-1} \tag{4}$$

3.3 Second Stage Regression

T cross-sectional regression, one for each time period, to estimate the risk premium. In matrix form, we obtain a vector $\boldsymbol{\lambda}_t$ of risk premia for each period:

$$\underset{N\times(M+1)}{\boldsymbol{r}_t} = \underset{N\times(M+1)}{\hat{\boldsymbol{\beta}}}\underset{(M+1)\times 1}{\boldsymbol{\lambda}_t} \tag{5}$$

3.3.1 Estimating Risk Premia

The risk premium of a factor reveals how much money investors are willing to part with in order to bear the risk of that factor. Estimating risk premia for tradable factors, like the market portfolio in the CAPM, reduces to finding the factor's sample average excess return. Many theoretical models, however, are constructed with respect to non-tradable characteristics like consumption, inflation, liquidity, and so on. Any of these elements risk premium can be estimated by building its tradable counterpart. We use two-stage regressions to construct tradable counterparts of a non-tradable factor.

The risk premia for each macro variable is estimated:

$$\hat{\lambda} = \left(\hat{\beta}^{\top}\hat{\beta}\right)^{-1}\hat{\beta}^{\top}\bar{r}. \tag{6}$$

First and second-stage estimations were then repeated for each year in the sample, yielding a time series of estimates of its associated risk premium for each macro variable.

3.4 Rolling Window Approach

The Fama-MacBeth procedure described above is usually performed on a static sample of data, yielding a single set of estimated betas and lambdas. This approach can be effective in some cases. Still, it may fail to capture the dynamics of financial markets where factor sensitivities (betas) and risk premiums (lambdas) can be time-varying. A rolling window approach is applied in this analysis to deal with this issue. A rolling window is essentially a fixed-size subset of a time-ordered data set. This technique allows for more dynamic analysis, considering the most recent observations and discarding older ones as the window "rolls" through the data. By doing this, we can capture evolving trends and changes over time that a static analysis would miss. In this research, we choose a window size of 60 months (5 years).

3.4.1 Step 1: Selection of the Time Window and Estimation of Betas

Beginning with June 1985, a retrospective window of 60 months is used for the calculation. Thus, the initial sample spans from June 1980 to May 1985. Within this window, the asset returns are regressed against the chosen risk factors to estimate the factor loadings, also known as the betas. This estimation corresponds to the first stage of the Fama-MacBeth procedure. Mathematically, the model takes the form of equation 2.

3.4.2 Step 2: Estimation of Lambdas for the Current Month

Upon deriving the betas, these factor loadings are used to compute the risk premiums, or lambdas (λ), for the subsequent month, in this case, June 1985. This is achieved through a cross-sectional regression of the average portfolio returns on the estimated betas, the second stage of the Fama-MacBeth procedure. The model is represented in equation 5.

3.4.3 Step 3: Rolling the Window Forward

After obtaining the beta and lambda estimates for June 1985, the rolling window is moved forward by one month. Consequently, the new time window spans from July 1980 to June 1985. This set of observations is now used to estimate the betas, which subsequently aid in estimating the lambdas for July 1985.

This procedure is repeated iteratively, moving the window forward month by month and applying the two-stage Fama-MacBeth procedure to each rolled window. This process yields a series of beta and lambda estimates, providing insight into their evolution over time. Thus, the rolling window approach is a flexible tool for studying the temporal dynamics of factor loadings and risk premiums.

3.5 Unconditional Risk Premia Estimation

In this section, we focus on the relation between portfolio returns and macro variables (especially for oil macro variable) unconditionally motivated by Chen et al. [1986]. Previous literature finds no significant unconditional risk premia for the macro variables. As a result, the macro variables are not priced unconditionally in the cross-section. For the implementation, we use 49 testing portfolio returns as r_i in the left-hand side of the equation 2. We find the factor loadings (betas) in the first stage on mentioned macroeconomic variables. Then in the second stage, we perform the cross-section regressions of the portfolio's excess returns on factor loadings to find the risk premia for each macroeconomic variable. At the end of this process, we end up with the risk premia time series of all macro variables unconditionally. We can also find the p-values of risk premia to see whether they are statistically significant or not.

3.6 Conditional Risk Premia Estimation

In this section, we want to see if macro factors are price conditionally in the cross-section. The objective is to bring the focus to periods when investors really care about macro factors. We expect the risk factors to be priced during those times. To do so, we use macroeconomic attention indices (MAI) and split the months in the sample into four groups based on attention (in quartiles). So, we identify the dates with high attention (quartile 3) and low attention (quartile 0). Then we apply the first-stage regression to see the factor loading for each group and perform the second-stage regression to find the risk premia of macro variables in both the high and low-attention groups.

3.7 Comprehensive Investigation of Risk Factors:

This methodology section systematically investigates the relationship and interaction among the macroeconomic attention measures (MAI), lambdas (risk premiums), and the absolute value of lambdas. This analysis covers two major time spans - the complete sample period from 1985-06 and beyond and the specific months characterized by statistically significant lambdas (p-value less than 0.05). Such categorization is strategic as it offers distinct perspectives on how these variables behave under average conditions versus periods of marked risk premiums.

3.7.1 Full Sample Analysis

In the initial phase, the focus is placed on the entire dataset, encompassing the complete timeline from June 1985 to the most recent available data. This inclusive scope provides a broader context, enabling a well-rounded understanding of how the attention measures, lambdas, and absolute lambdas relate and influence each other under various market conditions.

- Examination by Lambda Quartiles: The data is divided into quartiles based on the lambda values derived from two stages Fama and MacBeth [1973] along with a rolling window. This stratification enables an in-depth study of how different degrees of risk premiums, from the lowest to the highest quartile, associate with variations in attention measures.

- Examination by Attention Quartiles: The roles are then reversed, with the data being grouped into quartiles according to attention measures. This allows us to scrutinize how lambdas behave and fluctuate across different levels of investor attention.

- Examination by Attention Quartiles (Absolute Lambdas): A similar analysis is conducted with the absolute lambdas, focusing on the magnitude of the risk premium, irrespective of its direction. By analyzing the data segmented by attention quartiles, we can discern how the absolute magnitude of risk premiums is distributed across varying degrees of investor attention.

3.7.2 Evaluation of Months with Statistically Significant Lambdas

This methodology narrows our analysis to specific months where lambdas (risk premiums) are statistically significant. This focused examination aims to understand how attention measures, lambdas, and absolute lambdas interact when risk premiums are notably high.

In this targeted analysis, we follow similar steps to those used in the full sample analysis but apply them to this specific subset of data (months with significant lambdas).

By comparing the full sample analysis results with those from the months of significant lambdas, we can gain insights into how the relationships between attention measures, lambdas, and absolute lambdas can change under different market conditions. This comparison helps us better understand how investor attention and risk premiums behave under varying market situations.

4 Empirical Results

The empirical analysis in this study utilized a dataset consisting of 49 industry portfolios and macroeconomic variables. The main objective is to estimate the risk premiums, represented by lambdas, associated with oil, DEI, and UI factors using Fama and MacBeth [1973] along with a full sample and rolling window approach. First, We did an experiment based on sections 3.5 and 3.6. We used the first stage regression of Fama and MacBeth [1973] on the "full sample" to calculate the factor loadings of the macro variables (we do not have a rolling window at this stage). The average factor loadings for each industry portfolio, along with its fraction of significance, is available in Table 5 located in the appendix. For example, for the household industry portfolio, the average factor loadings are 34.66, and the fraction of significance is 0.33, which means 2 out of 6 factor loadings are statistically significant.

After obtaining the factor loadings, we proceed to estimate the risk premia associated with these variables via second-stage regression without a rolling window, with particular emphasis on oil. When considering the oil's price of risk without accounting for investor attention (unconditionally), we find results that align with existing literature. Most studies have reported insignificant risk premia for macro variables, which poses an intriguing puzzle. It appears peculiar that the economy's performance does not adequately explain stock returns. In our study, we unconditionally investigate the oil price of risk from 1980 to 2019. We find that the oil price of risk is insignificant during this time frame. For 77 percent of the sample, the p-value is more than 0.05 (insignificant) and 23 percent less than 0.05 (significant). This finding adds further complexity to understanding the relationship between macroeconomic variables and stock returns. The average price of risk for each of the macro variables without a rolling window is in Table 4. Based on this table, the average risk premia for the DEI factor is 0.0008, and its p-value is 0.2514. The p-value of all macroeconomic variables in Table 4 is more than 0.05, which shows they are all unconditionally insignificant on the full sample.

Also, Figure 4 shows the time series of risk premia for each macro variable along with their distribution on the full sample unconditionally. Figure 5 also indicates the p-value of the oil's risk premia unconditionally on the full sample, which is mostly insignificant (p-value greater than 0.05, gray and black points).

In our second experiment, we check the price of risk when investors pay more attention to these macroeconomic variables (conditionally). As discussed in section 3.6, we separately estimate the risk premia for four attention groups. The goal is to shift the spotlight to moments when investors are most concerned about macro variables. We anticipate that the risk variables will be valued at such times. In this study, we put focus on oil prices. We run Fama-MacBeth regression for each sample to estimate the factor loadings and lambdas separately. The results for oil's risk premia and associated p-value in both low and high quartiles are shown in Table 6 of the appendix. Figure 6 depicts the oil's risk premia along with p-values in each quartile of attention. The size of the dots indicates how significant the p-value is. The bigger the dots, the more significant the risk premia is. Also, the color of each dot indicates the quartile of the attention on which the oil's risk premia is calculated. In this study, we expect that bigger dots majorly be in red. From the figure, the results seem consistent with the previous literature regarding the insignificance of risk premia.

The following experiment allows us to dynamically estimate risk premiums over time, considering a 60-month rolling window period. The estimation process was conducted for each month starting from 1985-06, following two main steps, beta and lambda estimation. A rolling window approach was adopted, where the betas were estimated using the previous 60 months of data ($t - 60$ to $t - 1$). For example, for the month 1985-06, the betas were estimated using data from 1980-06 to 1985-05. Estimating lambdas, representing the risk premiums associated with the macro factors, was a crucial step in the analysis. These lambdas were estimated monthly on the full sample period from 1985-06 to 2019-09. The estimation of lambdas utilized the betas estimated in the previous step ($t - 60$ to $t - 1$). By regressing the portfolio returns on the estimated betas, the lambdas were derived for the current month (t). Lambdas for the macro variables (precisely, oil, DEI, and UI) were estimated, and the associated p-values were calculated to determine the statistical significance of the estimated risk premiums. The oil price of risk is estimated at -1.76 for June 1985, and its p-value is 0.58. The full results are presented in Figures 10, 11, and 12 of the appendix to provide a clear overview of the estimated lambdas and their corresponding p-values for oil, UI, and DEI.

To further explore the relationship between lambdas and investor attention, we analyze the full sample based on section 3.7.1. We split the lambdas into different quartiles and calculated the average attention within each quartile. This allows us to examine the variations in average attention across varying levels of lambdas. By analyzing the average attention measures in each lambda subsample, we gain insights into how investor attention varies based on the magnitude of the risk premiums. In analyzing the UI factor, we compute the mean of attention for each quartile of lambda. The means for the first, second, third, and fourth quartiles are 0.03468, -0.05891, -0.03847, and 0.04343, respectively. In addition to analyzing the relationship between lambdas and investor attention, we conducted a reverse analysis by grouping the months based on attention levels. This involved categorizing the months into different attention groups (quartiles) and calculating the average lambdas and average absolute lambdas within each attention group. This reverse analysis provided insights into how the risk premiums and their magnitudes vary across different levels of investor attention. To focus on the significant lambdas, we filtered out the lambdas that were not statistically significant based on section 3.7.2. We then repeated the analysis by splitting the remaining significant lambdas into quartiles. Similar to the previous step, we calculated the average attention within each lambda quartile. Furthermore, we also examined the quartiles of attention and calculated the average lambda and absolute lambda within each attention quartile. The complete results of these analyses are summarized in Tables 7, 8, and 9 in the appendix. To complement the study, we also conducted box plot visualizations to explore further the relationship between lambdas, investor attention, and risk factors. The box plots were generated for both the full sample period (starting from 1985-06) and the sample of months with statistically significant lambdas. The box plots were organized, with each risk factor represented in a separate plot. The box plots included the following:

- Box plot of attention measures, grouped by lambda quartiles
- Box plot of lambdas, grouped by attention quartiles
- Box plot of absolute lambdas, grouped by attention quartiles

The results of these box plot analyses are summarized in Figures 7, 8, and 9. According to Figure 8, the box plot exhibits a non-linear relationship between lambda and attention, especially evident in the fluctuations in the mean of attention for different lambda quartiles. The full sample analysis shows that when lambda is either very low or high (extreme quartiles), attention tends to be positive. In contrast, mid-range lambda values correspond to negative attention. For both categories (full sample and significant only), as the value of attention increases, the absolute magnitude or impact of lambda also intensifies, as demonstrated by the ascending values in the mean of absolute lambda. Based on the Figure 9, it's evident that attention plays a significant role in affecting lambda. In the "full sample", as attention increases, the absolute value of lambda also shows an increasing trend, especially significant in the higher attention quartile where mean of absolute lambda reaches 0.00374. This trend is even more pronounced in the "significant only" sample, with the highest attention quartile showing a mean of absolute lambda at 0.00855. These findings support the earlier conclusion: when attention is high, certain factors might be priced more heavily, as the average absolute lambda (a measure of pricing) increases alongside attention. This underscores the pivotal role of attention in the model. However, potential outliers and the aforementioned noise in the data should be taken into account when drawing broader conclusions.

The results align with the existing body of literature, which has consistently identified the inherent difficulties in accurately measuring the impact of certain variables, primarily due to high levels of noise or statistical variability. This "noise" could stem from multiple sources, including other unaccounted external factors, volatility in the dataset, or non-linear relationships among variables, all of which obscure the underlying patterns we aim to discern.

Despite the persistent noise issue, even when our analysis is conditioned on the level of attention, our results provide insightful findings regarding the pivotal role of "attention" in our model. Those factors "might" be priced when attention is high (the average absolute lambda increases with attention for most risk factors). U-shape and increasing line relation between average absolute lambda and attention are not significant due to the outliers.

Table 4: This table presents valuable insights into the average price of risk associated with each macro variable on the full sample. Through the utilization of second-stage regression on the entire sample, without conditions, we clearly understand how much the market rewards us for bearing the associated risks tied to these macro factors. Examining the p-values of the risk premia, we find that, on average, they exceed the critical value of 0.05 for all macroeconomic variables. Consequently, there is insufficient evidence to reject the null hypothesis. As a result, they are insignificant and align with previous literature, which is a puzzling issue.

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
MP	-0.0040	0.0044	-0.9090	0.3633	-0.0126	0.0046
UI	-0.0006	0.0011	-0.5500	0.5823	-0.0029	0.0016
DEI	0.0008	0.0007	1.1469	0.2514	-0.0006	0.0022
UTS	-0.0057	0.0095	-0.6005	0.5482	-0.0243	0.0129
UPR	-0.0003	0.0037	-0.0744	0.9407	-0.0075	0.0070
OIL	-17.389	21.953	-0.7921	0.4283	-60.417	25.639

Figure 4: This figure shows the time series of risk premia for each macroeconomic variable and their density derived from second-stage regression on the whole sample without considering investors' attention. The figures show that the market compensates, holding risks associated with different factors differently through time. Also, the distribution of some risk premia is more heavily tailed than the others and, of course, has different peaks.

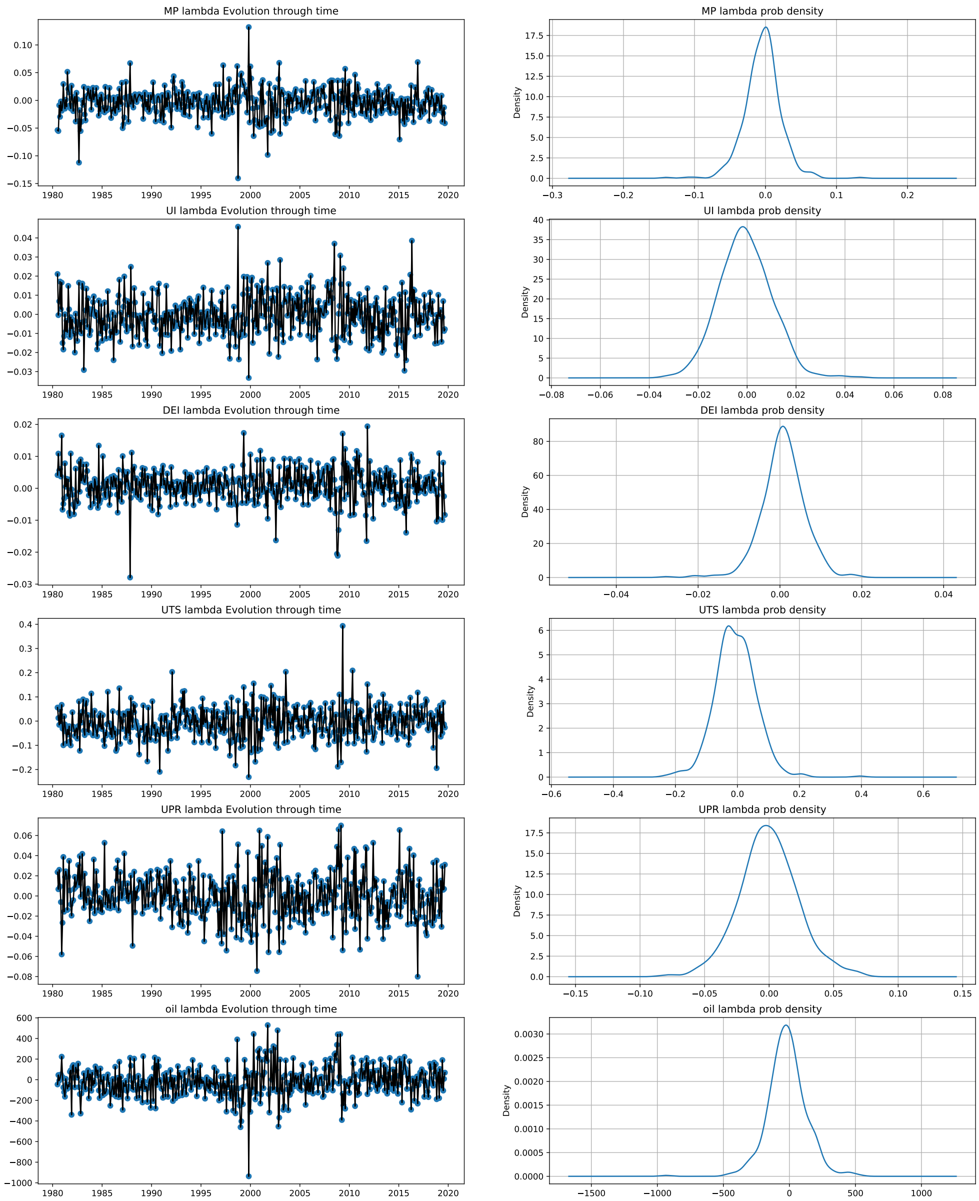


Figure 5: In the figure provided, the blue line represents the risk premia of oil between the years 1980 to 2019. This risk premium is calculated using the second stage regression method proposed by Fama and MacBeth [1973] on the full sample, but without considering the investors' attention to this risk. The dots on the figure are associated with the p-values of the oil's price of risk. The p-value indicates the statistical significance of the price of risk. When the p-value is less than 0.05, it is considered significant and depicted in red. On the other hand, when the p-value falls between 0.05 and 0.1 or greater than 0.1, it is considered insignificant and is depicted in black or gray color, respectively. From the figure, it is evident that the majority of the p-values are gray, indicating that they are not statistically significant. These results align with the existing literature, which has found the relationship between oil and stock returns puzzling. In other words, when calculating the risk premia over the entire window from 1980 to 2019 without considering the attention to this specific risk, it appears that oil cannot explain the variations in stock returns.

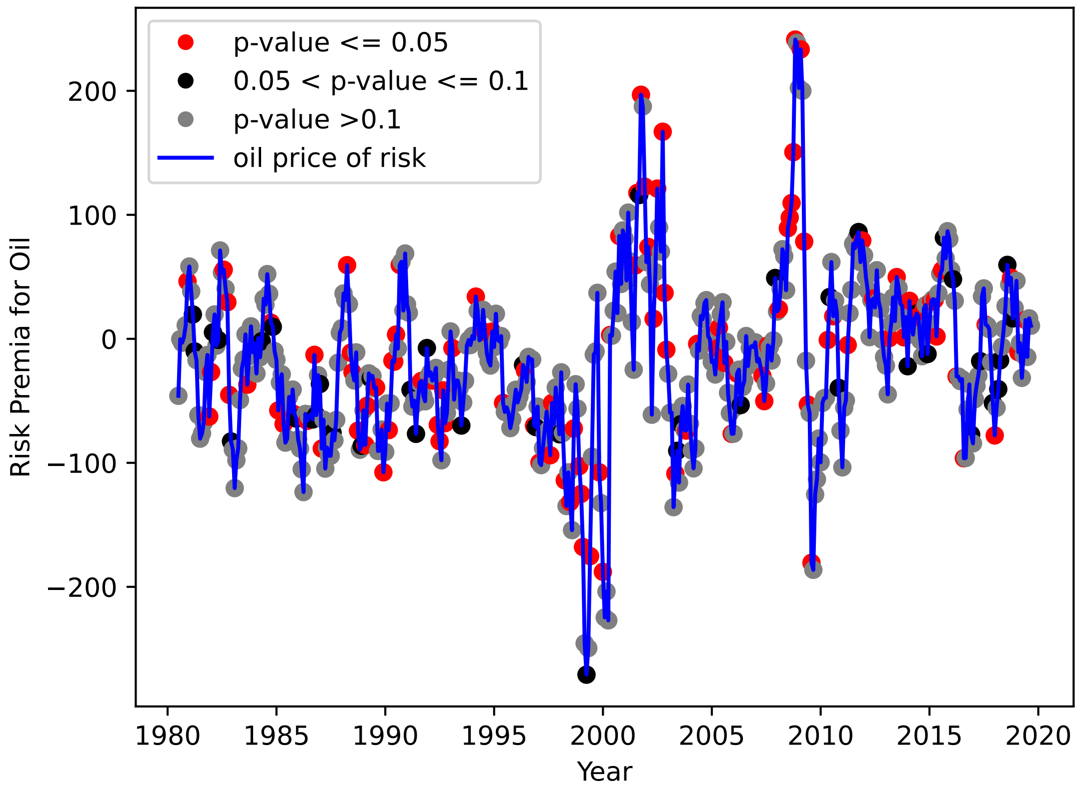


Figure 6: In the figure provided, the black line represents the risk premia of oil between the years 1980 to 2019. This risk premium is calculated using the second stage regression method proposed by Fama and MacBeth [1973] on different attention groups (not on the full sample), considering the investors' attention to this risk. The dots on the figure are associated with the p-values of the oil's price of risk. The size of the dots represent how much it is significant or not. The bigger the dots, the more significant the risk premia is. Each dot's color specifies the attention group on which the lambda is calculated.

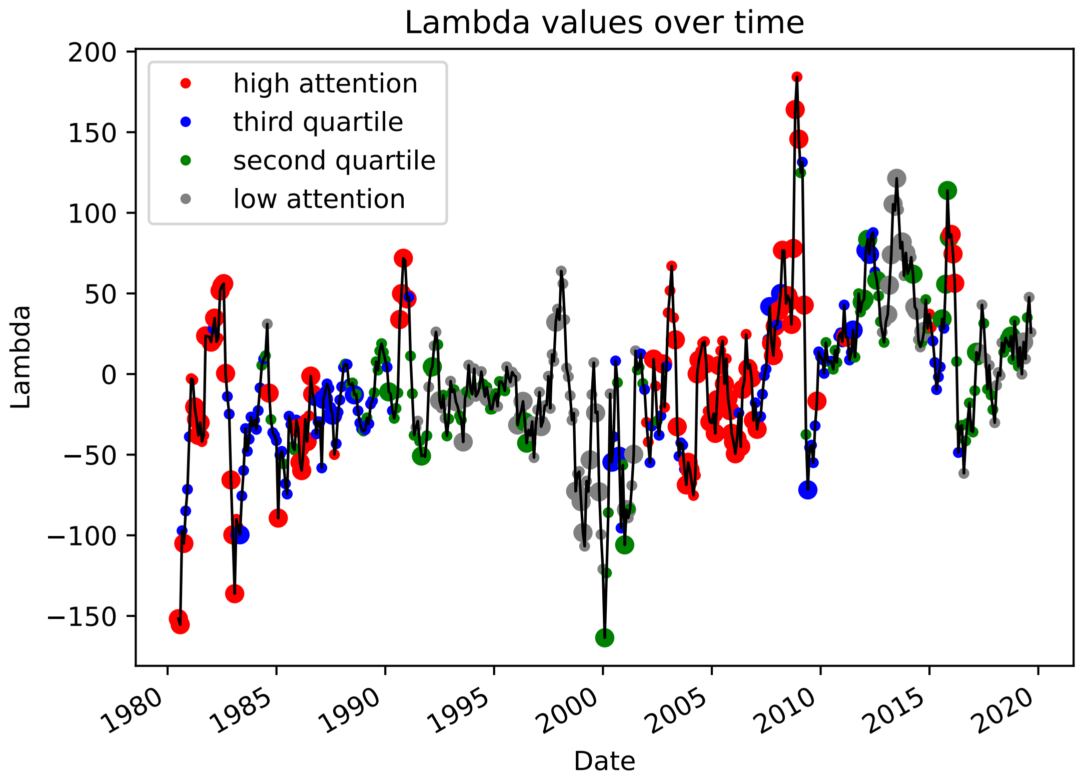


Figure 7: Box plots showing the relationship between attention measures, lambdas (risk premiums), and absolute lambdas for the oil macro variable. The x-axis represents the quartiles of either lambdas or attention measures, depending on the specific box plot, while the y-axis represents the corresponding variable (attention measures, lambdas, or absolute lambdas). The green triangles indicate the mean values of the distributions, providing additional information about the central tendencies of the data. The figure offers insights into how attention measures and risk premiums interact and influence each other for oil variables.

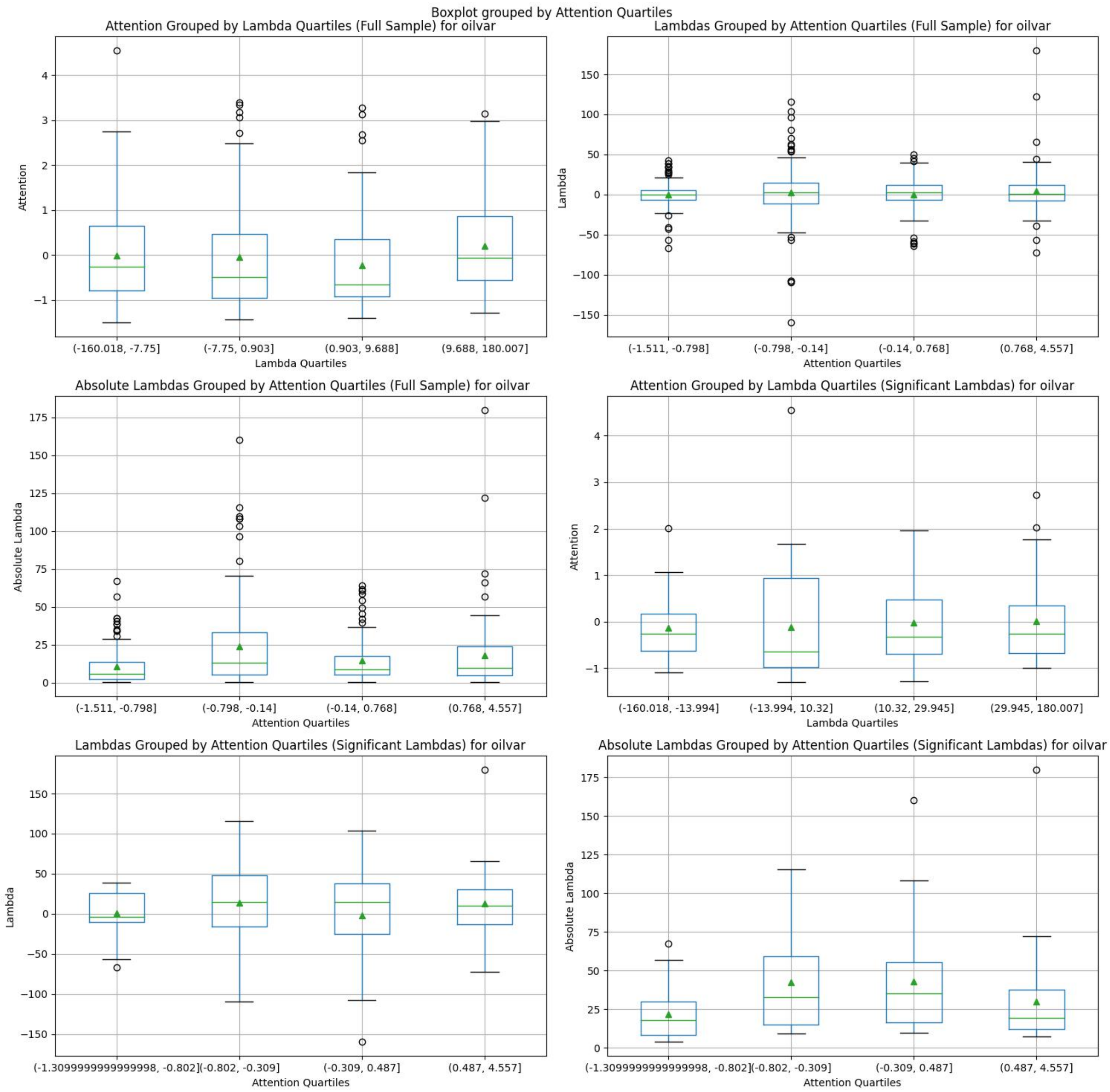


Figure 8: Box plots showing the relationship between attention measures, lambdas (risk premiums), and absolute lambdas for change in expected inflation (DEI) macro variable. The x-axis represents the quartiles of either lambdas or attention measures, depending on the specific box plot, while the y-axis represents the corresponding variable (attention measures, lambdas, or absolute lambdas). The green triangles indicate the mean values of the distributions, providing additional information about the central tendencies of the data. The figure offers insights into how attention measures and risk premiums interact and influence each other for DEI variables.

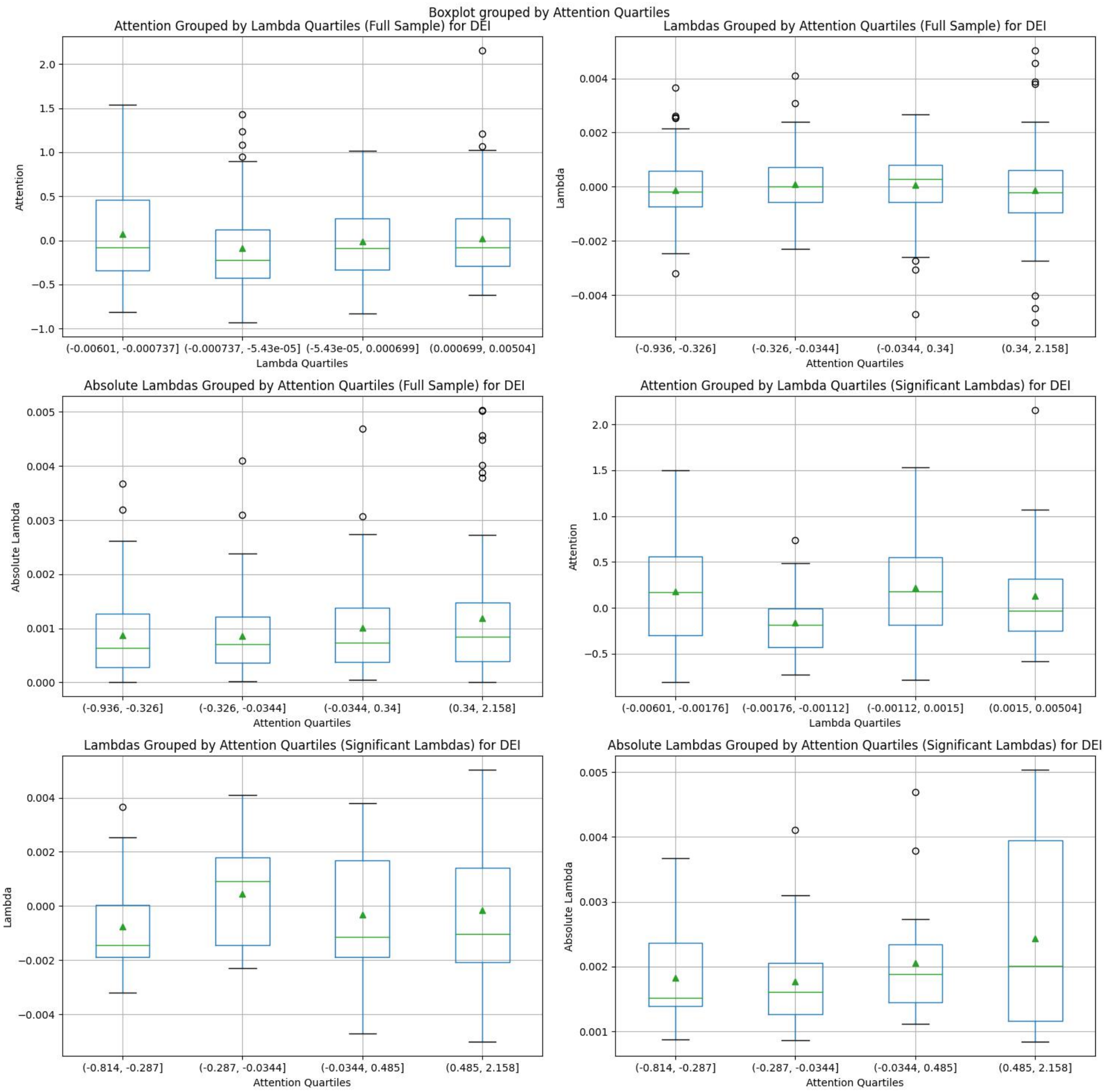
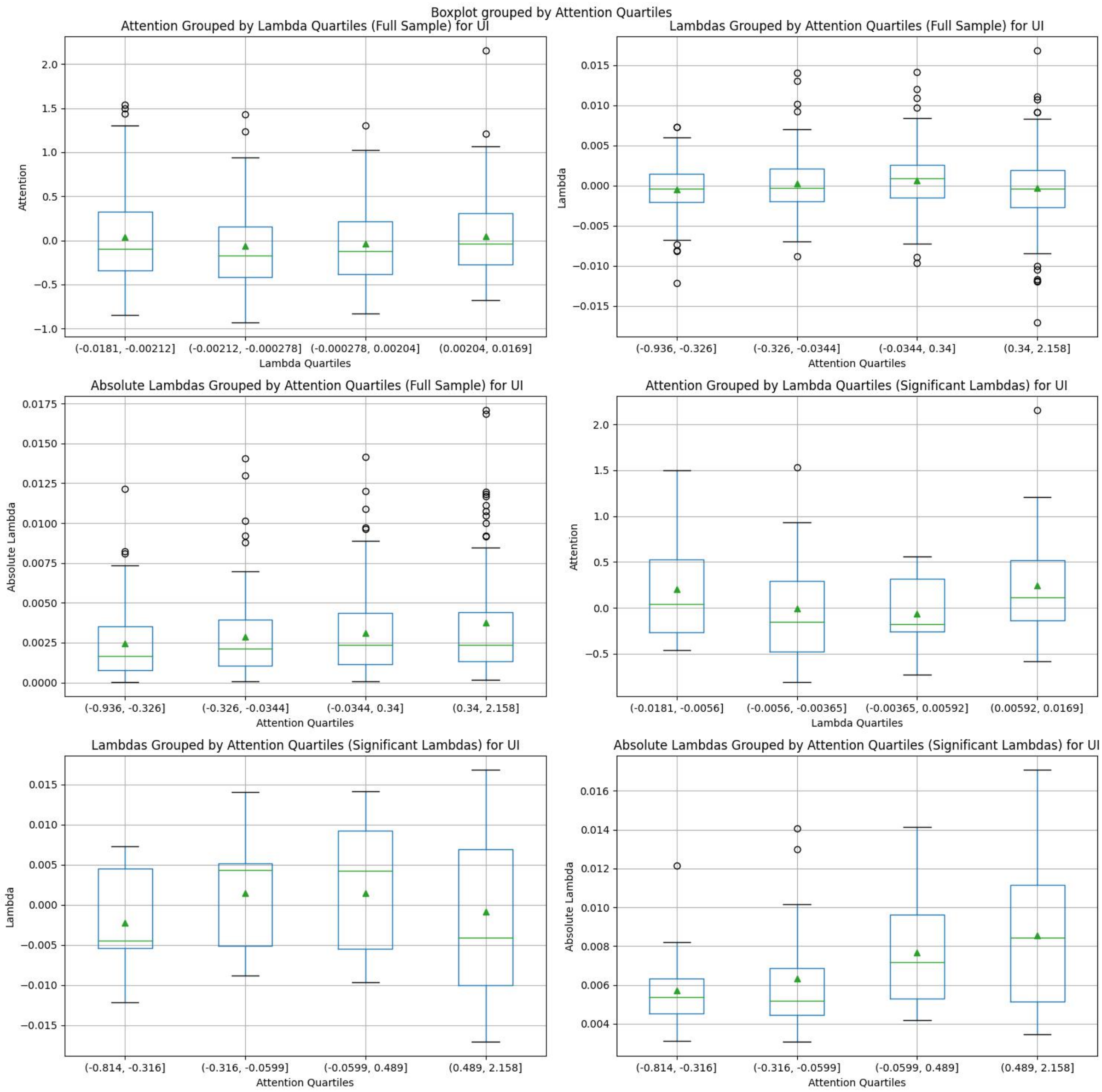


Figure 9: Box plots showing the relationship between attention measures, lambdas (risk premiums), and absolute lambdas for unexpected inflation (UI) macro variable. The x-axis represents the quartiles of either lambdas or attention measures, depending on the specific box plot, while the y-axis represents the corresponding variable (attention measures, lambdas, or absolute lambdas). The green triangles indicate the mean values of the distributions, providing additional information about the central tendencies of the data. The figure offers insights into how attention measures and risk premiums interact and influence each other for UI variables.



5 Conclusion

This paper sought to apply the Arbitrage Pricing Theory (APT) to probe the complexities of determining risk premia within financial markets and to shed further light on the enigmatic relationship between economic activities and stock returns. It also aspired to understand the impact of investor attention to macroeconomic variables on the associated risk premia.

Our study confirms that the application of macroeconomic attention indices, as developed by Fisher et al. [2022], can significantly assist in comprehending the fluctuations in risk premia, especially during periods of high investor attention. However, intriguingly, the research yielded results aligned with previous literature in that risk premia often proved statistically insignificant. These findings, therefore, further enhance the existent financial puzzle.

Furthermore, the study leveraged the same macroeconomic variables as in Chen et al. [1986], including industrial production, unexpected inflation, change in expected inflation, term premium, risk premium, and oil. The research also employed Fisher et al. [2022]'s attention data for inflation and oil.

Through various experiments and analyses, our study unveiled intricate relationships between attention and risk premia, yielding insights that, though not statistically significant due to potential outliers, still contribute valuable information to the ongoing discourse. Still, my results also point to the role of attention and that those factors "might" be priced when attention is high. Unconditional attention and macroeconomic factors failed to account for stock returns in line with prior literature. Even when conditioning these factors on attention, most proved statistically insignificant, adding to the mystery surrounding the impact of economic activities on stock returns.

In conclusion, while this thesis validates the effectiveness of APT in scrutinizing risk premia and the impact of attention to macroeconomic risks on these premia, it also underscores a perplexing anomaly within financial markets. Our findings contribute to a deeper understanding of the APT and its application to contemporary financial practices and indicate the need for continued investigation into the unpredictable dynamics of financial markets, the function of risk premia, and the elusive relationship between economic activities and stock returns.

The paper, therefore, opens doors for future exploration. Not only does it challenge assumptions and methodologies underlying endogenous attention theories, but it also prompts questions about the missing control variables in current financial models. The research is a call to action for further investigation, not just in understanding the interplay between attention and risk premia but also in seeking the missing pieces of the puzzle.

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Appendices

A Additional Tables

Table 5: The table presents a comprehensive analysis of various industry portfolios, examining the average factor loadings of six macroeconomic variables on the full sample and the proportion of factor loadings that exhibit statistical significance (defined as being less than 0.05). The significance level indicates the strength of the relationship between the variables and the portfolios. A significance fraction of 0 shows that no factor loadings within a specific portfolio are statistically significant. Conversely, a significance fraction of 0.16 implies that one of the six factor loadings associated with the portfolio demonstrates statistical significance. For instance, in the case of the clothes industry portfolio (Clths), three of the factor loadings are deemed statistically significant. These factor loadings were derived from the initial stage regression analysis conducted on the entire sample without considering the investor's attention.

Portfolios	**Average of Factor Loadings**	**Fraction of Significance**
Agric	101.58	0.00
Food	22.89	0.00
Soda	37.92	0.16
Beer	2.07	0.16
Smoke	21.49	0.16
Toys	92.24	0.00
Fun	158.60	0.16
Books	110.10	0.33
Hshld	34.66	0.33
Clths	84.04	0.5
Hlth	122.45	0.33
MedEq	42.87	0.16
Drugs	4.31	0.16

Portfolios	Average of Factor Loadings	Fraction of Significance
Chems	82.90	0.00
Rubb	119.32	0.33
Txtls	85.93	0.16
BldMt	67.91	0.16
Cnstr	64.02	0.16
Steel	85.05	0.00
FabPr	139.43	0.16
Mach	124.86	0.16
ElcEq	62.91	0.00
Autos	79.06	0.16
Aero	59.76	0.33
Ships	91.63	0.00
Guns	32.13	0.16
Gold	115.28	0.16
Mines	147.40	0.00
Coal	166.49	0.00
Oil	130.46	0.16
Util	24.91	0.00
Telcm	48.99	0.00
PerSV	32.68	0.16
BusSV	82.91	0.5
HardW	44.20	0.00
Softw	123.37	0.00
Chips	75.27	0.00
LabEq	141.99	0.16
Paper	45.39	0.00

Portfolios	**Average of Factor Loadings**	**Fraction of Significance**
Boxes	68.57	0.00
Trans	81.39	0.33
Whlsl	105.78	0.16
Rtail	64.42	0.16
Meals	12.21	0.33
Insur	2.58	0.00
RlEst	75.18	0.00
Fin	85.94	0.00
Other	54.82	0.00

Table 6: The table contains the risk premium estimation for oil price and its p-value both on high and low attention groups. The lambdas and p-values are conducted by applying second stage regression of Fama-MacBeth on the subset of sample (not the whole sample), on the dates when attention to oil is "high" or "low" according to MAI.

High Attention Group			**Low Attention Group**		
Date	**Oil Price of Risk**	**P-value**	**Date**	**Oil Price of Risk**	**P-value**
1980-06-30	-151.75	0	1991-05-31	-36.63	0.473
1980-07-31	-159.1	0.002	1991-06-30	-80.35	0.088
1980-09-30	-128.68	0	1991-12-31	101.12	0.198
1981-01-31	56.94	0.053	1992-03-31	37.74	0.137
1981-02-28	14.61	0.52	1992-04-30	5.06	0.92
1981-03-31	-229.07	0	1992-06-30	-107.78	0.029
1981-04-30	-49.68	0.035	1992-07-31	29.18	0.501
1981-05-31	-65.09	0.008	1992-09-30	-48.07	0.252
1981-06-30	91.4	0.002	1992-12-31	32.62	0.398
1981-07-31	-13.4	0.458	1993-03-31	-92.75	0.005
1981-08-31	37.52	0.216	1993-04-30	-78.89	0.191
1981-09-30	141.38	0	1993-07-31	-92.26	0.028
1981-10-31	-51.53	0.216	1993-08-31	134.57	0.011
1981-11-30	-66.76	0.015	1993-10-31	18.92	0.733
1981-12-31	71.65	0	1993-11-30	-63.58	0.089
1982-02-28	77.33	0	1994-01-31	2.97	0.947
1982-03-31	53.25	0.059	1994-02-28	31.67	0.406
1982-04-30	-38.31	0.193	1994-03-31	-58.23	0.226
1982-05-31	109.62	0	1994-04-30	41.44	0.268
1982-06-30	89.81	0.001	1994-05-31	-4.62	0.902
1982-07-31	44.73	0.049	1994-07-31	-43.88	0.196
1982-08-31	-256.68	0	1994-09-30	-96.38	0.003

High Attention Group			Low Attention Group		
Date	**Oil Price of Risk**	**P-value**	**Date**	**Oil Price of Risk**	**P-value**
1982-11-30	-135.59	0	1995-02-28	19	0.61
1982-12-31	-114.51	0	1995-07-31	62.38	0.15
1983-01-31	-174.14	0	1995-08-31	-22.01	0.493
1983-02-28	20.24	0.506	1995-09-30	-20.45	0.671
1983-03-31	-61.96	0.051	1995-10-31	34.77	0.366
1984-08-31	-251.2	0	1995-11-30	-26.56	0.557
1985-01-31	-222.84	0	1995-12-31	-38.04	0.329
1985-12-31	-72.59	0.002	1996-01-31	-117.35	0.005
1986-01-31	-60.42	0.01	1996-02-29	10.31	0.785
1986-02-28	-78.05	0.006	1996-03-31	-0.52	0.989
1986-03-31	-24.2	0.334	1996-04-30	70.52	0.035
1986-04-30	42.06	0.148	1996-07-31	-68.39	0.111
1986-05-31	-57.96	0.027	1996-08-31	-10.49	0.809
1986-06-30	23.25	0.363	1996-09-30	51.81	0.347
1986-07-31	87.31	0.004	1996-10-31	-63.77	0.081
1986-08-31	-145.4	0	1996-11-30	20.22	0.674
1987-08-31	-36.58	0.251	1996-12-31	-62.3	0.131
1990-08-31	171.5	0	1997-01-31	-2.81	0.956
1990-09-30	96.71	0.004	1997-02-28	-138.73	0.008
1990-10-31	114.58	0.005	1997-03-31	71.4	0.083
1990-11-30	-65.93	0.064	1997-04-30	-5.6	0.922
1990-12-31	-103.75	0	1997-05-31	22.62	0.603
2001-12-31	-2.86	0.917	1997-06-30	44.99	0.295
2002-01-31	-14.86	0.667	1997-07-31	-122.46	0.091
2002-04-30	89.4	0.044	1997-08-31	62.01	0.164

High Attention Group			Low Attention Group		
Date	**Oil Price of Risk**	**P-value**	**Date**	**Oil Price of Risk**	**P-value**
2002-05-31	-20.38	0.399	1997-09-30	45.97	0.396
2002-09-30	229.92	0	1997-10-31	139.84	0.012
2002-10-31	-72.28	0.187	1997-11-30	71.2	0.25
2002-12-31	66.57	0.094	1997-12-31	5.3	0.921
2003-01-31	14.54	0.601	1998-01-31	58.86	0.239
2003-02-28	30.93	0.268	1998-02-28	15.3	0.794
2003-03-31	37.71	0.251	1998-03-31	-88.34	0.086
2003-04-30	-154.23	0	1998-04-30	-39.67	0.394
2003-05-31	-191.63	0	1998-05-31	38.77	0.352
2003-10-31	-212.72	0	1998-06-30	-65.08	0.144
2003-11-30	-107.38	0	1998-07-31	-32.47	0.585
2003-12-31	-71.69	0.02	1998-08-31	41.43	0.611
2004-01-31	16.17	0.56	1998-09-30	-379.06	0
2004-02-29	-23.88	0.368	1998-10-31	25.05	0.813
2004-03-31	22.83	0.269	1998-11-30	47.45	0.447
2004-04-30	164.64	0	1998-12-31	-177.17	0.026
2004-05-31	-55.57	0.019	1999-01-31	-147.91	0.019
2004-06-30	-39.21	0.084	1999-02-28	-8.85	0.889
2004-07-31	46.29	0.164	1999-03-31	-136.87	0.126
2004-08-31	-18.16	0.437	1999-04-30	-13.96	0.875
2004-09-30	-59.45	0.006	1999-05-31	165.28	0.002
2004-10-31	-11.74	0.639	1999-06-30	65.93	0.348
2004-11-30	-96.23	0.002	1999-07-31	-29.1	0.527
2004-12-31	-42.64	0.053	1999-08-31	-195.62	0.001
2005-01-31	81.03	0	1999-09-30	-132.88	0.077

High Attention Group			Low Attention Group		
Date	**Oil Price of Risk**	**P-value**	**Date**	**Oil Price of Risk**	**P-value**
2005-02-28	-91.68	0	1999-10-31	-311.77	0.004
2005-03-31	66.15	0.001	1999-11-30	6.59	0.923
2005-04-30	115.42	0	1999-12-31	-63.17	0.515
2005-05-31	-41.93	0.086	2000-04-30	130.4	0.089
2005-06-30	-6.01	0.79	2001-01-31	128.56	0.043
2005-07-31	-78.97	0.009	2001-02-28	-65.23	0.45
2005-08-31	2.26	0.889	2001-04-30	-49.65	0.406
2005-09-30	-81.21	0.002	2001-05-31	102.67	0.03
2005-10-31	69.57	0.002	2001-06-30	119.4	0.068
2005-11-30	-126.06	0	2012-10-31	-36.59	0.399
2005-12-31	-38.81	0.022	2012-12-31	18.04	0.56
2006-01-31	-122.43	0	2013-01-31	153.96	0.009
2006-02-28	58.44	0.003	2013-02-28	129.96	0
2006-04-30	-55.87	0.02	2013-03-31	120.66	0
2006-05-31	87.46	0	2013-04-30	151.67	0.0016
2006-06-30	-8.04	0.603	2013-05-31	34.17	0.43
2006-07-31	51.32	0.095	2013-06-30	137.83	0.004
2006-08-31	-68.88	0.009	2013-07-31	37.12	0.42
2006-09-30	29.46	0.149	2013-08-31	-13.94	0.715
2006-10-31	-105.94	0	2013-09-30	144.63	0.001
2006-11-30	-70.35	0	2013-10-31	26.36	0.53
2007-01-31	-47.29	0.034	2013-11-30	119.02	0
2007-02-28	-30.47	0.142	2013-12-31	60.24	0.121
2007-09-30	-96.96	0.004	2014-02-28	29.14	0.42
2007-10-31	-69.45	0.043	2014-04-30	-95.35	0.006

High Attention Group			Low Attention Group		
Date	**Oil Price of Risk**	**P-value**	**Date**	**Oil Price of Risk**	**P-value**
2007-11-30	107.72	0	2014-05-31	106.66	0.001
2008-01-31	115.06	0.003	2014-06-30	-49.41	0.149
2008-03-31	63.71	0.009	2014-07-31	28.48	0.543
2008-04-30	-71.26	0.104	2014-09-30	120.34	0.008
2008-05-31	-89.24	0.003	2016-07-31	-93.44	0.057
2008-06-30	117.67	0	2017-04-30	47.54	0.193
2008-07-31	95.7	0.004	2017-05-31	30.41	0.4
2008-08-31	68.19	0.007	2017-07-31	-69.59	0.126
2008-09-30	346.27	0	2017-09-30	39.12	0.326
2008-10-31	445.71	0	2018-01-31	69.66	0.14
2008-11-30	32.08	0.478	2018-02-28	48.78	0.312
2008-12-31	-113.78	0.011	2018-03-31	27.64	0.412
2009-03-31	-185.78	0	2018-04-30	59.44	0.246
2009-10-31	56.27	0.047	2019-02-28	103.17	0.018
2011-02-28	-57.4	0.019	2019-03-31	-33.63	0.373
2011-03-31	18.93	0.441	2019-04-30	91.95	0.035
2014-12-31	3.85	0.849	2019-05-31	20.73	0.744
2015-01-31	-20.4	0.571	2019-07-31	32.34	0.49
2015-12-31	53.3	0.024	2019-08-31	-27.74	0.652

Table 7: Mean of attention, lambda, and absolute lambda in different scenarios for UI

Full Sample		
Lambda Quartiles	**Mean of Attention**	
(-0.0181, -0.00212]	0.034 68	
(-0.00212, -0.000278]	−0.058 91	
(-0.000278, 0.00204]	−0.038 47	
(0.00204, 0.0169]	0.043 43	
Attention Quartiles	**Mean of Lambda**	**Mean of Absolute Lambda**
(-0.936, -0.326]	−0.000 45	0.002 47
(-0.326, -0.0344]	0.000 21	0.002 88
(-0.0344, 0.34]	0.000 62	0.003 10
(0.34, 2.158]	−0.000 26	0.003 74
Significant Only		
Lambda Quartiles	**Mean of Attention**	
(-0.0181, -0.0056]	0.200 11	
(-0.0056, -0.00365]	−0.010 98	
(-0.00365, 0.00592]	−0.064 08	
(0.00592, 0.0169]	0.246 86	
Attention Quartiles	**Mean of Lambda**	**Mean of Absolute Lambda**
(-0.814, -0.316]	−0.002 24	0.005 71
(-0.316, -0.0599]	0.001 46	0.006 33
(-0.0599, 0.489]	0.001 48	0.007 65
(0.489, 2.158]	−0.000 84	0.008 55

Table 8: Mean of attention, lambda, and absolute lambda in different scenarios for DEI

Full Sample		
Lambda Quartiles	Mean of Attention	
(-0.00601, -0.000737]	0.068 719	
(-0.000737, -5.43e-05]	−0.091 683	
(-5.43e-05, 0.000699]	−0.014 575	
(0.000699, 0.00504]	0.018 500	
Attention Quartiles	Mean of Lambda	Mean of Absolute Lambda
(-0.936, -0.326]	−0.000 118	0.000 866
(-0.326, -0.0344]	0.000 098	0.000 861
(-0.0344, 0.34]	0.000 056	0.001 004
(0.34, 2.158]	−0.000 129	0.001 186
Significant Only		
Lambda Quartiles	Mean of Attention	
(-0.00601, -0.00176]	0.180 857	
(-0.00176, -0.00112]	−0.160 096	
(-0.00112, 0.0015]	0.217 406	
(0.0015, 0.00504]	0.128 222	
Attention Quartiles	Mean of Lambda	Mean of Absolute Lambda
(-0.814, -0.287]	−0.000 758	0.001 830
(-0.287, -0.0344]	0.000 446	0.001 767
(-0.0344, 0.485]	−0.000 321	0.002 056
(0.485, 2.158]	−0.000 165	0.002 434

Table 9: Mean of attention, lambda, and absolute lambda in different scenarios for oil

Full Sample		
Lambda Quartiles	Mean of Attention	
(-160.018, -7.75]	−0.006 737	
(-7.75, 0.903]	−0.043 176	
(0.903, 9.688]	−0.229 204	
(9.688, 180.007]	0.206 436	
Attention Quartiles	Mean of Lambda	Mean of Absolute Lambda
(-1.511, -0.798]	0.002 417	10.572 399
(-0.798, -0.14]	2.166 374	23.916 216
(-0.14, 0.768]	0.109 626	14.700 104
(0.768, 4.557]	4.874 323	17.895 387
Significant Only		
Lambda Quartiles	Mean of Attention	
(-160.018, -13.994]	−0.142 319	
(-13.994, 10.32]	−0.123 263	
(10.32, 29.945]	−0.028 247	
(29.945, 180.007]	0.006 255	
Attention Quartiles	Mean of Lambda	Mean of Absolute Lambda
(-1.31, -0.802]	0.737 172	21.710 012
(-0.802, -0.309]	13.486 900	42.518 942
(-0.309, 0.487]	−1.961 111	43.034 998
(0.487, 4.557]	13.172 137	30.075 786

B Additional Figures

Figure 10: Estimated Risk Premiums (Lambda) and Associated P-values (mean and standard deviation). For the factor "oil" with a "60-month rolling window" using a dataset comprising 49 industry portfolios and macroeconomic variables. The figures present the results of a two-stage cross-sectional regression analysis performed on financial market data. The lambda values represent the estimated risk premiums associated with the factor oil, derived from a 60-month rolling window. The corresponding p-values measure the statistical significance of the oil factor's influence over this period.

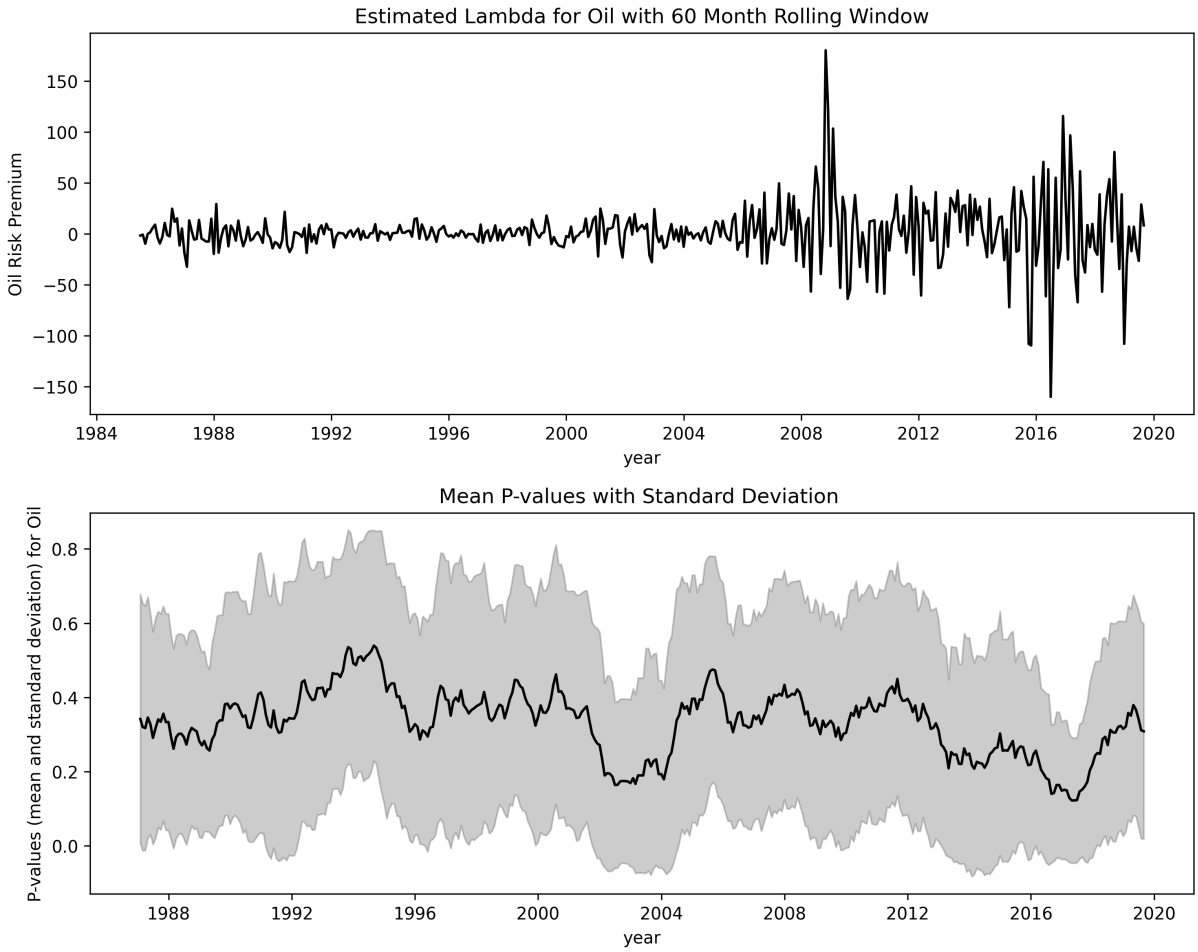

Figure 11: Estimated Risk Premiums (Lambda) and Associated P-values (mean and standard deviation). For the factor "unexpected inflation" with a "60-month rolling window" using a dataset comprising 49 industry portfolios and macroeconomic variables. The figures present the results of a two-stage cross-sectional regression analysis performed on financial market data. The lambda values represent the estimated risk premiums associated with the factor unexpected inflation, derived from a 60-month rolling window. The corresponding p-values measure the statistical significance of the unexpected inflation factor's influence over this period.

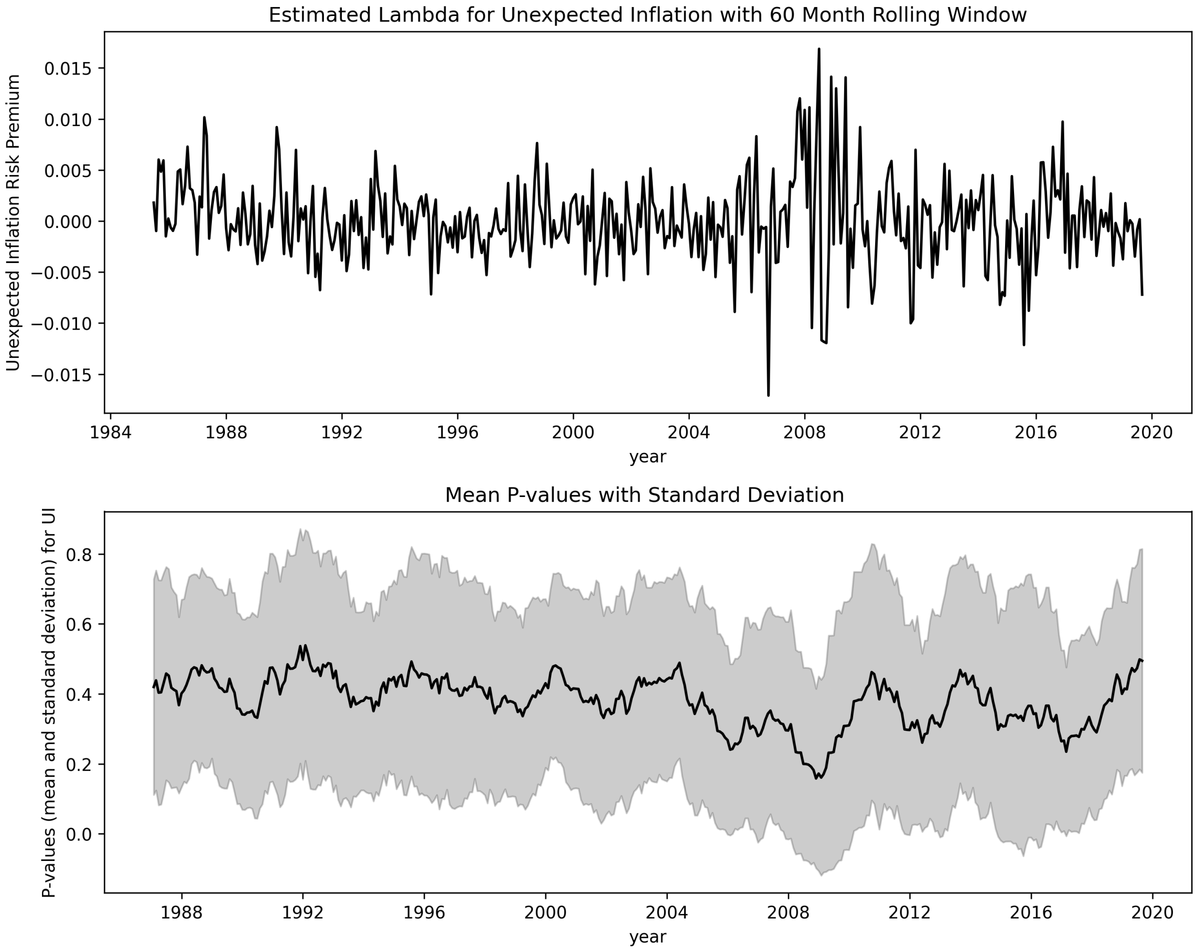

Figure 12: Estimated Risk Premiums (Lambda) and Associated P-values (mean and standard deviation). For the factor "Change in Expected Inflation" with a "60-month rolling window" using a dataset comprising 49 industry portfolios and macroeconomic variables. The figures present the results of a two-stage cross-sectional regression analysis performed on financial market data. The lambda values represent the estimated risk premiums associated with the factor change in expected inflation, derived from a 60-month rolling window. The corresponding p-values measure the statistical significance of the change in expected inflation factor's influence over this period.