Essays on Economic Uncertainty and Financial Markets

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by

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Declaration

I, Semih Kerestecioglu, declare that this thesis entitled, "Essays on Economic Uncertainty and Financial Markets", is completed on my own and has not been previously submitted.

I confirm that:

- I have read and understood the University's PGR Policy on Plagiarism and Dishonest Use of Data.
- I have acted honestly, ethically and professionally in conduct leading to assessment for the programme of study.
- I have not copied material from another source nor committed plagiarism nor fabricated, falsified or embellished data when completing the attached material.
- I have not copied material from another source, nor colluded with any other student in the preparation and production of this material.
- If an allegation of suspected academic malpractice is made, I give permission to the University to use source-matching software to ensure that the submitted material is all my own work.

Parts of this thesis have been presented in various ways. A working paper which is the product of Chapter 1 and 2, has been presented in an internal seminar at the University of Liverpool and shared via SSRN to improve for publication. Moreover, a paper based on Chapter 2 was presented at 12th International Accounting and Finance Doctoral Symposium, Politecnico di Milano, Milan, Italy, and The NWSSDTP Job Market and Employability Skills Workshop for Accounting and Finance, University of Liverpool in 2019.

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Abstract

This thesis examines the role of economic uncertainty in investors' decision process and analysts' forecast bias. The first empirical chapter investigates the effect of firm-level exposure to economic uncertainty (EUE) on cross-sectional returns through differentiating the mispricing from ambiguity-premium effects. Conditional on a common mispricing index, I find that EUE induces disagreement among investors, which amplifies mispricing. The highest EUE quintile produces a significantly higher mispricing alpha than the unconditional mispricing effect. By contrast, the high-minus-low EUE portfolio in the non-mispricing group generates a significant positive premium in the sense of the ambiguity-return trade-off. The EUE-induced mispricing effect is different from existing limits of arbitrage explanations, such as idiosyncratic risk. The ambiguity premium is a new source of the risk premium that is robust to the latest risk models.

The second empirical chapter studies the role of market-wide sentiment in relation to the mispricing and the ambiguity effects documented in the first study. Considering the presence of the market-wide sentiment combined with short-sale constraints, I find larger mispricing spread in stocks with high EUE following high-sentiment periods. This mispricing effect is stronger following the periods with both increasing economic uncertainty and high sentiment. It suggests that economic uncertainty indeed leaves more room for the sentiment effect in the market. The ambiguity premium in the non-mispricing group, however, is significant only following low-sentiment periods during which the mispricing effect vanishes. This is consistent with the previous finding that the market pricing is more rational when investor sentiment is relatively low.

The final empirical chapter examines whether there is an effect of EUE on analysts' optimism. Existing literature shows that equity analysts have an optimistic bias. I find that analysts are even more optimistic for stocks with higher EUE. This is especially true following periods with high economic uncertainty. This study confirms that such an increase in optimism is for incentives given that high uncertainty reduces their reputation costs by lowering the chance of them being caught for such bias. The effect is more pronounced when firm-specific information quality (measured by earnings quality and information availability at the market level) is lower, and investors are less sophisticated (measured by the proportion of institutional ownership). Finally, analysts issuing optimistic view for stocks with higher exposure to economic uncertainty impede the price efficiency in the market. The EUE-induced mispricing is significantly apparent among stocks with high optimism.

This thesis contributes to the literature in several ways. First, economic uncertainty has two seemingly contradicting mechanisms in asset pricing, including the ambiguity premium and the mispricing effects. This thesis reaches a clear conclusion that both mechanisms are at work through disentangling the two effects, which has not been studied by the existing literature where these two mechanisms are studied in isolation. Second, I identify EUE as a common mispricing component across anomalies, which is different from but complements investor sentiment and arbitrage risk, contributing to existing studies by suggesting that mispricing has common components across stocks. Finally, analyst optimism for incentives exacerbates the mispricing effect of economic uncertainty. This finding complements studies which suggest that analyst bias impedes the price efficiency in the market.

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Chapter 1

1 Introduction

Economic uncertainty is a relevant state variable for investment decisions. It measures the extent that the prospect of the economy is unpredictable using the available information and models (Jurado, Ludvigson and Ng, 2015). In a period with high economic uncertainty, economic agents are more likely to be conservative in their investment and reduce their future consumption. Bloom (2009) shows that time-varying shocks in macro uncertainty are linked to real economic activity and asset prices. Moreover, it affects the quality of information which matters to security analysts in their forecasts as their role is to analyse public and non-public information at various levels (Healy and Palepu, 2003; Amiram et al., 2017). In this regard, the goal of this thesis is to examine the effect of economic uncertainty on investors and security analysts in their decision processes with three empirical chapters.

1.1 Research Background and Motivation

There is a distinct difference between uncertainty and risk. In the seminal study of Knight (1921), this difference is concentrated on the probability distribution of an event. If the future is unknown with a known probability distribution of all possible outcomes in that event, this refers to risk. However, if the probability distribution is unknown, it refers to uncertainty. Specifically, Jurado, Ludvigson and Ng (2015) define economic uncertainty as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents. Intuitively, it is about whether the economy has become more or less predictable (Jurado, Ludvigson and Ng, 2015). In asset pricing literature, economic uncertainty affects asset prices in two channels: beliefs and preferences.

First, the divergence of opinions among investors is an important source of mispricing in stock markets (Hong and Stein, 2007). This is because stocks are more likely to reflect the valuation made by investors with an optimistic view, whereas pessimists are less likely to be involved in the valuation due to short-sale constraints (Miller, 1977). Disagreement about asset prices and the level of divergence in opinions become larger with uncertainty as it leaves more room for investors to follow their own subjective estimations and to ignore objective valuations (Hirshleifer, 2001). For instance, Hong and Sraer (2016) link the market-wide uncertainty and disagreement on firms' earnings to the market-beta anomaly. They show that stocks with a high market beta exhibit larger disagreement, resulting in overpricing and lower expected return. Li (2016) extends their argument considering disagreement on macro-factors and finds that stocks with larger exposure to macro-disagreement generate an anomalously lower expected return in a high economic uncertainty period. In this regard, economic uncertainty can be a factor which exacerbates the disagreement between optimists and pessimists. Therefore, stocks exposed to a high level of uncertainty in the economy have a larger dispersion of opinions, resulting in overpricing and lower expected return. I refer to this effect as the mispricing effect of economic uncertainty, which amplifies the tension between optimists and pessimists in the belief channel.

In other literature, economic uncertainty is priced in the sense of the ambiguity-return trade-off. Bali, Brown and Tang (2017, p. 473) highlight that *"studies that link uncertainty to second-order risk aversion indicate that investors care not only about the mean and variance of asset returns, but also on the uncertainty of events over which the future return distribution occurs."* In other words, stocks exposed to economic uncertainty can affect investors' preference. In this regard, Anderson, Ghysels, and Juergens (2009) show that macro uncertainty carries a positive premium and provide significant evidence in their empirical analyses using dispersion in the economic forecast as a measure of economic uncertainty. This line of the literature suggests that investors would demand extra compensation in the form of higher expected return to hold stocks with higher exposure to economic uncertainty. I refer to this effect as the ambiguity-premium effect in the preference channel.

These two lines of literature conclude that economic uncertainty has two contradicting effects on cross-sectional returns. It exacerbates heterogenous beliefs among investors and predicts a negative relationship between firms' economic uncertainty exposure and expected returns. However, it also affects the preference of investors facing uncertainty in the sense of the ambiguity-return trade-off. As these two effects can be observed in the market at any time, the first challenge of this thesis is to disentangle them.

In traditional asset pricing theory, the value of securities is determined by rational investors and irrational pricing attributed to investor sentiment is ignored. However, relevant studies have shown the role of sentiment in financial markets, leading to significant mispricing in assets. For instance, Stambaugh, Yu and Yuan (2012) suggest that disagreement between optimists and pessimists is more pronounced due to the presence of market-wide sentiment combined with short-sale constraints. During high-sentiment periods, investors' beliefs are more likely to play a significant role in asset prices. During low-sentiment periods, by contrast, the optimistic valuation tends to vanish, and asset prices are more likely to reflect the view of rational investors (Stambaugh, Yu and Yuan, 2012). Therefore, isolating investors' behaviours in different periods motivates this thesis to provide further understanding into those two opposite effects of economic uncertainty on cross-sectional returns.

Consistent with the psychology literature, people are prone to rely more on their heuristics rather than facts in their judgements under uncertainty (Kahneman and Tversky, 1973). In financial markets, when uncertainty is high, investors are more likely to follow their own subjective estimations and to ignore objective valuations, leading to more irrational behaviours (Hirshleifer, 2001). For instance, Birru and Young (2020) show that the predictability of market-wide sentiment in both aggregate and cross-sectional returns is stronger when the market-level uncertainty, measured by the VIX, is high. They suggest that in periods with higher uncertainty, the effect of sentiment is prone to be more pronounced and rational investors are even more limited to offset the effect of irrational ones due to the less reliable information flow. In this regard, this thesis, furthermore, considers the effect of macroeconomic uncertainty on the market-wide sentiment by examining investors' behaviours towards two effects of EUE on cross-sectional returns.

Several studies have shown analysts' bias in their forecasts (i.e., Stickel, 1990; Chopra, 1998; Lim, 2001). This is mainly due to their incentive concerns, consistent with the rational framework. Brown et al. (2015) show that analysts find direct contact with management useful in producing and improving their earnings forecasts and stock recommendations. This enables them to acquire information about the firm and its industry from the management. Issuing an upward forecast is more likely to help analysts have a better relationship with managers (Lim, 2001). This is because managers are able to increase their compensation with favourable forecasts which lead to higher capital market valuation (Lim, 2001). In addition, given that upward forecasts tend to encourage investors to trade more, analysts are more likely to generate more trading volume for the brokerage firm they work for, resulting in higher trading commissions (Cowen, Groysberg and Healy, 2006). However, their invective concerns in forecasts with upward bias is harmful to their career in the long term. Jackson (2005) supports this conjecture and finds that investors update analyst reputations after detecting optimistic forecasts in the long term and follow analysts with better reputations accordingly. Due to reputation costs, analysts are concerned about losing the opportunity of getting promoted to high-status brokerage houses or securing their jobs in the industry (i.e., Fama, 1980; Lim, 2001). Therefore, analysts are in a trade-off between their reputation and incentive concerns resulted from optimistic forecasts.

In financial markets, security analysts are intermediaries who provide forecasts and recommendations by collecting and analysing factors from firm-, market- and macro-levels (Healy and Palepu, 2003; Amiram et al., 2017). The quality of information at these levels affects their issues. Economic uncertainty is one of those factors affecting information quality at the macro-level as it is related to the prospect of the economy which is unpredictable using the available information and models (Bloom, 2009; Jurado, Ludvigson and Ng, 2015). Considering forecast optimism in the rational framework where analysts are in a trade-off between their reputation and incentive concerns, another motivation of this thesis is to understand whether analysts behave more optimistic for incentives in their issues with less career concern for firms which are more highly exposed to economic uncertainty.

1.2 Measuring Economic Uncertainty

There are various proxies and indices used to measure the macro-level uncertainty in literature. For instance, several studies rely on market volatility, due to its significant relationship between real activity and uncertainty (i.e., Bloom, 2009; Bakeart, Hoerova and Duca, 2013; Bali and Zhou, 2016). However, Jurado, Ludvigson and Ng (2015) argue that financial market volatility may not reflect economic uncertainty accurately, since it may vary over time due to changes in risk-aversion, leverage or sentiment.

Other studies use dispersion in forecasts (i.e., Mankiw and Reis, 2002; D'amico and Orphanides, 2008; Anderson, Ghysels and Juergens, 2009; Li, 2016). During high uncertainty time, dispersion in forecasts are expected to be high, and there is larger disagreement in the surveys on macroeconomic indicators (Bachmann, Elstner and Sims, 2013). However, forecasts may not clearly show expectations about the whole economy and may give subjective responses due to their pecuniary interests and individual biases. Additionally, the dispersion of analyst forecasts might be affected by heterogeneity in the business cycle, even if there is no shift in uncertainty in economic fundamentals (Jurado, Ludvigson and Ng, 2015).

Considering those arguments on different measures at an aggregate level, this study uses the economic uncertainty index introduced by Jurado, Ludvigson and Ng (2015) as the main measurement in this thesis. This index is constructed based on various macroeconomic series, not on any single (or a small number of) economic indicator (Jurado, Ludvigson and Ng, 2015). By using this measure, they show that it can capture uncertainty in different macro variables at the same time, across companies, industries, markets and regions.

Figure 1.1 depicts the economic uncertainty index by Jurado, Ludvigson and Ng (2015). It shows that there are sharp rises in the index during recession periods, defined by NBER with grey shades, when lower investment, consumption and economic growth occur. It is worth noting that during the first half of 2020, the index reaches the highest level after the great recession of 2007-2009, due to COVID-19 which is classified as a pandemic by World Health Organization (WHO) in March 2020.

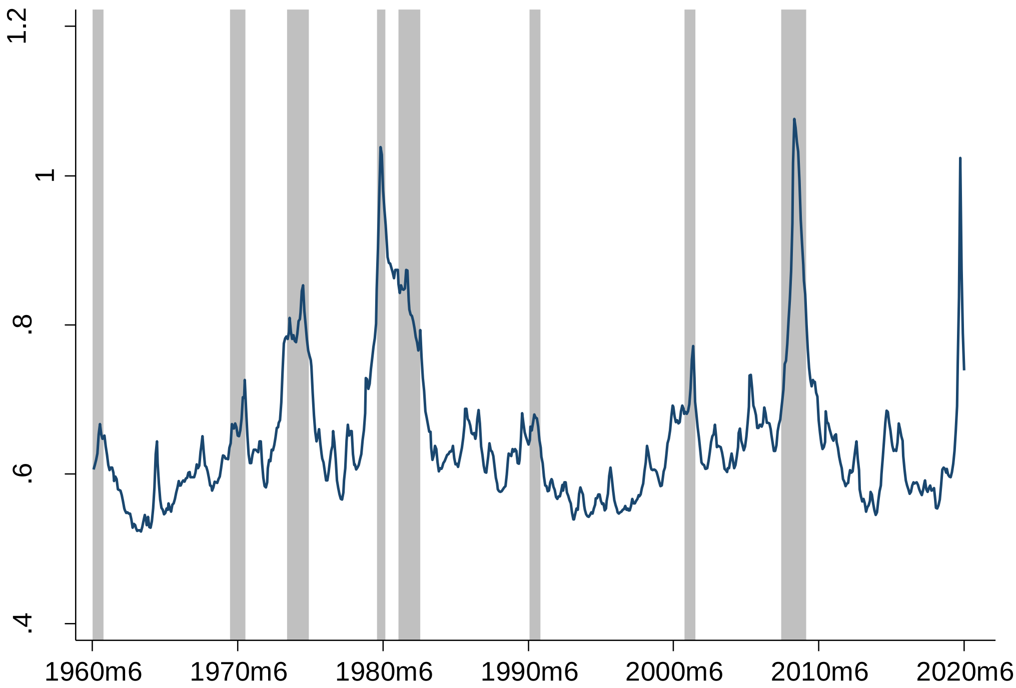

Figure 1.1 Economic Uncertainty Index

This figure illustrates the economic uncertainty index by Jurado, Ludvigson and Ng (2016). NBER recession periods are shaded with grey: 1960-61, 1969-70, 1973-75, 1980, 1981-82, 1990-91, 2001, 2007-2009. The sample period is from June 1960 to June 2020.

There are two distinct advantages of using the economic uncertainty index. First, it removes all forecastable components of the conditional volatility on indicators, consistent with the theoretical definition of uncertainty, rather than risk. Second, it has the advantage of capturing the uncertainty in the whole economy instead of the uncertainty in only a single economic indicator (Jurado, Ludvigson and Ng, 2015).

Along with the economic uncertainty index, I use various indices and proxies as alternative measures in robustness checks of this thesis, such as dispersions in the Survey of Professional Forecasters (D'Amico and Orphanides, 2008; Glas and Hartman, 2016; Li, 2016), variance risk premium index (Bali and Zhou, 2016), the degree of ambiguity in the

U.S. stock market (Brenner and Izhakian, 2018) and the economic policy uncertainty index (Baker, Bloom, and Davis, 2016).

1.3 Summary of the Essays

1.3.1 Economic Uncertainty: Mispricing and Ambiguity Premium

The first empirical chapter (Chapter 2) investigates the effect of economic uncertainty on asset prices following two concepts: the mispricing and the ambiguity-premium effects. Economic uncertainty exacerbates heterogenous beliefs among investors, making optimists more optimistic and pessimists more pessimistic. It predicts a negative relationship between firms' economic uncertainty exposure and expected returns (Hong and Sraer, 2016; Li, 2016). Economic uncertainty also affects the preference of investors facing uncertainty in the sense of the ambiguity-return trade-off, predicting a positive relationship between firms' economic uncertainty exposure and expected returns (Anderson, Ghysels, and Juergens, 2009; Bali and Zhou, 2016; Bali, Brown and Tang, 2017). The main conjecture of Chapter 2 is that both the ambiguity premium and the mispricing mechanisms can be observed at any time. A clear conclusion can only be reached as these two effects can be disentangled.

First, a common mispricing measure (MIS) proposed by Stambaugh, Yu and Yuan (2012; 2015) is adopted to identify cross-sectional variation for overpriced and underpriced stocks. Using various firm-level characteristics, I capture investors' biased beliefs about companies. Importantly, this measure can also help identify stocks which are *least* affected by investors' biased beliefs, neither overpriced nor underpriced. If economic uncertainty exacerbates heterogenous beliefs which are the source of mispricing, stocks exposed to higher economic uncertainty will induce larger disagreement about those firm-level characteristics in the mispricing measure, leading to more apparent mispricing. Simultaneously, the preference of investors facing uncertainty in the sense of the ambiguity-return trade-off is observed in stocks that are least influenced by these mispricing characteristics. In other words, economic uncertainty yields a positive premium in a group of stocks, called "non-mispricing" group. This empirical setting in Chapter 2 offers a practical way to disentangle those two different effects of economic uncertainty on investors' beliefs and preferences using firm-level data in the market.

Chapter 2 has two main hypotheses. First, if EUE-induced disagreement is a common source of mispricing, the mispricing effect, measured by the long-short portfolio sorted by MIS, will be the strongest in the group of stocks with the highest EUE. Second, for stocks experiencing the least influence of mispricing measured by the MIS, called "non-mispricing" group, the ambiguity-premium effect of EUE will be the dominant effect, and therefore a positive relationship between EUE and expected return is expected.

In Chapter 2, this study examines the effect of economic uncertainty on the cross-section of stock returns in the US markets between 1970 and 2019. Empirically, I measure stock's exposure to economic uncertainty (EUE) by estimating the sensitivity of stock returns to log changes of the economic uncertainty index by Jurado, Ludvigson and Ng (2015). Consistent with Hong and Sraer (2016) and Li (2016), I capture the exposure by using the absolute value of the economic uncertainty beta, since disagreement (return volatility) is larger for stocks with a higher absolute level of correlation with economic uncertainty regardless of a positive or negative sign.

Following Stambaugh, Yu and Yuan (2015), the main analysis is based on portfolios independently double-sorted on EUE and MIS. I provide significant evidence to support my predictions. First, the mispricing spread, the difference between underpriced and overpriced portfolios, generates the largest alpha in the highest EUE quintile, with an annualised alpha of 9%. This spread is also larger than the unconditional mispricing spread, with an annualised alpha of 3.96%, confirming that mispricing in stock returns is more pronounced as exposed to greater macro-level uncertainty. Second, high-minus-low EUE portfolio yields a positive premium in the non-mispricing group, with an annualised alpha of 4.2%, implying that economic uncertainty is priced in the sense of the ambiguity-return trade-off in the group of stocks which are least subject to mispricing.

I examine how two channels of the EUE effect are influenced by alternative risk models including Fama-French models, q-factor (Hou, Xue, and Zhang, 2015), q5 (Hou et al., 2020) and the mispricing (Stambaugh and Yuan, 2017) models. In general, the influence of the mispricing effect induced by EUE on the anomalies diminishes when using more elaborated multifactor models but remains significant in most of the models, such as models with Fama-French factors including an aggregate liquidity factor, q-factor and the mispricing models. By contrast, the ambiguity-premium effect of EUE remains strong when other risk factors are controlled. This chapter shows that EU-induced ambiguity premium is different from various risk factors introduced in previous studies. This finding is consistent with the view where investors demand additional compensation for bearing uncertainty (Anderson, Ghysels and Jurgens, 2009).

Finally, this study examines the EUE effect on cross-sectional returns in the context of limits-to-arbitrage. Considering Stambaugh, Yu and Yuan (2015) suggesting that idiosyncratic volatility (IVOL) deters arbitrageurs from correcting mispricing, resulting in high levels of mispricing among stocks with high IVOL, to examine whether IVOL has an impact on EUE-induced mispricing, I extend the main analyses of double-sorting to three dimensions. I find that EUE and IVOL are two different sources of frictions that affect mispricing. Consistent with the limits of arbitrage context, Chapter 2 uncovers EUE as a source of arbitrage friction that is not captured by the IVOL.

1.3.2 Economic Uncertainty, Investor Sentiment and Cross-Sectional Returns

In the second empirical chapter (Chapter 3), this thesis examines the link between market-wide sentiment and investors' attitude to assets with different levels of EUE to explore behavioural insights into those two effects of economic uncertainty on the cross-section of stock returns. Existing studies have shown the role of market-wide sentiment in mispricing. Stambaugh, Yu, and Yuan (2012, p. 290) suggest that *"[D]uring such periods (high investor sentiment), the most optimistic views about many stocks tend to be overly optimistic, and many stocks tend to be overpriced. During low-sentiment periods, the most optimistic views about many stocks tend to be those of the rational investors, and thus mispricing during those periods is less likely."* I, therefore, predict that the EUE-induced mispricing effect will be more pronounced following the high-sentiment period. In contrast, the ambiguity-premium effect should be less affected by market-wide sentiment and more likely to be observed following low-sentiment periods when investors behave more rationally, as Stambaugh, Yu, and Yuan (2012) suggest.

I quantify market-wide sentiment using an index developed by Baker and Wurgler (2006). As introduced in Chapter 2, I measure EUE by estimating the sensitivity of stock return to log changes of economic uncertainty proposed by Jurado, Ludvigson, and Ng (2015).

Consistent with the prediction, I show that the EUE-induced mispricing effect is only observed following periods with high sentiment with an annualized alpha of 16.2%. By contrast, the ambiguity-premium effect is only observable following the low-sentiment period with an annualized premium of 6.36%. It suggests that when investors are more rational, during the low-sentiment period, the ambiguity aversion is more likely to be reflected and observed in the price. This finding provides further supporting evidence that the ambiguity-premium effect is more likely to be attributed to rational pricing rather than mispricing.

I extend the prediction by considering the interaction between market-wide sentiment and macro-level uncertainty. Uncertainty refers to an event with an unknown distribution that causes difficulties to forecast objective probabilities (Knight, 1921). In the absence of probabilities, investors are more likely to follow their own subjective estimations and to ignore objective valuations, leading to more irrational behaviours and larger disagreement (Hirshleifer, 2001). This is also consistent with psychology literature suggesting that people tend to rely more on their heuristics rather than facts in their judgements and predictions under uncertainty (Kahneman and Tversky, 1973). In this regard, Birru and Young (2020) suggest that investor sentiment has a stronger market-wide effect on cross-sectional returns in periods with higher uncertainty. They show that when the VIX is high, proxying for the market level uncertainty, market-wide sentiment has more power to predict the aggregate market and cross-sectional returns. This finding is consistent with Garcia (2013) which suggests that sentiment has a more prominent role during recession periods.

Empirically, I find that the effect of market-wide sentiment on the EUE-induced mispricing is the strongest in periods with high market-wide sentiment and high macroeconomic uncertainty. In addition, the ambiguity premium effect is only observed in periods with more rational behaviours but increasing macro-level uncertainty. Those findings in Chapter 3 also provide evidence that macro-level uncertainty matters for investors' irrationality as the strongest sentiment effect is observed when economic uncertainty is high.

1.3.3 Incentivised Optimism: Economic Uncertainty and Analyst Forecast

The first two empirical chapters have examined effects of economic uncertainty on investors' decision process. Specifically, I have shown that investors treat stocks with different EUE in different ways based on their beliefs and preferences. I further examine these effects by differentiating investors' behaviour with the market-wide sentiment. In the last empirical chapter (Chapter 4), I investigate the effect of economic uncertainty on the analysts' decision process in earnings forecast and stock recommendations.

In the conjecture of Chapter 4, EUE may give more room to analysts to be more optimistic for incentives with less career concern due to its effect on information quality. Intuitively, investors are more likely to face more difficulties in estimating the outlook of companies with larger EUE. Therefore, stock's exposure to economic uncertainty makes it more difficult for investors to verify analysts' forecasts. This condition is more likely to tilt the balance of analysts' trade-off to be more optimistic for incentives in their forecast as the chance of being caught is relatively lower leading to a lower reputational concern. Therefore, Chapter 4 hypothesises that optimism in analysts' forecasts increases with stock exposure to economic uncertainty.

Considering the forecast bias in the rational framework, private information could be one of the key sources for stocks with higher uncertain payoffs (Lim, 2001). Therefore, analysts tend to publish optimistic forecasts for stocks with high EUE for better managerial relationships to access private information. Additionally, optimistic forecasts encourage investors with an optimistic view to buy, which generates more trading volume (Cowen, Groysberg and Healy, 2006). Stocks with uncertain payoffs are more likely to be held by optimists rather than pessimists (i.e., Cao, Wang and Zhang, 2005; Easley and O'Hara, 2009; Epstein and Schneider, 2010). Therefore, analysts tend to expect a higher trading commission by publishing upward forecast for stocks with high EUE.

In Chapter 4, I measure monthly analyst optimism at the firm-level as the difference between one-year consensus earnings forecasts and actual value scaled by prior month stock price (i.e., Lim, 2001; Larocque, 2012; Henderson and Marks, 2013; Engelberg, Mclean and Pontiff, 2018). This is different from existing studies (i.e., Cowen, Grosyberg and Healy, 2006; Hugon, Kumar and Lim, 2016; Chang and Choi, 2017) which study the relative analysts' optimism for the same stock, because using consensus optimism measure mitigates the effect of extreme values in forecasts as the skewness in the distribution of earnings and forecasts concerns the analyses (Zhang, 2006).

This study empirically shows a significant relationship between EUE and analysts upward bias in both earnings forecasts and stock recommendations. For instance, monthly consensus forecasts of one-year earnings are 3.6% larger than the actual value for stocks in the highest EUE group. Indeed, EUE-induced analyst optimism is observed only in the subsample where firms have lower earnings quality and less available market-level information. Those results suggest that analysts are more optimistic in order to have a better relationship with managers to access private information for stocks with high EUE.

Optimistic forecast bias in the rational framework can potentially result in reputational costs and career concerns for analysts (Jackson, 2005). Consistent with this view, I empirically find that analysts are more likely to move down from a higher-status brokerage house to a lower one due to issuing optimistic earnings forecasts. However, analysts who publish upward earnings forecasts for stocks with high EUE are less likely to lose their positions in a high-status brokerage house. Collectively, these findings suggest that EUE-induced optimism is more likely to allow analysts to hide their bias as investors tend to have more difficulties in verifying the valuation of stocks with high uncertain payoffs (Ackert and Anthassakos, 1997). In other words, analysts can blame their optimistic bias in those stocks affected by macro-level uncertainty on the vague informational environment.

Finally, several studies suggest that analyst optimism impedes price efficiency, thus there is significant mispricing in anomalies (Engelberg, McLean and Pontiff, 2018; Guo, Li and Wei, 2020). I interact main findings in Chapter 2 with EUE-induced analyst optimism to further investigate whether their bias exacerbates mispricing in stocks with high EUE as a result of their incentive concerns. I find that EUE-induced mispricing is significantly apparent in the group with high consensus optimism. Moreover, the ambiguity-premium effect is only significantly observed in the group of stocks with low consensus optimism. These findings suggest that analysts with an optimistic view for stocks with high EUE impede the price efficiency in the market, resulting in significant mispricing.

1.4 Research Contribution

1.4.1 Contributions to Asset Pricing Literature

This thesis contributes to asset pricing literature in several ways. Previous studies have shown that macroeconomic uncertainty induces mispricing in the stock market, leading to a negative relationship between firms' economic uncertainty exposure and expected returns (Hong and Sraer, 2016; Li, 2016). It also generates a premium in the sense of the ambiguity-return trade-off, predicting a positive relationship between firms' economic uncertainty exposure and expected returns (Anderson, Ghysels, and Juergens, 2009; Bali and Zhou, 2016; Bali, Brown and Tang, 2017). However, relevant studies have yet to reach a clear conclusion in these two mechanisms of economic uncertainty. This study contributes to the literature by showing that the apparently contradicting effects of economic uncertainty (i.e., mispricing effect versus ambiguity premium) on cross-sectional returns are both significantly at work. Controlling different types of investor responses in the market by using the firm-level mispricing measure in Chapter 2, this study is able to disentangle these two mechanisms. Investors biases are more pronounced for stocks with greater exposure to macroeconomic uncertainty, leading to stronger mispricing. In addition, their preferences are influenced by stocks with larger EUE, producing an ambiguity premium in the sense of the ambiguity-return trade-off.

This study shows that economic uncertainty connects the aggregate disagreement effect to mispricing, consistent with Hong and Sraer (2016). They use the CAPM beta as a proxy for exposure to aggregate uncertainty. Empirically they show that stocks with higher absolute betas suffer more overpricing, due to larger disagreement among investors. Considering findings in Chapter 2, this study extends their work by identifying one common source of disagreement that influences many different anomalies and also carries an observable "risk" premium.

Considering the mispricing effect of EUE, this thesis provides evidence to the existing literature showing that its effect can be a common driver of well-known market anomalies. Stambaugh and Yuan (2017) argue that anomalies manifest mispricing and there are common components across assets leading to mispricing. For instance, Stambaugh, Yu and Yuan (2012) suggest that the presence of market-wide sentiment exacerbates mispricing due to its significant effect on the divergence of opinions Furthermore, Stambaugh, Yu and Yuan (2015) suggest that arbitrage asymmetry with arbitrage risk measured by idiosyncratic volatility deters arbitrageurs, resulting in apparent mispricing in stock markets. Findings in Chapter 2 regarding the mispricing effect of EUE show that exposure to economic uncertainty might be one of these common components that amplify investors' belief biases, and further drives anomalies. Lastly, this study further controls for arbitrage risk such as idiosyncratic volatility and shows that EUE is a new source of arbitrage limit to the mispricing literature (Nagel, 2005; Stambaugh, Yu and Yuan, 2015).

This study contributes to the literature by providing further insights into two opposite effects of EUE on cross-sectional returns from a behavioural perspective in Chapter 3. In the literature, previous studies have shown the significant role of market-wide sentiment in stock returns through its effect on beliefs and preferences (Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012). Hong and Stein (2007) suggest that the general source of mispricing is a disagreement between optimistic and pessimistic investors. This disagreement is more pronounced during the high sentiment period, leading to significant mispricing in subsequent returns (Stambaugh, Yu and Yuan, 2012). Chapter 3 shows that EUE amplifies mispricing, especially following a high sentiment period, confirming that EUE escalates cross-sectional dispersion in investors' views. This identifies EUE as a common mispricing component across anomalies in the market, which is different from but complements investor sentiment (Nagel, 2005; Stambaugh, Yu, and Yuan, 2012 and 2015).

This thesis, furthermore, provides evidence that there is an ambiguity premium following a low-sentiment period as the rational expectation is pervasive in Chapter 3. It is a result of rational demand, consistent with the theoretical model introduced by Anderson, Gjhysels and Jurgens (2009). This finding complements Shen, Yu and Zhao (2017) who show that macro-risk carries a significant premium following a low sentiment period.

This study shows that macro-level uncertainty matters for investors' irrationality as the strongest sentiment effect is observed when economic uncertainty is high. Findings in Chapter 3 suggest that uncertainty causes subjective valuations increasing sentiment-driven investors' trades. This finding contributes to Birru and Young (2020) who suggest that the sentiment effect is more significant and rational investors' views are more limited to counterbalance irrational ones when market uncertainty is higher. Moreover, it is also consistent with Garcia (2013) suggesting that during recession periods sentiment has an important role in financial markets.

1.4.2 Contributions to Security Analysts Literature

This thesis contributes to the literature on security analysts. Previous studies examine the effect of market uncertainty and financial crises on analyst performance. For instance, Amiram et al. (2017) show that analysts issue forecasts more often when the volatility on market return is high, implying that they are timelier during periods with higher market uncertainty. However, their accuracy is lower. They suggest that analysts underreact to news, measured by stock price movement. In addition, Loh and Stulz (2018) provide evidence suggesting that due to their career concerns, analysts put more effort into their forecast when uncertainty is high during financial crises. This thesis extends those studies by examining the effect of economic uncertainty on analyst optimism in forecasts and recommendations based on rational bias. In particular, this study explores that stock exposure to economic uncertainty mitigates analysts' dilemma between improving management access and losing their reputation. My findings support Chang and Choi (2017) who find a positive relationship between market uncertainty, measured by VIX, and analyst optimism. They claim that analysts' optimism during high market uncertainty period is due to less reputational costs and more trading commission benefits.

This thesis is related to the importance of reputation for analysts' career in the industry that limits their incentive concerns (Fama,1980; Lim, 2001). Several studies suggest that analysts are more likely to lose their jobs or move down from a high-status brokerage house to a low one due to their optimism in earnings forecasts (Jackson, 2005; Groysberg, Healy and Maber, 2011; Chang and Choi, 2017). Findings are consistent with this view in Chapter 4. However, this concern is less likely for analysts when the informational environment is vague. Specifically, this study provides strong evidence that analysts are able to hide their bias for incentives as experiencing less career concern when issuing optimistic forecasts for stocks with higher EUE. I, therefore, unveil another important conditional variable to understand determinants of analysts' optimism for incentives.

Finally, this thesis contributes to Engelberg, McLean and Pontiff (2018) and Guo, Li and Wei (2020) suggesting that analyst optimism impedes the price efficiency and results in significant mispricing in anomalies. Findings in Chapter 4 further show that analyst optimism in forecasts for stocks with higher EUE tends to mislead investors, exacerbating mispricing.

1.4.3 Contributions to Practice

This study offers a practical application to investment management literature, considering findings in Chapter 2. Song (2020) shows that when systematic factors are not properly accounted for this will lead to a mismatch of mutual fund skill and scale. Economic uncertainty is a relevant state variable affecting investment decisions alongside macro-risk factors (Bloom, 2009; Jurado, Ludvigson and Ng, 2015). Therefore, exposure to economic uncertainty can be considered to evaluate fund managers' portfolio compositions to understand how economic uncertainty may affect the performance of a certain manager's strategy. Moreover, Barber, Huang and Odean (2016) show that sophisticated investors evaluate fund performance with more sophisticated benchmarks rather than the market model. For those investors, EUE could be taken into account to improve the benchmark model.

The rest of the thesis is organised as follows. Chapter 2, 3 and 4 present the three empirical chapters. Chapter 5 concludes the thesis with the limitations.

Chapter 2

2 Economic Uncertainty: Mispricing and Ambiguity Premium

2.1 Introduction

Economic uncertainty (EU) has become an accustomed reality for policy, business, and investment decision-makers. One recent and ongoing example is the heightened economic uncertainty caused by the Covid-19 pandemic. During this period, I have made two observations about the financial markets. First, the tug of war between optimists and pessimists in the market is intensified. This is exemplified by the record-breaking daily gains and losses closely clustered in the leading equity benchmark indices around the world.[1] Second, some investors prefer to watch from the sidelines by moving their money out of the equity market temporarily and watching for bargains for their long-term investments.[2] These phenomena represent two different responses from investors to economic uncertainty. While both of these phenomena have been studied separately, the existing

[1] For example, in one month in March 2020, the S&P 500 index experienced two of the top 20 historical best daily performance and three of the worst 20 daily performance since its introduction in 1923. In fact, two of these large episodes are next to each other: on March 12, 2020 with a return of −9.51% and March 13, 2020 with a return of 9.29%. See https://en.wikipedia.org/wiki/List_of_largest_daily_changes_in_the_S%26P_500_Index [accessed June 29, 2020]. If I look at the oil price during the period, a similar extreme volatility can be observed.

[2] There is anecdotal evidence suggesting that investors first fall back to cash and then move on to safe assets such as gold during this period. See https://www.cnbc.com/2020/04/20/coronavirus-why-gold-is-seen-as-a-safe-haven-investment-in-a-crisis.html?__source=newsletter%7Cmakeit [accessed June 29, 2020].

studies have not been able to present a coherent framework to study both of these effects. This leads to inconclusive findings on the impact of EU on asset pricing.

These two responses are broadly related to studies on how economic uncertainty affects investors' beliefs and preferences. First, EU amplifies biases in individuals' beliefs by making optimists more optimistic and pessimists more pessimistic. Hirshleifer (2001) argues that uncertainty leaves more room for investors to follow their own subjective estimations and to ignore objective valuations. Investors' heterogeneous beliefs about the fundamental value can be a source of mispricing (Hong and Stein, 2007). When there are contrasting beliefs among investors, Miller (1977) shows that stocks will be in general overpriced as this is more likely to reflect optimists' views than pessimists' in light of short-sale constraints. In a theoretical model, Hong and Sraer (2016) suggest that there is a link between the market-wide uncertainty and the disagreement of firm value. They suggest that aggregate level uncertainty has an important role in belief formation. They show that stocks with high absolute capital asset-pricing model (CAPM) betas are more sensitive to aggregate disagreement than those with low absolute CAPM betas, leading to overpricing in the high beta stocks due to the presence of short-sale constraints. In this context, stocks with higher exposures to economic uncertainty (more sensitive to aggregate disagreement) will suffer more disagreement on the evaluation of the company's outlook. Therefore, these stocks will be more likely to experience overpricing and have *lower* expected returns. I refer to this effect as the mispricing effect of economic uncertainty, which amplifies the tension between optimists and pessimists.

Second, people prefer certain over uncertain outcomes. Uncertain outcomes have been classified into two groups by Knight (1921): one referred to as risk, which is defined as an event with known distribution; and the other as uncertainty, which is an event with unknown distribution. Knight (1921) contends that people are more averse to uncertainty than risk. In this regard, stocks' exposures to economic uncertainty will affect investors' preference for these stocks. Anderson, Ghysels, and Juergens (2009) show that macro uncertainty carries a positive premium in equilibrium in a dynamic model, and they find supportive empirical evidence using dispersion in the Survey of Professional Forecasters as a measure of uncertainty. In a nutshell, this line of literature predicts that investors would demand a premium from stocks with exposures to economic uncertainty. I refer to this effect as the ambiguity-premium effect, and it applies to those uncertainty-averse investors who would prefer to stay on the sidelines unless the expected compensation is high enough.

These two explanations regarding investors' behaviour in response to economic uncertainty have conflicting predictions on the relationship between firms' economic uncertainty exposure (EUE) and cross-sectional returns.[3] The ambiguity-premium effect predicts a positive correlation between EUE and expected returns, while the mispricing effect predicts a negative one. It is not surprising that existing studies provide mixed evidence on the relationship between EUE and expected returns.[4]

[3] I define EUE as the absolute sensitivity of the return to the change of economic uncertainty. Empirically, it is estimated by the absolute value of the regression coefficient from a time series regression of a stock's returns on log changes of economic uncertainty index while controlling for other risk factors such as Fama-French market factors. More detailed discussion can be found in Section 2.3.2

[4] Li (2016) fails to find any predictive power of disagreement exposure on future cross-sectional returns unconditional of macro disagreement states. When studying the relationship conditional on the state of macro disagreement, he finds that stocks with higher exposures to macro disagreement earn lower future returns, which provides some support to the mispricing effect as proposed by Hong and Sraer (2016). Bali, Brown, and Tang (2017) also find a negative relationship between the uncertainty beta estimated using Jurado Ludvigson and Ng (2015), the uncertainty index and expected return. These results are consistent with both the mispricing argument and ambiguity premium effect under the hedging argument in the context of Merton's (1973) ICAPM. By contrast, Anderson, Ghysels, and Juergens (2009) and Bali and Zhou (2016) provide evidence supporting a positive uncertainty premium. The mixed findings in those studies may also be due to the use of different economic uncertainty proxies. Brenner and Izhakian (2018) study the time-varying ambiguity premium at the market level. They find that the ambiguity premium is positive when the expected probability of the positive outcome is high, while the ambiguity premium is negative when the expected probability of the negative outcome is high.

The challenge of obtaining a clear inference from the studies mentioned above is that both the ambiguity premium and the mispricing mechanisms are at work. A clear conclusion can only be drawn when these two effects can be disentangled. The mispricing argument suggests that disagreement is a general source of mispricing (Hong and Stein, 2007). However, what information sources investors use to form their optimistic or pessimistic beliefs about the company are not specified in these models. It is, therefore, a useful identification strategy to study the effect of economic uncertainty when investors already have heterogeneous beliefs in the first place. To this end, the mispricing score (MIS) proposed by Stambaugh, Yu, and Yuan (2012; 2015) using firm-level characteristics provides a measure of cross-sectional variation for overpricing and underpricing stocks.[5] If the disagreement is a source of mispricing, higher exposure to economic uncertainty will induce larger disagreement in investors' assessment of those firm-level value relevant characteristics and will lead to more apparent mispricing. In other words, high firm-level exposure to economic uncertainty will exacerbate investors' mispricing of other firm characteristics in the MIS, making optimists more optimistic and pessimists more pessimistic. In addition, stocks in the non-mispricing group (neither overpriced nor underpriced) according to MIS can be used to study a 'pure' ambiguity-premium effect by examining a subset of stocks that are not influenced by these known mispricing characteristics.[6]

I have the following two main hypotheses: 1) If EUE-induced disagreement is a common source of mispricing, I expect that the mispricing effect (measured by the long-short portfolio sorted by MIS) will be the strongest in the group of stocks with the highest

[5] Eleven firm characteristics are taken into account for MIS construction. Please see Section 2.3.1 for details.

[6] A similar approach is adopted in Stambaugh and Yuan (2017) when they construct their size factor using stocks least likely to be mispriced, that is, in the middle mispricing group. They show that when controlling for the mispricing effect a much clearer and strong size premium is documented that is nearly twice that implied by the familiar Fama-French version of SMB.

EUE; and 2) For stocks experiencing the least influence of mispricing measured by the MIS (that is, those in the middle portfolio sorted by MIS), the ambiguity-premium effect of EUE will be the dominant effect, and therefore a positive relationship between EUE and expected return is expected.

Empirically, I measure EUE by estimating the sensitivity of stock return to log changes of economic uncertainty proposed by Jurado, Ludvigson, and Ng (2015, hereafter JLN). They define economic uncertainty as to the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents.[7] I broadly follow Bali, Brown, and Tang (2017) to estimate stocks exposure in five-year rolling regressions controlling for known risk factors.[8] Following Hong and Sraer (2016) and Li (2016), I capture the exposure by using the absolute value of the economic uncertainty beta, since disagreement (return volatility) is larger for stocks with a higher level of correlation with economic uncertainty regardless of a positive or negative sign.

My main analyses examine the post-formation, risk-adjusted alphas of 25 portfolios independently double-sorted by EUE and MIS. I adjust the portfolio return for known risk factors using a Fama and French (2016, hereafter FF) six-factor model.[9] I find support for both mispricing and ambiguity-premium effects in the period between 1970 and 2019 in the US markets.

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[7] Jurado, Ludvigson, and Ng's aggregate macroeconomic uncertainty measure is constructed with a wide range of economic data. They show that such a measure is better at capturing quantitively important uncertainty episodes than other popular financial market-based proxies, such as the VIX index.
[8] One important modification I made in our empirical setting is that, instead of using the level of economic uncertainty, as in Bali, Brown, and Tang (2017), I use log changes of economic uncertainty as the level is very persistent. Log changes of economic uncertainty are more suitable to capture unexpected innovations in the uncertainty with close-to-zero expectation, which is an important requirement of pricing factors in the context of arbitrage pricing theory, suggesting that unexpected innovations in macroeconomic variables concerns investors about their future investment and consumption, influencing the indirect utility of real wealth and asset prices (i.e., Merton, 1973; Ross, 1976; Chen, Roll, and Ross, 1986; Bali, Subrahmanyam, and Wen, 2020).
[9] Those risk factors are market excess return (MKT), size (SMB), value (HML), momentum (UMD), investment (IA), and profitability (ROE). Other risk models are also tested in Section 2.5.1.

First, the mispricing effect is the strongest in the group of stocks with the highest EUE, supporting my first hypothesis. The annualized mispricing alpha (that is the alpha of the portfolio that longs underpriced and shorts overpriced stocks) is 9% with a t-statistic of 3.86 in the highest EUE quintile. This is more than double the unconditional mispricing effect that does not consider the EUE effect (with an annualized alpha of 3.96%) in my sample.

Second, I identify a clear EUE ambiguity premium in the group of stocks that are the least affected by the mispricing index of Stambaugh, Yu, and Yuan (2015). In this middle mispricing quintile, which I refer to as the "non-mispricing" group, alphas change from negative to positive as EUE increases from low to high, supporting my second hypothesis that ambiguity-averse investors would demand higher returns for stocks with higher EUE. The annualized alpha of the high-minus-low EUE portfolio within the "non-mispricing" quintile, measuring the EUE ambiguity premium, is 4.2% with a t-statistic of 2.17.

Further insights of EUE on cross-sectional pricing can be gained by examining the asymmetric effect of EUE on over- and underpricing. I show that after controlling for the ambiguity-premium effect, overpricing is more prominently observed than underpricing due to short-sale constraints (Stambaugh, Yu and Yuan, 2012).[10] In fact, only the overpriced legs are significant and monotonically increased with EUE while none of the underpriced legs are significant. Overall, this provides evidence supporting that disagreement and short-sale constraint induces more overpricing (Hong and Sraer, 2016). Furthermore, since overpricing is stronger than underpricing, the average mispricing effect is negative. When I examine all stocks in the high EUE group without differentiating mispricing, the positive

[10] To see a pure mispricing effect, I control for the ambiguity premium by removing the ambiguity premium from the over- and underpriced legs.

ambiguity premium and the negative mispricing effect almost cancel each other out, generating a close-to-zero alpha.

I confirm the robustness of my finding in Fama-MacBeth (1973) and double-cluster panel regressions on excess return with firm-level risk controls. Specifically, it shows that the base MIS effect is negative (high MIS measures overpricing); the interaction effect of MIS and EUE is negative and significantly supports EUE, amplifying the mispricing effect; and finally, after controlling for the EUE's interaction with MIS, the base EUE effect becomes positive and significant. This base EUE effect captures the pure ambiguity-premium effect confirming the overall positive ambiguity premium for high EUE stocks.

I also conduct a series of further analyses to examine links between the EUE and cross-sectional returns with alternative specifications and to substantiate the impact of the two channels.

Distinguishing periods with increasing or decreasing economic uncertainty, I show that both mispricing and ambiguity-premium effects are mainly observed following a period of increasing uncertainty. This confirms that the increase in uncertainty both drives disagreements and triggers ambiguity aversion.

To understand the marginal contribution of bringing EUE into the cross-sectional asset pricing, I examine how two channels of the EUE effect are influenced by alternative risk models including a seven-factor model (FF's five factors, a momentum factor and an additional liquidity factor), q-factor (Hou, Xue, and Zhang, 2015), q5 (Hou et al., 2020) and the mispricing (Stambaugh and Yuan, 2017, hereafter MSP) models. In general, the mispricing effect of EUE on the identified mispricing anomalies is weakened as more elaborated multifactor models are used as a benchmark model but remains significant in most of the models such as Fama-French models including an aggregate liquidity factor, q-factor and the mispricing models. By contrast, the ambiguity-premium effect of EUE remains strong when other risk factors are controlled with more elaborated risk models. In fact, the largest ambiguity premium comes from the q5 model, where the unconditional mispricing effect is fully explained. This demonstrates the robustness of the EUE ambiguity premium as a new factor that is different from existing risk factors and existing known mispricing.

To study whether the source of uncertainty matters, I extend my empirical study to consider alternative macro uncertainty measures including the dispersion of the Survey of Professional Forecasters (Li, 2016), the index of economic policy uncertainty (Baker, Bloom, and Davis, 2016), the variance risk premium (Bali and Zhou, 2016), and the ambiguity degree index (Brenner and Izhakian, 2018). The mispricing effect is robust to all alternative uncertainty measures, whereas the ambiguity premium only can be observed by using JLN's aggregated economic uncertainty measure (the main measure used in this paper), the dispersion of analysts' forecast for GDP, and the index of economic policy uncertainty. My results suggest that uncertainty about GDP and economic policy are the main sources of ambiguity that induce a clear price response reflecting investors' ambiguity aversion. These further tests also highlight the advantage of using a comprehensive and aggregated economic uncertainty measure, such as the JLN series, which can capture both the ambiguity premium and mispricing effects.

Finally, I study these two channels of effects with controls and interactions with well-known mispricing conditions such as limits of arbitrage. I show that the higher the EUE for a stock, the larger the divergence of opinion measured by volume turnover (Hong and Stein, 2007), idiosyncratic volatility (Stambaugh, Yu, and Yuan, 2015) and analysts' forecast dispersions (Diether, Malloy, and Scherbina, 2002). This confirms that exposure to economic uncertainty induces disagreement at the stock level.

Among these disagreement measures, the idiosyncratic volatility (IVOL) is the only one that can predict next-period EUE, suggesting that there is a potential commonality between these two. Can the EUE mispricing effect capture IVOL effects? To unravel the effect of IVOL from that of EUE on mispricing, I extend my main analyses of double-sorting to three dimensions. I find that EUE and IVOL are two different sources of friction that affect mispricing. The EUE effects on mispricing are more prominent in the group with *low* IVOL where traditional mispricing effect is weaker as arbitrage friction is low. From the limits of arbitrage points of view, I uncover EUE as a source of arbitrage friction that is not captured by the IVOL. Furthermore, I find that the ambiguity-premium effect is also strong in the group of stocks with low arbitrage friction, confirming that the ambiguity premium is not due to mispricing and consistent with the nature of the "risk" premium instead.

This study contributes to the literature by disentangling the ambiguity premium from the mispricing effect of economic uncertainty on cross-sectional asset pricing. Existing factor models (FF, q5, or MSP) are useful to predict expected cross-sectional returns regardless of whether they are rational compensation for systematic risk or reflect common sources of mispricing (Hirshleifer and Jiang, 2010; Kozak, Nagel, and Santosh, 2018). This study shows that these two channels of effects need not be mutually exclusive. Exposure to economic uncertainty will not only amplify investors' biased beliefs, leading to stronger mispricing, but also affect investors' preference producing an ambiguity premium. I provide evidence that links the aggregate disagreement to mispricing, supporting the theoretical proposition of Hong and Sraer (2016). Empirically, they use the CAPM beta as a proxy for exposure to aggregate uncertainty and show that stocks with higher absolute betas will suffer more overpricing. This helps explain the beta anomaly. My study extends their work by identifying one common source of macro uncertainty that influences many different anomalies and also carries an observable "risk" premium.

This study extends studies of economic uncertainty and the effect of ambiguity in asset pricing. My study reconciles the seemingly contradicting findings of the coexistence of the positive and negative effects of EUE on the expected return when studied in isolation. I provide a unified framework enabling us to attribute the effects of EUE to two different economic interpretations. Empirically, I identify a positive EU-induced ambiguity premium that is different from existing risk factors and robust to the latest multifactor asset-pricing models. Brenner and Izhakian (2018) attribute observations of time series variation in the ambiguity premium to the change of investors' attitude toward ambiguity. My cross-sectional analysis shows that this could be due to the asymmetric effect of ambiguity on mispricing. Controlling for mispricing, the ambiguity premium is positive. A positive ambiguity premium provides support to theoretical models (Anderson, Ghysels, and Juergens, 2009) and is consistent with the general view that people dislike uncertainty and should be compensated by a positive premium as they require for bearing risk.

In this study, findings regarding the asymmetric impacts on overpricing and underpricing provide further insights into the effect of EUE as a common economic driver of well-known market efficiency anomalies. Stambaugh and Yuan (2017) argue that anomalies partly reflect mispricing, and that mispricing has common components across stocks. They construct a mispricing factor to capture common components. However, the underlying economic driver for the common components has yet to be studied in depth. This study shows that exposure to economic uncertainty could be one of these common components that amplify investors' belief biases, which drive anomalies. This identifies EUE as a common mispricing component across anomalies in the market, which is different from but complements arbitrage risk (Nagel, 2005; Stambaugh, Yu, and Yuan, 2012 and 2015).

My findings also have a direct implication for practical investment management. My approach enables fund managers and investors to capture and report sources of alphas with improved clarity. Investors need to differentiate fund managers' skills from high returns generated by fund managers through exposures to common systematic factors (Song, 2020). Taking EUE into consideration in portfolio attribution analysis would enable investors to understand how economic uncertainty may affect the performance of a certain manager's strategy (for example, those anomalies-/factors- driven strategies). Besides, given that EUE is new to the literature, investors may be able to identify the manager's "hidden" (alpha) skills that reflect the economic uncertainty-induced ambiguity premium. In other words, EUE can be a part of a more advanced benchmark model for sophisticated investors to use in evaluating and selecting funds (Barber, Huang, and Odean, 2016).

The rest of the chapter is organized as follows. Section 2.2 reviews the literature and develops my main hypotheses. Section 2.3 presents my data. Section 2.4 presents main findings. Section 2.5 reports robustness and further tests. Section 2.6 concludes.

2.2 Literature Review and Hypotheses Development

2.2.1 Economic Uncertainty Measurement

The main difference between risk and uncertainty is related to the probability distribution of an event. If the future is unknown with a known probability distribution of all possible outcomes in that event, this refers to risk. However, if the probability distribution is unknown, it refers to uncertainty. In other words, risk can be estimated and quantified with an objective distribution that all investors can use to make certain assumptions and predictions. However, uncertainty is unidentifiable and unmeasurable, thus those investors are unable to predict the likelihood of an event (Knight, 1921). Anderson, Ghysels, and Juergens (2009) see uncertainty as investors' confidence in their estimation about the unknown mean and their errors in the approximation of a true conditional mean for the state variable.

JLN (2015) define uncertainty as the conditional volatility of the purely unforecastable component of the future value of the series. Therefore, uncertainty is about whether a state variable has become more or less predictable, that is less or more uncertain (Jurado, Ludvigson and Ng, 2015). An economic uncertainty index is then constructed as a weighted average of as many as 132 macroeconomic variables by JLN (2015). This measure of economic uncertainty index has two distinct advantages. First, it emphasizes the conditional volatility after removing all forecastable components, which puts it more in line with the theoretical definition of uncertainty instead of risk. Second, it has the advantage of capturing the uncertainty of the economy instead of the uncertainty of just one particular economic indicator through aggregating a large number of economic indicators. In my empirical study, I adopt this measure of economic uncertainty as my main measure.

2.2.2 Economic Uncertainty, Disagreement, and Mispricing

Hong and Sraer (2016) link the market-wide uncertainty to the disagreement of firm value in a theoretical model. They show that macro uncertainty is important to belief formation, and the traditional CAPM beta also captures the degree of a stock exposure to the market-wide uncertainty. A higher beta will lead to more disagreement in a stock. Building on Miller (1977), this will lead to overpricing in the high beta stocks and hence explain the beta anomaly.[11] In this regard, their theory suggests that stocks with higher EUE will experience overpricing and have lower expected return subsequently. Li (2016) tests Hong and Sraer's (2016) argument by focusing on disagreement measured by the exposure to a series of factor portfolios constructed by the Survey of Professional Forecasters database.[12] He finds supporting evidence that stocks with higher EUE earn lower returns only in the subperiod of high EU.

Many studies have shown that uncertainty at both the aggregate and firm levels cause disagreement (for example D'Amico and Orphanides, 2008; Bachmann, Elstner, and Sims, 2013; Anderson, Ghysels, and Juergens, 2009; Sadka and Scherbina, 2007). Hirshleifer (2001) argues that uncertainty leaves more room for investors to follow their own subjective estimations and to ignore objective valuations, and therefore reduces the quality of information used in stock valuation. Harrison and Kreps (1978) and Scheinkman and Xiong (2003) argue that in a dynamic setting, stocks with more investors' disagreement will have higher price–earnings ratios and lower subsequent returns. In other words, higher exposure to uncertainty would amplify the value effect. Bali and Zhou (2016) show that incorporating the uncertainty beta provides both statistical and economic success in explaining some stock market anomalies (Small–Big for the size anomaly, Value–Growth for the book-to-market anomaly, and HiTech–Telcm for the industry anomaly). This line of literature suggests that

[11] Miller (1977) argues that asset prices will be more likely to reflect the valuation made by optimists than pessimists when there is a high level of heterogenous beliefs, resulting in overpricing and lower future return. The core of this argument is built on the fact that short-sale constraints make it more restricted and/or more costly for pessimists to express their opinions through their trading activities. The increase in heterogenous beliefs will exacerbate this asymmetry and lead to more apparent overpricing. Strong support for this can be found in the literature subsequently (Diether, Malloy, and Scherbina, 2002; and Chen, Hong, and Stein, 2002).
[12] Li (2016) constructs macro-factors by measuring macro disagreement on GDP growth, inflation rate, treasury bill rate, industrial production, and nonresidential fixed investment from the Survey of Professional Forecasters database.

exposure to economic uncertainty can lead to overpricing and also be a common factor affecting existing mispricing anomalies.

I hypothesise that higher exposure to economic uncertainty will exacerbate investors' disagreement about those valuation characteristics used to construct MIS and lead to stronger heterogeneous beliefs about the stock value. One possible reason is that investors become overconfident about their private information (Hirshleifer, 2001). Stronger disagreement would further lead to more apparent mispricing. I refer to this effect as the mispricing effect of EUE. Therefore, my first hypothesis is as below:

H_1: Mispricing spreads, sorted by MIS, are larger among stocks with higher EUE relative to those with lower EUE.

2.2.3 Economic Uncertainty and Ambiguity Premium

When facing uncertainty, investors seem to expect the worst situation (Anderson, Hansen, and Sargent, 2003). Maenhout (2004) shows that if investors are concerned that their model of stock returns is misspecified, they will charge a substantially higher equity premium as compensation for the perceived ambiguity in the probability distribution. Heath and Tversky (1991) argue that ambiguity aversion has much to do with how competent an individual feels when assessing the relevant distribution. For example, Warren Buffett steered clear of dotcom stocks, even during the height of the tech boom in the late 1990s, and he is also reluctant to invest in technology companies because he is not confident in estimating their values.[13] In short, uncertainty will alter investors' preferences.

[13] https://www.forbes.com/sites/simonmoore/2019/05/05/buffetts-relationship-with-tech-stocks-its-complicated/#31f3a5dc63da [accessed June 29, 2020].

Among studies on economic uncertainty, Anderson, Ghysels, and Juergens (2009) measure economic uncertainty by using the dispersion in the Survey of Professional Forecasters. They show that securities that are positively correlated with their EU measures have higher expected returns, implying that uncertainty-averse investors demand higher returns as a compensation. Bali and Zhou (2016) provide further support for this conjecture, showing that equity portfolios that are highly correlated with variance risk premium (VRP, a proxy for financial and economic uncertainty) carry a significant premium relative to those that are uncorrelated or minimally correlated with VRP. In general, this line of research proposes a positive risk premium effect of a stock's exposure to economic uncertainty.[14] I refer to this effect as the ambiguity-premium effect of economic uncertainty. Therefore, my second hypothesis is as below:

H_2: There is a positive relationship between EUE and future returns for stocks in the non-mispricing group which is the least influenced by mispricing captured by MIS.

It is important to note that my ambiguity-premium hypothesis is conditional on removing the general mispricing effect. Stambaugh, Yu, and Yuan (2015) show that the asymmetric effect of IVOL on the different mispricing legs leads to inconclusive empirical

[14] There is another stream of literature studying the uncertainty premium based on the ICAPM (Merton, 1973) (see, for example, Ozoguz, 2008; Bali, Brown, and Tang, 2017). They show that there is a positive uncertainty premium. The theoretical argument is similar to those discussed above, and it suggests that for risk-averse investors assets that covary positively with future investment opportunities have higher average returns. Different from the traditional risk-sharing literature, they focus on the directional correlation for hedging purpose argument. In other words, they propose that assets that have a negative correlation with uncertainty have higher "uncertainty risk". These stocks should carry a premium. Such argument relies on investors being able to predict the future state (the unexpected changes in uncertainty in this case). However, the challenge of this argument is that investors are not able to predict future economic uncertainty, therefore arguing that they will take a directional hedging position against the foundation for the discussion of uncertainty. For this reason, our discussion focuses on the absolute level of exposure to economic uncertainty, avoiding the directional interpretation. Empirically I measure the exposure by the absolute value of the beta coefficients. In a robustness test, I also show the results obtained without taking the absolute value of EU beta. It confirms that there is no obvious asymmetry in the results for positive and negative beta and taking absolute value of the exposure beta present a consistent and simplified interpretation of the empirical findings. See Table A-I.5 in Appendix II for more details.

relationships observed between IVOL and expected return. In a similar vein, my hypotheses developed above suggest that the asymmetric effect of EUE on different mispricing legs will affect the conclusion of the pure EUE risk premium effect. Particularly, for stocks with higher EUE, the positive EUE risk premium is more apparent in the underpriced leg (with higher expected returns) since both the risk premium and the mispricing effects work in the same direction. By contrast, in the overpriced leg, the positive effect of the ambiguity premium will be reduced by the negative expected return due to the mispricing effect. Therefore, I expect that the ambiguity-premium effect will be more clearly captured by a group of stocks that are less affected by mispricing. To this end, the middle quintile sorted on mispricing would be a good candidate portfolio to be considered as "orthogonal" to mispricing (neither over- nor underpriced with respect to those firm characteristics). The variation of EUE and expected return in this group of stocks captures a "purer" ambiguity-premium effect compared with other mispricing groups. Similarly, I expect that the "pure" mispricing effect in the over- and underpriced legs can only be observed when the positive ambiguity-premium effect is properly controlled (see more discussion on this in Section 2.4.2).

2.3 Data and Measure

The dataset used in my empirical analyses contains all common stocks (with share codes 10 and 11) on the NYSE, Amex, and NASDAQ. Stocks whose prices are less than $5 per share are excluded from the dataset since those assets are hard to short (Asquith, Pathak, and Ritter, 2005). Monthly asset returns and companies' fundamental values are from the merged CRSP-Compustat database from July 1965 to December 2019. To calculate monthly analyst forecast dispersion, data on analysts' earnings estimates are from the unadjusted I/B/E/S summary database starting from December 1981.

2.3.1 *Mispricing Measure*

Following Stambaugh, Yu, and Yuan (2015), the mispricing measure (MIS) is constructed based on 11 market anomalies. Their detailed definitions can be found in Appendix II. Stocks with the highest MIS scores are assigned as the most overpriced, while those with the lowest MIS scores are assigned as the most underpriced. Stambaugh, Yu, and Yuan (2015) show that MIS minimises noisy measures of anomaly-specific effects. Thus, I have a single factor in identifying the degree of mispricing more accurately in the market. Additionally, they find that long-short portfolios formed on MIS have a higher average return relative to individual-anomaly portfolios, indicating that the new MIS measure is better at identifying mispricing in the market.[15]

2.3.2 *Economic Uncertainty Exposure*

Existing studies have relied on different proxies to measure uncertainty in the economy. For instance, several papers use market volatility, due to its significant relation with real activity (for example, Bloom, 2009; Bekaert, Hoerova, and Duca, 2013; Bali and Zhou, 2016). However, JLN (2015) argue that financial market volatility may not reflect economic uncertainty accurately, since it may vary over time due to changes in risk aversion, leverage, or sentiment.

Other studies use dispersion in forecasts (for example, Mankiw and Reis, 2002; D'Amico and Orphanides, 2008; Anderson, Ghysels, and Juergens, 2009; Li, 2016). It is

[15] Monthly mispricing scores for each stock from July 1965 to December 2016 are collected from Robert F. Stambaugh's website and I updated them to December 2019. See more details related to mispricing score formation at: http://finance.wharton.upenn.edu/~stambaug/ .

expected that during time with high uncertainty, forecasts are dispersed, and surveys show a higher level of disagreement on macro-indicators (Bachmann, Elstner, and Sims, 2013). However, forecasts may not clearly show expectations about the whole economy and may give subjective responses due to their pecuniary interests and individual biases. Additionally, the dispersion of analyst forecasts might be affected by heterogeneity in the business cycle, even if there is no shift in uncertainty in economic fundamentals (JLN, 2015).

Considering those arguments on different measures of economic uncertainty, I use the uncertainty index constructed by JLN (2015). This index is constructed based on 132 micro-series, not on any single (or a small number of) economic indicators, measuring uncertainty in the whole economy. JLN (2015) show that using this measure can capture uncertainty in different macro variables at the same time across companies, industries, markets, and regions. The index is obtained from Sydney Ludvigson's website.[16]

To measure innovations in economic uncertainty, I use monthly logarithmic changes in the index (ΔUNC_t).[17]

$$\Delta UNC_t = ln\left(\frac{UNC_t}{UNC_{t-1}}\right) \tag{2.1}$$

I estimate the uncertainty beta from a rolling regression for each stock with the following model, using previous 60-month observations:[18]

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[16] https://www.sydneyludvigson.com/data-and-appendixes/.

[17] Unexpected innovations in macroeconomic variables concern investors about their future investment and consumption, influencing the indirect utility of real wealth and asset prices. Thus, using the changes in economic uncertainty is consistent with the literature (for example, Merton, 1973; Ross, 1976; Chen, Roll, and Ross, 1986; Bali, Subrahmanyam, and Wen, 2020). The level of the index is non-stationary with a Dickey-Fuller statistic of −2.152, while its logarithmic difference is stationary with a Dickey-Fuller statistic of −13.678.

[18] I require at least 24 months of non-missing observation for each stock to estimate the model.

$$R_{i,t} = \alpha_{i,1} + \beta_{i,1}\Delta UNC_t + \beta_{i,2}MKT_t + \beta_{i,3}SMB_t + \beta_{i,4}HML_t + \beta_{i,5}UMD_t + \beta_{i,6}IA_t + \beta_{i,7}ROE_t + \varepsilon_{i,t} \tag{2.2}$$

where $R_{i,t}$ is the monthly excess return of stock i in month t. ΔUNC_t is a proxy for innovations in economic uncertainty in month t. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French factors in month t.[19] Definitions are given in Appendix II. These factors are from Kenneth French's website.[20]

Once I have estimated the monthly EU beta for each stock during the sample period, I use the absolute value of EU betas for all analyses in this study. This approach is consistent with relevant studies (Hong and Sraer, 2016; Li, 2016). In Hong and Sraer's (2016) prediction, aggregate disagreement is positively associated with the absolute value of market beta.[21] This is because disagreement is higher for stocks returns that are highly correlated with uncertainty regardless of the positive or negative sign. The use of the absolute value also matches my intention to examine the impact of EU on the uncertainty of a stock's return distribution (the variance of the distribution). A large magnitude of the beta, no matter whether it is positive or negative, makes the variance of the return more sensitive to the change of economic uncertainty.[22]

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[19] In EUE estimation, I exclude the liquidity factor introduced by Pastor and Stambaugh (2003), which is different from Bali, Brown and Tang (2017). This is because Pastor and Stambaugh (2003) do not consider stocks traded on NASDAQ in the liquidity factor, while those stocks are included in my sample. However, the main results are similar when I estimate EUE with the inclusion of the liquidity factor to this model.

[20] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html .

[21] In Table A-I.5 of Appendix I, I also report results obtained without taking the absolute value of the EU beta. I show that there is no obvious asymmetry in findings for stocks with positive and negative EU betas. Grouping stocks by their absolute EU betas improves the clarity of the interpretation and a consistent connection to the theoretical argument.

[22] I examine correlations between the log change of economic uncertainty and the other risk factors in Table A-I.1 of Appendix I. The correlations are very low with a maximum of -0.148 for the correlation with the market factor.

2.4 Empirical Analyses

2.4.1 Economic Uncertainty Exposure and Mispricing Index

I employ bivariate portfolio analyses to examine the relation between EUE and cross-sectional expected returns conditional on general mispricing of stocks. Following Stambaugh, Yu, and Yuan (2015), at the end of each month t, five portfolios are formed by sorting on individual stocks' EUE estimated in Equation (2.2) up to month t. Then, independently another five portfolios are constructed by sorting on stocks' mispricing score (MIS) in month t. Finally, 25 EUE-MIS portfolios are formed as intersections of five EUE and five MIS groups, and value-weighted returns are calculated during month $t + 1$.[23] The first set of the 25 portfolios is formed in July 1970.

Before examining the portfolio returns, I study the distribution of EUE among these portfolios. Table 2.1 reports the average EUE (in Panel A) and the number of stocks (in Panel B) in 25 portfolios. Panel A shows that overpriced stocks (the Overpriced row) have higher EUE compared to underpriced ones (the Underpriced row). The averages of EUE for the five MIS portfolios monotonically decrease from 0.684 for the overpriced group to 0.618 for the underpriced group. This pattern holds in all subgroups with varying EUE.

Furthermore, examining the number of stocks in the portfolio shows that the overpriced high EUE portfolio has the highest number of stocks (161) among the 25 portfolios. It confirms that among overpriced stocks (the Overpriced row), more of them have a higher EUE; and among stocks with high EUE (the high EUE column), more of

[23] When I form 50 (10x5) EUE-MIS portfolios, the main results remain the same.

them are overpriced rather than underpriced.[24] Given that I use independent sorting, the distribution of stocks suggests a strong association between overpricing and high EUE. It supports my hypothesis that EUE could be a common determinant of mispricing.

Table 2.1 Economic Uncertainty Exposure of the 25 EUE-MIS portfolios

This table reports the average EUE and the number of stocks of the 25 EUE-MIS portfolios in Panels A and B, respectively. The EUE is the absolute beta coefficient estimated in Equation (2.2). Variable definitions are listed in Appendix II. The pooled average of stocks in each portfolio over the sample period is reported. The sample period is from July 1970 to December 2019.

	Low EUE	2	3	4	High EUE	All Stocks
			Average EUE			
1 Overpriced	0.139	0.267	0.455	0.752	1.805	0.684
2	0.126	0.258	0.449	0.745	1.681	0.652
3 Non-mispricing	0.121	0.254	0.446	0.741	1.615	0.635
4	0.118	0.253	0.446	0.741	1.562	0.624
5 Underpriced	0.117	0.253	0.445	0.739	1.534	0.618
All stocks	0.124	0.257	0.448	0.744	1.639	
			Average No of Stocks			
1 Overpriced	95	96	104	115	161	570
2	112	112	112	115	120	571
3 Non-mispricing	120	119	115	113	105	572
4	121	122	119	113	96	572
5 Underpriced	124	123	121	116	90	574
All stocks	572	572	572	572	571	

2.4.2 Economic Uncertainty Exposure and Cross-sectional Return: Bivariate Sort

I next examine the risk-adjusted returns of these 25 value-weighted portfolios.[25] Those portfolios are rebalanced at the end of each month during the sample period. The risk-adjusted returns are alphas estimated by the following augmented Fama and French (2016) six-factor model:

[24] There are on average 2,859 stocks in each month in our sample, which is comparable to previous studies. For instance, Stambaugh, Yu, and Yuan (2015) report 3,113 stocks in each month on average, while this figure is 2,414 in Liu, Stambaugh, and Yuan (2018).

[25] Analyses of excess returns (return minus risk-free rate) of these portfolios can be found in Table A-I.2 of Appendix I. The results are consistent with the main findings.

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} UMD_t + \beta_{p,5} IA_t + \beta_{p,6} ROE_t + \varepsilon_{i,t} \tag{2.3}$$

where $R_{p,t}$ is the excess return of portfolio p in month t and $\alpha_{p,1}$ is adjusted return. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French factors in month *t*. Finally, t-statistics are reported in parentheses using Newey-West (1987) robust standard errors.

Panel A of Table 2.2 reports the alphas for the 25 EUE-MIS portfolios. I also report risk-adjusted returns on average and univariate sorted portfolios for MIS (the last two columns) and EUE (the last two rows), respectively. I refer to the spread returns in the univariate sorted portfolios as measuring the unconditional MIS and unconditional EUE effects. Panel A confirms that there is significant unconditional mispricing. The alpha of the long-short portfolio is 0.33% per month with a t-statistic of 3.57, as shown in the univariate MIS column. However, the unconditional EUE effect on cross-sectional return is statistically insignificant as reported in the univariate EUE row. As I examine in the following analyses, this insignificant effect is due to the negative mispricing effect and the positive ambiguity-premium effect of EUE cancelling each other out.

Turning our attention to the 25 double-sorted portfolios, I show that mispricing alphas are significant in four of the EUE quintiles and the mispricing effects (in the Underpriced-Overpriced row) are increasing from the low to high EUE groups in general. Specifically, I observe the strongest mispricing in the high EUE quintile with an alpha of 0.75% per month (9% per annum, $t = 3.86$). This is more than double the unconditional mispricing alpha (0.33% per month). These findings show that stocks with higher EUE experience stronger mispricing in the market, supporting my first hypothesis.

Table 2.2 Risk-adjusted Returns of 25 Portfolios Double-sorted by EUE and MIS

This table reports the risk-adjusted returns on 5 MIS (EUE) and 25 EUE-MIS value-weighted portfolios in Panel A. The 25 portfolios are formed by independently sorting on EUE and the mispricing scores. The mean of 5 MIS (EUE) portfolios is reported in Average MIS (EUE) column (row). The 5 MIS (EUE) portfolios are formed by sorting individual stocks on their mispricing scores (EUE), reported in univariate MIS (EUE) column (row). Panel B reports the ambiguity-premium adjusted returns on the difference between each double-sort portfolio and the corresponding value in the middle mispricing quintile called "non-mispricing" group. The risk-adjusted returns are estimates of alphas estimated in Equation (2.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2019. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Low EUE	2	3	4	High EUE	High-Low	Average MIS	Univariate MIS
				Panel A: Mispricing alphas				
1 Overpriced	-0.03	-0.25**	-0.47***	-0.38***	-0.44***	-0.41***	-0.31***	-0.29***
	(-0.33)	(-2.15)	(-3.35)	(-2.98)	(-3.84)	(-2.74)	(-4.54)	(-3.90)
2	-0.14	0.13	-0.23**	0.10	-0.06	0.08	-0.04	-0.03
	(-1.61)	(1.39)	(-2.19)	(0.84)	(-0.51)	(0.55)	(-0.86)	(-0.56)
3 Non-mispricing	-0.11	0.09	0.03	-0.00	0.24*	0.35**	0.05	0.01
	(-1.27)	(0.97)	(0.32)	(-0.01)	(1.74)	(2.17)	(1.21)	(0.20)
4	0.04	0.03	-0.11	0.00	0.28*	0.24	0.05	0.01
	(0.56)	(0.36)	(-1.23)	(0.02)	(1.89)	(1.37)	(1.05)	(0.23)
5 Underpriced	0.01	0.10	0.01	0.05	0.31**	0.30*	0.09**	0.04
	(0.10)	(1.56)	(0.09)	(0.50)	(2.05)	(1.81)	(2.08)	(1.15)
Underpriced−	0.04	0.35**	0.47***	0.43***	0.75***	0.71***	0.41***	0.33***
Overpriced	(0.30)	(2.55)	(2.73)	(2.76)	(3.86)	(3.15)	(4.45)	(3.57)
Average EUE	-0.05	0.02	-0.16***	-0.05	0.07	0.11		
	(-1.26)	(0.43)	(-3.06)	(-0.84)	(0.85)	(1.21)		
Univariate EUE	-0.00	0.07	-0.10**	0.01	0.09	0.09		
	(-0.04)	(1.57)	(-2.36)	(0.13)	(1.15)	(0.96)		
				Panel B: Ambiguity premium adjusted alphas				
1 Overpriced	0.08	-0.35**	-0.49***	-0.38**	-0.68***	-0.75***		
	(0.55)	(-2.48)	(-3.01)	(-2.13)	(-4.00)	(-3.56)		
2	-0.04	0.04	-0.26**	0.10	-0.30**	-0.27		
	(-0.31)	(0.35)	(-1.98)	(0.60)	(-2.11)	(-1.41)		
3 Non-mispricing	0.00	0.00	0.00	0.00	0.00	0.00		
4	0.15	-0.07	-0.14	0.00	0.04	-0.11		
	(1.29)	(-0.55)	(-1.18)	(0.02)	(0.24)	(-0.57)		
5 Underpriced	0.12	0.00	-0.02	0.05	0.07	-0.05		
	(1.08)	(0.03)	(-0.18)	(0.34)	(0.36)	(-0.21)		
Underpriced−	0.04	0.35**	0.47***	0.43***	0.75***	0.71***		
Overpriced	(0.30)	(2.55)	(2.73)	(2.76)	(3.86)	(3.15)		

Examining the EUE effect in the middle quintile of the mispricing (the "3 Non-mispricing" row of Panel A), the high-low EUE portfolio generates a significant alpha of 0.35% per month (4.2% annualized) with a t-statistic of 2.17. It confirms that exposure to

EU is priced in non-mispricing portfolios. This finding provides evidence for the existence of the ambiguity premium, which is different from those mispricing factors and known risk factors, supporting my second hypothesis.

Traditionally, overpricing is more prominently observed than underpricing due to short-sale constraints (Stambaugh, Yu, and Yuan, 2012). I confirm this finding in Panel A. The monthly high-low EUE alpha is −0.41% in the overpricing group and 0.30% in the underpricing group in Panel A. However, when I test the statistical significance, the absolute magnitude of these two alphas are not statistically different from each other. This is because the returns in both mispricing legs would also be affected by the ambiguity-premium effects. In other words, stocks with a high level of EUE would have a positive ambiguity premium attached to them. This not only applies to the non-mispricing group, but also all other stocks regardless of their mispricing status. To see a pure mispricing effect, I control for the ambiguity premium by longing the overpriced (or underpriced) leg and shorting the corresponding middle "non-mispricing" group for each of the EUE quintiles. Intuitively, the ambiguity premium recorded by the non-mispricing group would also be applied to all stocks with the same level of EUE quintile. As expected, Panel B shows that after removing the ambiguity-premium effect overpricing is much more prominent than underpricing. Alphas of overpriced portfolios become more negative as EUE increases from low to high, confirming the amplification effect of EUE on overpricing stocks. By contrast, there is no evidence of the EUE effect on the underpriced leg. This evidence provides further support to my first hypothesis that disagreement and short-sale constraints contribute to overpricing instead of underpricing and is consistent with the model of Hong and Sraer (2016).

Finally, comparing the combined (average) effect of EUE shown in the "univariate EUE" (Average EUE) row to the pure ambiguity-premium effect in the non-mispricing row, I can see that the overall "ambiguity premium" disappeared in the univariate EUE sorted portfolios. This is because the average negative mispricing effect (the effect of EUE is more prominent among overpriced stocks than among underpriced stocks, as I discussed above) reduces the overall positive risk premium.

Overall, my results document that EUE has two effects on cross-sectional asset pricing. There is significant and economically large mispricing among stocks with high EUE and a positive risk premium effect in the non-mispricing group. The mispricing effect is more apparent in overpricing, which produces a negative effect on stock returns. When considering the overall EUE effect on the high EUE stocks, this negative mispricing effect cancels out the positive risk premium effect, and I cannot observe a clear EUE effect on the cross-sectional returns. These findings demonstrate the importance of disentangling the two channels of effects in order to understand the economic impact of EUE on asset pricing.

2.4.3 Economic Uncertainty Exposure and Cross-sectional Return: Regressions

In the last section, I study the risk-adjusted returns for bivariate-sorted portfolios. The results are intuitive and practically relevant to investment return from the factor investing point of view. In this section, I examine my hypotheses at the stock level using the traditional Fama-MacBeth (1973) cross-sectional regressions. Petersen (2009) shows that the Fama-MacBeth procedure gives downward-biased standard errors despite Newey-West's (1987) adjustment used in estimations.[26] Therefore, I also employ a series of panel

[26] For more details and extensive literature re-examined and compared using different estimation methods, see Petersen (2009).

regressions for double-clustered standard errors at the firm and year levels. I test the effect of firm-level EUE exposure on monthly excess returns by the following model:

$$Y_{p,t+1} = \lambda_{0,t} + \lambda_1 EUE_{p,t} + \lambda_2 MIS_{p,t} + \lambda_3 MIS * EUE_{p,t} + \sum_{J=4}^{n} \lambda_j X_{p,t}$$

$$+ Fixed\ Effects + \varepsilon_{i,t} \tag{2.4}$$

where $Y_{p,t+1}$ is the excess return for stock p in month $t+1$. $X_{p,t}$ is a set of stock-specific variables in month t for stock p, including β^{CAPM}, $DISP$, $IVOL$, TO, $SIZE$, MOM, REV, BM, $ILLIQ$, ROE, and I/A. All variables are defined in Appendix II. In Fama-MacBeth regressions, I control for industry fixed effect and standard errors are robust using Newey-West (1987) with three lags. In panel regressions, firm/industry and year fixed effects are included, and standard errors are double-clustered at the firm/industry and year levels (Cameron, Gelbach, and Miller, 2011). I report the regression results in Table 2.3.

Panel A reports the Fama-MacBeth regressions with industry fixed effect. It shows that without controlling for other factors, EUE is negatively correlated with the next period's return cross-sectionally. Controlling for the mispricing index itself does not change the sign. The benchmark MIS effect as shown in Equation 2 is negative as expected since the higher the MIS index, the more overpriced the stock. What I am interested in is the main specification in which the EUE's mispricing effect is controlled for in Equations 3 and 4. When the interaction between EUE and MIS is included, the coefficient for the

Table 2.3 Fama-MacBeth and Panel Regressions of Excess Returns

This table reports Fama-MacBeth cross-sectional and panel predictive regressions of monthly excess returns in Equation (2.4). Variable definitions are listed in Appendix II. In Fama-MacBeth regressions, industry fixed effect is included, and standard errors are robust using Newey-West (1987) with 3 lags. In panel regressions, firm/industry and year fixed effects are included, and standard errors are double-clustered at the firm and the year levels. The slope coefficients are in percent and t-statistics are reported in parentheses. The sample period for the full specification is from December 1981 to December 2019, due to DISP availability. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Fama-MacBeth regressions				Panel B: Panel regressions							
	1	2	3	4	1		2		3		4	
EUE	-0.166***	-0.087**	0.454***	0.463***	0.005	-0.209**	0.033	-0.130	0.289*	0.475***	0.583***	0.620***
	(-3.47)	(-2.05)	(4.53)	(2.71)	(0.081)	(-2.066)	(0.538)	(-1.306)	(1.951)	(3.614)	(2.723)	(2.990)
MIS		-0.028***	-0.021***	-0.009***			-0.024***	-0.032***	-0.021***	-0.024***	-0.009	-0.019***
		(-8.92)	(-6.43)	(-3.07)			(-5.189)	(-7.870)	(-4.234)	(-5.564)	(-1.470)	(-3.649)
EUE*MIS			-0.010***	-0.009***					-0.005**	-0.011***	-0.007**	-0.012***
			(-6.18)	(-2.78)					(-2.226)	(-6.620)	(-2.124)	(-2.969)
β^{CAPM}				0.010							-0.151	-0.105
				(0.09)							(-0.699)	(-0.749)
DISP				-0.059							0.002	0.000
				(-0.96)							(0.528)	(0.011)
IVOL				-9.319**							39.997***	13.011
				(-2.55)							(2.746)	(1.061)
TO				0.015							-0.192***	-0.028
				(0.45)							(-3.396)	(-0.677)
SIZE				-0.000**							-0.000***	-0.000*
				(-2.29)							(-2.744)	(-1.868)
MOM				0.278*							-0.565**	-0.239
				(1.80)							(-2.615)	(-1.052)
REV				-3.430***							-1.989**	-0.727
				(-7.89)							(-2.209)	(-0.817)
BM				0.067							0.780***	0.210*
				(0.84)							(4.579)	(1.835)
ILLIQ				5.855							0.027	-0.078*
				(0.88)							(1.150)	(-1.965)
ROE				0.845**							-0.004	-0.004
				(2.22)							(-1.114)	(-1.375)
I/A				-0.207***							-0.289***	-0.199***
				(-3.37)							(-3.847)	(-3.664)
Constant	0.880***	2.237***	1.868***	1.288***	0.794***	0.937***	1.980***	2.469***	1.801***	2.042***	0.581	1.622***
	(3.85)	(13.42)	(11.96)	(7.25)	(18.761)	(13.466)	(8.346)	(11.205)	(7.084)	(8.851)	(1.649)	(4.525)

(Continued)

Table 2.3 – *Continued*

	Panel A: Fama-MacBeth regressions				Panel B: Panel regressions							
	1	2	3	4	1		2		3		4	
obs	1701548	1697868	1697868	612206	1701730	1702076	1697533	1697868	1698052	1698389	612055	612206
R-sq	0.047	0.053	0.054	0.134	0.029	0.013	0.029	0.015	0.029	0.015	0.034	0.014
Adj R-sq	0.043	0.049	0.049	0.116	0.019	0.013	0.020	0.015	0.020	0.015	0.022	0.014
Firm FE	N/A	N/A	N/A	N/A	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	N/A	N/A	N/A	N/A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm	N/A	N/A	N/A	N/A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year	N/A	N/A	N/A	N/A	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Interaction of EUE and MIS is negative. Higher EUE would amplify the negative mispricing effect that I observed in the benchmark MIS coefficient, which supports my mispricing hypothesis. Furthermore, when the mispricing effect is fully controlled for by the benchmark MIS and the interaction, the EUE coefficient is positive and significant (0.45%, $t = 4.53$). This captures the ambiguity-premium effect and supporting my hypothesis of a positive ambiguity premium once the EUE-induced mispricing effect is controlled for. The results are consistent after controlling for other firm-level characteristics and using alternative panel data estimation methods in Panel B.

2.4.4 Time Series Variation of Economic Uncertainty

In this section, I further examine whether time-varying economic uncertainty affects the cross-sectional mispricing and ambiguity premium. If EUE induces heterogeneous beliefs in the stock valuation, such effect is likely to be stronger following periods of increasing economic uncertainty. This is because such heterogenous beliefs are exacerbated in these periods.

To test this prediction, I divide the sample into two groups: month t is an increasing (decreasing) EU month if the change of the EU index in month t is positive (negative). There are 276 increasing and 318 decreasing EU months in my sample, respectively.

I obtain risk-adjusted returns following the increasing and decreasing EU periods by modifying my main model using two subperiod intercept dummies:

$$R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t$$
$$+ \beta_{p,4} UMD_t + \beta_{p,5} IA_t + \beta_{p,6} ROE_t + \varepsilon_{i,t} \quad (2.5)$$

where $R_{p,t}$ is the excess return of portfolio p in month t. $d_{H,t-1}$ and $d_{L,t-1}$ are dummy variable indicating increasing and decreasing EU periods, respectively. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors in month t. Table 2.4 reports risk-adjusted returns following increasing and decreasing EU periods in different EUE groups.

Consistent with the prediction, the EUE effect on mispricing is much stronger following periods of increasing EU in Panel A. The spread between underpriced and overpriced legs in the high EUE group is significant (1.12% per month, $t = 3.76$) after the increasing EU period. This is higher than the unconditional mispricing spread (0.44% per month, $t = 3.04$) following the same period. By contrast, as shown in Panel B, following the decreasing EU periods, the spread of mispricing portfolios in high EUE group is about half of that following the increasing EU periods. Additionally, the monotonic increasing pattern of returns with EUE is less clear.

Similarly, I show that the ambiguity-premium effect is only observable following periods with increasing uncertainty. The alpha of high-low EUE portfolios in the non-mispricing group is significant (0.44% per month, $t = 2.06$) which is higher than the whole sample period results shown in Table 2.2.

Overall, the subperiod analysis further confirms that increasing uncertainty is the main driver of the EUE effect on asset pricing. Practically, a mispricing investment strategy that is concentrated on only stocks in the highest EUE quintile and only invested following periods of increasing economic uncertainty would earn a risk-adjusted return of 13.44% per annum (1.12%×12) based on FF-6 factor-alpha. This is more than three times the unconditional mispricing strategy shown in Table 2.2. The ambiguity premium is also found to be higher following a period with increasing economic uncertainty. This suggests that economic uncertainty is indeed a driver for this ambiguity premium.

Table 2.4 Portfolio returns following increasing and decreasing EU periods

The table reports the risk-adjusted returns on 5 MIS (EUE) and 25 EUE-MIS value-weighted portfolios following increasing and decreasing EU periods in Panel A and B respectively. The 25 portfolios are formed by independently sorting on EUE and the mispricing scores. The mean of 5 MIS (EUE) portfolios is reported in Average MIS (EUE) column (row). The 5 MIS (EUE) portfolios are formed by sorting individual stocks on their mispricing scores (EUE), reported in univariate MIS (EUE) column (row). The risk-adjusted returns are estimates of alphas estimated in Equation (2.5). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2019. If the change of the EU index by Jurado, Ludvigson and Ng (2015) in month t-1 is positive (negative), then month t is increasing (decreasing)-EU month. There are 276 increasing and 318 decreasing EU months, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Low EUE	2	3	4	High EUE	High-Low	Average MIS	Univariate MIS
			Panel A: High EU Period					
1 Overpriced	-0.13	-0.12	-0.48***	-0.50***	-0.52***	-0.39*	-0.35***	-0.33***
	(-0.82)	(-0.74)	(-2.63)	(-2.92)	(-3.05)	(-1.71)	(-3.40)	(-2.95)
2	-0.15	0.21	-0.23	0.03	-0.11	0.048	-0.05	-0.03
	(-1.13)	(1.41)	(-1.61)	(0.18)	(-0.58)	(0.21)	(-0.76)	(-0.49)
3 Non-mispricing	-0.21	0.07	0.038	-0.04	0.24	0.44**	0.02	-0.04
	(-1.56)	(0.59)	(0.29)	(-0.25)	(1.24)	(2.06)	(0.32)	(-0.65)
4	0.06	-0.06	-0.21	-0.08	0.33	0.27	0.01	-0.05
	(0.60)	(-0.54)	(-1.60)	(-0.64)	(1.52)	(1.07)	(0.083)	(-0.83)
5 Underpriced	-0.01	0.22**	0.07	0.23	0.60***	0.61**	0.22***	0.11*
	(-0.06)	(2.10)	(0.59)	(1.52)	(2.72)	(2.55)	(3.44)	(1.82)
Underpriced−	0.12	0.34*	0.55**	0.73***	1.12***	1.00***	0.57***	0.44***
Overpriced	(0.60)	(1.70)	(2.34)	(3.34)	(3.76)	(2.99)	(4.13)	(3.04)
Average EUE	-0.09	0.07	-0.16**	-0.07	0.11	0.20		
	(-1.49)	(0.95)	(-2.12)	(-0.89)	(1.00)	(1.49)		
Univariate EUE	-0.027	0.09	-0.09	-0.01	0.18	0.21		
	(-0.49)	(1.53)	(-1.38)	(-0.13)	(1.56)	(1.48)		
			Panel B: Low EU Period					
1 Overpriced	0.06	-0.37**	-0.46***	-0.27	-0.36**	-0.42**	-0.28***	-0.24***
	(0.46)	(-2.46)	(-2.70)	(-1.58)	(-2.43)	(-2.18)	(-3.43)	(-2.92)
2	-0.13	0.07	-0.24*	0.16	-0.02	0.11	-0.03	-0.02
	(-1.24)	(0.55)	(-1.71)	(1.09)	(-0.14)	(0.63)	(-0.53)	(-0.31)
3 Non-mispricing	-0.02	0.11	0.02	0.03	0.24	0.26	0.08	0.05
	(-0.19)	(0.92)	(0.17)	(0.22)	(1.40)	(1.22)	(1.40)	(0.96)
4	0.02	0.10	-0.02	0.08	0.24	0.21	0.09	0.06
	(0.25)	(1.03)	(-0.18)	(0.73)	(1.43)	(1.02)	(1.64)	(1.18)
5 Underpriced	0.02	-0.01	-0.05	-0.11	0.05	0.03	-0.02	-0.01
	(0.19)	(-0.12)	(-0.54)	(-0.90)	(0.24)	(0.12)	(-0.38)	(-0.24)
Underpriced−	-0.04	0.36**	0.41*	0.16	0.41*	0.45	0.26**	0.23**
Overpriced	(-0.22)	(2.06)	(1.91)	(0.78)	(1.71)	(1.57)	(2.34)	(2.13)
Average EUE	-0.01	-0.02	-0.15**	-0.02	0.03	0.04		
	(-0.22)	(-0.37)	(-2.49)	(-0.33)	(0.29)	(0.32)		
	0.02	0.05	-0.11**	0.02	0.01	-0.09		
Univariate EUE	(0.47)	(0.95)	(-2.00)	(0.33)	(0.13)	(-0.07)		

2.5 Further Analyses

In this section, I provide further analyses to examine links between the EUE and cross-sectional returns and further identify the two channels of impacts.

I first consider the rational channel. I examine to what extent the existing cross-sectional risk model can explain these two types of EUE effect. I then extend my empirical study to consider alternative macro uncertainty measures to understand the source of information of my EUE measure. Finally, I study these two channels controlling for limits of arbitrage.

2.5.1 Can Alternative Risk Models Explain Two Channels of EUE Effect?

If the real pricing process is driven by a multifactor risk model, to obtain a clear inference of a new factor, one needs to control for known factors. With the gradual development of the multifactor model literature adding more and more risk factors to the list, I would like to understand what the marginal contribution is of bringing the EUE into the consideration in the cross-sectional asset pricing. To this end, I examine the robustness of my findings with alternative risk models.

In my main results in Table 2.2, I use an augmented FF six-factor model defined in Equation (2.3). Panel A of Table 2.5 reports risk-adjusted returns on the selected EUE-MIS portfolios with the market model and two alternative versions of the augmented FF factor models. It shows that both mispricing and ambiguity-premium effects are robust to these risk model specifications in Panel A. The mispricing alphas are statistically significant, ranging from 0.50% to 1.05% per month in the high EUE group. Except for the CAPM model, these alphas are larger than the unconditional mispricing return. The ambiguity premium decreases as more factors are included.

In addition to FF models, I also consider the q-factor (Hou, Xue, and Zhang, 2015; Hou et al., 2020) and the MSP models (Stambaugh and Yuan, 2017).[27] The results are reported in Panel B.

The effect of EUE on the mispricing is significant when using the q4 and MSP models. The monthly alpha of the "Underpriced−Overpriced" portfolio in the high EUE portfolio is 0.80% ($t = 3.41$) for the q4 model and 0.38% ($t = 2.10$) for the MSP model. The exception is when the q5 model is considered. It can fully account for the mispricing effects as indicated by the insignificant alpha of the Underpriced−Overpriced portfolio in the high EUE group. This reveals more insights into the economic driver of the EUE mispricing effect. In the q5 model, Hou et al. (2020) introduce intangibles investments as a part of the expected growth factor. They show that this model can capture mispricing in various anomalies successfully when compared to the q4 and MSP models. The fact that adding this additional factor takes away the EUE-induced mispricing effect suggests that EUE shares similar economic drivers with the expected growth factor. Potentially, EU is a state variable that affects future consumption and investment opportunities/decisions.

Importantly, EUE ambiguity premiums in non-mispricing groups are strong in all models. Alphas on "high-low" portfolios constructed on EUE in the third mispricing groups are significant, 0.44% per month ($t = 1.94$), 0.47% per month ($t = 2.35$) and 0.42% per month ($t = 3.04$) in the q4, q5, and MSP models, respectively.

[27] See Appendix II for a detailed description of the factors. The monthly value of the mispricing up to December 2016 and the q-factors are from http://finance.wharton.upenn.edu/~stambaug/ and http://global-q.org/factors.html, respectively.

Table 2.5 Effect of Different Risk Models

This table reports the risk-adjusted returns on overpriced, underpriced, and non-mispricing double-sort portfolios. The portfolios are formed by independently sorting on EUE and the mispricing scores. The univariate MIS (EUE) portfolios is reported in univariate MIS (EUE) column (row). The risk-adjusted returns are estimates of alphas from the following models:

$CAPM$: $R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \varepsilon_{i,t}$

$FF5$: $R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}IA_t + \beta_{p,5}ROE_t + \varepsilon_{i,t}$,

$FF7$: $R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}UMD_t + \beta_{p,5}IA_t + \beta_{p,6}ROE_t + \beta_{p,7}LIQ_t + \varepsilon_{i,t}$

$q4$: $R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \beta_{p,2}QSMB_t + \beta_{p,3}QIA_t + \beta_{p,4}QROE_t + \varepsilon_{i,t}$

$q5$: $R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \beta_{p,2}QSMB_t + \beta_{p,3}QIA_t + \beta_{p,4}QROE_t + \beta_{p,5}QEG_t + \varepsilon_{i,t}$

MSP : $R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \beta_{p,2}MSMB_t + \beta_{p,3}MGMT_t + \beta_{p,4}PERF_t + \varepsilon_{i,t}$

$R_{p,t}$ is the excess return of portfolio p in month t and $\alpha_{p,1}$ is adjusted return in percent. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors and LIQ_t is the level of aggregate market liquidity in month *t*.. $QSMB_t$, QIA_t, $QROE_t$ and QEG_t are Hou, Xue and Zhang (2015) and Hou et al. (2020) q-factors in month t. $MSMB_t$ $MGMT_t$, and $PERF_t$ are Stambaugh and Yuan (2017) mispricing factors in month t. Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2016 for MSP and. to December 2019 for the other models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Low	High	H-L	Uni MIS	Low	High	H-L	Uni MIS	Low	High	H-L	Uni MIS
	Panel A: CAPM and Fama French models											
	CAPM				FF5				FF7			
1 Overpriced	-0.15	-0.45***	-0.30*	-0.62***	-0.22*	-0.58***	-0.37**	-0.47***	-0.04	-0.33***	-0.29	-0.24***
	(-1.14)	(-3.80)	(-1.89)	(-6.57)	(-1.82)	(-4.32)	(-2.46)	(-4.66)	(-0.32)	(-2.68)	(-1.62)	(-3.12)
3 Non-mispricing	-0.13	0.31*	0.44**	-0.00	-0.14*	0.31**	0.45***	-0.01	-0.09	0.24	0.34*	0.01
	(-1.28)	(1.75)	(1.97)	(-0.10)	(-1.76)	(2.12)	(2.61)	(-0.32)	(-0.95)	(1.62)	(1.76)	(0.35)
5 Underpriced	0.02	0.34*	0.32*	0.24***	0.07	0.46***	0.40**	0.12***	-0.03	0.17	0.20	0.01
	(0.27)	(1.88)	(1.65)	(4.83)	(0.91)	(2.75)	(2.27)	(2.65)	(-0.36)	(1.13)	(1.19)	(0.28)
Underpriced−	0.17	0.80***	0.62***	0.87***	0.28*	1.05***	0.76***	0.59***	0.01	0.50**	0.49**	0.25***
Overpriced	(1.01)	(3.41)	(2.65)	(6.59)	(1.80)	(4.29)	(3.25)	(4.47)	(0.08)	(2.58)	(2.03)	(2.61)
Univariate EUE	0.10**	-0.15	-0.24*		-0.01	0.13	0.14		-0.01	0.06	0.07	
	(2.02)	(-1.33)	(-1.67)		(-0.26)	(1.43)	(1.29)		(-0.13)	(0.75)	(0.65)	

(Continued)

Table 2.5 – *Continued*

	Low	High	H-L	Uni MIS	Low	High	H-L	Uni MIS	Low	High	H-L	Uni MIS
Panel B: Investment Based q and Mispricing models												
	q4				q5				MSP			
1 Overpriced	-0.15	-0.45***	-0.30*	-0.38***	-0.05	-0.17	-0.12	-0.11	0.12	-0.21*	-0.33*	-0.07
	(-1.14)	(-3.80)	(-1.89)	(-3.24)	(-0.40)	(-1.30)	(-0.70)	(-1.06)	(1.11)	(-1.76)	(-1.93)	(-1.20)
3 Non-mispricing	-0.13	0.31*	0.44**	0.01	-0.07	0.40**	0.47**	0.10**	-0.07	0.36**	0.42**	0.06
	(-1.28)	(1.75)	(1.97)	(0.14)	(-0.68)	(2.39)	(2.25)	(2.21)	(-0.65)	(2.58)	(2.46)	(1.24)
5 Underpriced	0.02	0.34*	0.32*	0.07	-0.19**	0.06	0.25	-0.13***	-0.15*	0.17	0.32*	-0.08**
	(0.27)	(1.88)	(1.65)	(1.29)	(-2.25)	(0.35)	(1.23)	(-2.65)	(-1.87)	(1.12)	(1.70)	(-2.25)
Underpriced−	0.17	0.80***	0.62***	0.45***	-0.14	0.23	0.37	-0.02	-0.26*	0.38**	0.64***	-0.01
Overpriced	(1.01)	(3.41)	(2.65)	(2.90)	(-0.83)	(1.10)	(1.55)	(-0.14)	(-1.91)	(2.10)	(2.70)	(-0.16)
Univariate EUE	-0.00	0.14	0.14		-0.06	0.21*	0.27**		-0.05	0.18**	0.23**	
	(-0.03)	(1.21)	(1.00)		(-1.33)	(1.90)	(1.99)		(-1.13)	(2.05)	(2.00)	

Collectively, results obtained when using alternative risk models reveal further insights regarding the two channels of the EUE effect. In general, when a given risk model cannot explain the unconditional mispricing, EUE's amplification of the mispricing effect would also be more apparent. EUE's influence on known mispricing anomalies is weakened as more elaborated multifactor models are used as a benchmark model in general. This suggests that the EUE-induced mispricing effects are partly correlated with the underlying economic drivers of those risk factors. By contrast, the ambiguity-premium effect of EUE remains strong when other risk premiums are controlled with more elaborated risk models. In fact, the largest ambiguity premium comes from the q5 model when the mispricing effect is fully explained. This demonstrates the robustness of the EUE-induced ambiguity premium as a new factor that is different from existing risk and mispricing factors.

2.5.2 Does the Measure of Uncertainty Matter?

Previous studies have used different proxies for economic uncertainty, including the Survey of Professional Forecasters (for example, D'Amico and Orphanides, 2008; Glas and Hartman, 2016; Li, 2016), VRP (Bali and Zhou, 2016), and the JLN measure (Bali, Brown, and Tang, 2017). Mixed findings in the previous literature may be due to the choice of proxies. To verify if my findings are unique due to the use of the JLN uncertainty measure, I provide a unified study to compare the difference among these measures.

For analysis using macro forecasters' dispersions, following Li (2016), I consider dispersion in various economic forecasts including GDP, industrial production (INPR), and nonresidential fixed investment (RNRSN) at the growth rates, and unemployment rate (UNEM), Treasury-bill (TBILL), and inflation rate (CPI). The cross-sectional forecast dispersions are measured as the difference between the 75th percentile and 25th percentile of quarterly forecasts from the Survey of Professional Forecasters (SPF) database.[28] I estimate quarterly macro-disagreement beta for each measure separately from a 20-quarter rolling regression for each stock with the model specified in Equation (2.2) by replacing ΔUNC_t with the log changes of these macro-dispersion proxies. Similar to the main analysis, I measure the exposure to these macro-dispersions by the absolute value of beta (hereafter ADSM). Since this measure is updated quarterly, the same beta from the prior quarter-end is used to form the monthly portfolios in each quarter. Finally, the 25 ADSM-MIS portfolios are formed as intersections of five ADSM-beta and the five MIS groups, and value-weighted portfolio returns are calculated.

The results in Table 2.6 provide additional evidence to support my main findings that EU measured by macro-disagreement amplifies mispricing of the anomalies. The alphas of the "Underpriced−Overpriced" portfolios in the high ADSM quintiles are statistically positive for all dispersion measures, ranging from 0.56% to 0.84% per month. These results suggest that my findings regarding the amplification effect are not specific to a particular uncertainty measure. However, the ambiguity-premium effect is less observable in the non-mispricing group when using these proxies,[29] and it only exists when using the dispersion of growth in GDP forecast. The alpha of the "high-low" portfolio constructed on ADSM^{GDP} beta is significant (0.34% per month, $t = 2.28$). This suggests that exposure to the uncertainty of GDP is one of the most important sources of ambiguity for which investors demand a premium.

[28] https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters . To form each of those macro-disagreement proxies, I take the mean value of the available forecast dispersion at all forecast horizons (Li, 2016).

[29] Similarly, the unconditional effect of these macro-disagreement exposures is not observable with the exception of using the TBILL dispersion. This is consistent with Li (2016), who fails to find the unconditional pricing effect.

Table 2.6 Source of Uncertainty I: Macro-disagreement measured by the Survey of Professional Forecasters

This table reports the risk-adjusted returns on overpriced, underpriced, and non-mispricing double-sort portfolios. Those macro-disagreement variables are forecast dispersion in the unemployment rate (UNEM), growth in GDP, industrial production (INPR), nonresidential fixed investment (RNRSN), the level of Treasury-bill (TBILL) and inflation rate (CPI). The portfolios are formed by independently sorting on the absolute value of macro-disagreement (ADSM) betas and the mispricing score. The univariate ADSM (MIS) portfolios are reported in the Univariate ADSM (MIS) row (column). The risk-adjusted returns are estimates of alphas estimated in Equation (2.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from January 1974 for UNEM, GDP and INPR, and from October 1986 for RNRSN, TBILL, and CPI to December 2019. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Low $ADSM^{GDP}$	High $ADSM^{GDP}$	High – Low	Low $ADSM^{INPR}$	High $ADSM^{INPR}$	High – Low	Low $ADSM^{UNEM}$	High $ADSM^{UNEM}$	High – Low	Univariate MIS
1 Overpriced	-0.23	-0.37***	-0.15	-0.11	-0.25**	-0.15	0.02	-0.55***	-0.57***	-0.29***
	(-1.62)	(-3.12)	(-0.79)	(-0.88)	(-2.16)	(-0.82)	(0.16)	(-4.05)	(-2.82)	(-3.80)
3 Non-mispricing	-0.17*	0.18	0.34**	-0.14	0.10	0.24	-0.17	-0.07	0.10	-0.01
	(-1.79)	(1.50)	(2.28)	(-1.43)	(0.85)	(1.51)	(-1.63)	(-0.55)	(0.58)	(-0.21)
5 Underpriced	0.02	0.19	0.17	0.03	0.51***	0.48***	-0.01	0.30*	0.31*	0.04
	(0.20)	(1.30)	(0.91)	(0.30)	(3.28)	(2.90)	(-0.17)	(1.91)	(1.75)	(1.04)
Underpriced−	0.25	0.56***	0.31	0.13	0.76***	0.63***	-0.03	0.84***	0.88***	0.34***
Overpriced	(1.47)	(3.11)	(1.36)	(0.94)	(3.76)	(2.60)	(-0.22)	(4.16)	(3.43)	(3.47)
Univariate	-0.03	-0.00	0.02	-0.03	0.14*	0.16*	-0.02	0.06	0.08	
	(-0.78)	(-0.06)	(0.24)	(-0.66)	(1.84)	(1.79)	(-0.37)	(0.69)	(0.71)	
	Low $ADSM^{TBILL}$	High $ADSM^{TBILL}$	High – Low	Low $ADSM^{RNRSN}$	High $ADSM^{RNRSN}$	High – Low	Low $ADSM^{CPI}$	High $ADSM^{CPI}$	High – Low	
1 Overpriced	-0.18	-0.40**	-0.22	-0.18	-0.24	-0.06	0.19	-0.43**	-0.25	-0.35***
	(-1.33)	(-2.44)	(-1.04)	(-1.24)	(-1.56)	(-0.29)	(-1.33)	(-2.35)	(-1.07)	(-3.81)
3 Non-mispricing	0.03	-0.17	-0.19	-0.11	-0.03	0.08	-0.19	-0.07	0.12	0.03
	(0.25)	(-1.08)	(-1.07)	(-0.93)	(-0.18)	(0.39)	(-1.16)	(-0.55)	(0.50)	(0.64)
5 Underpriced	-0.01	0.43**	0.44*	0.15	0.41***	0.26	-0.03	0.38**	0.41**	-0.00
	(-0.12)	(2.25)	(1.87)	(1.37)	(2.91)	(1.40)	(-0.33)	(2.15)	(1.98)	(-0.12)
Underpriced−	0.17	0.83***	0.66**	0.33*	0.65***	0.32	0.16	0.81***	0.65**	0.35***
Overpriced	(0.94)	(3.25)	(2.01)	(1.84)	(2.87)	(1.09)	(0.98)	(3.16)	(2.23)	(3.14)
Univariate	-0.01	0.09	0.10	0.00	0.07	0.07	-0.03	0.10	0.13	
	(-0.31)	(0.96)	(0.87)	(0.03)	(0.92)	(0.72)	(-0.52)	(1.02)	(0.98)	

Table 2.7 Source of Uncertainty II: Macro-disagreement measured by the Survey of Professional Forecasters

This table reports the risk-adjusted returns on 25 EPUE/VRE/ADE-MIS value-weighted portfolios. The 25 portfolios are formed by independently sorting on EPUE/VRE/ADE betas and the mispricing score. The univariate 5 EPUE/VRE/ADE (MIS) portfolios are reported in the univariate row (column). The risk-adjusted returns are estimates of alphas estimated in Equation (2.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from January 1990 for EPUE, January 1995 for VRE, and from March 1998 for ADE to December 2019. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Economic Policy Uncertainty Index				Variance Risk Factor				Ambiguity Degree Index			
	Low EPUE	High EPUE	High-Low	Univariate MIS	Low VRE	High VRE	High-Low	Univariate MIS	Low ADE	High ADE	High-Low	Univariate MIS
1 Overpriced	-0.17	-0.30*	-0.12	-0.36***	-0.27	-0.48***	-0.22	-0.40***	-0.38*	-0.73***	-0.35	-0.42***
	(-1.11)	(-1.95)	(-0.58)	(-3.58)	(-1.57)	(-2.69)	(-0.91)	(-3.49)	(-1.71)	(-3.38)	(-1.16)	(-3.42)
3 Non-mispricing	0.11	0.52***	0.41*	0.03	-0.05	0.30	0.35	0.02	0.03	0.29*	0.26	0.05
	(0.99)	(2.92)	(1.92)	(0.63)	(-0.39)	(1.43)	(1.36)	(0.34)	(0.19)	(1.68)	(1.05)	(0.80)
5 Underpriced	-0.02	0.34*	0.36*	0.00	-0.08	0.29	0.36	0.02	-0.02	-0.03	-0.01	0.02
	(-0.20)	(1.81)	(1.68)	(0.01)	(-0.80)	(1.55)	(1.56)	(0.47)	(-0.28)	(-0.24)	(-0.05)	(0.31)
Underpriced−Overpriced	0.16	0.64**	0.48	0.36***	0.19	0.77***	0.58**	0.42***	0.36	0.70***	0.34	0.44***
	(0.84)	(2.49)	(1.50)	(3.00)	(1.02)	(3.44)	(2.00)	(3.10)	(1.48)	(2.78)	(1.09)	(2.99)
Univariate	0.01	0.28***	0.27**		-0.02	0.13	0.15		-0.03	0.03	0.06	
	(0.14)	(3.09)	(2.58)		(-0.33)	(1.26)	(1.18)		(-0.60)	(0.31)	(0.47)	

In addition to the dispersion of these macro forecasts, Baker, Bloom, and Davis (2016) develop an index of economic policy uncertainty (EPU) based on newspaper coverage frequency, and demonstrate its relevance to firm-level volatility, investment, and innovations.[30] Bali and Zhou (2016) study the VRP as a proxy for economic uncertainty.[31] Brenner and Izhakian (2018) measure the degree of ambiguity by the volatility of probabilities of outcomes abstracted from high-frequency S&P 500 derivative data.[32] I repeat the same analyses with these three uncertainty proxies. As in my EUE estimation, I estimate these uncertainty exposure betas from a 60-month rolling regression for each stock by replacing ΔUNC_t with the log changes of the EPU index, variance risk factor, or the log change of ambiguity degree index in Equation (2.2).[33] I collect the absolute value of monthly estimated EPU exposure (EPUE), variance risk exposure (VRE), and ambiguity degree exposure (ADE) for each stock. Then, I form 25 independent double-sorted EPUE/VRE/ADE-MIS portfolios.

Table 2.7 reports the main findings. Similar to my finding in Table 2.6, using these alternative uncertainty measures reproduces the mispricing effect but less of the ambiguity-premium effect. Among these three, the VRE captures the strongest mispricing effects, but it is smaller than that in my main result. For the ambiguity premium, no evidence of it is found in VRE or ADE.[34] However, there is evidence of the high EPUE that has a

[30] The monthly economic policy uncertainty index is taken from: https://www.policyuncertainty.com/.
[31] They define the variance risk premium factor as "the difference between expected variance under the risk-neutral measure and expected variance under the objective measure in the U.S. equity market." The monthly factor is taken from Zhou's website: https://sites.google.com/site/haozhoupersonalhomepage/
[32] I am grateful to Yud Izhakian for sharing his ambiguity index data.
[33] Since the variance risk premium factor itself is a risk factor that measures innovation in the variance risk premium series, I do not record a difference like other macroeconomic uncertainty proxies.
[34] This finding of the absence of an overall ambiguity premium is consistent with Brenner and Izhakian (2018), who show that an ambiguity premium is contingent on the expected probability of the positive and negative outcomes. I show that aggregate ambiguity will have an asymmetric effect on stocks that are subject to over- and underpricing, which complements their findings. However, it poses a question on the risk interpretation of the return effect their measure captures. Their ambiguity measure is different from the macroeconomic uncertainty measure I use. Their measure's measurement is a probability-based measure that relies on market data to capture the volatility in the probability. What drives the underlying ambiguity is not specified under

significant positive alpha, and the high-low EPUE produces a 0.41% monthly ambiguity premium ($t = 1.92$).

Collectively, these further tests highlight the advantage of using a comprehensive and aggregated economic uncertainty measure, such as the JLN series, which can capture both an ambiguity premium and mispricing effects. While the mispricing effect is robust to all alternative uncertainty measures, a pure ambiguity premium can only be observed by using JLN's aggregated economic uncertainty measure, the dispersion of analysts' forecasts for GDP, and the EPU index. It suggests that the source of ambiguity from the uncertainty of GDP and economic policy are the key determinants of ambiguity aversion in asset pricing.

2.5.3 Does Economic Uncertainty Lead to Disagreement?

I build my hypotheses on the assumption that high EUE leads to high disagreement on valuation, which amplifies mispricing (with short-sale constraints) and induces a risk premium due to ambiguity aversion. Therefore, I would expect that EUE would have a direct impact on traditional disagreement measures such as volume (Hong and Stein, 2007), idiosyncratic volatility (Stambaugh, Yu, and Yuan, 2015) and analysts' forecast dispersions (Diether, Malloy, and Scherbina, 2002). I test the effect of firm-level EUE on individual stocks' disagreement variables by firm-level panel regressions in Table 2.8.

The results in Table 2.8 show that EUE can positively predict next-period stock-level disagreements proxied by each of those three variables, even after control for their

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such empirical measure. This is possibly the reason that even controlling for mispricing, their measure still does not carry a significant premium.

own lagged terms and other time-varying firm characteristics. Consistent with my conjecture, the higher the EUE for a stock, the larger the divergence of opinion, providing

Table 2.8 Economic Uncertainty Exposure and Firm-Level Disagreements

This table reports panel predictive regressions of firm-level disagreement and EUE using the following model;

$$Y_{p,t} = \lambda_0 + \lambda_1 EUE_{p,t-1} + \sum_{J=2}^{n} \lambda_j X_{p,t-1} + Fixed\ Effects + \varepsilon_{i,t}$$

where $Y_{p,t}$ is one of the disagreement variables for stock p in month t, such as DISP, IVOL, TO, and EUE. $X_{p,t-1}$ is a set of stock-specific variables in month $t-1$ for stock p, including those disagreement variables, SIZE, MOM, REV, BM, ILLIQ. Variable definitions are listed in Appendix II. Firm and year fixed effects are included in the model to control for heterogeneity across firms and the influence of time series. Standard errors are double-clustered at the firm and the year levels. The slope coefficients are in percent and t-statistics are reported in parentheses. The sample period is from December 1981 to December 2019, due to DISP availability. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DISP	IVOL	TO	EUE
EUE	0.019***	0.001***	0.069***	0.909***
	(2.926)	(12.499)	(7.378)	(116.122)
DISP	0.330***	0.000***	0.002***	0.000
	(8.578)	(3.162)	(4.804)	(0.694)
IVOL	1.302***	0.235***	-11.650***	0.273***
	(3.255)	(17.432)	(-7.692)	(3.431)
TO	0.008*	0.000	0.615***	0.001
	(1.765)	(1.092)	(32.458)	(1.365)
SIZE	-0.000	-0.000***	-0.000***	-0.000
	(-1.239)	(-3.043)	(-7.001)	(-1.158)
MOM	-0.038***	-0.000	0.131***	0.004***
	(-3.194)	(-0.617)	(4.280)	(3.641)
REV	-0.022	-0.009***	-0.135*	-0.018**
	(-1.160)	(-10.725)	(-1.945)	(-2.542)
BM	0.014**	0.000	-0.011**	0.000
	(2.408)	(0.911)	(-2.082)	(0.834)
ILLIQ	0.001	0.000**	0.011**	-0.001**
	(0.528)	(2.630)	(2.603)	(-2.055)
Constant	0.184***	0.014***	0.766***	0.049***
	(10.291)	(55.745)	(27.564)	(8.644)
Observation	630173	630190	630150	630190
R-sq	0.152	0.473	0.683	0.931
Adj R-sq	0.142	0.466	0.679	0.930
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes

support for dynamic models documented in Harrison and Kreps (1978) and Hong and Sraer (2016).[35] By contrast, only idiosyncratic volatility can positively predict next-period

[35] Consistent results can also be found in the double-sort portfolios. In Table A-I.3 of Appendix I, stocks with high EU exposure tend to have higher turnover, high idiosyncratic volatility, and analyst earnings forecast dispersion, showing that those assets are difficult to value and subject to a high level of disagreement.

firm-level exposure to economic uncertainty. This suggests that IVOL captures firm-specific factors that are relevant to stocks' exposures to macro uncertainty.[36]

2.5.4 Limits of Arbitrage and Mispricing

There is a positive relation between IVOL and mispricing in anomalies as shown by Stambaugh, Yu, and Yuan (2015). IVOL deters arbitrageurs from correcting mispricing, resulting in high levels of mispricing among stocks with high IVOL. Furthermore, they show that short-sale constraints induce arbitrage asymmetry and make the effect of IVOL on overpricing much stronger than that on underpricing. Both IVOL and EUE-induced mispricing effects are built on similar key arguments such as disagreement, short-sale constraints, and limits of arbitrage. The causality analyses in the previous section further confirm the interlinks between these two firm-level measures. Can the EUE mispricing effect simply be a reflection of the IVOL effect? To unravel the effect of IVOL from that of EUE on mispricing, I extend my main analyses of double-sorting to three dimensions. I form 50 portfolios by independently sorting stocks into two IVOL, five EUE, and five MIS groups.

Table 2.9 reports risk-adjusted returns on 25 value-weighted EUE-MIS portfolios for low and high IVOL groups in Panels A and B, respectively. Consistent with findings in existing literature, mispricing is stronger in stocks with a higher idiosyncratic risk. In fact, the univariate mispricing effect is only significant in the high IVOL group. My focus is to

[36] At the market level, I expect that high EU is likely to induce more disagreement and hence more trading volume (Hong and Stein, 2007). To test this, I run a time series causality regression between the change of aggregate turnover in the S&P 500 index and change of EU for the sample period between July 1965 and December 2019. I find that innovations in the EU index can positively predict the next period change of the aggregate turnover at a 5% significance level, but no evidence for the reverse causality. See results in Table A-I.4 of Appendix I.

Table 2.9 Triple Sorts on IVOL, EUE, and MIS

This table reports risk-adjusted returns on 50 value-weighted portfolios formed by sorting independently stocks on the two IVOL, 5 EUE, and 5 MIS groups. The 5 MIS (EUE) portfolios are formed by sorting individual stocks on their mispricing scores (EUE), reported in univariate MIS (EUE) column (row) for each IVOL group. The results among low and high IVOL groups are reported in Panel A and Panel B, respectively. The risk-adjusted returns are estimates of alphas estimated in Equation (2.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2019. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Low EUE	2	3	4	High EUE	High-Low	Univariate MIS
			Panel A: Low IVOL				
Overpriced	0.02	-0.17	-0.40***	-0.28**	-0.41**	-0.42**	-0.11
	(0.15)	(-1.46)	(-3.00)	(-1.98)	(-2.28)	(-2.18)	(-1.50)
2	-0.11	0.04	-0.25**	0.04	-0.36**	-0.25	-0.08
	(-1.10)	(0.43)	(-1.99)	(0.32)	(-2.37)	(-1.42)	(-1.21)
3 Non-	-0.14	0.09	-0.13	-0.13	0.35	0.49**	0.01
mispricing	(-1.46)	(0.88)	(-1.42)	(-1.02)	(1.63)	(2.07)	(0.12)
4	0.05	0.01	-0.04	-0.06	0.25	0.20	0.00
	(0.69)	(0.09)	(-0.45)	(-0.52)	(1.64)	(1.07)	(0.01)
Underpriced	-0.05	0.11*	-0.00	-0.05	0.25	0.30*	0.01
	(-0.69)	(1.68)	(-0.05)	(-0.47)	(1.50)	(1.70)	(0.19)
Underpriced−	-0.07	0.28**	0.39***	0.23	0.66***	0.72***	0.12
Overpriced	(-0.53)	(2.03)	(2.75)	(1.38)	(2.76)	(2.73)	(1.33)
Univariate	-0.03	0.10*	-0.08	-0.06	0.00	0.03	
EUE	(-0.57)	(1.70)	(-1.52)	(-0.85)	(0.03)	(0.36)	
			Panel B: High IVOL				
Overpriced	-0.40**	-0.72***	-0.72***	-0.53***	-0.52***	-0.12	-0.67***
	(-2.29)	(-4.53)	(-3.55)	(-3.21)	(-3.99)	(-0.60)	(-6.31)
2	-0.22	-0.04	-0.27	0.01	0.02	0.23	-0.22**
	(-1.21)	(-0.22)	(-1.65)	(0.06)	(0.11)	(1.03)	(-2.21)
3 Non-	-0.04	0.09	0.19	-0.04	0.05	0.09	-0.00
mispricing	(-0.25)	(0.49)	(1.23)	(-0.22)	(0.31)	(0.41)	(-0.02)
4	0.32*	0.00	-0.16	0.13	0.13	-0.20	-0.02
	(1.68)	(0.00)	(-0.85)	(0.92)	(0.71)	(-0.78)	(-0.16)
Underpriced	0.44**	0.06	0.17	0.34**	0.37*	-0.07	0.30***
	(2.47)	(0.34)	(1.25)	(2.02)	(1.89)	(-0.30)	(3.26)
Underpriced−	0.83***	0.78***	0.89***	0.87***	0.89***	0.05	0.97***
Overpriced	(3.20)	(3.27)	(3.53)	(3.71)	(3.82)	(0.17)	(7.05)
Univariate	-0.01	-0.11	0.02	0.01	-0.11	-0.10	
EUE	(-0.12)	(-1.10)	(0.16)	(0.07)	(-1.06)	(-0.77)	

understand the EUE effect after controlling for IVOL. Among stocks with low IVOL in Panel A, the monthly alpha of the "Underpriced−Overpriced" portfolio in the high EUE quintile is significant (0.66%, $t = 2.76$), which is more than five times of the insignificant univariate mispricing effect (monthly alpha of 0.12%, $t = 1.33$). The ambiguity premium is also strongly presented in this group of stocks. The monthly premium of 0.49% (that is, 5.88% per annum, $t = 2.07$) is higher than the premium for the full sample reported in Table 2.2 (that is, 4.2% per annum).

For stocks with high IVOL in Panel B, mispricing is much stronger in general and presented in every EUE group. However, there is no significant difference among the EUE quintiles, suggesting that EUE plays little role in affecting the level of mispricing in this high IVOL group. Furthermore, there is no ambiguity premium either.

Overall, these findings show that EUE and IVOL are two different sources of friction that induce mispricing. The effect of EUE on mispricing is more prominent in the group with low IVOL, where traditionally the mispricing effect is weak as arbitrage friction is low. From the limits of arbitrage point of view, I uncover EUE as a source of arbitrage friction that is not captured by the IVOL. Furthermore, consistent with findings in previous sections, the ambiguity-premium effect is stronger when the overall unconditional mispricing effect is weak. I find that the ambiguity-premium effect is strong in the group of stocks with low arbitrage friction, further confirming its nature of "risk" premium instead of another mispricing factor.[37]

2.5.5 Other Considerations

Bali, Brown, and Tang (2017) study the effect of economic uncertainty on cross-sectional return with a similar setting to this study. I extend their works in several ways. First, methodologically I make one important modification in their empirical setting. Instead of

[37] I also examine the effect of EU on mispricing considering other proxies for limits of arbitrage and short-sale constraints such as institutional ownership (Nagel, 2005) and size (Lee, Shleifer, and Thaler, 1991) reported in Table A-I.6 of Appendix I. In particular, the EUE mispricing effects are significant in both subsamples with high and low limits of arbitrage measures; and are slightly more pronounced in the samples with a higher level of limits to arbitrage (i.e., fewer institutional investors and smaller in size). Consistent with our main finding in this section, the ambiguity premium effects are only found in the subsample where there is lower level of mispricing given a lower limit of arbitrage (for example, more institutional ownership and larger in size).

using the level of economic uncertainty, I use the changes of economic uncertainty as the level is very persistent. The use of the change makes it more suitable to capture unexpected innovations in the uncertainty with a close-to-zero expectation, which is an important requirement of pricing factors in the context of arbitrage pricing theory (for example, Merton, 1973; Ross, 1976; Chen, Roll, and Ross, 1986). This research design is also adopted by a more recent study by Bali, Subrahmanyam, and Wen (2020), who study macroeconomic uncertainty in the bond market. Second, building on theoretical studies such as Hong and Sarer (2016), I measure the exposures with the absolute value of the beta coefficient that capture the nature of non-directional uncertainty. In Table A-I.5 of Appendix I, I show the benefit of using absolute EUE, which enables us to capture the ambiguity premium and the mispricing effect more clearly in the line with theoretical arguments. Particularly, it demonstrates a symmetric impact of the most negative and most positive EU betas on mispricing. The analysis confirms that using the absolute value of the coefficient would simplify the interpretation of results and enable us to identify the ambiguity premium that would not be able to be observed when using the raw signed coefficients.

Another consideration is the long-term predictive power of the EUE on both effects. In Table A-I.7 of Appendix I, I show that in the FF6 model the EUE mispricing effect persists in five future months (the alphas of each of the next 12 months are studied). The ambiguity premium does not show persistence at all. By contrast, when the mispricing is accounted for by models such as q5, there is little sign of mispricing but a strong presence of the ambiguity premium up to 11 future months in Table A-I.7 and Figure A-I.1. These analyses further confirm that EUE's role in mispricing is mainly amplifying the existing mispricing, which can be explained by more elaborated asset-pricing models. However, the ambiguity-premium effect is strong and clearly quantifiable when mispricing effects are fully controlled for.

2.6 Conclusion

This study revisits the role of economic uncertainty in cross-sectional asset pricing. I unify two main channels of the impact, ambiguity premium, and mispricing, in a framework of cross-sectional analyses. The foundation of my conjecture is to recognize heterogeneity among investors. Economic uncertainty would affect some investors' demand for compensation of ambiguity aversion and also other investors' biases in evaluating firm characteristics in cross-sectional pricing. Empirically, I separate these two effects by interacting EUE with an aggregate mispricing measure of Stambaugh, Yu, and Yuan (2012; 2015).

This study shows that the observed EUE effect will not simply be positive or negative but depend on the combination of demand for an ambiguity premium and the stocks' other mispricing characteristics. This evidence could be a starting point for further theoretical development of a unified risk premium and mispricing model. The robustness of my finding of a positive ambiguity premium suggests that EUE is a good candidate as an additional risk factor, which can be used to explain and predict cross-sectional stock returns. My findings also have direct practical implications on the attribution of return-on-investment strategies.

2.7 Appendix I: Additional Results

Table A-I.1 Correlations

This table reports correlation coefficients among risk factors used to estimate EUE betas in Panel A and among betas estimated in Equation (2.2) . Variable definitions are listed in Appendix II. The sample period is from July 1970 to December 2019.

			Panel A: Risk Factors				
	ΔUNC	*MKTRF*	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
ΔUNC	1						
MKTRF	-0.148	1					
SMB	-0.090	0.249	1				
HML	0.016	-0.257	-0.066	1			
MOM	0.091	-0.166	-0.066	-0.190	1		
RMW	-0.027	-0.249	-0.381	0.131	0.097	1	
CMA	0.040	-0.380	-0.052	0.687	0.014	0.033	1
			Panel B: Betas				
	β^{EUE}	β^{MKTRF}	β^{SMB}	β^{HML}	β^{MOM}	β^{RMW}	β^{CMA}
β^{EUE}	1						
β^{MKTRF}	-0.004	1					
β^{SMB}	0.108	0.094	1				
β^{HML}	-0.026	0.011	0.088	1			
β^{MOM}	-0.051	-0.053	-0.014	0.125	1		
β^{RMW}	-0.107	0.261	0.311	0.129	-0.071	1	
β^{CMA}	-0.015	0.277	0.101	-0.547	-0.113	0.236	1

One of the concerns of applying multifactor model is the potential multicollinearity among factors. Table A-I.1 reports time-series correlations among factors and cross-sectional correlations among betas in Panels A and B, respectively. Panel A shows that ΔUNC has a low correlation with existing factors. Panel B shows that EUE beta has low correlation with other betas. The highest correlation is with SMB beta (11%). It suggests that similar firm characteristics affect the firm's sensitivity to both economic uncertainty and size effect.

Table A-I.2 Excess returns of 25 portfolios double sorted by EUE and MIS

This table reports excess returns (raw return minus risk free rate) on 5 MIS (EUE) and 25 EUE-MIS value-weighted portfolios in Panel A. The 25 portfolios are formed by independently sorting on EUE and the mispricing scores. Mean returns of 5 MIS (EUE) portfolios are reported in Average MIS (EUE) column (row). 5 MIS (EUE) portfolios are formed by sorting individual stocks on their mispricing scores (EUE), reported in Univariate MIS (EUE) column (row). Panel B reports the ambiguity-premium adjusted returns, which are difference between each double-sort portfolio return and the corresponding value in the middle mispricing quintile called "non-mispricing" group. Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2019. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	Low EUE	2	3	4	High EUE	High-Low	Average MIS	Univariate MIS
				Panel A: Mispricing alphas				
1 Overpriced	0.37	0.15	0.06	0.19	-0.06	-0.42**	0.14	0.13
	(1.57)	(0.59)	(0.20)	(0.67)	(-0.17)	(-2.03)	(0.54)	(0.50)
2	0.46**	0.68***	0.46**	0.63**	0.58*	0.12	0.56**	0.54**
	(2.28)	(3.20)	(1.98)	(2.42)	(1.87)	(0.61)	(2.49)	(2.49)
3 Non-mispricing	0.58***	0.68***	0.68***	0.61***	0.87***	0.29	0.68***	0.64***
	(2.90)	(3.52)	(3.09)	(2.59)	(2.86)	(1.41)	(3.21)	(3.15)
4	0.70***	0.72***	0.59***	0.70***	1.02***	0.32	0.75***	0.69***
	(4.00)	(3.85)	(2.96)	(2.99)	(3.48)	(1.50)	(3.74)	(3.71)
5 Underpriced	0.75***	0.81***	0.79***	0.81***	1.10***	0.35*	0.85***	0.78***
	(4.42)	(4.91)	(4.47)	(4.07)	(4.08)	(1.75)	(4.83)	(4.73)
Underpriced−Overpriced	0.39**	0.66***	0.73***	0.62***	1.16***	0.77***	0.71***	0.65***
	(2.46)	(3.77)	(3.96)	(3.40)	(5.12)	(3.50)	(5.06)	(4.31)
Average EUE	0.57***	0.61***	0.51**	0.59***	0.70**	0.13		
	(3.15)	(3.24)	(2.50)	(2.61)	(2.49)	(0.80)		
	0.64***	0.67***	0.57***	0.63***	0.67**	0.03		
Univariate EUE	(3.74)	(3.83)	(2.99)	(2.92)	(2.37)	(0.20)		
				Panel B: Ambiguity premium adjusted alphas				
1 Overpriced	-0.21	-0.53***	-0.62***	-0.42***	-0.93***	-0.71***		
	(-1.58)	(-3.58)	(-4.23)	(-2.64)	(-5.11)	(-3.63)		
2	-0.12	0.00	-0.22*	0.02	-0.29**	-0.17		
	(-1.15)	(0.01)	(-1.90)	(0.16)	(-2.07)	(-0.97)		
3 Non-mispricing	0.00	0.00	0.00	0.00	0.00	0.00		
4	0.12	0.04	-0.09	0.09	0.15	0.02		
	(1.23)	(0.38)	(-0.82)	(0.71)	(0.97)	(0.13)		
5 Underpriced	0.17	0.13	0.11	0.21	0.23	0.05		
	(1.60)	(1.17)	(0.91)	(1.50)	(1.21)	(0.27)		
Underpriced−Overpriced	0.39**	0.66***	0.73***	0.62***	1.16***	0.77***		
	(2.46)	(3.77)	(3.96)	(3.40)	(5.12)	(3.50)		

Table A-I.2 replicates main results in Table 2.2 by examining the excess portfolio return instead of their risk-adjusted alphas. It can be seen that the mispricing effect shown in this table is consistent with the main finding and stronger. For example, for the high EUE group, the Underpriced−Overpriced return is 1.16% per month, which is much higher than the risk-adjusted return reported in Table 2 (0.75%). For the ambiguity premium effect, I cannot observe EUE risk premium in the non-mispricing group. This confirms the importance of identifying the EUE risk premium when other risks have been taken into consideration. It is also consistent with the fact that EUE risk premium is more likely to be observed when more elaborated risk model is considered.

Table A-I.3 Disagreement variables of 25 EUE-MIS portfolios

This table reports average disagreement variables of 25 EUE-MIS portfolios. Panel A, B and C report the average value of long-term analyst forecast dispersion (DISP), idiosyncratic volatility (IVOL) and stock turnover (TO) for each portfolio, respectively. Variable definitions are listed in Appendix II. The sample period, except for DISP, is from July 1970 to December 2019, and that for DISP starts from December 1981 to December 2019.

	Low EUE	2	3	4	High EUE	All Stocks
			Panel A: Average DISP			
Overpriced	0.448	0.430	0.396	0.435	0.461	0.434
2	0.379	0.429	0.391	0.442	0.560	0.440
3	0.447	0.373	0.401	0.442	0.605	0.454
4	0.353	0.333	0.380	0.375	0.434	0.375
Underpriced	0.292	0.309	0.369	0.335	0.360	0.333
All Stocks	0.384	0.375	0.387	0.406	0.484	
			Panel B: Average IVOL			
Overpriced	2.075	2.114	2.224	2.437	2.878	2.346
2	1.834	1.874	1.973	2.160	2.584	2.085
3	1.701	1.760	1.868	2.038	2.459	1.965
4	1.624	1.663	1.758	1.964	2.362	1.874
Underpriced	1.584	1.625	1.714	1.897	2.305	1.825
All Stocks	1.763	1.807	1.908	2.099	2.518	
			Panel C: Average TO			
Overpriced	1.009	1.039	1.110	1.287	1.638	1.216
2	0.850	0.874	0.948	1.075	1.453	1.040
3	0.813	0.830	0.906	1.043	1.379	0.994
4	0.833	0.853	0.915	1.031	1.352	0.997
Underpriced	0.898	0.925	0.976	1.078	1.414	1.058
All Stocks	0.881	0.904	0.971	1.103	1.447	

Table A-I.3 reports firm-level disagreement measurements in 25 EUE-MIS portfolios. It confirms that mispricing and EUE can clearly group stocks with different degree of firm level disagreement. Specifically, firm-level disagreements are positively correlated with EUE and higher for overpriced than underpriced stocks.

Table A-I.4 Time-series regression of aggregate turnover

This table reports the time-series regressions of changes in S&P500 turnover and log changes in EU index on macroeconomic variables and the market excess return using the following model;

$$Y_{p,t} = \alpha_{p,1} + \beta_{p,2}\Delta\mathrm{TO}_{t-1} + \beta_{p,3}\Delta\mathrm{UNC}_{t-1} + \beta_{p,4}MKT_{t-1} + \sum_{J=1}^{4}\beta_J X_{J,t-1} + \varepsilon_{i,t}$$

where $Y_{p,t}$ is changes either in S&P500 turnover (ΔTO) or in EU index (ΔUNC) in month t. MKT_{t-1} is the market excess return in month $t-1$. $X_{1,t-1} \cdots X_{4,t-1}$ are four macroeconomic variables: the default premium, the term premium, the real interest rate and inflation rate in month $t-1$. The slope coefficients are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1965 to December 2019. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	ΔTO	ΔUNC
ΔTO	-0.453***	-0.006
	(-13.779)	(-1.392)
ΔUNC	0.664**	0.550***
	(2.233)	(12.094)
MKT	0.142	0.012
	(0.855)	(0.687)
Default Premium	0.187	-0.551***
	(0.118)	(-3.166)
Term Premium	0.352	-0.172**
	(0.624)	(-2.497)
Real Interest Rate	3.606	0.152
	(1.356)	(0.428)
Inflation Rate	3.118	-0.125
	(1.211)	(-0.368)
Constant	-0.013	0.008***
	(-0.800)	(3.950)
Observations	654	654
F-stat	27.52	46.75

Table A-I.4 reports Granger causality test results between changes of economic uncertainty index and changes of share turnover in the S&P500 for the sample period between July 1965 and December 2019. It confirms that an increase in EU induces a positive change in next period turnover in the S&P500 while the reverse causality is absent.

Table A-I.5 Raw Signed Economic Uncertainty Exposure of the 25 EU-MIS portfolios

This table reports average EU coefficients and the number of stocks of 25 EU-MIS portfolios in Panels A and B, respectively. EU coefficients are the beta coefficient estimated in Equation (2.2). The pooled average of stocks in each portfolio and over the sample period is reported. Panel C reports risk-adjusted returns on 5 EU and 25 EU-MIS value-weighted portfolios. The 25 portfolios are formed by independently sorting on EU and the mispricing score. The mean of 5 EU portfolios is reported in Average EU row. 5 EU portfolios are formed by sorting individual stocks on their EU betas, reported in Univariate EU row. Panel D reports the risk-adjusted returns on the difference between each double-sort portfolio and the corresponding value in the middle mispricing quintile called "non-mispricing" group. The risk-adjusted returns are estimates of alphas estimated in Equation (2.3) Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2019. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	Low EU	2	3	4	High EU	All Stocks
			Panel A: Average EU			
Overpriced	-1.358	-0.333	0.007	0.357	1.362	0.007
2	-1.210	-0.330	0.007	0.352	1.227	0.009
3	-1.160	-0.328	0.007	0.348	1.155	0.004
4	-1.103	-0.330	0.009	0.350	1.115	0.008
Underpriced	-1.081	-0.327	0.008	0.350	1.078	0.006
All Stocks	-1.182	-0.330	0.008	0.351	1.187	
			Panel B: Average Number of Stocks			
Overpriced	135	98	95	102	140	570
2	116	112	111	112	119	571
3	111	118	120	116	108	572
4	106	122	121	120	103	572
Underpriced	104	122	124	122	101	574
All Stocks	572	572	572	572	571	

	Low EU	2	3	4	High EU	High-Low EU	High-3 EU	Low-3 EU
				Panel C: Mispricing alphas				
Overpriced	-0.50***	-0.29**	-0.02	-0.40***	-0.33**	0.17	-0.31*	-0.48***
	(-3.87)	(-2.28)	(-0.15)	(-2.64)	(-2.48)	(0.96)	(-1.88)	(-2.93)
2	-0.07	0.04	-0.14	-0.12	0.11	0.17	0.24*	0.07
	(-0.44)	(0.43)	(-1.54)	(-1.22)	(0.90)	(0.82)	(1.70)	(0.38)
3	0.03	0.17	-0.12	0.03	0.18	0.15	0.30*	0.15
	(0.25)	(1.43)	(-1.34)	(0.37)	(1.49)	(0.77)	(1.83)	(0.95)
4	0.00	-0.02	0.06	-0.05	0.14	0.14	0.08	-0.06
	(0.01)	(-0.21)	(0.90)	(-0.55)	(1.16)	(0.88)	(0.53)	(-0.46)
Underpriced	0.01	0.01	-0.01	0.14**	0.23*	0.22	0.24	0.02
	(0.08)	(0.07)	(-0.08)	(1.99)	(1.77)	(1.22)	(1.51)	(0.11)
Underpriced−	0.51***	0.30**	0.01	0.53***	0.56***	0.05	0.55***	0.49**
Overpriced	(2.98)	(2.27)	(0.07)	(3.07)	(3.36)	(0.24)	(2.59)	(2.43)
Average EU	-0.10	-0.02	-0.04	-0.08*	0.07	0.17		
	(-1.31)	(-0.32)	(-1.13)	(-1.70)	(0.94)	(1.46)		
Univariate EU	-0.07	0.01	0.01	-0.02	0.11	0.18		
	(-0.83)	(0.26)	(0.25)	(-0.39)	(1.53)	(1.49)		
				Panel D: Ambiguity premium adjusted alphas				
Overpriced	-0.53***	-0.47***	0.10	-0.43**	-0.51***	0.02	-0.61**	-0.63***
	(-3.44)	(-2.74)	(0.69)	(-2.52)	(-2.91)	(0.10)	(-2.51)	(-3.02)
Underpriced	-0.02	-0.17	0.11	0.10	0.05	0.07	-0.06	-0.14
	(-0.14)	(-1.18)	(1.02)	(0.99)	(0.29)	(0.30)	(-0.29)	(-0.68)
Underpriced−	0.51***	0.30**	0.01	0.53***	0.56***	0.05	0.55***	0.49**
Overpriced	(2.98)	(2.27)	(0.07)	(3.07)	(3.36)	(0.24)	(2.59)	(2.43)

Table A-I.5 reports results of using the raw instead of the absolute EU beta in the paper. Panel A reports the value of betas for 25 portfolios. It shows that the distribution of betas are symmetrical around the middle EU quintiles, whose betas are close to zero. Panel B shows that overpriced stocks tend to have both very negative and positive EU betas while underpriced stocks tend to have less of these two extremes. The middle EU quintile has a contrasting distribution among the over and underpriced stocks in comparison to those two extreme quintiles. Panel C reports the FF6-factor alphas for those 25 portfolios. It confirms that the main finding in the paper regarding the close to zero beta and high absolute beta is not driven by just either side of the extreme EU quintile.

For mispricing effect, it can be observed that there are significant monthly alphas in both the most negative (0.51% with $t = 2.98$) and most positive (0.56% with $t = 3.36$) EU beta quantiles. These significant mispricing results observed in extreme EU groups are due to significant overpricing in those extreme EU groups. This finding is consistent with my main discussion, suggesting that the source of mispricing is from overpriced legs and stocks with high exposure to EU are more likely to experience overpricing, regardless their positive or negative signs.

While the overpriced-underpriced alphas for both of high and low EU quintiles are significant, their difference (High-Low) is not significantly different from each other (0.05% with a t-statistic of 0.24). For the ambiguity premium effect, similarly, there is no significant difference in High-Low EU group. Panel D also confirms the asymmetry in over and underpriced stocks are consistent with main findings. Overall, this analysis confirms the advantage of using the absolute EU beta to capture the exposure to EU. It is consistent with the theoretical definition of capturing the uncertainty in the distribution (variance) and present a simplified interpretation to empirical results by grouping large absolute EU betas with both positive and negative signs together.

Table A-I.6 Limits of Arbitrage and Mispricing Effect

This table reports risk-adjusted returns on 50 value-weighted portfolios formed by independently sorting on the two IO/SIZE, the five EUE and the five MIS groups. 5 MIS (EUE) portfolios are formed by sorting individual stocks on their mispricing scores (EUE), reported in Univariate MIS (EUE) column (row) for each group. The risk-adjusted returns are estimates of alphas estimated in Equation (2.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period for SIZE is from July 1970 to December 2019, and that for IO starts from April 1980 to December 2019. ***, ** and * indicates significance at the 1%, 5% and 10% levels, respectively.

	Low EUE	High EUE	H-L	Uni MIS	Low EUE	High EUE	H-L	Uni MIS
	Low IO				Low SIZE			
Overpriced	-0.03	-0.63***	-0.60**	-0.55***	-0.26**	-0.73***	-0.47***	-0.58***
	(-0.13)	(-2.89)	(-1.97)	(-3.86)	(-2.25)	(-6.52)	(-3.26)	(-8.23)
Non-	0.14	0.28	0.14	0.31**	0.03	0.04	0.01	0.09*
mispricing	(0.87)	(1.20)	(0.45)	(2.52)	(0.33)	(0.37)	(0.05)	(1.93)
Underpriced	0.17	0.55**	0.39	0.19*	0.37***	0.57***	0.20	0.44***
	(1.05)	(2.33)	(1.41)	(1.80)	(3.86)	(4.60)	(1.62)	(6.45)
Underpriced	0.19	1.18***	0.99**	0.73***	0.62***	1.30***	0.67***	1.02***
−Overpriced	(0.84)	(3.72)	(2.38)	(4.20)	(4.17)	(8.02)	(3.37)	(10.41)
Uni EUE	0.15	-0.19	-0.34*		0.07	-0.18***	-0.25***	
	(1.26)	(-1.21)	(-1.67)		(1.22)	(-2.60)	(-3.36)	
	High IO				High SIZE			
Overpriced	-0.06	-0.41**	-0.35*	-0.25***	-0.02	-0.36***	-0.34**	-0.19***
	(-0.48)	(-2.38)	(-1.77)	(-2.81)	(-0.21)	(-2.73)	(-2.06)	(-2.80)
Non-	-0.08	0.35*	0.43*	-0.10	-0.11	0.28*	0.39**	-0.02
mispricing	(-0.65)	(1.76)	(1.94)	(-1.61)	(-1.28)	(1.85)	(2.28)	(-0.45)
Underpriced	-0.05	0.37*	0.42**	0.01	0.00	0.29*	0.29	0.04
	(-0.60)	(1.95)	(1.99)	(0.14)	(0.02)	(1.78)	(1.62)	(0.99)
Underpriced	0.01	0.77***	0.76***	0.26**	0.02	0.65***	0.63**	0.23**
−Overpriced	(0.06)	(3.14)	(2.72)	(2.38)	(0.17)	(3.05)	(2.58)	(2.50)
Uni EUE	-0.03	0.17	0.20*		-0.01	0.09	0.10	
	(-0.60)	(1.57)	(1.71)		(-0.32)	(1.19)	(1.09)	

Limits of arbitrage deter arbitragers to eliminate mispricing (i.e., Miller, 1977; Stambaugh, Yu and Yuan, 2012). I examine the effect of EU on mispricing considering other proxies for limits of arbitrage and short-sale constraints, such as institutional ownership (IO) (Nagel, 2005) and SIZE (Lee, Shleifer and Thaler, 1991).

Table A-I.6 reports risk-adjusted returns on 50 value-weighted triple-sort portfolios. These findings are consistent with the general mispricing explanation, where the effect of EUE on mispricing would be the strongest among stocks with highest short-sale constraints (lower institutional ownership and smaller sizes). Nevertheless, the EUE's impact on mispricing is still observed in the other half of stocks as well, suggesting that EUE is different from institutional ownership or size effect.

It is worth noting that EU risk-premium only appears in the non-mispricing group among stocks suffering from low short-sale constraints. It indicates that the ambiguity-premium effect is more observable when the general mispricing effect is relatively weaker.

Table A-I.7 High − Low EUE portfolio alphas months after the formation

This table reports risk-adjusted returns on Overpriced−Underpriced portfolios in High−Low EUE group (Mispricing Alpha), and on High−Low EUE portfolios in Non-mispricing group (Ambiguity Premium) based on the 25 EUE-MIS value-weighted portfolios. 25 portfolios are formed by independently sorting on EUE and the mispricing scores. The analysis for each month is similar to those reported in Table 2 of the main text. I conduct the similar analysis by using the next n^{th} month risk-adjusted return. The risk-adjusted returns are estimates of alphas from the following models:

$$FF6 \quad : R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}UMD_t + \beta_{p,5}IA_t + \beta_{p,6}ROE_t + \varepsilon_{i,t}$$

$$q5 \quad : R_{p,t} = \alpha_{p,1} + \beta_{p,1}MKT_t + \beta_{p,2}QSMB_t + \beta_{p,3}QIA_t + \beta_{p,4}QROE_t + \beta_{p,5}QEG_t + \varepsilon_{i,t}$$

where $R_{p,t}$ is the excess return of portfolio p in month t and $\alpha_{p,1}$ is adjusted return in percent. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors in month t. $QSMB_t$, QIA_t, $QROE_t$ and QEG_t are Hou, Xue and Zhang (2015) and Hou et al. (2020) q-factors in month t. Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2019. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	n=1	n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
Panel A. FF6												
Mispricing Alpha	0.71***	0.47**	0.49**	0.51**	0.39*	0.19	0.24	0.16	0.26	0.42*	0.33	0.21
	(3.15)	(2.31)	(2.41)	(2.37)	(1.78)	(0.80)	(1.17)	(0.73)	(1.25)	(1.76)	(1.47)	(0.83)
Ambiguity Premium	0.35**	0.22	0.23	-0.06	-0.02	0.03	0.24	0.28	0.16	0.19	0.31	0.08
	(2.17)	(1.32)	(1.45)	(-0.42)	(-0.11)	(0.18)	(1.41)	(1.63)	(1.03)	(1.02)	(1.64)	(0.50)
Panel B. q5												
Mispricing Alpha	0.37	0.20	0.19	0.40**	0.25	0.10	0.09	-0.08	0.07	0.21	0.14	0.06
	(1.55)	(0.91)	(0.79)	(2.05)	(1.02)	(0.37)	(0.40)	(-0.34)	(0.28)	(0.78)	(0.50)	(0.20)
Ambiguity Premium	0.47**	0.40*	0.39**	0.14	0.20	0.26	0.38*	0.39*	0.32*	0.33	0.55**	0.20
	(2.25)	(1.80)	(2.01)	(0.91)	(0.89)	(1.07)	(1.76)	(1.82)	(1.71)	(1.53)	(2.52)	(0.96)

Table A-I.7 reports the long-term predictive power of the EUE on both the mispricing and the ambiguity premium effects using FF6 and q5 models. It shows that, when using the FF6-factor model, the mispricing effect persists to Month 5, while the ambiguity premium effect is no longer observable after Month 1. By contrast, when q5 model is accounted for, the ambiguity premium effect is significant up to Month 11, whereas the mispricing effect disappears.

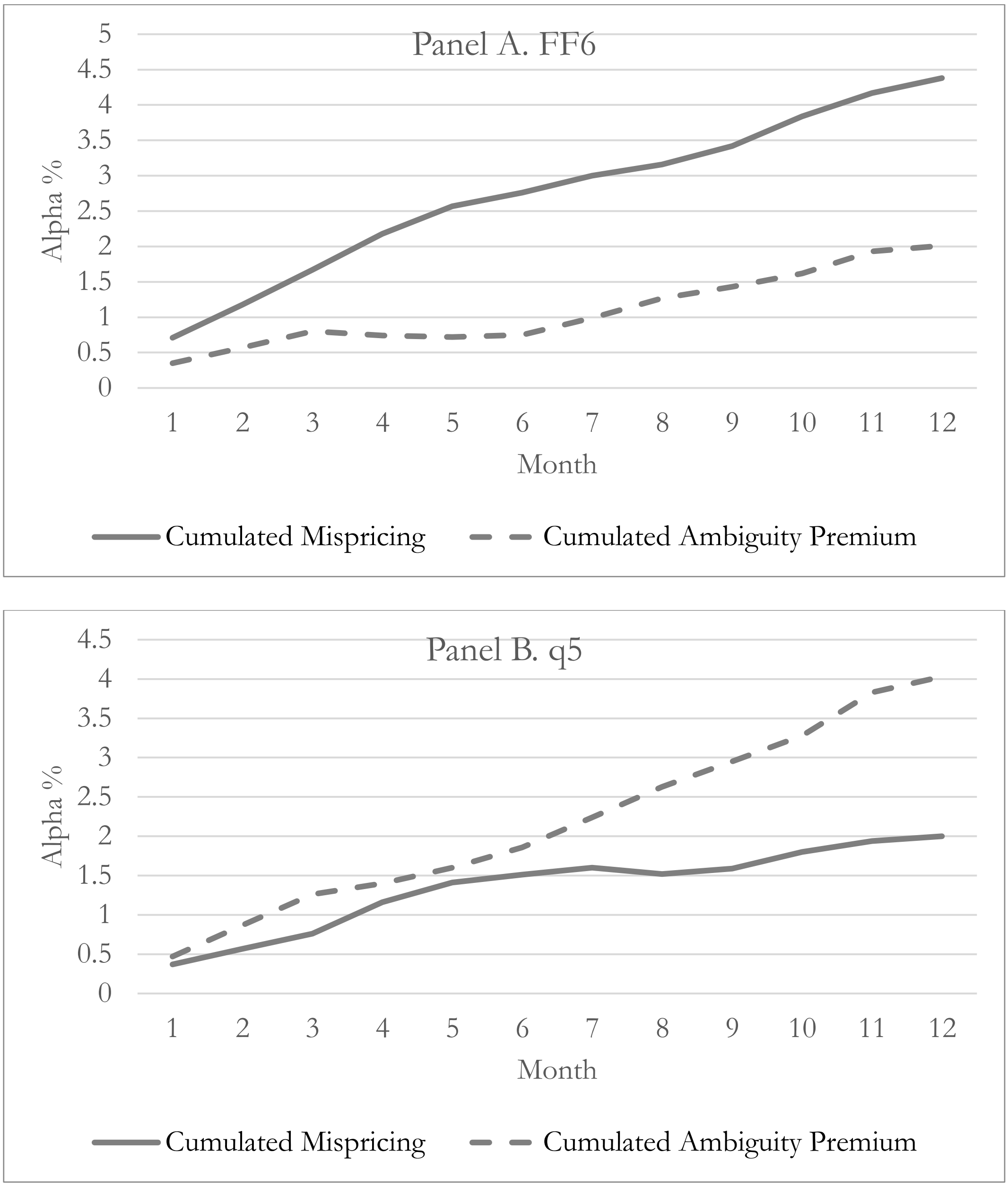

Figure A-I.1 Cumulative Alphas in Different Horizons

This figure plots the risk-adjusted cumulative returns on High−Low EUE group (Mispricing Alpha), and on High−Low EUE portfolios in Non-mispricing group (Ambiguity Premium) based on the 25 EUE-MIS value-weighted portfolios. The risk-adjusted returns are estimates of alphas from FF6 and q5 models reported in Panel A and B, respectively. The sample period is from July 1970 to December 2019.

Chapter 3

3 Economic Uncertainty, Investor Sentiment and Cross-Sectional Returns

3.1 Introduction

In the previous chapter, I have examined the effect of economic uncertainty exposure (EUE) on cross-sectional returns disentangling the mispricing from the ambiguity-premium effect. While economic uncertainty exacerbates heterogeneous beliefs among investors, making optimists more optimistic and pessimists more pessimistic, it also affects the preference of investors facing uncertainty in the sense of the ambiguity-return trade-off. In this regard, the former predicts a negative relationship between firms' economic uncertainty exposure and expected returns, but the latter predicts a positive one. These two contradicting predictions have been clarified using the mispricing scores (MIS), introduced by Stambaugh, Yu and Yuan (2012; 2015), which enable us to identify the mispricing degree at the firm level. Consequently, I show that the mispricing alpha in stocks with the highest EUE group is higher than the unconditional one, while the high-minus-low EUE portfolio in the non-mispricing group, which is the middle portfolio sorted by MIS, generates a significant premium.

In classical theory, asset prices are determined by rational investors and mispricing induced by sentiment-driven irrationality is counterbalanced. There would be, thus, no significant role of sentiment on prices (Baker and Wurgler, 2006). Existing studies, however, show that sentiment-driven irrationality among investors deters arbitrageurs to counterbalance noise trading, resulting in significant price deviation from fundamental values despite the absence of fundamental risk.[38] Investors exhibit more irrationality during high-market sentiment than low-market sentiment periods, implying a link between market-wide sentiment and time-varying investor behaviours (Baker and Stein, 2004). Specifically, Stambaugh, Yu and Yuan (2012) show that the presence of market-wide sentiment combined with short-sale constraints exacerbates the disagreement among investors, causing significant mispricing in cross-sectional returns. Therefore, in this chapter, I examine the role of market-wide sentiment in relation to the two effects of EUE on cross-sectional returns. In other words, this study explores sentiment-driven behaviours as at least a partial explanation for the impact of EUE on asset prices by differentiating investor behaviours at market-level.

Following Stambaugh, Yu and Yuan (2012), I conjecture that market-wide sentiment as an important determinant of mispricing will make the EUE induced mispricing more prominent. During high-market sentiment periods, irrational investors determine those stocks' value. The valuation made by rational ones, however, is not involved in the prices due to short-sale constraints (Miller, 1977). Furthermore, high-market sentiment will exacerbate the disagreement effect induced by EUE, which leads to stronger mispricing, as irrational investors are more likely to follow their own valuations for those assets (Hirshleifer, 2001). Therefore, my first hypothesis is that the mispricing effect, measured by the long-short portfolio sorted by MIS, in stocks with the highest EUE is stronger following a period of high-market sentiment than low-market sentiment periods.

[38] DeLong et al (1990), Shleifer and Vishny (1997), Baker and Stein (2004) Baker and Wurgler (2006; 2007), Fong and Toh (2014) and Shen, Yu and Zhao (2017).

During low-market sentiment period, by contrast, the irrational valuations on those stocks tend to vanish and the price will be more likely to reflect the view of the rational investors. This will lead to not only lower mispricing, as Stambaugh, Yu and Yuan (2012) suggest, but also the effect of ambiguity premium stronger. For instance, Shen, Yu and Zhao (2017) show that macroeconomic risk factors are priced in cross-sectional stocks returns consistent with the risk-return trade-off following low-market sentiment when the market is more rational. The ambiguity premium is driven by investors' rational preference for lower ambiguity, thus such an effect will be more clear in the market condition that more likely to reflect this group of investors' view. Therefore, my second hypothesis is that there is a positive relationship between EUE and expected returns following the low-market sentiment period for stocks in the middle portfolio sorted by MIS, called non-mispricing group, which are subject to the least mispricing. In other words, I expect that the ambiguity-premium effect becomes apparent following a period of low-market sentiment in which investors behave more rationally according to Stambaugh, Yu and Yuan (2012).

I quantify market-wide sentiment using an index developed by Baker and Wurgler (2006). They consider various measures and form a composite index by taking the first principal component of those proxies.[39] As introduced in the first chapter, I measure EUE by estimating the sensitivity of stock return to log changes of economic uncertainty proposed by Jurado, Ludvigson, and Ng (2015, hereafter JLN). In my main analyses, I examine the risk-adjusted returns on 25 portfolios independently double-sorted by EUE and MIS, following different market-wide sentiment periods. The risk-adjusted returns are the alphas estimated by using a Fama-French (2016, hereafter FF) six-factor model.[40]

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[39] Those proxies are the closed-end fund discount, NYSE share turnover, the number of and the mean of first-day returns on IPOs, the equity share in new issues and the dividend premium.

[40] Those risk factors are market excess return (MKT), size (SMB), value (HML), momentum (UMD), investment (IA), and profitability (ROE).

In the US markets between 1970 and 2018, I observe the significant mispricing effect following the high-market sentiment period, while the ambiguity-premium effect becomes apparent with the former arbitraged away following the low- market sentiment period, supporting my hypotheses.

Specifically, the annualized mispricing alpha in the highest EUE group is 16.2% with a t-statistic of 4.49 following the high-market sentiment period, which is about double the mispricing effect (with an annualized alpha of 9%) in the whole sample reported in the previous chapter and is more than triple the unconditional mispricing effect (with an annualized alpha of 4.68%) following the same period. Second, the ambiguity premium in the non-mispricing group, which is the middle mispricing quintile, yields an annualized alpha of 6.36% with a t-statistic of 2.15 following the low-market sentiment period. This figure is more than that (with an annualized alpha of 4.2%) in the whole sample reported in the previous chapter.

I also show that there is a positive relationship between market-wide sentiment and the mispricing effect of EUE in time-series regressions. In other words, I show the predictability of market-wide sentiment on EUE-induced mispricing, however not on the ambiguity premium effect, confirming that market-wide sentiment exacerbates mispricing due to short-sale constraints (Stambaugh, Yu and Yuan, 2012). This finding is robust after controlling for macroeconomic effects.

Next, I re-examine two contradicting effects of EUE following different market-wide sentiment periods with alternative risk models such as a seven-factor model (FF's five factors, a momentum factor and an additional liquidity factor), q-factor (Hou, Xue, and Zhang, 2015), q5 (Hou et al., 2020) and the mispricing (Stambaugh and Yuan, 2017, hereafter MSP) models. Following the high-market sentiment period, the mispricing effect shrinks as more elaborated multifactor models are used to adjust the excess returns but remain significant. The mispricing alphas are significant in the high EUE group ranging from 0.82% to 2.07% per month, suggesting that EUE-induced mispricing following the high-market sentiment period is not able to be explained by the existing models.

Following the low- market sentiment period, by contrast, the ambiguity-premium effect in the non-mispricing group remains significant with the mispricing effect arbitraged away, except for the CAPM model. The EUE premium is even larger with more comprehensive models than the counterpart in my main analysis when investors behave rationally. For instance, the monthly alpha of the high-minus-low EUE portfolio in the non-mispricing group is 0.71% for the q4 model, 0.76% for the q5 model and 0.80% for the MSP model following the low-market sentiment period. This finding once again confirms that the EUE premium is a new factor that is different from the existing risk factor as rational investors demand in the sense of the ambiguity-return trade-off suggested in the previous chapter.

I further explore the interaction between market-wide sentiment and macro-level uncertainty. Macroeconomic uncertainty amplifies biases in investors' beliefs due to its unpredictable informational environment as discussed in the previous chapter. It leaves more room for investors to follow their own subjective estimations and to ignore objective valuations, resulting in more irrational behaviours and larger disagreement among them (Hirshleifer, 2001). This is also consistent with psychology literature suggesting that people tend to rely more on their heuristics rather than the facts in their judgements and predictions under uncertainty (Kahneman and Tversky, 1973). In this regard, Birru and Young (2020) suggest that in times of larger uncertainty, the effect of market-wide sentiment is prone to be more pronounced and rational investors are even more limited to offset the effect of irrational ones due to less reliable information flow. They show that the predictability of market-wide sentiment in both aggregate and cross-sectional returns is stronger when the market-level uncertainty, measured by VIX, is high. Therefore, I predict that the mispricing effect would be the strongest in the intersection of high market-wide sentiment and high macroeconomic uncertainty.

I confirm this in my empirical findings. The monthly mispricing alpha in the highest EUE group is 1.74% with a t-statistic of 3.79 following the periods of both high EU and high-market sentiment. This figure is larger than the mispricing effect (with a monthly alpha of 1%) following the periods of low EU and high-market sentiment periods. Second, the ambiguity premium effect is only observed when in periods with more rational behaviour but increasing macro-level uncertainty. The high-minus-low EUE portfolio in the non-mispricing group has a monthly alpha of 1.02% with a t-statistic of 2.67 following high EU and low-market sentiment periods. This further confirms that EUE is priced as rational investors demand ambiguity premium when macroeconomic uncertainty increases and their preference is more likely to be reflected during the period of low-market sentiment.

Finally, I study the robustness of my finding controlling for proxies of short-sale constraints such as SIZE and idiosyncratic volatility (IVOL). First, the mispricing effect of EUE is more pronounced following the high-market sentiment period in high short-sale constrained groups, namely low SIZE and high IVOL. This finding is consistent with Miller (1977) and Stambaugh, Yu and Yuan (2012), suggesting that during the high-market sentiment period, rational investors are limited to exploit the optimists' valuation resulting in significant overpricing in subsequent anomaly returns as the main source of mispricing. However, I still observe a significant mispricing effect of EUE following the high-market sentiment period in low short-sale constrained groups. It implies that EUE can be a different source of arbitrage friction which deters rational investors from arbitraging away optimistic mispricing, as shown in the first chapter. Finally, following the low-market sentiment period, the EUE premium in the non-mispricing group is significant among only stocks with low short-sale constraints, as the rational expectation.

I also perform several other robustness tests. First, I extend my empirical analysis considering the economic policy uncertainty index (Baker, Bloom and Davis, 2016) as an alternative measure of macro uncertainty. The findings are consistent with my main results. Second, following the literature (Lemmon and Portniaguina, 2006; Bergman and Roychowdhury, 2008), the University of Michigan Consumer index, used as an alternative measure of market-wide sentiment, provides additional support to my main hypotheses.

This study contributes to the literature by providing further insights into the two opposite effects of EUE on cross-sectional returns from a behavioural perspective. Existing studies show that market-wide sentiment combined with short-sale constraints affects investors' beliefs and preferences (Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012). Regarding this, isolating investors' behaviours in different states present us an empirical setting to be able to see that exposure to economic uncertainty could be one of these common components that amplify investors' belief biases, which drive anomalies. The general source of mispricing is a disagreement between optimists and pessimists (Hong and Stein, 2007). Empirically, this study shows that EUE amplifies mispricing, especially following a high-market sentiment period, confirming that EUE escalates cross-sectional dispersion in investors' views. This shows that EUE can be a common mispricing component across anomalies in the market (Nagel, 2005; Stambaugh, Yu, and Yuan, 2012 and 2015).

This study is related to Shen, Yu and Zhao (2017) showing that macro-risk is priced in cross-sectional returns as a risk premium when the market is more rational. I provide evidence that there is a positive ambiguity premium observed following a low-market sentiment period as the rational expectation is pervasive. It is a result of rational demand consistent with the theoretical model introduced by Anderson, Gjhysels and Jurgens (2009).

Findings in Chapter 3 also provide evidence that macro-level uncertainty matters for investors' irrationality as the strongest sentiment effect is observed when economic uncertainty is high. Although the scope of this study is not to shed light on why uncertainty affects time-varying sentiment in-depth, my results suggest that uncertainty causes subjective valuations and further increases sentiment-driven investors' trades, supporting existing studies (Garcia, 2013; Birru and Young, 2020).

The rest of the chapter is organized as follows. Section 3.2 reviews the literature and develops my main hypotheses. Section 3.3 presents my data. Section 3.4 presents the main findings. Section 3.5 reports robustness and further tests. Section 3.6 concludes.

3.2 Literature Review and Hypotheses Development

3.2.1 Investor Sentiment and Mispricing

In traditional asset pricing theory, securities' value is determined by rational investors and mispricing caused by investor sentiment is ignored. Even if there are some irrational investors, arbitrageurs counterbalance their demands. Thus, there would be no effect of sentiment on prices (Baker and Wurgler, 2006). However, DeLong et al. (1990) show that the irrationality of sentiment-driven investors causes a risk in asset prices that deters arbitrageurs to take a position against noise trading. Consequently, prices tend to deviate from fundamental values despite the absence of fundamental risk. Baker and Wurgler (2006) also suggest that mispricing is caused by sentiment-driven traders and limits to arbitrage. Specifically, they find that stocks which tend to have subjective valuation are subject to the effect of market-wide sentiment.[41] Thus, those assets generate subsequent low returns as they are hard to arbitrage by arbitrageurs.

Stambaugh, Yu and Yuan (2012) investigate the presence of market-wide investor sentiment on various anomalies considering two important concepts in literature. The first concept is that investor sentiment has a time-varying market-wide component and influences stocks prices in the same direction at the same time. The second concept is that short-sale constraints limit the ability of arbitrageurs to exploit overpricing (Miller, 1977). Combining those concepts, they show that stock prices tend to diverge from fundamental values during high-market sentiment periods since prices are mostly affected by optimistic investors while pessimists are limited to offset the optimism in trades. Therefore, overpricing is more pronounced as the main source of mispricing in anomalies following high-market sentiment periods (Stambaugh, Yu and Yuan, 2012).

Considering those concepts, Shen, Yu and Zhao (2017) document that stocks with high macro-risk, measured by stocks' sensitivity to macroeconomic risk factors, generate lower returns following high-market sentiment periods. They suggest that firms with high macro-betas are more likely to be speculated in their valuation, thus are affected by market-wide sentiment. This is consistent with Hong and Sraer (2016) suggesting that high macro-beta assets are subject to larger disagreement between optimists and pessimists. By contrast, those assets generate a significant risk premium only following low-market sentiment periods as investors tend to be more rational.

[41] Those assets are young, small-sized, highly volatile, unprofitable and distressed.

In a nutshell, existing studies document the sentiment effect in cross-sectional returns that the traditional finance theory ignores. Those studies suggest that the presence of market-wide sentiment can be at least a partial explanation for mispricing.

3.2.2 Investor Sentiment and Two Tales of Economic Uncertainty Exposure

There are two effects of economic uncertainty exposure on cross-sectional returns documented in the previous chapter. Consistent with Hong and Sraers (2016) and Li (2016), macro uncertainty influences beliefs, making optimists more optimistic and pessimists more pessimistic. It also concerns investors with rational expectation by affecting future consumption and investment decisions (Bloom, 2009). Identifying the mispricing degree at the firm level measured by the mispricing score (MIS), the mispricing channel shows a larger mispricing spread in stocks with the highest EUE relative to the unconditional one formed by MIS. The ambiguity channel, by contrast, shows that EUE is priced at a premium in the non-mispricing group, i.e., the middle portfolio sorted by MIS

Building on prior literature, this study examines whether there is a significant role of market-wide sentiment in those two effects of EUE on cross-sectional returns. To understand links between them, I apply two prominent concepts suggested by Stambaugh, Yu and Yuan (2012).

First, market-wide sentiment has a common component that exerts investors' beliefs to make the EUE-induced mispricing more prominent. During high market-wide sentiment periods, irrational investors are more likely to determine stock prices, thus stocks with high EUE experience overpricing as irrational investors are more likely to follow their own valuations for those assets. Second, the presence of short-sale constraints limits rational traders to offset the irrational trade in those assets, resulting in larger EUE-induced disagreement and lower subsequent returns. Therefore, my first hypothesis is as below:

H_1: Mispricing spread, sorted by MIS, among stocks with the highest EUE is larger following high-market sentiment than low-market sentiment periods.

On the other hand, during low-market sentiment periods, investors tend to behave more rational, and prices are close to their fundamental values. (Stambaugh, Yu and Yuan, 2012). While the mispricing effect of EUE is lower, its ambiguity premium effect appears due to investors' rational preference for lower ambiguity. Therefore, my second hypothesis is as below:

H_2: There is a positive relationship between EUE and expected returns following the low-sentiment period for stocks in the non-mispricing group which are subject to the least mispricing captured by MIS.

3.3 Data and Measures

The dataset used in my empirical analyses contains all common stocks (with share code of 10 and 11) on the NYSE, Amex, and NASDAQ. Stocks whose prices are less than $5 per share are excluded from the dataset since those assets are hard to short (Asquith, Pathak, and Ritter, 2005). Monthly asset returns and companies' fundamental values are from the merged CRSP-Compustat database from July 1965 to December 2018.

3.3.1 *Investor Sentiment Index*

Baker and Wurgler (2006) form a composite index to measure market-wide sentiment (hereafter, the BW sentiment index). The index is the first principal component of six sentiment proxies: the number of initial public offerings (IPOs), the average first-day returns of IPOs, the dividend premium, the closed-end fund discount, the New York Stock Exchange (NYSE) turnover, and the equity share in new issues. The monthly BW sentiment index starts from July 1965 to December 2018, and is obtained from Jeffrey Wurgler's website.[42]

3.3.2 *Mispricing Measure*

Following Stambaugh, Yu, and Yuan (2015), the mispricing measure (MIS) is constructed based on 11 market anomalies. Their detailed definitions can be found in Appendix II. Stocks with the highest MIS scores are assigned as the most overpriced, while those with the lowest MIS scores are assigned as the most underpriced. Stambaugh, Yu, and Yuan (2015) show that MIS minimizes noisy measures of anomaly-specific effects. Thus, I have a single factor in identifying the degree of mispricing more accurately in the market. Additionally, they find that long-short portfolios formed on MIS have a higher average return relative to individual-anomaly portfolios, indicating that the new MIS measure is better at identifying mispricing in the market.[43]

[42] http://people.stern.nyu.edu/jwurgler/

[43] Monthly mispricing scores for each stock from July 1965 to December 2016 are collected from Robert F. Stambaugh's website and I updated them to December 2019. See more details related to mispricing score formation at: http://finance.wharton.upenn.edu/~stambaug/.

3.3.3 *Economic Uncertainty Exposure*

Existing studies have relied on different proxies to measure uncertainty in the economy. For instance, several papers use market volatility, due to its significant relation with real activity (for example, Bloom, 2009; Bekaert, Hoerova, and Duca, 2013; Bali and Zhou, 2016). However, JLN (2015) argue that financial market volatility may not reflect economic uncertainty accurately, since it may vary over time due to changes in risk aversion, leverage, or sentiment.

Other studies use dispersion in forecasts (for example, Mankiw and Reis, 2002; D'Amico and Orphanides, 2008; Anderson, Ghysels, and Juergens, 2009; Li, 2016). It is expected that during time with high uncertainty, forecasts are dispersed, and surveys show a higher level of disagreement on macro-indicators (Bachmann, Elstner, and Sims, 2013). However, forecasts may not clearly show expectations about the whole economy and may give subjective responses due to their pecuniary interests and individual biases. Additionally, the dispersion of analyst forecasts might be affected by heterogeneity in the business cycle, even if there is no shift in uncertainty in economic fundamentals (JLN, 2015).

Considering those arguments on different measures of economic uncertainty, I use the uncertainty index constructed by JLN (2015). This index is constructed based on 132 micro-series, not on any single (or a small number of) economic indicators, measuring uncertainty in the whole economy. JLN (2015) show that using this measure can capture uncertainty in different macro variables at the same time across companies, industries, markets, and regions. The index is obtained from Sydney Ludvigson's website.[44]

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[44] https://www.sydneyludvigson.com/data-and-appendixes/.

To measure innovations in economic uncertainty, I use monthly logarithmic changes in the index (ΔUNC_t).[45]

$$\Delta UNC_t = ln\left(\frac{UNC_t}{UNC_{t-1}}\right) \tag{3.1}$$

I estimate the uncertainty beta from a rolling regression for each stock with the following model, using previous 60-month observations:[46]

$$\begin{aligned} R_{i,t} = \alpha_{i,1} + \beta_{i,1}\Delta UNC_t + \beta_{i,2}MKT_t + \beta_{i,3}SMB_t + \beta_{i,4}HML_t \\ + \beta_{i,5}UMD_t + \beta_{i,6}IA_t + \beta_{i,7}ROE_t + \varepsilon_{i,t} \end{aligned} \tag{3.2}$$

where $R_{i,t}$ is the monthly excess return of stock i in month t. ΔUNC_t is a proxy for innovations in economic uncertainty in month t. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French factors in month t. Definitions are given in Appendix II. These factors are from Kenneth French's website.[47]

Table 3.1 reports the correlation matrix for each factor and index. Except for HML and IA, the correlations between all variables are low, from -0.39 to 0.25, showing that there is no potential collinearity in estimations of this study. Particularly, the sentiment and

45 Unexpected innovations in macroeconomic variables concern investors about their future investment and consumption, influencing the indirect utility of real wealth and asset prices. Thus, using the changes in economic uncertainty is consistent with the literature (for example, Merton, 1973; Ross, 1976; Chen, Roll, and Ross, 1986; Bali, Subrahmanyam, and Wen, 2020). The level of the index is non-stationary with a Dickey-Fuller statistic of −2.152, while its logarithmic difference is stationary with a Dickey-Fuller statistic of −13.678.
46 I require at least 24 months of non-missing observation for each stock to estimate the model.
47 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

economic uncertainty indices do not affect each other. This might be due to the sentiment index orthogonalised by several macroeconomic factors (Baker and Wurgler, 2006).[48] It is not surprising the correlation between HML and IA is high, 0.69. Fama and French (2015) show that this is caused by the highest return variances in those factors' construction, and the high correlation between them is artificial.

Table 3.1 Correlations

This table reports correlation coefficients among risk factors used to estimate EUE in Equation (3.2). Variable definitions are listed in Appendix II. The sample period is from July 1970 to December 2018.

	UNC	ΔUNC	SENT	MKT	SMB	HML	MOM	IA	ROE
UNC	1								
ΔUNC	0.082	1							
SENT	-0.117	0.024	1						
MKT	-0.108	-0.158	-0.026	1					
SMB	0.079	-0.093	-0.051	0.246	1				
HML	-0.007	0.014	0.084	-0.264	-0.073	1			
MOM	-0.049	0.103	0.023	-0.152	-0.058	-0.181	1		
IA	0.061	0.042	0.061	-0.378	-0.054	0.688	0.013	1	
ROE	0.009	-0.026	0.176	-0.252	-0.382	0.129	0.099	0.032	1

Once I have estimated the monthly EU beta for each stock during the sample period, I use the absolute value of EU betas for all analyses in this study. This approach is consistent with relevant studies (Hong and Sraer, 2016; Li, 2016). In Hong and Sraer's (2016) prediction, aggregate disagreement is positively associated with the absolute value of market beta. This is because disagreement is higher for stocks returns that are highly correlated with uncertainty regardless of the positive or negative sign. The use of the absolute value also matches my intention to examine the impact of EU on the uncertainty of a stock's return distribution (the variance of the distribution). A large magnitude of the beta, no matter whether it is positive or negative, makes the variance of the return more sensitive to the change of economic uncertainty.

[48] Those factors are the growth in industrial production, the growth in durable, nondurable, and service consumption, the growth in employment and the flag for NBER recession.

3.4 Empirical Analyses

3.4.1 Economic Uncertainty Exposure: High versus Low Sentiment

I use the BW sentiment index to identify high- and low-market sentiment periods following Baker and Wurgler (2007). If the value of the BW sentiment index in month t is positive (negative), then month t is a high (low)-market sentiment month. There are 308 high- and 275 low-market sentiment months in my sample, respectively.

I employ bivariate portfolio analyses to examine the relation between EUE and cross-sectional expected returns conditional on the general mispricing of stocks. Following Stambaugh, Yu, and Yuan (2015), at the end of each month t, five portfolios are formed by sorting on individual stocks' EUE estimated in Equation (3.2) up to month t. Then, independently another five portfolios are constructed by sorting stocks on their mispricing scores (MIS) in month t. Finally, 25 EUE-MIS portfolios are formed as intersections of five EUE and five MIS groups, and value-weighted returns are calculated during month $t + 1$. The first set of the 25 portfolios is formed in July 1970.

I first examine the average EUE and the number of stocks in 25 portfolios in different sentiment states. Focusing on the distribution of EUE in those portfolios in Panel A of Table 3.2, I significantly observe in the overpriced quintile that sentiment-driven investors tilt their portfolios towards stocks with higher EUE during high-mrket sentiment periods than low-market sentiment periods. There is an increasing trend in the average of EUE on five MIS portfolios from 0.684 for the underpriced group to 0.763 for the overpriced group. This trend is more pronounced than that during the low-market sentiment period, increasing from 0.547 for the underpriced group to 0.595 for the overpriced group.

In Panel B, the overpriced portfolio in the high EUE has on average 180 stocks during high-market sentiment period which is more than that (138) during low-market sentiment periods, confirming that EUE-induced disagreement is larger during high-market sentiment periods, thus irrational investors are more likely to overinvest in stocks with high EUE relative to low-market sentiment periods, resulting in more pronounced overpricing as the main source of mispricing in cross-sectional returns following high-market sentiment periods.

Comparing the distribution of EUE among these portfolios in the whole sample documented in the second chapter, I support my conjecture that there is a significant role of market-wide sentiment in relation to two effects of EUE on cross-sectional returns, especially to its mispricing one.

3.4.2 Portfolio Analyses

I next examine risk-adjusted returns of these 25 value-weighted portfolios. Those portfolios are rebalanced at the end of each month during the sample period. The risk-adjusted returns are alphas estimated by the following augmented Fama and French (2016) six-factor model using two subperiod intercept dummies:

$$R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} UMD_t + \beta_{p,5} IA_t + \beta_{p,6} ROE_t + \varepsilon_{i,t} \tag{3.3}$$

Table 3.2 Economic Uncertainty Exposure: High- versus Low-Market Sentiment

This table reports the average EUE and the number of stocks of the 25 EUE-MIS portfolios during high- and low-market sentiment periods in Panels A and B, respectively. The EUE is the absolute beta coefficient estimated in Equation (3.2). Variable definitions are listed in Appendix II. If the value of the sentiment index by Baker and Wurgler (2006) in month t is positive (negative), month t is high (low)-market sentiment month. There are 308 high and 275 low-market sentiment months, respectively. The sample period is from July 1970 to December 2018.

	High-Market Sentiment Period						Low-Market Sentiment Period					
	Low EUE	2	3	4	High EUE	All Stocks	Low EUE	2	3	4	High EUE	All Stocks
	Panel A: Average EUE											
Overpriced	0.161	0.296	0.504	0.830	2.022	0.763	0.113	0.234	0.403	0.667	1.559	0.595
2	0.145	0.286	0.494	0.821	1.882	0.726	0.104	0.228	0.400	0.664	1.459	0.571
3	0.138	0.281	0.491	0.817	1.804	0.706	0.102	0.225	0.397	0.659	1.408	0.558
4	0.134	0.280	0.492	0.817	1.740	0.693	0.100	0.225	0.398	0.659	1.369	0.550
Underpriced	0.133	0.279	0.489	0.814	1.703	0.684	0.100	0.226	0.397	0.659	1.354	0.547
All Stocks	0.142	0.284	0.494	0.820	1.830		0.104	0.228	0.399	0.662	1.430	
	Panel B: Average No of Stocks											
Overpriced	101	103	112	127	180	623	90	90	95	102	138	515
2	122	122	122	126	132	624	101	101	102	103	108	515
3	132	130	127	122	114	624	107	108	103	103	96	517
4	134	134	130	123	103	624	108	109	108	104	88	516
Underpriced	136	135	133	126	95	625	111	110	107	105	86	518
All Stocks	625	624	624	624	624		517	516	516	516	516	

where $R_{p,t}$ is the excess return of portfolio p in month t. $d_{H,t-1}$ and $d_{L,t-1}$ are dummy variable indicating high and low-market sentiment periods, respectively. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors in month t.

Table 3.3 reports the risk-adjusted returns on 25 EUE-MIS portfolios following different market sentiment periods. I also report risk-adjusted returns on average and univariate portfolios for MIS (the last two columns) and EUE (the last two rows) following different periods.

Panel A presents alphas following the high-market sentiment period. Alphas on the mispricing spreads, reported in the Underpriced-Overpriced row, increase monotonically from the lowest to highest EUE groups following high-market sentiment periods. Specifically, the largest mispricing alpha is significantly observed in the high EUE group with an alpha of 1.35% per month ($t = 4.49$) following the same period. This is is about double the mispricing effect (0.75% per month, $t = 3.86$) in the whole sample reported in the previous chapter and is more than triple the alpha of the univariate mispricing (0.39%, $t = 3.25$) following the same period.

For those results following low-market sentiment periods reported in Panel B, only two alphas of the "Underpriced−Overpriced" portfolios in the second and third EUE groups are significant. The EUE group does not explain the change of the mispricing effect. The unconditional mispricing effect, the alpha of the "Underpriced−Overpriced" portfolio constructed on MIS (0.29%, $t = 2.18$), is much weaker than that following high-market sentiment periods, consistent with Stambaugh, Yu, and Yuan (2012) suggesting that the existence of a mispricing effect only during high-market sentiment periods.

These findings confirm that market-wide sentiment has a significant role in the EUE-induced mispricing, supporting my first hypothesis.

Table 3.3 Portfolio Returns following High- and Low-Market Sentiment Periods

The table reports the risk-adjusted on 5 MIS (EUE) and 25 EUE-MIS value-weighted portfolios following high- and low-market sentiment periods in Panel A and B respectively. The 25 portfolios are formed by independently sorting on EUE and the mispricing scores. The mean of 5 MIS (EUE) portfolios is reported in Average MIS (EUE) column (row). 5 MIS (EUE) portfolios are formed by sorting individual stocks on their mispricing scores (EUE), reported in Univariate MIS (EUE) column (row). The risk-adjusted returns are estimates of alphas estimated in Equation (3.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2018. If the value of the sentiment index by Baker and Wurgler (2006) in month t is positive (negative), month t is high (low)-market sentiment month. There are 308 high and 275 low sentiment months, respectively. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	Low EUE	2	3	4	High EUE	High-Low	Average MIS	Univariate MIS
			Panel A: High-Market Sentiment Period					
1 Overpriced	-0.095	-0.13	-0.45***	-0.51***	-0.74***	-0.65***	-0.39***	-0.32***
	(-0.63)	(-0.99)	(-3.53)	(-3.42)	(-4.50)	(-2.72)	(-4.89)	(-3.68)
2	-0.14	0.33***	-0.22	0.16	-0.015	0.12	0.025	0.035
	(-1.06)	(2.66)	(-1.59)	(0.91)	(-0.085)	(0.59)	(0.34)	(0.54)
3 Non-mispricing	-0.046	0.13	0.065	-0.026	0.23	0.28	0.071	0.045
	(-0.39)	(1.00)	(0.54)	(-0.16)	(1.40)	(1.43)	(1.26)	(0.83)
4	-0.088	-0.00	-0.27**	-0.077	0.27	0.36	-0.032	-0.080
	(-0.96)	(-0.00)	(-2.20)	(-0.62)	(1.50)	(1.64)	(-0.54)	(-1.43)
5 Underpriced	0.019	0.12	0.084	0.047	0.61***	0.59**	0.18**	0.071
	(0.20)	(1.37)	(0.68)	(0.31)	(2.71)	(2.47)	(2.55)	(1.28)
Underpriced−Overpriced	0.11	0.26	0.54***	0.55***	1.35***	1.24***	0.56***	0.39***
	(0.61)	(1.54)	(3.07)	(2.63)	(4.49)	(3.58)	(4.56)	(3.25)
Average EUE	-0.069	0.092	-0.16**	-0.081	0.072	0.14		
	(-1.24)	(1.49)	(-2.38)	(-1.10)	(0.75)	(1.20)		
Univariate EUE	-0.018	0.11*	-0.093	-0.034	0.100	0.12		
	(-0.37)	(1.74)	(-1.34)	(-0.46)	(0.97)	(0.96)		
			Panel B: Low-Market Sentiment Period					
1 Overpriced	0.014	-0.40**	-0.54**	-0.25	-0.10	-0.11	-0.26**	-0.28**
	(0.11)	(-2.32)	(-2.51)	(-1.32)	(-0.69)	(-0.66)	(-2.46)	(-2.48)
2	-0.17	-0.092	-0.30**	0.0096	-0.029	0.14	-0.12*	-0.097
	(-1.37)	(-0.68)	(-2.09)	(0.067)	(-0.19)	(0.70)	(-1.77)	(-1.36)
3 Non-mispricing	-0.17	0.031	-0.034	0.066	0.36*	0.53**	0.049	-0.029
	(-1.56)	(0.28)	(-0.29)	(0.47)	(1.71)	(2.15)	(0.82)	(-0.49)
4	0.16	0.061	0.071	0.11	0.39*	0.23	0.16***	0.12**
	(1.59)	(0.58)	(0.59)	(0.87)	(1.86)	(0.98)	(2.59)	(2.13)
5 Underpriced	-0.041	0.081	-0.030	0.050	0.072	0.11	0.026	0.015
	(-0.39)	(0.91)	(-0.30)	(0.36)	(0.38)	(0.51)	(0.49)	(0.31)
Underpriced−Overpriced	-0.054	0.48**	0.51*	0.30	0.17	0.23	0.28**	0.29**
	(-0.31)	(2.32)	(1.95)	(1.38)	(0.73)	(0.81)	(2.25)	(2.18)
Average EUE	-0.044	-0.065	-0.17**	-0.0032	0.14	0.18		
	(-0.90)	(-1.05)	(-2.41)	(-0.041)	(1.33)	(1.42)		
Univariate EUE	-0.015	0.034	-0.10**	0.060	0.16	0.18		
	(-0.28)	(0.69)	(-1.97)	(0.78)	(1.47)	(1.29)		

Focusing on the EUE effect in the middle quintile of the mispricing portfolios, called the non-mispricing group, I observe a significant positive relationship between EUE and expected returns only following low-market sentiment periods. In Panel B of Table 3.3, the high-minus-low EUE portfolio generates a significant alpha of 0.53% per month with a t-statistic of 2.15, which is more than that (0.35% per month) in the whole sample reported in the first chapter. This finding suggests that EUE is more likely to be priced as a premium when investors are more rational, supporting my second hypothesis.

Overall, my results document that the presence of market-wide sentiment influences the effects of EUE on cross-sectional returns. The mispricing effect is significantly apparent when investors are irrational and the rational ones are limited in high-market sentiment periods. This effect is even more pronounced compared to the whole sample period documented previously. By contrast, the ambiguity-premium effect becomes clear with the former being arbitraged away following low-market sentiment periods, implying that it is more likely to be attributed to rational pricing instead of mispricing.

3.4.3 Predictive Regressions

In the previous section, I study risk-adjusted returns on portfolios by comparing within two sentiment periods, where periods are assigned simply with dummy variables. In this section, I examine my hypotheses using predictive regressions to test whether the BW sentiment index predicts excess returns on double-sort portfolios controlling for Fama and French (2016) market factors. I investigate the predictive power of the sentiment index on monthly double-sort portfolio returns by the following model:

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1} S_{t-1} + \beta_{p,2} MKT_t + \beta_{p,3} SMB_t + \beta_{p,4} HML_t + \beta_{p,5} UMD_t + \beta_{p,6} IA_t + \beta_{p,7} ROE_t + \varepsilon_{i,t} \quad (3.4)$$

where $R_{p,t}$ is the excess return of portfolio p in month t. S_{t-1} is the lagged level of BW sentiment index. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors in month t.

Table 3.4 reports the slope coefficients of the lagged BW sentiment index on the mispricing spreads from the low to high EUE groups, and on the high-minus-low EUE portfolio in the non-mispricing group.

I find that slope coefficients for the mispricing spreads are positive and monotonically increase from the low to high EUE groups. In the univariate specification, one standard deviation increase in the market sentiment leads to an increase in the value-weighted returns on the "Underpriced−Overpriced" portfolio in the high EUE group by 0.87% per month with a t-statistic of 3.60. When I control for Fama and French factors, the coefficient of the lagged sentiment index on the mispricing spread in the high EUE group remains positive and statistically significant (0.63%, $t = 2.84$). These findings further support my first hypothesis that the higher the market-wide sentiment the larger the EUE-induced mispricing.

Examining the predictive power of the lagged sentiment index on the ambiguity premium effect, I show a significant negative relationship in the univariate specification. One standard deviation decrease in the sentiment leads to an increase in the high-minus-low EUE portfolio in the non-mispricing group by 0.38% per month with a t-statistic of -2.02, supporting my second hypothesis that the lower the market-wide sentiment the larger the ambiguity premium. However, controlling for the market risk factors, the slope coefficient of the lagged sentiment index becomes statistically insignificant. It shows that market-wide sentiment may only be able to capture the mispricing which is a result of sentiment-related demand and limits to arbitrage, rather than the classical risk-return trade-off attributed to the rational demand (Baker and Wurgler, 2006).

Table 3.4 Predictive Regressions of the Mispricing Spread and the Ambiguity Premium

The table reports estimate of β coefficients on the mispricing spread in EUE quintile and the ambiguity premium in the non-mispricing group in by the following models:

Univariate:

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1}S_{t-1} + \varepsilon_{p,t}$$

FF6:

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1}S_{t-1} + \beta_{p,2}MKT_t + \beta_{p,3}SMB_t + \beta_{p,4}HML_t + \beta_{p,5}UMD_t + \beta_{p,6}IA_t + \beta_{p,7}ROE_t + \varepsilon_{i,t}$$

FF6+Macro:

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1}S_{t-1} + \beta_{p,2}MKT_t + \beta_{p,3}SMB_t + \beta_{p,4}HML_t + \beta_{p,5}UMD_t + \beta_{p,6}IA_t + \beta_{p,7}ROE_t + \sum_{J=1}^{4} m_J X_{J,t-1} + \varepsilon_{i,t}$$

$R_{p,t}$ is the excess return of portfolio p in month t. S_{t-1} is the lagged level of the BW sentiment index. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors in month t. $X_{1,t-1} \cdots X_{4,t-1}$ are four lagged macroeconomic variables: the default premium, the term premium, the real interest rate and inflation rate. Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2018. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	Low EUE	2	3	4	High EUE	High-Low EUE	High-Low EUE
	Underpriced-Overpriced						Non-mispricing
Univariate	0.33*	0.45*	0.16	0.43**	0.87***	0.53**	-0.38**
	(1.83)	(1.90)	(0.89)	(2.32)	(3.60)	(2.53)	(-2.02)
FF6	0.11	0.24	-0.03	0.25*	0.63***	0.53**	0.06
	(0.69)	(1.24)	(-0.18)	(1.67)	(2.84)	(2.28)	(0.47)
	0.14	0.28	0.04	0.24	0.58**	0.44*	0.08
FF6+ Macro	(0.90)	(1.25)	(0.24)	(1.43)	(2.50)	(1.81)	(0.51)

Baker and Wurgler (2006) have removed macro-related variations from the sentiment index by regressing the raw sentiment index on six macro-variables[49]. Therefore, to investigate whether the effect of market-wide sentiment on the findings in time-series is

[49] These variables are the growth in industrial production, the growth in durable, nondurable, and service consumption, the growth in employment and the flag for NBER recession.

robust after adding macroeconomic variables, I additionally consider four lagged macroeconomic factors in Equation (3.4), following Stambaugh Yu and Yuan (2012). Those factors are the lagged default premium, the difference between BAA and AAA bonds, the lagged term premium, the difference between 20-year and 1-year treasuries., the lagged real interest rate, the difference between 30-day T-bill and Consumer Price Index inflation rate, and the lagged the inflation rate.[50]

Controlling for additional four macro-variables, the presence of market-wide sentiment on the EUE-induced mispricing persists in Table 3.4. The magnitude of the coefficient and its significance level on the mispricing spread in the high EUE group is close to those documented earlier. However, there is no predictive power of the sentiment index on the ambiguity premium after controlling for macroeconomic factors.

3.5 Further Analyses

In this section, I provide further analyses to examine links between market-wide sentiment and these two channels of the EUE.

I first examine to what extent the existing cross-sectional risk model can explain the market-wide sentiment effect in relation to these two types of EUE effect. I then extend my empirical study to consider the interaction of the market-wide sentiment and macro uncertainty. I also study the market-wide sentiment effect considering the presence of short-sale constraints and using an alternative sentiment index. Finally, I provide the robustness of my main findings by using stock exposure to economic policy uncertainty.

[50] The bond yields and inflation are gathered from Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/, and the T-bill return is gathered from CRSP.

3.5.1 Alternative Risk Models

To provide more evidence to the market-wide sentiment effect on the two channels of EUE in cross-sectional returns, I examine the robustness of my findings with alternative risk models discussed in the first chapter.

Along with the Fama French six-factor model in my main analysis, I also report the risk-adjusted returns on mispricing spreads and the ambiguity premium in the non-mispricing group using the market model and two alternative versions of the augmented Fama French factor models in Table 3.5. I show that the mispricing effect is robust to these risk models following the high-market sentiment period. The mispricing alphas are statistically significant in the high EUE group, ranging from 2.07% to 1.12% per month. These figures are larger than those reported in the whole sample reported in the first chapter. For the low-market sentiment period, the subsequent alphas of ambiguity premium in the non-mispricing group remain significant, except for CAPM, when investors behave more rationally. Interestingly, the ambiguity premium is even larger than in the main analysis as the aggregate liquidity factor is additionally considered.

I additionally report the risk-adjusted returns with the q-factor (Hou, Xue, and Zhang, 2015; Hou et al., 2020) and the MSP models (Stambaugh and Yuan, 2017) in Table 3.5.

Following the high-market sentiment period, EUE-induced mispricing is significant in all q-factor and MSP models. The monthly alpha of the mispricing spread in the high EUE portfolio is 1.38% ($t = 4.08$) for the q4 model, 0.82% ($t = 2.72$) for the q5 model and 0.83% ($t = 3.16$) for the MSP model. These alphas are larger than those reported for the whole sample in Chapter 2. Moreover, conditional on market-wide sentiment, the mispricing effect cannot be captured by the existing models.

Table 3.5 Effect of Different Risk Models following High- and Low-Market Sentiment Periods

This table reports the risk-adjusted returns on overpriced, underpriced and non-mispricing double-sort portfolios following high- and low-market sentiment periods. The portfolios are formed by independently sorting on EUE and the mispricing scores. The risk-adjusted returns are estimates of alphas from the following models:

$CAPM: R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \varepsilon_{i,t}$

$FF5 \;:\; R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} IA_t + \beta_{p,5} ROE_t + \varepsilon_{i,t}$

$FF7 \;:\; R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} UMD_t + \beta_{p,5} IA_t + \beta_{p,6} ROE_t + \beta_{p,7} LIQ_t + \varepsilon_{i,t}$

$q4 \;:\; R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} QSMB_t + \beta_{p,3} QIA_t + \beta_{p,4} QROE_t + \varepsilon_{i,t}$

$q5 \;:\; R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} QSMB_t + \beta_{p,3} QIA_t + \beta_{p,4} QROE_t + \beta_{p,5} QEG_t + \varepsilon_{i,t}$

$MSP \;:\; R_{p,t} = \alpha_H d_{H,t-1} + \alpha_L d_{L,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} MSMB_t + \beta_{p,3} MGMT_t + \beta_{p,4} PERF_t + \varepsilon_{i,t}$

$R_{p,t}$ is the excess return of portfolio p in month t. $d_{H,t-1}$ and $d_{L,t-1}$ are dummy variable indicating following high and low-market sentiment periods. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors and LIQ_t is the level of aggregate market liquidity in month t. $QSMB_t$, QIA_t, $QROE_t$ and QEG_t are Hou, Xue and Zhang (2015) and Hou et al. (2020) q-factors in month t. $MSMB_t$ $MGMT_t$, and $PERF_t$ are Stambaugh and Yuan (2017) mispricing factors in month t. Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2016 for MSP and to December 2018 for the other models. If the value of the sentiment index by Baker and Wurgler (2006) in month t is positive (negative), month t is high (low)-market sentiment month. There are 308 high and 275 low sentiment months, respectively. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	High-Market Sentiment Period			Low-Market Sentiment Period		
	Low EUE	High EUE	High-Low EUE	Low EUE	High EUE	High-Low EUE
			CAPM			
Non-mispricing	0.13	-0.09	-0.22	-0.15	0.35	0.50
	(1.17)	(-0.47)	(-0.91)	(-1.19)	(1.41)	(1.62)
Underpriced− Overpriced	0.70***	2.07***	1.37***	0.32	0.60**	0.28
	(3.23)	(6.66)	(4.12)	(1.55)	(2.37)	(1.04)
			FF5			
Non-mispricing	-0.09	0.32*	0.41**	-0.20*	0.42*	0.62**
	(-0.77)	(1.95)	(2.06)	(-1.80)	(1.88)	(2.35)
Underpriced− Overpriced	0.40*	1.70***	1.30***	0.14	0.41	0.27
	(1.90)	(4.58)	(3.57)	(0.69)	(1.57)	(0.98)
			FF7			
Non-mispricing	-0.03	0.25	0.29	-0.16	0.39*	0.55**
	(-0.28)	(1.41)	(1.30)	(-1.21)	(1.83)	(2.03)
Underpriced− Overpriced	0.09	1.12***	1.03***	-0.09	-0.17	-0.08
	(0.45)	(3.98)	(2.98)	(-0.50)	(-0.62)	(-0.26)
			q4			
Non-mispricing	-0.02	0.26	0.28	-0.23*	0.49*	0.71**
	(-0.20)	(1.38)	(1.22)	(-1.73)	(1.85)	(2.17)
Underpriced− Overpriced	0.22	1.38***	1.17***	0.08	0.23	0.15
	(0.90)	(4.08)	(3.36)	(0.39)	(0.87)	(0.52)
			q5			
Non-mispricing	0.02	0.35*	0.33	-0.18	0.58**	0.76**
	(0.18)	(1.88)	(1.45)	(-1.24)	(2.42)	(2.45)
Underpriced− Overpriced	-0.08	0.82***	0.91***	-0.23	-0.36	-0.12
	(-0.36)	(2.72)	(2.65)	(-1.15)	(-1.37)	(-0.43)
			MSP			
Non-mispricing	0.06	0.15	0.09	-0.21*	0.58***	0.80***
	(0.49)	(0.73)	(0.36)	(-1.68)	(2.75)	(3.03)
Underpriced− Overpriced	-0.23	0.83***	1.06***	-0.30*	-0.12	0.18
	(-1.30)	(3.16)	(3.09)	(-1.69)	(-0.48)	(0.61)

Following low-market sentiment periods, by contrast, the ambiguity-premium effect in the non-mispricing group remains significant with the mispricing effect arbitraged away. The EUE premium is even larger with more comprehensive models than the counterpart in my main analysis when investors behave rationally, and in the whole sample reported in the first chapter. The monthly alpha of the high-minus-low EUE portfolio in the non-mispricing group is 0.71% for the q4 model, 0.76% for the q5 model and 0.80% for the MSP model following low-market sentiment periods. These findings suggest that the EUE premium is a new factor that is different from the existing risk factor as rational investors demand in the sense of the ambiguity-return trade-off consistent with the previous chapter.

3.5.2 Interaction of Economic Uncertainty and Market-wide Sentiment

In this section, I further examine my hypotheses with the interaction between market-wide sentiment and macro-level uncertainty. If macro uncertainty leaves more room for investors to behave more irrationally and have a larger disagreement, the sentiment effect tends to be more pronounced in periods with increasing EU (Hirshleifer, 2001; Birru and Young, 2020). Therefore, I expect that the presence of market-wide sentiment on the EUE-induced mispricing is the strongest in the intersection of high market-wide sentiment and high macroeconomic uncertainty periods.

To test this prediction, I further divide the sample into four periods: increasing EU and high-market sentiment, increasing EU and low-market sentiment, decreasing EU and high-market sentiment, and decreasing EU and low-market sentiment. If the change of the EU index in month t is positive (negative) then month t is an increasing (decreasing) EU. High and low-market sentiment months are classified in the same manner as described in

Section 3.4.1. Four periods are the interaction of these two-way classifications. There are 143 (127) months with increasing EU and high (and low)-market sentiment, and 165 (148) months with decreasing EU and high (and low)-market sentiment.

I obtain risk-adjusted returns following each of four periods by the following model:

$$R_{p,t} = \sum_{J=1}^{4} \alpha_J d_{J,t-1} + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} UMD_t + \beta_{p,5} IA_t + \beta_{p,6} ROE_t + \varepsilon_{i,t} \quad (3.5)$$

where $R_{p,t}$ is the excess return of portfolio p in month t. $d_{J,t-1}$ is dummy variable indicating each of the four periods in month $t-1$. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors in month t. Table 3.6 reports risk-adjusted returns following each of the four periods in different EUE groups.

Consistent with the prediction, the EUE effect on mispricing is much stronger following increasing EU and high-market sentiment periods. The monthly mispricing alpha in the highest EUE group is 1.74% with a t-statistic of 3.79. This figure is larger than the mispricing effect (with a monthly alpha of 1%) following the periods with low EU and high-market sentiment. Additionally, it is the largest mispricing spread observed in the entire study.

Second, the ambiguity premium effect is only observed in periods with more rational behaviours but increasing macro-level uncertainty. The high-minus-low EUE portfolio in the non-mispricing group has a monthly alpha of 1.02% with a t-statistic of 2.67 following high EU and low-market sentiment periods. This is almost double the ambiguity premium observed following unconditional low-market sentiment periods

(0.53%, $t = 2.15$) reported in Table 3.3, and is the highest premium documented in both chapters.

Table 3.6 The Interaction of Market-wide Sentiment and Economic Uncertainty

This table reports the risk-adjusted returns on overpriced, underpriced and non-mispricing double-sort portfolios following four different periods: increasing EU and high-market sentiment, increasing EU and low-market sentiment, decreasing EU and high-market sentiment, and decreasing EU and low-market sentiment.. The portfolios are formed by independently sorting on EUE and the mispricing scores. The risk-adjusted returns are estimates of alphas estimated in Equation (3.5). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2018. If the change of the EU index by Jurado, Ludvigson and Ng (2015) in month t is positive (negative) then month t is an increasing (decreasing) EU. High and low-market sentiment months are classified in the same manner with the value of the sentiment index by Baker and Wurgler (2006). There are 143 (127) increasing EU and high (and low)-market sentiment, and 165 (148) decreasing EU and high (and low)-market sentiment months. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	High-Market Sentiment Period			Low-Market Sentiment Period		
	Low EUE	High EUE	High-Low EUE	Low EUE	High EUE	High-Low EUE
	Panel A: Increasing EU Period					
1 Overpriced	-0.18	-0.95***	-0.77**	-0.11	-0.07	0.04
	(-0.72)	(-4.21)	(-2.02)	(-0.56)	(-0.29)	(0.14)
3 Non-mispricing	-0.10	0.03	0.13	-0.36*	0.66*	1.02***
	(-0.60)	(0.14)	(0.49)	(-1.88)	(1.86)	(2.67)
5 Underpriced	0.07	0.79**	0.72**	-0.14	0.51*	0.64*
	(0.52)	(2.34)	(1.99)	(-0.86)	(1.69)	(1.95)
Underpriced−	0.25	1.74***	1.49***	-0.02	0.58	0.60
Overpriced	(0.85)	(3.79)	(2.68)	(-0.08)	(1.44)	(1.52)
	Panel B: Decreasing EU Period					
1 Overpriced	-0.02	-0.55**	-0.54**	0.12	-0.12	-0.24
	(-0.10)	(-2.55)	(-1.97)	(0.71)	(-0.64)	(-0.94)
3 Non-mispricing	0.00	0.41*	0.41	-0.02	0.11	0.12
	(0.03)	(1.79)	(1.44)	(-0.12)	(0.44)	(0.39)
5 Underpriced	-0.03	0.44*	0.47*	0.04	-0.30	-0.34
	(-0.22)	(1.67)	(1.72)	(0.26)	(-1.24)	(-1.19)
Underpriced−	-0.01	1.00***	1.01**	-0.08	-0.19	-0.10
Overpriced	(-0.04)	(2.87)	(2.58)	(-0.38)	(-0.62)	(-0.26)

Overall, these findings confirm that macro-level uncertainty leaves more room for irrational behaviours in traders and the effect of sentiment, consistent with previous studies (Garcia, 2013; Birru and Young; 2020). Furthermore, EUE is priced as rational investors demand ambiguity premium when macroeconomic uncertainty increases, and their preference is more likely to be reflected during the period of low-market sentiment.

3.5.3 Short-sale Constraints

Combining with short-sale constraints, the presence of market-wide sentiment is significantly observed in cross-sectional returns as arbitrageurs are not able to offset sentiment-driven traders (Miller, 1977; Stambaugh, Yu and Yuan, 2012). Therefore, I extend my main analyses distinguishing the level of short-sale constraints in double-sort portfolios following different sentiment states.

The average returns on small-sized stocks are influenced more by market-wide sentiment relative to large-sized ones as individual investors are more likely to hold smaller and lower-priced stocks in their portfolios, and their trading activities are affected by sentiment (Lee, Shleifer and Thaler, 1991; Kumar and Lee, 2006; Baker and Wurgler, 2007). To examine the size effect, I form 50 portfolios by independently sorting stocks into two SIZE, five EUE, and five MIS groups.

Consistent with the prediction, Panel A of Table 3.7 shows that the effect of market-wide sentiment on the EUE-induced mispricing is stronger in small-size stocks relative to large-size ones. For small-cap stocks, the risk-adjusted return on the mispricing spread in the high EUE group is significantly 1.59% per month ($t = 7.13$) while it is significantly 1.30% ($t = 3.97$) for large-cap stocks following high-market sentiment period. Furthermore, considering the significant EUE-induced mispricing in the low SIZE group following low-market sentiment periods (1.05%, $t = 4.89$), rational traders are not able to arbitrage away the mispricing in small-cap stocks even if investors' views are sufficiently dispersed in low-market sentiment periods.

The ambiguity premium is significantly observed in the non-mispricing group with stocks with high SIZE (monthly alpha of 0.58%, $t = 2.19$), but not with low SIZE,

Table 3.7 Short-sale Constraints

This table reports the risk-adjusted returns on overpriced, underpriced and non-mispricing portfolios, formed by independently sorting on the two SIZE/IVOL, the five EUE and the five MIS groups, following high- and low-market sentiment periods. The risk-adjusted returns are estimates of alphas estimated in Equation (3.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2018. If the value of the sentiment index by Baker and Wurgler (2006) in month t is positive (negative), month t is high (low)-market sentiment month. There are 308 high and 275 low-market sentiment months, respectively. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	High-Market Sentiment Period			Low-Market Sentiment Period			High-Market Sentiment Period			Low-Market Sentiment Period		
	Low EUE	High EUE	High-Low EUE	Low EUE	High EUE	High-Low EUE	Low EUE	High EUE	High-Low EUE	Low EUE	High EUE	High-Low EUE
	Panel A: Size Effect											
	Low SIZE						High SIZE					
1 Overpriced	-0.38**	-0.88***	-0.49***	-0.16	-0.61***	-0.45**	-0.08	-0.69***	-0.61**	0.02	0.02	-0.00
	(-2.47)	(-5.59)	(-2.73)	(-1.02)	(-4.20)	(-2.17)	(-0.52)	(-3.70)	(-2.31)	(0.18)	(0.11)	(-0.02)
3 Non-mispricing	0.11	-0.00	-0.11	-0.08	0.12	0.19	-0.05	0.28	0.33	-0.18	0.40*	0.58**
	(0.81)	(-0.03)	(-0.52)	(-0.61)	(0.90)	(1.09)	(-0.40)	(1.55)	(1.57)	(-1.57)	(1.74)	(2.19)
5 Underpriced	0.42***	0.71***	0.29	0.36***	0.44***	0.08	0.01	0.61**	0.59**	-0.05	0.04	0.08
	(3.12)	(3.84)	(1.53)	(3.04)	(2.90)	(0.48)	(0.15)	(2.55)	(2.36)	(-0.45)	(0.18)	(0.35)
Underpriced−	0.80***	1.59***	0.78***	0.52***	1.05***	0.53**	0.10	1.30***	1.20***	-0.07	0.02	0.09
Overpriced	(4.00)	(7.13)	(2.89)	(2.62)	(4.89)	(1.98)	(0.50)	(3.97)	(3.22)	(-0.39)	(0.07)	(0.29)
	Panel B: Idiosyncratic Risk											
	Low IVOL						High IVOL					
1 Overpriced	0.07	-0.55**	-0.62**	-0.07	-0.23	-0.16	-0.79***	-0.86***	-0.07	-0.02	-0.15	-0.14
	(0.41)	(-2.39)	(-2.16)	(-0.52)	(-0.95)	(-0.65)	(-3.46)	(-4.26)	(-0.21)	(-0.06)	(-0.98)	(-0.56)
3 Non-mispricing	-0.10	0.39	0.49*	-0.17	0.41	0.58*	0.05	0.04	-0.01	-0.24	0.15	0.40
	(-0.70)	(1.49)	(1.70)	(-1.42)	(1.42)	(1.79)	(0.18)	(0.19)	(-0.02)	(-1.20)	(0.65)	(1.27)
5 Underpriced	0.01	0.52**	0.51*	-0.16	-0.01	0.14	0.20	0.68**	0.47	0.69***	0.16	-0.54
	(0.12)	(2.00)	(1.87)	(-1.50)	(-0.06)	(0.61)	(0.89)	(2.51)	(1.54)	(2.83)	(0.61)	(-1.64)
Underpriced−	-0.05	1.08***	1.13***	-0.09	0.21	0.30	1.00***	1.53***	0.54	0.71**	0.31	-0.40
Overpriced	(-0.27)	(3.10)	(2.78)	(-0.55)	(0.67)	(0.87)	(3.03)	(4.41)	(1.24)	(2.00)	(1.09)	(-1.02)

following low-market sentiment periods.

As the second short-sale constraint proxy, I consider idiosyncratic risk (IVOL) that discourages arbitrageurs to correct stocks' prices. Since, arbitrageurs are concerned about return-to-risk performance over the short-term horizon, as they use capital supplied by investors who are more likely to withdraw funds if the short-term performance is poor. Therefore, volatile assets exhibit higher mispricing and are subject to investor sentiment as a result of noise trading activity pushing prices away from fundamentals (Ali, Hwang and Trombley, 2003; Stambaugh, Yu and Yuan, 2015). To examine the IVOL effect, I form 50 portfolios by independently sorting stocks into two IVOL, five EUE, and five MIS groups.

Panel B of Table 3.7 reports adjusted returns in both low and high IVOL groups. Consistent with existing studies, following high-market sentiment periods, the mispricing effect is stronger for stocks with higher IVOL. The risk-adjusted return on the mispricing spread in the high EUE group is significantly 1.53% per month ($t = 4.41$) for high IVOL stocks following high-market sentiment periods, which is higher than the corresponding alpha (monthly alpha of 1.08%, $t = 3.10$) for low IVOL stocks following the same period.

The ambiguity premium is significantly observed in the non-mispricing group for low IVOL stocks following both high and low-market sentiment periods. This observation implies that even if sentiment-driven investors play a significant role when market-wide sentiment is high, the rational demand is apparent among low IVOL stocks.

Overall, the mispricing effect of EUE is more pronounced following high-sentiment periods in high short-sale constrained groups, namely high IVOL and low SIZE groups. It suggests that during high-market sentiment periods, rational investors are limited to exploit the irrational valuation resulting in significant overpricing in subsequent anomaly returns as the main source of mispricing (Miller, 1977; Stambaugh, Yu and Yuan, 2012).

However, I still observe a significant mispricing effect of EUE following the high-market sentiment period in low short-sale constrained groups. It implies that EUE can be a different source of arbitrage friction which deters rational investors from arbitraging away irrational mispricing, as shown in the second chapter. Finally, following low-market sentiment periods, the EUE premium in the non-mispricing group is significant among only stocks with low short-sale constraints, as the rational expectation.

3.5.4 Alternative Sentiment Index

In this section, I investigate whether my results are robust when using an alternative sentiment index. Previous studies have used the Consumer Sentiment index by the University of Michigan to measure investor sentiment (Lemmon and Portniaguina, 2006; Bergman and Roychowdhury, 2008). The Michigan sentiment index is constructed by conducting a monthly survey which is mailed to a number of randomly selected households and asks their opinion about the economy, starting monthly from January 1978. [51] Therefore, the Michigan index might be more related to the sentiment in the economy rather than in stock markets. Following Stambaugh, Yu and Yuan. (2012), I use residuals taken from a regression of the Michigan index on the six macro-related variables used by Baker and Wurgler (2006).[52] This allows us to remove macro-related information from the index. I estimate slope coefficients of Michigan index on double-sort portfolios in time-series regressions similar to Equation (3.4) by replacing the lagged BW sentiment index with the lagged Michigan index.

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[51] The index is obtained from http://www.sca.isr.umich.edu/tables.html.
[52] The six macro-related variables are the growth in industrial production, the growth in durable, nondurable and service consumption, the growth in employment and a flag for NBER recessions. The series are from Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/.

Table 3.8 reports slope coefficients of the lagged Michigan index on the mispricing spreads from the lowest to highest EUE groups, and on the high-minus-low EUE portfolio in the non-mispricing group. The coefficient of the lagged Michigan index on the mispricing spread in the high EUE group is significantly positive (0.04%, $t = 2.06$), suggesting my first hypothesis still holds when using the Michigan index. However, the slope coefficient on the ambiguity premium in the non-mispricing group is statistically insignificant, consistent with Table 3.4, confirming that Michigan Index proxying for market-wide sentiment may also not be able to predict the classical risk-return trade-off attributed to the rational demand.

Table 3.8 Predictive Regressions of the Mispricing Spread and the Ambiguity Premium: the Michigan Index

The table reports estimate of β coefficients on the mispricing spread in EUE quintile and the ambiguity premium in the non-mispricing group in by the following models:

Univariate:

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1}M_{t-1} + \varepsilon_{p,t}$$

FF6:

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1}M_{t-1} + \beta_{p,2}MKT_t + \beta_{p,3}SMB_t + \beta_{p,4}HML_t + \beta_{p,5}UMD_t + \beta_{p,6}IA_t + \beta_{p,7}ROE_t + \varepsilon_{i,t}$$

FF6+Macro:

$$R_{p,t} = \alpha_{p,1} + \beta_{p,1}M_{t-1} + \beta_{p,2}MKT_t + \beta_{p,3}SMB_t + \beta_{p,4}HML_t + \beta_{p,5}UMD_t + \beta_{p,6}IA_t + \beta_{p,7}ROE_t + \sum_{J=1}^{4} m_J X_{J,t-1} + \varepsilon_{i,t}$$

$R_{p,t}$ is the excess return of portfolio p in month t. M_{t-1} is the lagged level of the Michigan index. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French market factors in month t. $X_{1,t-1} \cdots X_{4,t-1}$ are four lagged macroeconomic variables: the default premium, the term premium, the real interest rate and inflation rate. Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from July 1970 to December 2018. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	Low EUE	2	3	4	High EUE	High-Low EUE	High-Low EUE
	Underpriced-Overpriced						Non-mispricing
Univariate	0.03	0.03	0.02	0.04**	0.07***	0.05**	-0.04
	(1.50)	(1.49)	(1.13)	(2.29)	(3.00)	(2.10)	(-1.52)
FF6	0.00	0.01	-0.01	0.01	0.04**	0.04*	-0.01
	(0.20)	(0.35)	(-0.52)	(0.85)	(2.06)	(1.73)	(-0.78)
	0.00	0.00	0.00	0.01	0.04**	0.04	-0.00
FF6+ Macro	(0.23)	(0.17)	(0.26)	(0.36)	(2.06)	(1.59)	(-0.23)

3.5.5 Economic Policy Uncertainty Index

In my analyses, I rely on the JLN uncertainty index in beta estimation to form double-sort portfolios. To understand whether the role of market-wide sentiment in the two effects of EUE on cross-sectional returns depends on index selection, I additionally use the economic policy index (EPU) developed by Baker, Bloom and Davis (2016). As in my EUE estimation, I estimate these uncertainty exposure betas from a 60-month rolling regression for each stock by replacing ΔUNC_t with the log changes of the EPU index, in Equation (3.2). Once I collect the absolute value of monthly estimated EPU exposure (EPUE), I form 25 independent double-sorted EPUE-MIS portfolios. The first set of the 25 portfolios is formed in February 1990.

Table 3.9 presents risk-adjusted returns on EPEU-MIS portfolios following different market sentiment periods. Similar to my main findings reported in Table 3.3, I observe a significant role of market-wide sentiment in the two effects of EPEU on cross-sectional returns. Following high-market sentiment periods, the average alpha of the mispricing spread in the high EPUE is significantly 1% per month ($t = 2.80$), which is larger than that (0.64%, $t = 2.49$) reported in the previous chapter. Following low-market sentiment periods, the high-minus-low EPUE portfolio in the Non-mispricing group significantly generates 0.70% per month ($t = 2.41$) as its mispricing effect vanishes, which is almost double the ambiguity premium (0.41%, $t = 1.92$) documented previously.

Overall, I confirm that the market-wide sentiment effect is prominent in both the mispricing and the ambiguity premium sourced by different types of economic uncertainty.

Table 3.9 Economic Policy Uncertainty Index Portfolio Returns following High- and Low-Market Sentiment Periods

The table reports the risk-adjusted on 25 EPUE-MIS value-weighted portfolios following high- and low-market sentiment periods in Panel A and B, respectively. The 25 portfolios are formed by independently sorting on EPUE and the mispricing scores. The risk-adjusted returns are estimates of alphas estimated in Equation (3.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from January 1990 to December 2018. If the value of the sentiment index by Baker and Wurgler (2006) in month t is positive (negative), month t is high (low)-market sentiment month. There are 215 high and 133 low-market sentiment months, respectively. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	Low EPUE	2	3	4	High EPUE	High-Low EPUE
			Panel A: High-Market Sentiment Period			
Overpriced	-0.05	-0.24	-0.38**	-0.31	-0.42**	-0.37
	(-0.25)	(-1.20)	(-2.19)	(-1.59)	(-2.44)	(-1.48)
2	0.05	-0.33*	0.27	0.02	0.25	0.20
	(0.26)	(-1.68)	(1.49)	(0.10)	(1.00)	(0.64)
3 Non-mispricing	0.24	0.06	-0.20	-0.15	0.48**	0.24
	(1.40)	(0.48)	(-1.15)	(-0.81)	(2.21)	(0.81)
4	-0.13	-0.31**	-0.22*	-0.14	0.59**	0.73***
	(-1.07)	(-2.45)	(-1.73)	(-0.84)	(2.51)	(2.91)
Underpriced	0.03	0.03	-0.03	0.10	0.58**	0.55*
	(0.26)	(0.30)	(-0.22)	(0.69)	(2.06)	(1.70)
Underpriced−	0.07	0.27	0.36*	0.42*	1.00***	0.92**
Overpriced	(0.32)	(1.18)	(1.82)	(1.72)	(2.80)	(2.12)
			Panel B: Low-Market Sentiment Period			
Overpriced	-0.45*	-0.29	-0.67**	-0.79***	-0.14	0.32
	(-1.66)	(-1.09)	(-2.44)	(-2.75)	(-0.54)	(0.97)
2	-0.06	-0.31	-0.28	-0.33	0.15	0.22
	(-0.28)	(-1.46)	(-1.17)	(-1.64)	(0.66)	(0.77)
3 Non-mispricing	-0.08	-0.04	-0.26	-0.02	0.62**	0.70**
	(-0.56)	(-0.27)	(-1.53)	(-0.09)	(2.28)	(2.41)
4	0.30**	0.07	0.11	-0.08	0.14	-0.16
	(2.26)	(0.46)	(0.59)	(-0.31)	(0.46)	(-0.46)
Underpriced	-0.06	0.12	-0.17	-0.04	0.05	0.10
	(-0.47)	(1.04)	(-1.23)	(-0.18)	(0.19)	(0.36)
Underpriced−	0.39	0.41	0.50*	0.75*	0.18	-0.21
Overpriced	(1.21)	(1.26)	(1.70)	(1.93)	(0.59)	(-0.48)

3.6 Conclusion

In traditional asset pricing theory, investor sentiment has no role in explaining the cross-section of stock returns. Existing studies, however, have shown that market-wide sentiment has a significant influence in the stock market, and have highlighted the incorporation of its impact into the theory (i.e., Baker and Wurgler, 2006; 2007; Stambaugh, Yu and Yuan, 2012). This study investigates its influence in relation to the two effects of EUE on cross-sectional returns documented in the previous chapter. The contribution of this study to the literature is the empirical examination of the interaction between market-wide sentiment and investors' preferences to assets with different levels of EUE, and the exploration of behavioural insights into those EUE effects.

This study argues that the mispricing effect of EUE is dominant as investors are more irrational and the rational ones are limited in the high-market sentiment period. Consistent with this, it shows that there is larger mispricing spread in stocks with high EUE following the high-market sentiment period. This effect is even more pronounced compared to the whole sample period documented in Chapter 2. The ambiguity premium, by contrast, is significantly apparent with the mispricing effect vanishing following the low-market sentiment period as the market is more rational. This finding confirms that the ambiguity premium is attributed to investors' rational preference for lower ambiguity (Anderson, Ghysels and Jurgens, 2009), which is clearly observed when the market condition reflects this group of investors' views.

In the context of short-sale impediments, this study shows that the effect of market-wide sentiment on EUE-induced mispricing is stronger among small-sized and high idiosyncratic risk stocks. However, EUE-induced mispricing is still observed in low short-sale constrained groups, implying that EUE can be a different source of arbitrage documented in Chapter 2. As the rational expectation, the ambiguity premium effect is apparent following a low-market sentiment period among only stocks with low short-sale constraints.

Finally, this study finds that the mispricing effect is even much stronger in the intersection of high market-wide sentiment and high macroeconomic uncertainty. This finding suggests that economic uncertainty indeed leaves more room for the sentiment effect in the market (Garcia, 2003, Birru and Young, 2020).

Chapter 4

4 Incentivised Optimism: Economic Uncertainty and Analyst Forecasts

4.1 Introduction

In the first two empirical chapters, I study the effect of economic uncertainty on cross-sectional returns along with the consideration of market-wide sentiment presence. This chapter examines the effect of economic uncertainty on security analysts' bias in forecasts and stock recommendations.

Existing studies have shown optimistic bias in sell-side analysts' forecasts (i.e., Stickel, 1990; Chopra, 1998; Lim, 2001).[53] This bias is generally caused by their incentive concerns (Jackson 2005). For instance, Lim (2001) argues that an analyst publishing a favourable forecast for a company is more likely to build a better relationship with that company. Moreover, optimism in analysts' forecast generates trading volume for the brokerage firm they work for, resulting in receiving more trading commissions (Cowen, Groysberg and Healy, 2006). However, analysts' reputation concerns limit these incentives as investors are able to catch them out in the long term. In this regard, this behaviour with upward bias can be detrimental for analysts' reputation in their career as it will affect analysts to secure their position in the industry or get promotion to larger brokerage firms (Jackson,

[53] Our analyst optimism measure is calculated by subtracting the average analysts' forecast from actual earnings (i.e., Lim, 2001; Engelberg, Mclean and Pontif, 2018).

2005; Groysberg, Healy and Maber, 2011; Chang and Choi, 2017). Therefore, analysts are in a trade-off between their reputation and incentive concerns related to optimistic forecasts. One of these factors that may tilt this balance is the uncertainty of the firm's future outlook. Especially, how a firm's exposure to macroeconomic uncertainty would affect analysts behaviours has not been fully examined in the literature.[54]

Along with the incentive based optimism limited with analysts' reputation concerns, there are also different explanations for analyst optimism in the relevant literature. First, analysts with pessimistic view on a company are more likely to drop their forecasts. This is because the company might withhold inside information from those analysts. Due to missing pessimistic view this situation feeds analyst optimism in forecasts for that company, which is referred to self-selection bias (McNichols and O'Brien, 1997; Hayes, 1998; Das et al., 2006).[55] Second, analyst optimism is subject to cognitive biases.[56] Several studies find that analysts are more likely to underreact (overreact) to negative (positive) news, resulting in significant optimism in forecasts, which is more prominent with larger stock-level uncertainty (i.e. Mendenhall, 1991; Abarbanell and Bernard, 1992; Esterwood and Nutt, 1999; Zhang, 2006). Ertimur, Muslu and Zhang (2011) suggest that although those explanations are not mutually exclusive, the incentive based explanation has a dominant effect on analysts optimism.

Behavioural explanation based on analysts' underreaction to new information under uncertainty, which is inconsistent with the rational notion, could be the main force that

[54] Chang and Choi (2017) show that the market-level uncertainty affecting analysts' incentives results in optimistic bias in their forecasts. However, firm level exposure has not been studied.

[55] Considering the rational framework in analyst optimism, the self-selection bias complements analysts' incentive concerns. Since, the withdrawal of pessimistic forecasts is more likely to keep managerial relationships (McNichols and O'Brien, 1997). This study provides evidence consistent with the self-selection bias explanation in Section 4.5.4.

[56] Hirshleifer (2001) suggests that due to overconfidence analysts put more attention on their private information than public signals, thus their forecast tend to be optimistic. De Bondt and Thaler (1990) argue that analysts' optimism is due to overreaction to information leading to form extreme expectations.

makes analysts more optimistic for stocks with uncertain signals induced by economic uncertainty. However, Lim (2001) argues that the behavioural explanation due to cognitive biases is not clear enough to explain analysts optimism.[57] This is because one of the key sources in earnings forecasts is companies' private information, which becomes even more important for those with higher uncertain signals (Lim, 2001; Soltes, 2014; Brown et al. 2015).[58]

In this study, I conjecture that EUE may give more room to analysts to be more optimistic for incentives with less career concern due to its effect on information quality.[59] Economic uncertainty (EU) is one of these factors at the macro-level related to the prospect of the economy which is unpredictable using the available information and models (Bloom, 2009; Jurado, Ludvigson and Ng, 2015). Intuitively, it would be more difficult for investors to estimate the prospect of companies with higher EUE.[60] Therefore, stock exposure to economic uncertainty makes it harder for investors to verify analysts' forecasts.[61] This condition is more likely to tilt the balance of analysts' trade-off to be more optimistic for incentives in their forecast since the chance of being caught is relatively lower leading to a lower reputational concern. Therefore, I hypothesise that optimism in analysts' forecasts increases with stock exposure to economic uncertainty. This hypothesis is also built on the

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[57] For more details about the theoretical model on analyst rational optimism, see Lim (2001).

[58] Considering analysts underreaction to macroeconomic news (Hugon, Kumar and Lim, 2016), this study examines whether the behavioural explanation can hold. However, there is no strong evidence for this explanation. More details can be found in Section 4.5.5.

[59] Along with macroeconomic uncertainty, there are several factors which could affect information quality such as earnings precision, accruals quality and analyst consensus (i.e. Dechow and Dichew, 2002; Zhang, 2006; Ng, 2011). In this study, analyst consensus, as analyst dispersion, and accruals quality are controlled in empirical analyses.

[60] This specification allows us to differentiate analyst optimism level as not all companies are equally affected by macro uncertainty. For instance, companies having large investments or producing durable goods are more likely to be influenced by shocks in uncertainty, relative to those producing services or non-durable goods (i.e., Bloom, 2009; Gomes, Kogan and Yogo., 2009).

[61] This is especially for each individual company, users of analysts report would be more difficult to pinpoint the source of forecasting error in firms with higher sensitivity to EU since they only have limit observations. As a researcher I can quantify the effect with large sample and through statistical analyses.

three strands of literature on the incentives for analysts to produce a more favourable view on a firm with higher EUE than that with lower EUE.

First, Lim (2001) suggests that managers support positive forecasts while eliminating the flow of unfavourable ones. Since favourable forecasts which lead to higher capital market valuations increase their compensation levels. Lim (2001) further shows that optimistic forecasts tend to be larger for companies with higher uncertain payoffs and for analysts who are in a need of management access as an information source. Therefore, for stocks with high EUE, analysts are more likely to use optimistic forecasts to gain support from managers in order to access private information.

Second, several studies have modelled heterogeneity among investors and show that pessimistic investors reduce their participation in stocks with uncertain payoffs. Thus, those assets are held by only optimistic ones (i.e., Cao, Wang and Zhang, 2005; Easley and O'Hara, 2009; Epstein and Schneider, 2010).[62] Additionally, Cowen, Groysberg and Healy (2006) suggest that an optimistic forecast for a stock tend to encourage investors with an optimistic view to buy, which generates more trading volume.[63] Therefore, analysts might expect more trading commission by publishing optimistic view on stocks with high EUE. This is because investors with an optimistic view of the economy will be more likely to find confirmation of their belief in the analyst's report which will, in turn, increases their investment in such stocks.

Third, considering the negative effect of EU on the quality of information, analysts are less likely to be penalised due to publishing biased forecasts for stocks with high EUE.

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[62] For instance, Dimmock et al. (2016) test this theoretical model and find results consistent with this assumption.

[63] They further suggest that this trading volume is mostly made by retail investors, who are more subject to optimism in the market (Nagel, 2005).

In other words, due to the nature of high uncertainty, the accuracy of the forecast for this type of stocks (error variance is high) is harder to be verified (Ackert and Athanassakos, 1997).[64]

Empirically, I measure EUE by estimating the sensitivity of stock return to log changes of economic uncertainty proposed by Jurado, Ludvigson and Ng (2015, hereafter, JLN). They define economic uncertainty as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents.[65] I broadly follow Bali, Brown and Tang (2017) to estimate stocks exposure in 5-year rolling regressions controlling for known risk factors.[66] Following Hong and Sraer (2016) and Li (2016), I capture the exposure by using the absolute value of the economic uncertainty beta, since uncertainty is larger for stocks more highly correlated with economic uncertainty regardless of a positive or negative sign.

I measure monthly analyst optimism at the firm-level as the difference between one-year consensus earnings forecasts and actual value scaled by prior month stock price (i.e., Lim, 2001; Larocque, 2012; Henderson and Marks, 2013; Engelberg, Mclean and Pontiff, 2018). It is important to note that my measure of optimism is at the firm level. This is

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[64] Relatedly, during uncertain times analysts may have more opportunistic behaviours. This is because there is more likely to be a decline in trading volume resulting in lower broker profits in such times (Loh and Stulz, 2018) and their optimism is more likely to increase trading activity in market. For instance, Chang and Choi (2017) find a positive relationship between analyst optimism in forecasts and trading volume when market-level uncertainty, measured by VIX, is high. Additionally, gaining better access to inside information might become more important during bad times than normal times, hence analysts' incentive concern about managerial relationships is expected to be more prominent.

[65] Their aggregate macroeconomic uncertainty measure is constructed with a wide range of economic data. They show that such a measure is better at capturing quantitively important uncertainty episodes than popular financial market-based proxies, such as the VIX index.

[66] One important modification I made in our empirical setting is that, instead of using the level of economic uncertainty as in Bali, Brown and Tang (2017), I use log changes of economic uncertainty as the level is very persistent. The use of log change makes it more suitable to capture unexpected innovations in the uncertainty with close to zero expectation, which is an important requirement of pricing factors in the context of arbitrage pricing theory (i.e., Merton, 1973; Ross, 1976; Chen, Roll and Ross, 1986). This research design is consistent with a recent study by Bali, Subrahmanyam and Wen (2020) who study macroeconomic uncertainty in the bond market.

different from existing studies (i.e., Cowen, Grosyberg and Healy, 2006; Hugon, Kumar and Lim, 2016; Chang and Choi, 2017), which study the relative analysts' optimism for the same stock. This is because using consensus optimism measure mitigates the effect of extreme values in forecasts as the skewness in the distribution of earnings and forecasts may affect emprical analyses (Zhang, 2006).

I perform panel regressions of analyst optimism on EUE quintile ranks (Rank5) controlling for various firm and analyst characteristics.[67] In my empirical analyses, I find a significant positive relationship between EUE and analyst optimism in the sample between 1982 and 2018 in the US markets.

First, analyst optimism increases from the group with the lowest EUE to the group with the highest EUE and the strongest one is observed among stocks with the highest EUE. The monthly consensus forecasts for one-year earnings is 3.6% larger than the actual value for stocks in the highest EUE group. This value is more than triple the optimism in the lowest EUE group, which is 1% larger than the actual value. Furthermore, panel regression results confirm that firm-level consensus optimism is positively affected by stocks' EUE, supporting my hypothesis. Cross-section of earnings forecast optimism increases with firms' exposure to EU in quintile ranks, controlling for the firm- and industry-fixed effects, respectively.

I further show that EUE impact on analyst optimism is only observed following high EU periods. This confirms that EU is the driver of the EUE effect on forecast optimism. When EU is low, the relative difference in the sensitivity to EU will not affect

[67] Every month, stocks are sorted on prior month's EUE to form quintiles. To reduce the effect of outliers in OLS estimates, I only use EUE quintile ranks (Johnson, 2004; Zhang, 2006).

analysts behaviours. In other words, analysts behave similarly for high or low EUE firms following periods with low EU.

To substantiate the links between the optimism and analysts' incentive induced by the high EUE condition. I further examine analyst optimism in the context of different incentive explanations. First, considering the benefit of the optimistic forecasts, i.e., access to managerial information which may not be publicly available (Brown et al., 2015; Lim, 2001), I identify firms based on their earnings management quality.[68] I measure firms' discretionary accruals (DA) (Kothari et al., 2005) and then separate them into two groups. In panel regressions, my results show that a significant effect of EUE on consensus optimism is observed in the low earnings quality group (or high DA group). Moreover, following Frankel, Kothari and Weber (2006), I measure firms' available information at the market level and divide them into two groups.[69] Consistent with results in earnings quality analyses, the positive relationship between EUE and optimism is observed in stocks with low market-level information. Those results confirm that analysts are more optimistic in order to have a better relationship with managers to access private information for stocks with high EUE.

Second, I also examine EUE-induced analyst optimism based on investor sophistication as their optimism is more likely to be captured if there are more sophisticated investors in the market. The positive EUE and optimism relationship is observed among stocks with low institutional ownership. Since retail investors are less informed and may

[68] Conducting a series of interviews among several analysts, Brown et al. (2015) show the importance of private communication with managers as analysts are able to gather nonpublic information. They additionally find that for analysts the quality of earnings management is an important factor to control in the financial statements in forecast process, implying a negative relationship between earnings management quality and the need of private communication with managers.
[69] It is measured by taking monthly R-square from the market-model regression using daily excess returns for each stock in the sample. The higher the R-square, the more the information available in the market.

not be able to verify analysts' forecast especially for stocks with high EUE. By contrast, the positive relationship between EUE and optimism is not presented among stocks with high institutional ownership. This is not surprising as those investors are more sophisticated, and they are able to capture analysts' optimism for incentives in earnings forecasts, which may harm analysts' reputation (Jackson, 2005).

Third, I investigate whether high EUE can indeed reduce reputation costs of forecast optimism for analysts career concern. While optimistic bias in the forecast may harm analysts' reputation in long-term (Jackson, 2005; Groysberg, Healy and Maber, 2011; Chang and Choi, 2017), EUE-induced optimism might give analysts an opportunity to hide their bias as investors tend to have more difficulties to verify the valuation of stocks with high uncertain payoffs (Ackert and Athanassakos, 1997). In the analyst-level analyses, I show that analysts with an optimistic forecast for stocks with high EUE are less likely to lose their position in high-status brokerage house (Hong, Kubik and Solomon, 2000).[70]

EUE-induced optimism might be attributed to a lack of pessimistic coverage for those stocks. Analysts with a negative view might downgrade their forecasts for those assets. However, those firms might withhold inside information from those analysts, leading them to drop coverage of those firms. The missing pessimistic view on high EUE can increase the effect of optimistic opinions on the consensus (McNichols and O'Brien, 1997). In this regard, I show that the total number of forecasts issued by pessimistic analysts for companies with high EUE is in a negative trend. Moreover, this trend is also observed among the optimists covering those companies, suggesting that there are still optimists who are less willing to exploit EUE and more likely to drop coverage as facing larger EUE.

[70] Following Hong, Kubik and Solomon (2000), if a brokerage house has less than 25 analysts then it is classified as low-status brokerage house.

Interacting with brokerage size, this might be because the optimists working for larger brokerage houses have a higher quality of information environment and better relationship with firms (Jacob, Lys and Neale, 1999). Therefore, optimists working for those brokerage houses with these opportunities may decide to stop issuing their forecasts as facing higher uncertainty. Moreover, their career concerns may deter them from reflecting their optimism for those assets.

This study, furthermore, examines whether EUE-induced forecast optimism, at least, is partly related to behavioural biases considering analysts' underreaction to new information at a macroeconomic level. For instance, Zhang (2006) shows that analyst forecast optimism increases (decreases) following bad (good) news for stocks with higher information uncertainty inconsistent with forecast optimism based on the rational framework.[71] This is because analysts tend to underreact to new information, and this phenomenon is more pronounced with greater uncertainty (Hirshleifer, 2001). Moreover, Hugon, Kumar and Lim (2016) show that analysts are more likely to underreact to bad macro-related news, resulting in significant optimism in earnings forecasts following negative GDP growth news. Therefore, analysts may publish more (less) optimistic forecast for stocks with high EUE following negative (positive) GDP growth news due to their underreaction to news in earnings forecasts for such stocks.[72] In further tests, however, results fail to show that EUE-induced optimism, at least, is partly related to analysts' underreaction to macroeconomic news.

Another role of analysts in the market is to improve price efficiency with their forecasts and recommendations. Specifically, they are expected to issue a more optimistic

[71] Zhang (2006) measures information uncertainty at stock-level using analyst dispersion
[72] Macroeconomic news measures related to GDP growth are introduced in Section 4.5.5 in detail.

(pessimistic) view for underpriced (overpriced) stocks to correct mispricing in the market. However, recent studies find that analysts are more likely to issue optimistic views for overpriced stocks, exacerbating mispricing in anomaly returns and impeding the price correction (Engelberg, McLean and Pontiff, 2018; Guo, Li and Wei, 2020). Considering the main findings in Chapter 2, I interact EUE-induced mispricing in anomalies with EUE-induced analyst optimism in earnings forecasts. In this way, I further investigate whether their bias exacerbates anomaly mispricing in stocks with high EUE as a result of their incentive concerns. I find that the EUE effect on mispricing is significantly apparent in the group with high consensus optimism. Moreover, the ambiguity-premium effect is only significantly observed in the group of stocks with low consensus optimism. These results confirm that analysts issuing optimistic view for stocks with high EUE impede the price efficiency in the market resulting in significant mispricing.

Finally, I extend my empirical analysis by considering the economic policy uncertainty index (Baker, Bloom and Davis, 2016) as an alternative measure of macro uncertainty. These findings are consistent with my main results, implying that stocks' exposure to uncertainty in policy and regulations matters to analysts' optimism in earnings forecasts and stock recommendation along with exposure to uncertainty in the real economy. I also confirm my finding with an alternative measure of optimism by examining the stock recommendations. I show that analysts issue a higher rate of buy recommendations, while they reduce the rate of sell recommendations for stocks in the group with the highest EUE. There is an increase (decrease) in the annual average rate of buy (sell) recommendations by firms' exposure to EU in quintile ranks, controlling for firm- and industry-fixed effects, respectively. Moreover, in logistic regressions, I further confirm that analysts are more (less) likely to issue buy (sell) recommendations for those stocks in the analyst-level analysis.

This study contributes to the literature in several ways. First, several studies examine the effect of macro-level uncertainty on investor decision process (i.e., Anderson, Ghysels and Juergens, 2009; Bloom, 2009; Bali, Brown and Tang, 2017). Specifically, investors treat stocks with different EUE in different ways. While rational investors demand higher equity premium from high EUE stocks, irrational ones have a larger disagreement on such assets, exacerbating mispricing in equities, documented in the first chapter. My investigation is related to its effect on the analyst decision process. Through empirical analyses, this study reveals that analysts are more likely to have more incentive based response to higher EUE with less career concern, issuing more optimistic forecasts.

In this study, my findings contribute to previous studies examining the effect of market uncertainty and bad times on analyst performance. For instance, Amiram et al (2017) show that analysts issue forecasts more often, implying that they are timelier when market uncertainty is higher, however, their accuracy is lower. Amiram et al (2017) suggest that analysts underreact to news, measured by stock price movement. In addition, Loh and Stulz (2018) provide evidence suggesting that due to their career concerns, analysts put more effort into their forecast when uncertainty is high during financial crises.[73] Specifically, my findings complement Chang and Choi (2017) who find a positive relationship between market uncertainty, measured by the VIX, and analyst optimism. They explain analysts' optimism during high market uncertainty period with less reputational costs and more trading commission benefits (Lim, 2001; Jackson; 2005).

Second, this study is related to the importance of reputation for analysts' career in the industry that limits their behaviours for incentives (Fama,1980; Lim, 2001). Several

[73] Loh and Stulz (2018) define bad times which equal one for 1987 crisis, LTCM crisis in 1998 and the financial crisis in 2008, along with recessions defined by NBER.

studies suggest that analysts are more likely to lose their jobs or move down from a high-status brokerage house to a low one due to their optimistic forecasts for incentives in earnings (Jackson, 2005; Groysberg, Healy and Maber, 2011; Chang and Choi, 2017). However, this study shows that this concern is less likely for analysts when the informational environment is vague. Specifically, this study provides strong evidence that analysts are able to hide their optimism for incentives as experiencing less career concern when issuing optimistic forecasts for stocks with high EUE. This study unveils another important conditional variable to understand the determinant of analysts' optimistic behaviours for incentives.

Relatedly, this study offers a new firm-level measure of uncertainty that captures sensitivity to macro-related index while controlling for the other firm-level uncertainty measures, such as IVOL and analyst dispersion, which are widely used in the literature (Ackert and Athanassakos , 1997; Zhang, 2006). Therefore, from an investors perspective, EUE can be used to evaluate analyst performance in earnings forecasts in terms of optimistic bias.

Finally, this study is related to Engelberg, McLean and Pontiff (2018) and Guo, Li and Wei (2020). Their studies suggest that analyst optimism impedes price efficiency and results in significant mispricing in anomalies. Empirical results in this chapter support their findings and further show that due to incentive concerns, upward bias in forecasts for stocks with high EUE tends to mislead investors in anomaly investment strategy, worsening mispricing.

The rest of the chapter is organized as follows. Section 4.2 reviews the literature and develops my main hypotheses. Section 4.3 presents my data. Section 4.4 presents the main findings. Section 4.5 reports robustness and further tests. Section 4.6 concludes.

4.2 Literature Review and Hypothesis Development

4.2.1 Analyst Optimism

An extensive number of studies show an upward bias in analysts' earnings forecasts (i.e., Chopra, 1998; Hayes; 1998; Hong and Kubik, 2003). On the one hand, this optimism is a result of their incentives, such as generating brokerage revenue and maintaining access to management. First, Jackson (2005) shows that brokerage houses enjoy higher volume with optimism in their analysts' forecasts, generating more trading revenue and commissions. Second, Lim (2001) argue that optimistic bias in earnings forecast helps analysts access companies' managerial information which is not publicly available. Managers support positive forecasts while eliminating the flow of unfavourable ones since favourable forecasts which lead to higher capital market valuations increase their compensation levels. Lim (2001) finds significant support for this assumption.

On the other hand, another stream of literature argues that the optimism in earnings forecasts is subject to cognitive biases (i.e., De Bondt and Thaler, 1990; Easterwood and Nutt, 1999; Hirshleifer, 2001).[74] Several studies show that analysts tend to underreact to firm-level news such as past quarterly earnings and past returns (Mendenhall, 1991; Abarbanell and Bernard, 1992). For instance, Easterwood and Nutt (1999) find that analysts are more likely to underreact (overreact) to negative (positive) news, resulting in observable optimism in their earnings forecasts.

Lim (2001), however, argues that behavioural explanations for analyst optimism are not enough to explain the reason clearly. This is because one of the key sources in earnings

[74] Hirshleifer (2001) suggests that due to overconfidence analysts put more attention on their private information than public signals, thus their forecast tend to be optimistic. De Bondt and Thaler (1990) argue that analysts' optimism is due to overreaction to information leading to form extreme expectations.

forecasts is companies' private information. For instance, Brown et al. (2015) show that private communication with managers is more important in analysts' forecasts and stock recommendations than their own primary evaluation, which is consistent with Soltes (2014).[75, 76] Additionally, they find that despite issuing optimistic forecast leading to a loss in analysts' credibility with investors, they increase their chance to access management. In this situation, analysts face a trade-off between their forecast precision and improving management access as optimistic forecast helps them obtain managerial information discussed above. Therefore, analysts tend to report optimistic bias in a rational manner to produce accurate forecasts in the future (Lim, 2001; Brown et al., 2015).[77] Furthermore, considering the main revenue source for a brokerage house (Jackson, 2005, Cowen, Groysberg and Healy, 2006), analysts' optimism, which is expected to generate trading volume, is the result of their rational manners rather than behavioural biases.

Finally, analysts' performance is key for them to improve their reputation, allowing them to secure their positions in the industry or get promotion to larger brokerage firms. (Hong and Kubik, 2003). As their optimistic behaviours in earnings forecasts are prone to be captured by investors in the long-term, those incentives attributed to optimistic forecasts are limited by analysts' reputational concerns (Jackson, 2005; Groysberg, Healy and Maber, 2011; Chang and Choi, 2017).

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[75] Brown et al (2015) conduct 18 follow-up interviews with 365 analysts regarding various topics in their decision process.

[76] Soltes (2014) suggests that analysts are able to acquire further clarification about a company and its operations which is not publicly available. They have chance to discuss privately on their models used in forecasts.

[77] For more details about the theoretical model on analyst rational optimism, see Lim (2001).

4.2.2 Economic Uncertainty and Analyst Optimism

Economic uncertainty implies that the prospect of the economy is unpredictable using the available information and models. Therefore, uncertainty is about whether that state variable has become more or less predictable, that is, more or less uncertain (Jurado, Ludvigson and Ng, 2015). In the period of high EU, managers and investors are more likely to be conservative in their investment and reduce their future consumption (Bloom, 2009). They are more likely to experience more impediments to forecast the outlook for the economy implying that EU is one of the state variables linking to real activity and affecting investors' estimations. There is a larger deviation in fundamentals across firms and industries (Bloom, 2009). In a nutshell, EU affects the quality of information at various levels.

Analysts are intermediaries providing earnings forecasts and stock recommendations in stock markets by collecting and analysing pubic and non-public information from the firm-, market- and macro-level signals (Healy and Palepu, 2003; Amiram et al., 2017). The information quality in various levels matters to analysts in their forecasts (i.e., Chang and Choi, 2017; Loh and Stulz, 2018). In this study, considering the significant effect of EU on the quality of information, my main question is whether analyst optimism attributed to rational bias is influenced by EU.

In my conjecture, analysts' optimism for incentives in their forecasts become more pronounced while they are less concerned about their career. This is because analysts can ascribe their bias to a noisy informational environment caused by macro-level uncertainty. Therefore, analyst optimism increases with EU. More specifically, analysts can behave optimistically for incentives in their forecasts for companies with higher exposure to economic uncertainty. As those firms tend to be more affected by changes in economic uncertainty, the prospect of those companies is expected to be more difficult for investors to estimate.

Therefore, EUE gives more room to analysts to produce a more optimistic view on earnings forecasts for different incentives. First, private information is one of the key sources for analysts to improve their precision in forecasts. Lim (2001) shows that it becomes even more important for stocks with higher uncertain payoffs. To maintain a better relationship with managers to acquire that information, analysts are more likely to publish upward bias forecasts. This is because favourable forecasts are more supported by managers relative to unfavourable ones as the managers can have higher compensation with higher capital market valuation (Lim, 2001). Therefore, analysts tend to publish optimistic forecasts for stocks with high EUE for better managerial relationships to access private information, which might become more valuable in high EU periods.

Second, one of main revenues for analysts is from trading commissions, which tends to increase with optimistic forecast stimulating trading activity. However, this behaviour is limited to analysts' career concerns as investors are able to capture (Jackson, 2005; Cowen, Groysberg and Healy, 2006). In the market, investors tend to have more difficulties in verifying the valuation of stocks with high uncertain payoffs due to a vague informational environment (Ackert and Athanassakos, 1997), thus analysts are less likely to be concerned about their career by publishing more upward view on stocks with high EUE.[78] Moreover, considering heterogeneity among investors, those stocks are more likely to be held by optimistic investors, while pessimistic ones withdraw their investments in those assets (i.e., Cao, Wang and Zhang, 2005; Easley and O'Hara, 2009; Epstein and

[78] Loh and Stulz (2018) show that investors have more demand for forecast made by analysts, when the firm's performance is uncertain. Therefore, Chang and Choi (2017) suggest that optimism in earnings forecasts is prone to produce more trading activity and it is more pronounced when the market uncertainty, measured by VIX, is high.

Schneider, 2010).[79] Consequently, optimistic forecasts might encourage optimists to increase their investment in those assets, resulting in higher trading volume.

Finally, analysts' optimism for those incentives are limited to their career concern. This is because reputation plays an important role in the labour market (i.e., Fama, 1980; Lim, 2001). Previous studies show that job turnover increases among analysts with poor performance (Mikhail, Walther and Willis, 1999). However, this concern may vary with information quality (Hong and Kubik, 2003). Considering the negative effect of EUE on analyst forecast accuracy, analysts can ascribe their bias to vague signals (Ackert and Athanassakos, 1997). Additionally, the precision of forecast for those stocks are hard to be verified. Therefore, analysts are less likely to lose their job or move down to low-status brokerage house.

Taken all arguments discussed above, my hypothesis is as below:

H_1: There is a positive relationship between optimism in analysts' forecasts and stock exposure to economic uncertainty.

4.3 Data and Measures

The data on analysts' annual EPS forecast and stock recommendations used in my empirical analyses are taken from the Institutional Brokes' Estimate System (I/B/E/S). Following previous studies (i.e., Hong and Kubik, 2003; Chang and Choi, 2017), my sample focuses on one-year ahead earnings forecasts. To calculate EUE and various firm-level characteristics, I obtain the data from the merged CRSP-Compustat database.

[79] Following the literature related to limited participation and heterogeneity among investors, Bali, Brown and Tang (2017) suggest that investors having optimistic opinion about economic uncertainty are more likely to hold stocks exposed to high economic uncertainty. By contrast, pessimists reduce their participation in those assets.

4.3.1 Analyst Optimism

In this study, EPS forecasts sample covers annual earnings forecasts from January 1982 to December 2018 from an unadjusted detail file on IBES for all common stocks (with share codes 10 and 11) on the NYSE, Amex and NASDAQ. Similar to prior literature (i.e., Lim, 2001; Larocque, 2012; Henderson and Marks, 2013; Engelberg, Mclean and Pontiff, 2018), I measure analyst optimism as consensus optimism at the firm level by the following equation:

$$OPTIM_{i,m} = \frac{Mean(Value_{i,m,t}) - ActualEPS_{i,t}}{Price_{i,m-1}} \tag{4.1}$$

where $Value_{j,i,m,t}$ is one-year ahead earnings forecast of firm i during month m made by all analysts for fiscal-year t.[80] $ActualEPS_{i,t}$ is actual earnings announced by firm i for fiscal-year t. $Price_{i,m-1}$ is closing stock price of firm i in month $m - 1$.[81] I require a minimum of two analysts for consensus optimism measure in each month.

Another optimism measure is from the stock recommendation sample between January 1994 and December 2018. This sample contains categorical variables such as Buy/Strong Buy, Sell/Strong Sell, Underperform and Hold. Those variables allow us to measure analysts' optimism or pessimism. Anderson (2005) suggests that when a strong buy

[80] If there are more than one forecast made by the same analyst during the same month, I take the mean of those forecasts. Moreover, using the median value of forecasts in the nominator of the optimism measure does not affect results in this study. Lastly, if forecast revision date is after the announcement date, it is dropped in the main analyses. However, inclusion of those forecasts do not affect the results.

[81] If closing stock price is less than one dollar, then I drop it to eliminate the effect of outliers in our analyses.

(sell) is recommended by an analyst, this implies that the analyst has an optimistic (pessimistic) view of the prospect of the stock.

Following the previous literature (i.e., Cowen, Groysberg and Healy, 2006; Chang and Choi, 2017; Hirshleifer et al., 2021), there are one categorical and two binary variables. REC is a categorical variable where Buy or Strong Buy=3, Hold=2, and Sell or Strong Sell or Underperform=1. BUY is a binary variable which is 1 if analyst i issues Buy or Strong Buy, and 0 otherwise. SELL is a binary variable which is 1 if analyst i issues Sell or Strong Sell or Underperform, and 0 otherwise. Since analysts may not issue regularly, and their recommendations tend to be highly serially correlated, I only take their last recommendation each year (Hong and Kubik, 2003; Chang and Choi, 2017).

Finally, I measure stock recommendations at the firm-level with their issue percentage taken from consensus recommendations on IBES between January 1994 and December 2018. Buy percentage (BUYPCT) is the mean of buy recommendation percentage and Sell percentage (SELLPCT) is the mean of sell recommendation percentage for firm j in year t.

4.3.2 Analysts Characteristics

Following the literature (i.e., Cowen, Groysberg and Healy, 2006; Chang and Choi, 2017; Hirshleifer et al., 2020), there are three analysts characteristics. Coverage (COVER) is the number of companies covered by analyst i in year t. Analysts experience (EXPER) is the number of years from the starting year of analyst i in IBES. Brokerage Size (BRKSIZE) is the number of analysts hired by brokerage firm k of analyst i in year t. All those characteristics are in natural logarithm.

To measure analysts' career concerns, I form an analyst turnover variable. Following Hong, Kubik and Solomon (2000), if analyst i is employed by a brokerage company in year $t-1$ that has at least 25 analysts move in year t to a brokerage company that has less than 25 analysts, MOVEDOWN is 1 for analyst i, and 0 otherwise. This variable measures whether analysts lose their reputation by moving down from a high-status brokerage company to a low-status one.

4.3.3 Economic Uncertainty Exposure

Existing studies have relied on different proxies to measure uncertainty in the economy. For instance, several papers use market volatility, due to its significant relation between real activity (i.e., Bloom, 2009; Bekaert, Hoerova and Duca, 2013; Bali and Zhou, 2016). However, Jurado, Ludvigson and Ng (2015) argue that financial market volatility may not reflect economic uncertainty accurately, since it may vary over time due to changes in risk-aversion or leverage or sentiment.

Other studies use dispersion in forecasts (i.e., Mankiw and Reis, 2002; D'amico and Orphanidos, 2008; Anderson, Ghysels and Juergens, 2009; Li, 2016). It is expected that during high uncertainty time, forecasts are dispersed, and surveys have a larger disagreement on macro-indicators (Bachmann, Elstner and Sims, 2013). However, forecasts may not clearly show expectations about the whole economy and may give subjective responses due to their pecuniary interests and individual biases. Additionally, the dispersion of analyst forecasts might be affected by heterogeneity in the business cycle, even if there is no shift in uncertainty in economic fundamentals (Jurado, Ludvignson and Ng, 2015).

Considering those arguments on different measures of economic uncertainty, this study uses the uncertainty index constructed by Jurado, Ludvigson and Ng (2015). This index is based on 132 macro-series, not only on single (or a small number of) economic indicators, measuring uncertainty in the whole economy. By using this measure, I am able to capture uncertainty in different macro variables at the same time, across companies, industries, markets and regions (Jurado, Ludvigson and Ng, 2015).

To measure innovations in economic uncertainty, I use monthly logarithmic differences in the index (ΔUNC_t).[82]

$$\Delta UNC_t = ln\left(\frac{UNC_t}{UNC_{t-1}}\right) \tag{4.2}$$

Jurado, Ludvigson and Ng (2015) employ a wide range of macroeconomic time series: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labour costs, and capacity utilization measures. The index is obtained from Sydney Ludvigson's website.[83]

I estimate the uncertainty beta from a rolling regression for each stock every month with the following model using previous 60-month observations:[84]

[82] The level of the index is non-stationary with -1.953 Dickey-Fuller statistic, while its logarithmic difference is stationary with -12.819 Dickey-Fuller statistic.
[83] https://www.sydneyludvigson.com/data-and-appendixes/
[84] I require at least 24 months of non-missing observation for each stock to estimate a beta for the given month.

$$R_{i,t} = \alpha_{i,1} + \beta_{i,1}\Delta UNC_t + \beta_{i,2}MKT_t + \beta_{i,3}SMB_t + \beta_{i,4}HML_t + \beta_{i,5}UMD_t + \beta_{i,6}IA_t + \beta_{i,7}ROE_t + \varepsilon_{i,t} \quad (4.3)$$

where $R_{i,t}$ is the monthly excess return of stock i in month t. ΔUNC_t is a proxy for innovations in economic uncertainty in month t. MKT_t, SMB_t, HML_t, UMD_t, IA_t, and ROE_t are Fama and French factors in month t. These factors are from Kenneth French's website.[85] My annual EPS optimism sample is from January 1982, therefore the beta estimation starts from January 1977.

Once I have estimated monthly EU betas for each stock during the sample period, I consider the absolute value of betas for all analyses in this study. This is because, a large magnitude of the beta, no matter whether it is positive or negative, makes the variance of the return more sensitive to the change of economic uncertainty. Finally, I sort stocks on their EUE to form quintiles at the end of each month (Rank5). This allows us to reduce the effect of extreme values in EUE for OLS estimates consistent with Johnson (2004).

4.3.4 Firm Characteristics

In this study, I use several firm characteristics. Size ($SIZE$) is defined as the price of the share multiplied by the number of share outstanding. Book-to-market (BM) is computed as the book value of equity at the end of fiscal year t-1 divided by the market value of equity at the end of fiscal year t-1. Momentum (MOM) is the cumulative return of stock i from month t-12 to t-2. Stock illiquidity ($ILLIQ$) is defined as the ratio of the daily absolute stock return to the daily dollar trading volume averaged within the month. Analyst earnings

[85] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 4.1 Summary Statistics

This table reports correlation coefficients and summary statistics for the variables in Panel A and B, respectively. Variable definitions are listed in Appendix II. The sample period is from January 1982 for OPTIM and January 1994 for BUYPCT and SELLPCT to December 2018.

	OPTIM	BUYPCT	SELLPCT	Rank5	EXPER	BRKSIZE	COVER	IVOL	DISP	BM	SIZE	MOM	ILLIQ
						Panel A: Correlations							
OPTIM	1												
BUYPCT	.	1											
SELLPCT	.	-0.431	1										
Rank5	0.015	0.107	-0.010	1									
EXPER	-0.007	-0.179	0.067	-0.052	1								
BRKSIZE	-0.008	-0.206	0.161	-0.100	0.180	1							
COVER	0.007	-0.110	-0.025	-0.110	-0.197	-0.051	1						
IVOL	0.059	0.128	-0.017	0.238	-0.040	-0.135	-0.14	1					
DISP	0.011	-0.001	0.023	0.042	-0.015	-0.016	0.00	0.067	1				
BM	0.026	-0.135	0.042	-0.006	-0.073	-0.013	0.12	-0.006	0.038	1			
SIZE	-0.008	0.025	-0.005	-0.117	0.131	0.138	-0.04	-0.142	-0.024	-0.059	1		
MOM	-0.027	0.198	-0.085	0.038	-0.013	-0.069	-0.03	-0.027	-0.025	0.022	0.012	1	
ILLIQ	0.008	0.009	-0.014	0.009	-0.015	-0.048	0.00	0.058	0.007	0.073	-0.010	-0.019	1
						Panel B: Summary Statistics							
Observation	462,901	80,378	80,378	410,630	442,260	443,466	443,466	463,183	451,629	438,942	463,376	440,067	463,187
Mean	0.018	0.58	0.04	3.000	2.034	3.982	2.903	0.021	0.188	0.584	6.774	0.172	0.144
Std. Dev.	0.540	0.32	0.11	1.413	0.763	0.534	0.341	0.015	1.274	0.728	26.400	0.655	9.732
Median	0.001	0.60	0.00	3.000	2.238	4.047	2.890	0.017	0.043	0.474	1.059	0.092	0.003

forecast dispersion ($DISP$) is measured as the standard value of the mean forecast deviation of one-year earnings forecasts divided by the absolute of the mean forecast. Idiosyncratic volatility ($IVOL$) is defined as the standard deviation of the daily risk-adjusted return residuals computed by regressing each asset's daily return on four Fama and French market factors: MKT, SMB, HML, UMD.

Table 4.1 reports the correlation matrix and summary statistics for all variables. In Panel A, those coefficients show that there is no potential collinearity between variables. In Panel B, the monthly mean of the one-year consensus earnings forecast is 2% larger than actual earnings. Additionally, the annual mean of BUY recommendation rate is 58%, while this figure is only 4% for the annual rate of SELL recommendation, implying that analysts are more likely to give buy recommendation which is much higher than sell recommendation. Overall, Panel B shows that on average analysts are optimistic in their forecasts and stock recommendations consistent with previous studies (i.e., Hayes; 1998; Hong and Kubik, 2003; Chang and Choi, 2017).

4.4 Empirical Analyses

4.4.1 Economic Uncertainty Exposure and Analyst Optimism

In this section, I investigate the distribution of consensus optimism in EUE quintiles. Table 4.2 reports monthly averages of EUE and consensus optimism, and annual averages of buy and sell percentages in quintiles. In general, analysts issue earnings forecasts larger than actual earnings implying that they exhibit optimism in their forecasts, consistent with previous studies (i.e., Stickel, 1990; Chopra, 1998; Lim, 2001). Specifically, their optimism increases together with the EUE. The monthly mean of one-year consensus earnings forecasts is 1% larger than the actual earnings in the lowest EUE quintile, while it is 3.6% larger than the actual earnings in the highest EUE quintile. Consequently, the difference of the monthly mean one-year consensus earnings forecasts between the top and the bottom EUE quintiles is significantly 2.6% larger than the actual earnings with a t-statistic of 4.625.

Table 4.2 Economic Uncertainty Exposure and Consensus Optimism

This table reports summary statistics on the five EUE groups. Stocks are sorted on EUE each month, then the mean of monthly consensus optimism (OPTIM) and annual mean of buy (BUYPCT) and sell (SELLPCT) percentages are calculated. The EUE is the absolute beta coefficient estimated in Equation (4.3). T-statistics are reported in parentheses using standard errors clustered by firm. Variable definitions are listed in Appendix II. Sample is from January 1982 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	5-1
EUE	0.148***	0.304***	0.530***	0.886***	1.982***	1.834***
	(136.317)	(272.771)	(316.840)	(277.068)	(128.275)	(54.940)
OPTIM	0.010***	0.012***	0.015***	0.020***	0.036***	0.026***
	(17.187)	(14.775)	(14.026)	(10.153)	(6.330)	(4.625)
BUYPCT	0.524***	0.531***	0.546***	0.577***	0.608***	0.084***
	(132.225)	(139.519)	(151.812)	158.132)	(155.343)	(13.132)
SELLPCT	0.047***	0.045***	0.045***	0.044***	0.045***	-0.002
	(37.257)	(36.073)	(37.385)	(36.073)	(31.266)	(-0.755)

Moreover, I observe the same optimistic pattern in stock recommendations, considering BUY (SELL) recommendation is an indicator of optimism (pessimism) (Anderson, 2005). The annual average of BUY recommendation ratio increases from 52.4% for stocks with the lowest EUE to 60.8% for stocks with the highest EUE. The difference of the mean BUY recommendation ratio between the extreme EUE quintiles is 8.4% per year with a t-statistic of 13.132. By contrast, analysts are less likely to issue SELL recommendations, exhibiting a weak decreasing trend with EUE groups and an insignificant difference between the extreme quintiles. Overall, EUE induces optimism among analysts in their forecasts, supporting my hypothesis.

4.4.2 Economic Uncertainty Exposure and Analyst Optimism: Consensus Forecast

In my main analysis, I employ panel regressions. I examine the effect of firm-level EUE on one-year earnings consensus optimism with the following regression:

$$Y_{i,p,t} = \lambda_0 + \lambda_1 Rank5_{p,t-1} + \sum_{J=2}^{n} \lambda_j X_{i,p,t-1} + \sum_{J=n+1}^{m} \lambda_j Z_{p,t-1}$$
$$+ Fixed\ Effects + \varepsilon_{i,t} \quad (4.4)$$

where $Y_{i,p,t}$ is OPTIM for stock p in month t. $Rank5_{p,t-1}$ is EUE quintile for stock p in month $t-1$. $X_{i,p,t-1}$ is the mean of analyst-specific variables for stock p in month $t-1$, including $COVER$, $BROKERSIZE$ and $EXPER$. $Z_{p,t-1}$ is a set of stock-specific variables for stock p in month $t-1$, including $DISP$, $IVOL$, $SIZE$, MOM, BM and $ILLIQ$. Firm/industry and year fixed effects are included in the estimation to control for heterogeneity across firms/industry and the influence of time series. Finally, standard errors are double clustered at the firm-year levels (Cameron, Gelbach and Miller, 2011). I report regression results in Table 4.3.

Table 4.3 shows that coefficients on Rank5 are positive and statistically significant in all regressions, implying that firms' exposure to EU in quintile ranks can positively predict the next period firm-level consensus optimism in one-year earnings forecast even after control for the analyst and firm-level characteristics. Consistent with my conjecture that the larger the EU exposure for a stock, the higher the favourable forecasts made by analysts. This is because firms with higher EUE tend to be more affected by changes in economic uncertainty. When I divide the sample into two periods, the EUE effect is only significantly observed to predict the next period firm-level consensus optimism during increasing-EU

Table 4.3 Panel Regressions of Consensus Optimism

This table reports panel predictive regressions of one-year earnings consensus optimism for whole and different state samples using Equation (4.4). Variable definitions are listed in Appendix II. T-statistics are reported in parentheses. The sample period is from January 1982 to December 2018. Increasing- and decreasing-EU months are defined as the top and bottom quartile of the whole sample period, respectively. There are 101 increasing- and 115 decreasing-months. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Whole sample				Increasing EU Period		Decreasing EU Period	
Rank5	0.004**	0.006***	0.003**	0.002*	0.002**	0.001*	0.002	0.001
	(2.628)	(5.026)	(2.318)	(1.939)	(2.255)	(1.993)	(1.398)	(0.789)
EXPER			0.009*	0.014***	0.010**	0.005	0.018**	0.021*
			(1.968)	(2.863)	(2.401)	(1.070)	(2.461)	(2.023)
BRKSIZE			-0.003	-0.000	0.002	0.003	0.007	-0.001
			(-0.492)	(-0.107)	(0.349)	(0.670)	(0.631)	(-0.212)
COVER			0.004	0.007	0.009	0.010*	-0.015	-0.006
			(0.628)	(1.060)	(1.541)	(1.953)	(-1.368)	(-1.561)
IVOL			2.424***	2.569***	1.685***	2.072***	2.829***	2.931***
			(3.477)	(4.817)	(3.335)	(4.779)	(3.683)	(4.695)
DISP			0.002**	0.002**	0.003**	0.003*	0.002***	0.003***
			(2.280)	(2.645)	(2.369)	(1.966)	(3.351)	(3.389)
BEME			0.019***	0.015***	0.012*	0.010**	0.019**	0.015**
			(2.775)	(2.978)	(1.984)	(2.089)	(2.042)	(2.660)
SIZE			-0.000	0.000**	-0.000	0.000	-0.000	0.000**
			(-1.128)	(2.356)	(-1.038)	(1.662)	(-0.880)	(2.590)
MOM			-0.014***	-0.020***	-0.012***	-0.019***	-0.014***	-0.020***
			(-5.138)	(-5.489)	(-2.972)	(-2.863)	(-6.283)	(-8.230)
ILLIQ			0.001	0.000	0.000	0.001	0.000***	0.001***
			(1.566)	(0.715)	(0.525)	(0.815)	(2.780)	(2.835)
Constant	0.011***	0.006**	-0.063***	-0.090**	-0.079*	-0.083**	-0.067*	-0.072**
	(3.021)	(2.541)	(-2.971)	(-2.436)	(-2.026)	(-2.186)	(-2.039)	(-2.268)
Observation	409,547	410,190	395,312	395,829	93,703	94,742	97,060	98,046
R-sq	0.066	0.001	0.069	0.006	0.194	0.016	0.113	0.010
Adj R-sq	0.048	0.001	0.0512	0.00575	0.140	0.0151	0.0571	0.00947
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

periods.[86] This finding provides support for the effect of information quality distorted by EU on analysts' decision.[87]

4.4.3 Economic Uncertainty Exposure and Analyst Optimism: Stock Recommendations

In this section, I examine whether EUE affects analysts' stock recommendations. Using data on analysts' recommendations allows us to examine the difference of beliefs among analysts. For instance, when a strong buy (sell) is recommended by an analyst, this implies that the analyst has an optimistic (pessimistic) view of the prospect of the stock (Anderson, 2005). Additionally, stock recommendations are not based only on firms' earnings-related information, since analysts incorporate all relevant information about the firms to make buy/sell recommendation. (Chang and Choi, 2017).

To investigate the effect of EUE on analysts' recommendation behaviour, I employ the following model:

$$Prob(Y_{i,p,t}) = f(\lambda_0 + \lambda_1 Rank5_{p,t-1} + \sum_{J=2}^{n} \lambda_j X_{i,t-1} + \sum_{J=n+1}^{m} \lambda_j Z_{p,t-1} + Fixed\ Effects + \varepsilon_{i,t}) \tag{4.5}$$

[86] Increasing- and decreasing-EU months are defined as the top and bottom quartile of the whole sample period, respectively. There are 101 increasing- and 115 decreasing-months between January 1982 and December 2018.

[87] One may argue that disagreement on macroeconomic variables may be another channel which can drive the results instead of analyst optimism. This is because Hong and Sraer (2016) and Li (2016) show that during high EU periods, macro-level disagreement is high.

where $Y_{i,p,t}$ is either BUY or SELL binary variables for analyst i stock p in year t. $Rank5_{p,t-1}$ is EUE quintile for stock p at the end of year $t-1$. $X_{i,p,t-1}$ is a set of analyst-specific variables for analyst i in year $t-1$, including $COVER$, $BROKERSIZE$ and $EXPER$. $Z_{p,t-1}$ is a set of stock-specific for stock p variables at the end of year $t-1$, including $DISP$, $IVOL$, $SIZE$, MOM, $BM$and $ILLIQ$. Moreover, I use multinomial logistic regression regarding the same. In this model, $Y_{i,p,t}$ is REC where Buy or Strong Buy=3, Hold=2, and Sell or Strong Sell or Underperform=1. The usual sets of analysts and firm-level characteristics are included as well. In both logistic regression models, industry- and year-fixed effects are included in the estimation to control for heterogeneity industry and the influence of time-series.[88] Finally, standard errors are clustered at the analyst-level.

Table 4.4 reports odd probabilities that are exponentiated coefficients for logistic regression models. I show that odds ratios on Rank5 are statistically significant in all models where the dependent variable is BUY. Therefore, there is an increase in the probability of issuing buy recommendation by firms' exposure to EU in quintile ranks. These findings indicate that analysts are more likely to issue buy recommendations for the stocks with higher EUE. Additionally, the odds ratios on Rank5 in the models where the dependent variable is SELL show that sell-recommendations are less likely to be issued for those assets, despite statistically insignificant in the multinomial model.

I observe that EUE significantly boosts analysts' optimistic views, while significantly reduces their pessimistic opinions. These findings in Table 4.4 give more insight into the effect of EUE on analysts' behaviour, implying that analysts do not only

[88] Due to the large number of firms and analysts, their fixed effects are not included into the models. This limitation is also faced by Hirshleifer et al. (2021), who examine the effect of first impression on analysts' recommendation.

consider the effect of EU on firms' earnings but also incorporate its effect on all company-related information reflected by stock recommendations (Anderson, 2005; Chang and Choi, 2017).

Table 4.4 Logistic Regressions of Stock Recommendations

This table reports binomial and multinomial logistic regressions of stock recommendations using Equation (4.5). Variable definitions are listed in Appendix II. The slope coefficients are exponentiated and z-statistics are reported in parentheses. The sample period is from January 1994 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Sell	Buy	Rec		
			(Sell)	(Hold)	(Buy)
	1	2	3		
Rank5	0.983**	1.022***	0.993	-	1.021***
	(-2.571)	(6.532)	(-0.997)		(6.070)
EXPER	0.964**	1.013*	0.969*	-	1.009
	(-2.106)	(1.765)	(-1.826)		(1.207)
BRKSIZE	1.205***	0.878***	1.138***	-	0.892***
	(6.515)	(-14.910)	(4.604)		(-14.769)
COVER	1.032	0.941***	1.001	-	0.941***
	(1.152)	(-5.752)	(0.031)		(-5.984)
IVOL	11.986***	3.659***	36.305***	-	6.504***
	(3.769)	(3.259)	(5.254)		(4.515)
DISP	1.014***	1.001	1.017**	-	1.005
	(2.580)	(0.144)	(2.196)		(0.777)
BM	1.101***	0.943***	1.078***	-	0.954***
	(6.011)	(-5.983)	(4.824)		(-4.956)
SIZE	1.000***	1.000***	1.000*	-	1.000***
	(-4.064)	(10.401)	(-1.847)		(10.119)
MOM	0.630***	1.360***	0.731***	-	1.317***
	(-15.103)	(24.214)	(-10.034)		(21.959)
ILLIQ	0.737***	1.027	0.743***	-	1.020
	(-3.447)	(1.309)	(-3.354)		(1.192)
Constant	0.026***	1.803***	0.071***	-	1.888***
	(-22.828)	(9.818)	(-16.460)		(10.886)
Observation	248,176	248,176	248,176		
Pseudo R-sq	0.0435	0.0335	0.0318		
Industry FE	Yes	Yes	Yes		
Year FE	Yes	Yes	Yes		
Cluster by Analyst	Yes	Yes	Yes		

Finally, I further examine the effect of EUE on stock recommendations considering the percentage of buy/sell recommendations issued by all analysts for companies. This firm-level analysis gives information about consensus optimism. I examine it with the following estimation:

$$Y_{p,t} = \lambda_0 + \lambda_1 Rank5_{p,t-1} + \sum\nolimits_{J=2}^{n} \lambda_j X_{p,t-1} + \sum\nolimits_{J=n+1}^{m} \lambda_j Z_{p,t-1}$$
$$+ Fixed\ Effects + \varepsilon_{i,t} \quad (4.6)$$

where $Y_{p,t}$ is either BUYPCT or SELLPCT for stock p in year t. $Rank5_{p,t-1}$ is EUE quintile for stock p at the end of year $t-1$. $X_{i,p,t-1}$ is a set of analyst-specific variables for analyst i in year $t-1$, including $COVER$, $BROKERSIZE$ and $EXPER$. $Z_{p,t-1}$ is a set of stock-specific for stock p variables at the end of year $t-1$, including $DISP$, $IVOL$, $SIZE$, MOM, $BM$and $ILLIQ$. Firm/industry and year fixed effects are included in the estimation to control for heterogeneity across firms/industry and the influence of time series. Finally, standard errors are double clustered at the firm-year levels (Cameron, Gelbach and Miller, 2011).

Table 4.5 shows that coefficients on Rank5 are positive and statistically significant in all BUYPCT regressions, while it is significantly negative in SELLPCT regression controlling for firm-fixed effect. There is an increase (decrease) in the annual average rate of buy (sell) recommendations by firms' exposure to EU in quintile ranks, controlling for firm and industry-fixed effects, respectively. Those results provide additional evidence that there is a significant effect of EUE on analysts' optimism proxied by stock recommendation ratios.

Overall, my results have so far documented that analysts are more optimistic for stocks with higher exposure to economic uncertainty in both companies' earnings forecasts and stock recommendations.

Table 4.5 Panel Regressions of Stock Recommendations Percentages

This table reports panel predictive regressions of the percentage on buy/sell recommendations using Equation (4.6). Variable definitions are listed in Appendix II. T-statistics are reported in parentheses. The sample period is from January 1994 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	BUYPCT		SELLPCT	
	1	2	3	4
Rank 5	0.004***	0.009***	-0.001**	-0.000
	(3.180)	(5.872)	(-2.188)	(-1.203)
EXPER	-0.023***	-0.035***	0.005**	0.004**
	(-3.477)	(-5.117)	(2.604)	(2.327)
BRKSIZE	-0.063***	-0.082***	0.010***	0.022***
	(-10.342)	(-10.669)	(3.328)	(4.603)
COVER	-0.038***	-0.056***	0.004	0.000
	(-5.845)	(-6.895)	(1.685)	(0.042)
DISP	-1.144***	-0.479**	0.355***	0.363***
	(-7.580)	(-2.386)	(5.452)	(4.591)
IVOL	-0.005***	-0.005***	0.002***	0.002***
	(-4.303)	(-2.798)	(3.906)	(3.332)
BM	-0.046***	-0.029***	0.006***	0.003*
	(-6.585)	(-4.907)	(3.220)	(1.787)
SIZE	0.000***	0.000***	-0.000***	-0.000**
	(6.251)	(4.698)	(-3.820)	(-2.531)
MOM	0.055***	0.064***	-0.008***	-0.009***
	(5.657)	(5.397)	(-4.488)	(-4.383)
ILLIQ	0.000	0.001**	-0.000	-0.000***
	(0.820)	(2.374)	(-1.230)	(-3.583)
Constant	0.986***	1.110***	-0.025	-0.058***
	(31.959)	(35.621)	(-1.519)	(-3.068)
Observation	52,409	53,557	52,409	53,557
R-sq	0.521	0.201	0.390	0.084
Adj R-sq	0.461	0.201	0.313	0.0830
Firm FE	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes

4.5 Further Analyses

In this section, I provide further analyses to examine EUE-induced analyst optimism in the context of rational bias and EUE-induced mispricing in anomalies.

I first examine to what extent the quality of earnings management and the availability of firm-level information in the market can explain EUE-induced analyst optimism regarding firm management relationship. I then extend my empirical study to consider the level of investor sophistication regarding analysts' reputation concern. I also study their reputation concern considering their optimistic issues for stock with larger EUE. I furthermore examine the possible effect of self-selection bias on EUE-induced optimism. Finally, I provide the robustness of my main findings by using stock exposure to economic policy uncertainty.

4.5.1 Economic Uncertainty, Analyst Optimism and Firm Management

Analysts benefit from issuing optimistic forecast to maintain a private relationship with managers (Lim, 2001; Soltes, 2014). This enables them to gather information which is not publicly available to improve their forecast precision. Conducting a series of interview with analysts, Brown et al (2015, p.3) show that *"… analysts rate private phone calls as one of the most useful types of direct contact with management for purposes of generating their earnings forecasts and stock recommendations. Our follow-up interviews reveal that some analysts avoid asking questions during public conference calls and use private phone conversations to check the assumptions of their models, to gain qualitative insights into the firm and its industry, and to get other details not explained on public calls.*" Brown et al. (2015) also find that for analysts the quality of earnings management is an important factor to control in the forecast process, implying that there is more likely to be a negative association of earnings management quality with the need for private communication with managers.

Therefore, EUE-induced analysts' optimism tends to be more pronounced for stocks with low earnings quality as gaining private information from management has higher importance for those companies where managers are more likely to hide. I use

Table 4.6 Firm Management

This table reports panel predictive regressions of one-year earnings consensus optimism for different DA and RSQ samples using Equation (4.4). Variable definitions are listed in Appendix II. T-statistics are reported in parentheses. High and low DA (RSQ) groups are top and bottom quartiles. The sample period is from January 1982 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	High DA		Low DA		High RSQ		Low RSQ	
Rank5	0.002**	0.001*	0.004	0.002	-0.000	0.000	0.007**	0.006*
	(2.169)	(1.790)	(1.086)	(1.509)	(-1.150)	(0.133)	(2.133)	(1.964)
EXPER	0.008	0.009	-0.016	0.011**	0.005**	0.003*	0.016	0.023
	(1.554)	(0.970)	(-0.894)	(2.171)	(2.227)	(1.810)	(1.237)	(1.631)
BRKSIZE	0.001	-0.005	-0.018	0.008	0.004*	0.000	-0.004	-0.003
	(0.145)	(-1.094)	(-1.070)	(1.351)	(1.980)	(0.230)	(-0.330)	(-0.446)
COVER	0.011	-0.001	0.033	0.034	0.001	0.001	-0.001	0.009
	(1.428)	(-0.292)	(1.311)	(1.136)	(0.488)	(0.441)	(-0.104)	(0.559)
IVOL	0.816**	1.349***	4.311	4.112	0.716***	0.990***	2.828***	3.040***
	(2.701)	(4.775)	(1.172)	(1.554)	(3.060)	(4.636)	(2.978)	(3.763)
DISP	0.001**	0.002**	0.000	0.002	0.001	0.001**	0.000	0.002
	(2.061)	(2.378)	(0.183)	(0.774)	(1.363)	(2.341)	(0.399)	(1.530)
BEME	0.003	0.007**	0.010	0.012	0.009**	0.010***	0.025	0.020*
	(0.896)	(2.381)	(0.526)	(0.894)	(2.309)	(3.100)	(1.638)	(1.838)
SIZE	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(-0.443)	(0.738)	(-1.221)	(1.089)	(-0.078)	(1.360)	(-1.026)	(1.596)
MOM	-0.005***	-0.011***	-0.020*	-0.029**	-0.006***	-0.006***	-0.023***	-0.037***
	(-4.907)	(-5.190)	(-1.831)	(-2.260)	(-4.146)	(-4.259)	(-4.383)	(-5.268)
ILLIQ	0.002	0.001	-0.001	-0.001	0.000	0.002	0.001	0.000
	(1.020)	(1.623)	(-0.722)	(-0.868)	(0.027)	(0.887)	(1.507)	(0.353)
Constant	-0.060**	-0.014	-0.056	-0.219	-0.035**	-0.021*	-0.076*	-0.126*
	(-2.313)	(-0.731)	(-1.529)	(-1.345)	(-2.185)	(-1.739)	(-2.014)	(-1.705)
Observations	78,597	79,108	89,599	89,975	104,170	105,221	90,909	91,788
R-sq	0.528	0.007	0.057	0.006	0.203	0.020	0.103	0.006
Adj R-sq	0.498	0.00635	0.0133	0.00501	0.165	0.0192	0.0343	0.00582
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

discretionary accruals (DA) introduced by Kothari, Leone and Wasley (2005) to proxy for the level of earnings quality. Then I sort stocks on their prior year-end DA in quartiles.

Table 4.6 reports result estimated by Equation (4.4) for high and low DA groups which are top and bottom quartiles. In panel regressions, I show that EUE-induced analyst optimism is significantly observed in high DA groups where firms have low earnings quality. There is a significant increase of one-year earnings consensus optimism by Rank5, controlling for the firm and industry-fixed effects, respectively. However, there is no significant EUE- induced optimism in consensus forecasts for stock with high earnings quality (low DA group).

Moreover, following Frankel, Kothari and Weber (2006), I use daily excess returns for each stock to take monthly R-squares (RSQ) from the market-model regression in my sample. Then I group stocks on their prior month-end RSQ in quartiles. In this way, I am able to measure the availability of firm-level information in the market. The larger the RSQ for a firm the more the information available in the market, implying that there is less cost for analysts to acquire information. (Frankel, Kothari and Weber, 2006). Consistent with results in earnings quality analyses, in Table 4.6 I show that positive coefficients on Rank5 remain only significant in the low RSQ group, implying that EUE-induced optimism in consensus forecast is apparent for stocks having less information in the market. In the low RSQ group, there is a significant increase of one-year earnings consensus optimism by Rank5, controlling for the firm and industry-fixed effects, respectively.

Those results provide evidence suggesting that EUE-induced analyst optimism is a result of rational bias. Analysts are more likely to issue optimistic forecasts to maintain private communication with managers to access private information for stocks with high EUE as non-public information is more likely to be more valuable for those firms.

4.5.2 *Economic Uncertainty, Analyst Optimism and Institutional Ownership*

Analysts' optimistic bias is limited to their reputation concerns as their performance in forecast precision is an important aspect in the industry (Jackson, 2005), since their bias can be captured by investors, harming their reputation. Specifically, institutional investors are able to evaluate the quality of analysts' forecasts to capture their optimism as they are more sophisticated than retail investors (Cowen, Groysberg and Healy, 2006). Regarding this, I expect that EUE-induced optimism in consensus optimism is more pronounced for stocks with low institutional ownership. To test this effect, the proportion of institutional ownership (IO) for each stock is gathered quarterly from 13F filing on Thomson-Reuters. Then, I separate the sample into high and low IO groups based on the median of prior quarter-end IO. Table 4.7 reports regressions results estimated by Equation (4.4) for those groups.

Table 4.7 shows that EUE-induced consensus optimism is only observable in the low IO group. Therefore, there is an increase in consensus optimism for that group by firms' exposure to EU in quintile ranks, controlling for firm- and industry-fixed effects, respectively. However, the phenomenon that cross-section of earnings forecast optimism increasing with firms' exposure to EU disappears in high IO group.

These results suggest that analysts are rationally optimists when issuing their forecast for stocks with high EUE, since their reputational concerns limit them to exhibit an optimistic bias for such assets if those assets are held by sophisticated investors in the market (i.e., Lim, 2001 Cowen et al., 2006; Ljungqvist et al., 2007).

Table 4.7 Institutional Ownership

This table reports panel predictive regressions of one-year earnings consensus optimism for different IO samples using Equation (4.4). Variable definitions are listed in Appendix II. T-statistics are reported in parentheses. High and low IO groups are top and bottom medians. The sample period is from January 1982 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	High IO		Low IO	
Rank5	-0.000	-0.000	0.004**	0.003**
	(-0.066)	(-0.026)	(2.190)	(2.058)
EXPER	0.003	0.002	0.014*	0.022**
	(1.568)	(0.597)	(1.979)	(2.673)
BRKSIZE	0.004**	0.002	-0.002	0.001
	(2.236)	(0.941)	(-0.290)	(0.257)
COVER	0.003	0.002	-0.001	0.010
	(0.762)	(0.650)	(-0.120)	(0.908)
IVOL	0.709**	0.879***	3.296***	3.677***
	(2.620)	(3.305)	(3.278)	(4.193)
DISP	0.002*	0.002**	0.001	0.002*
	(1.785)	(2.131)	(0.905)	(1.866)
BEME	0.008***	0.008**	0.032**	0.018**
	(3.204)	(2.648)	(2.288)	(2.393)
SIZE	-0.000	-0.000	-0.000	0.000**
	(-0.672)	(-0.345)	(-0.908)	(2.203)
MOM	-0.007***	-0.009***	-0.020***	-0.027***
	(-4.529)	(-4.271)	(-4.164)	(-4.699)
ILLIQ	0.003	0.003	0.000	-0.000
	(0.974)	(1.013)	(0.729)	(-0.079)
Constant	-0.035*	-0.028	-0.085***	-0.144**
	(-1.695)	(-1.177)	(-3.392)	(-2.323)
Observations	211,952	212,249	182,911	183,580
R-sq	0.189	0.029	0.102	0.007
Adj R-sq	0.172	0.0290	0.0694	0.00661
Firm FE	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes

4.5.3 Economic Uncertainty, Analyst Optimism and Reputation

Despite optimistic forecasts providing incentives in the short-term, this behaviour is more likely to be detrimental for analysts' career in the long term. Jackson (2005) supports this conjecture and finds that investors update analyst reputations detecting optimism in forecasts for incentives in the long-term and follow analysts with better reputations accordingly. Due to reputation costs, analysts are concerned about getting promoted to high-status brokerage houses or securing their jobs in the industry (i.e., Fama, 1980; Lim, 2001). However, EUE-induced optimism is more likely to allow analysts to hide their bias as investors tend to have more difficulties verifying the valuation of stocks with high uncertain payoffs due to a vague informational environment (Ackert and Athanassakos, 1997). Therefore, I expect that analysts are less likely to suffer from reputational concern resulting from an upward view on stocks with high EUE.

Following the similar way of Chang and Choi (2017), I form analyst-level optimism measure. If analyst i issues a forecast greater than the actual value of firm j in year t, the optimistic score is 1, and 0 otherwise. The mean of these dummy variables across the companies that analyst i covers gives the aggregate optimistic score for analyst i in year t. Next, I sort analysts on their aggregate scores in five groups for each year to measure the level of their optimism. If analyst i is in the highest group, optimistic flag (OF) is 1 in year t, and 0 otherwise. If there are more than one forecast made by analyst i for firm j in year t, I first take the mean of those forecasts to calculate OF. Additionally, I also form an aggregate EUE score (EUE^{score}) by taking the average of monthly Rank5 for all stocks covered by analyst i in year t. Finally, I examine the effect of EUE-induced optimism on analysts' career concern with the following estimation:

$$Prob(Y_{i,t}) = f(\lambda_0 + \lambda_1 OF_{i,t-1} + \lambda_2 EUE_{i,t-1}^{score} + \lambda_3 OF * EUE_{i,t-1}^{score} + \sum_{J=2}^{n} \lambda_j X_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t}) \tag{4.7}$$

where $Y_{i,t}$ is MOVEDOWN binary variables for analyst i year t. $OF_{i,t-1}$ is optimistic flag for analyst i in year $t-1$. $EUE_{i,t-1}^{score}$ is the aggregate EUE score for analyst i in year $t-1$. $X_{i,t-1}$ is a set of analyst-specific variables for analyst i in year $t-1$, including $COVER$, $BROKERSIZE$ and $EXPER$. Year fixed effects are included in the estimation to control for the influence of time series. Finally, standard errors are clustered at the analyst level.

Table 4.8 Analyst Reputation

This table reports binomial logistic regressions of analysts' job turnover using Equation (4.7). Variable definitions are listed in Appendix II. The slope coefficients are exponentiated and z-statistics are reported in parentheses. The sample period is from January 1982 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3
OF	1.144***	1.700***	1.554***
	(3.092)	(4.834)	(3.906)
EUE^{score}		1.122***	1.122***
		(4.145)	(4.102)
$OF*EUE^{score}$		0.821***	0.838***
		(-3.891)	(-3.451)
EXPER			1.021
			(1.251)
BRKSIZE			1.049***
			(3.741)
COVER			0.916***
			(-3.872)
Constant	0.032***	0.026***	0.026***
	(-28.258)	(-26.671)	(-22.510)
Observation	78,018	77,151	74,707
Pseudo R-sq	0.0323	0.0329	0.0301
Year FE	Yes	Yes	Yes
Cluster by Analyst	Yes	Yes	Yes

Table 4.8 presents the odd probabilities that are the exponentiated coefficients for the logistic regression model. I find that coefficients on OF are positive and statistically significant in all specifications. Therefore, the odds of moving down from a higher-status brokerage house to a lower one is significantly 55% higher for analysts in the highest optimism quintile relative to analysts in lower optimism groups in the full specification. Consistent with the literature, my results suggest that analysts issuing optimistic forecast are

more likely to move down from high-status brokerage house to low-status ones in the subsequent period (Jackson, 2005; Groysberg, Healy and Maber, 2011; Chang and Choi, 2017). Therefore, their optimistic bias is more likely to be limited by their career concern in the future.

The interaction of $OF$and EUE^{score} is significant. It shows that the odds ratio for analysts in the highest optimism quintile is significantly -6% [$= exp(\lambda_2 + \lambda_3) - 1$] for a one-standard deviation increase in the aggregate EUE score in the full specification. Therefore, it is less likely for analysts issuing an optimistic forecast for stocks with high EUE to lose their job in a high-status brokerage firm in the subsequent period, since they can blame their optimistic bias for those stocks affected by macro-level uncertainty on the vague informational environment.

4.5.4 Economic Uncertainty and Self-selection

My empirical results have so far shown that analysts are biased in earnings forecasts for stocks with high EUE. This is mainly due to optimism for incentives with fewer career concerns. However, EUE-induced optimism might be attributed to a lack of pessimistic coverage for those stocks. Analysts who have career concern or simply have a negative view might downgrade their forecasts for those assets due to a poor informational environment. However, those firms might withhold inside information from those analysts. Therefore, they tend to drop coverage of those firms. The missing pessimistic view on high EUE can increase the effect of optimistic opinions on the consensus, leading to an upward bias in earnings forecast (McNichols and O'Brien, 1997).

In this regard, I further distinguish pessimistic and optimistic analysts based on their issues in one-year earnings forecasts. First, I re-calculate OPTIM, defined in Equation (4.1), for each forecast made by analyst i in year t, then I take the average of all OPTIMs for the same analyst in the same year. Finally, I sort analysts on the mean value of OPTIM to form quintiles every year ($Rank5^{OPTIM}$). Moreover, I also use EUE^{score} defined in Section 4.5.3, to measure the average EUE score for all stocks covered by analyst i in year t. To examine whether EUE causes the pessimists to drop their coverage, I employ the following model:

$$
\begin{aligned}
Y_{i,p,t} = \lambda_0 + \lambda_1 EUE_{i,t}^{score} + \lambda_2 Rank5_{i,t}^{OPTIM} + \lambda_3 Pessimists \ * EUE_{i,t}^{score} \\
+ \lambda_3 Optimists * EUE_{i,t}^{score} + \sum\nolimits_{J=4}^{n} \lambda_j X_{i,t-1} \\
+ \sum\nolimits_{J=n+1}^{m} \lambda_j Z_{i,t} \ + Fixed\ Effects + \ \varepsilon_{i,t}
\end{aligned}
\quad (4.8)
$$

where $Y_{i,t}$ is the total number of forecasts issued by analyst i in year t in natural logarithm. $EUE_{i,t}^{score}$ is the aggregate EUE score for analyst i in year t. $Rank5_{i,t}^{OPTIM}$ is OPTIM quintile for analyst i in year t. $Pessimists_{i,t}$ is 1 if analyst i in the bottom of OPTIM quintile in year t. $Optimists_{i,t}$ is 1 if analyst i in the top of OPTIM quintile in year t. $X_{i,t-1}$ is a set of analyst-specific variables for analyst i in year $t-1$, including $COVER$, $BROKERSIZE$ and $EXPER$. $Z_{i,t}$ is the mean of stock-specific variables for all firms covered by analyst i in year t, including $DISP$, $IVOL$, $SIZE$, MOM, BM and $ILLIQ$. Analyst and year fixed effects are included in the estimation to control for heterogeneity across analyst and the influence of time series. Finally, standard errors are double clustered at analyst-year levels (Cameron, Gelbach and Miller, 2011).

Table 4.9 Self-Selection

This table reports panel predictive regressions of the total number of forecasts using Equation (4.8). Variable definitions are listed in Appendix II. T-statistics are reported in parentheses. The sample period is from January 1982 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5
EUE^{score}	-0.010	0.022**	0.028***	0.013	0.013
	(-1.129)	(2.392)	(3.417)	(1.561)	(1.562)
$Rank5^{OPTIM}$	0.074***	0.097***	0.058***	0.056***	0.057***
	(10.136)	(8.859)	(6.945)	(6.745)	(6.802)
Pessimists* EUE^{score}		-0.036***	-0.032***	-0.032***	-0.034***
		(-2.913)	(-3.728)	(-3.812)	(-3.890)
Optimists* EUE^{score}		-0.074***	-0.055***	-0.054***	-0.024***
		(-8.502)	(-7.242)	(-7.233)	(-6.466)
Pess* EUE^{score} *BRK					0.000
					(0.338)
Opt* EUE^{score} *BRK					-0.009***
					(-3.463)
EXPER			-0.123***	-0.116***	-0.116***
			(-6.397)	(-6.006)	(-6.006)
BRKSIZE			-0.011*	-0.011	-0.005
			(-1.383)	(-1.234)	(-1.472)
COVER			0.509***	0.501***	0.501***
			(38.889)	(39.117)	(39.101)
IVOL				5.461***	5.478***
				(3.637)	(3.654)
DISP				-0.028*	-0.028*
				(-1.848)	(-1.846)
BM				-0.007	-0.007
				(-0.341)	(-0.325)
SIZE				-0.000***	-0.000***
				(-4.217)	(-4.221)
MOM				0.034**	0.034**
				(2.569)	(2.553)
ILLIQ				-0.002	-0.002
				(-0.651)	(-0.700)
Constant	2.631***	2.534***	2.003***	1.972***	1.966***
	(73.360)	(54.271)	(27.576)	(24.535)	(24.113)
Observations	95,780	95,780	79,036	78,609	78,609
R-sq	0.574	0.578	0.631	0.630	0.630
Adj R-sq	0.498	0.502	0.569	0.569	0.569
Analyst FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster by Analyst	Yes	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes	Yes

Table 4.9 shows that coefficients on $Rank5^{OPTIM}$ are positive and statistically significant in all regressions, implying that the total number of forecasts issued by analysts is more likely to increase with their optimism. In other words, analysts with pessimistic view tend to drop their coverage consistent with McNichols and O'Brien (1997). In particular, the pessimists covering stocks with larger EUE are more likely to withdraw forecast, shown

with the interaction of Pessimists and EUE^{score}. This negative trend is also observed among the optimists who follow firms exposed to higher macro uncertainty, indicated with the interaction of Optimists and EUE^{score}.

Compiling all findings related to EUE-induced optimism in the line with incentive concerns, this result suggests that there are still optimists who are less willing to exploit EUE and more likely to drop coverage for firms with larger EUE. Interacting with brokerage size, the negative coefficient in Specification (5) implies that optimistic analysts working for larger brokerage house tend to publish fewer forecasts for high EUE stocks. This might be because larger brokerage houses have a higher quality of the informational environment and better relationship with companies (Jacob, Lys and Neale, 1999). Therefore, optimists working for those brokerage houses with these opportunities may decide to stop issuing their forecasts as facing larger uncertainty. Moreover, their career concerns may deter them from reflecting their optimism for those assets.

4.5.5 Behavioural Explanation

In this study, the main conjecture relies on the rational argument where analysts are optimists in their forecast to gain incentives that are limited to their reputational concerns. This conjecture has empirically been confirmed. However, several studies argue that forecast bias is attributed to behavioural biases. For instance, Zhang (2006) shows that optimism in earnings forecasts increases (decreases) following bad (good) news for stock with higher information uncertainty inconsistent with analyst forecast optimism based on

Table 4.10 Behavioural Explanation

This table reports panel predictive regressions of one-year earnings consensus optimism for Bad and Good news on GDP growth samples using Equation (4.4). Variable definitions are listed in Appendix II. T-statistics are reported in parentheses. The sample period is from January 1982 to December 2018. News 1 is the difference between the actual real GDP growth and the median consensus real GDP growth forecast. News 2 is the difference between the actual real GDP growth and the actual real GDP growth for the same quarter last year. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, res2.pectively.

	News 1<0		News 1>0		News 2<0		News 2>0	
Rank5	0.003*	0.001	0.002	0.002	0.003*	0.001*	0.003	0.002
	(1.697)	(1.676)	(1.546)	(1.403)	(1.847)	(2.035)	(1.488)	(1.510)
EXPER	0.004	0.012***	0.012***	0.016**	0.004	0.010*	0.013***	0.016**
	(0.429)	(2.857)	(3.620)	(2.314)	(0.464)	(1.898)	(2.954)	(2.291)
BRKSIZE	-0.011	-0.002	0.003	0.001	-0.004	0.003	-0.003	-0.005
	(-0.985)	(-0.468)	(0.515)	(0.299)	(-0.416)	(0.833)	(-0.595)	(-1.545)
COVER	0.012	0.017	-0.004	-0.001	0.011	0.017	0.001	-0.003
	(0.877)	(1.296)	(-0.754)	(-0.444)	(0.835)	(1.392)	(0.118)	(-0.950)
IVOL	3.352**	3.102***	1.527***	2.062***	3.172***	3.038***	1.484***	1.895***
	(2.617)	(3.219)	(4.511)	(5.905)	(3.065)	(4.010)	(2.914)	(4.697)
DISP	0.001	0.002	0.002***	0.003***	0.002*	0.003**	0.001**	0.002**
	(1.539)	(1.299)	(2.973)	(3.643)	(1.940)	(2.097)	(2.671)	(2.559)
BEME	0.009*	0.006*	0.030**	0.024***	0.016**	0.014**	0.021*	0.017**
	(1.754)	(1.896)	(2.342)	(2.873)	(2.519)	(2.676)	(1.838)	(2.383)
SIZE	-0.000	0.000*	-0.000	0.000**	-0.000	0.000*	0.000	0.000**
	(-1.376)	(1.749)	(-0.690)	(2.211)	(-1.323)	(1.925)	(0.618)	(2.153)
MOM	-0.017***	-0.023***	-0.013***	-0.018***	-0.019***	-0.027***	-0.012***	-0.015***
	(-3.400)	(-4.252)	(-3.889)	(-4.728)	(-3.995)	(-4.807)	(-3.779)	(-4.803)
ILLIQ	0.000	-0.000	0.001***	0.001	0.001**	0.001*	-0.001	-0.001
	(0.444)	(-0.004)	(2.775)	(1.311)	(2.599)	(1.733)	(-0.745)	(-1.042)
Constant	-0.053*	-0.111	-0.054**	-0.068***	-0.080**	-0.130**	-0.048***	-0.038*
	(-1.800)	(-1.627)	(-2.452)	(-2.971)	(-2.580)	(-2.216)	(-2.765)	(-1.746)
Observations	174,956	175,687	219,539	220,142	211,430	212,241	179,572	180,220
R-sq	0.051	0.006	0.155	0.007	0.044	0.007	0.172	0.005
Adj R-sq	0.04	0.004	0.13	0.005	0.038	0.003	0.138	0.004
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

the rational framework.[89] This is because analysts tend to underreact to new information, and this is more pronounced with greater uncertainty (Hirshleifer, 2001). Furthermore, Hugon, Kumar and Lim (2016) show that analysts are more likely to underreact to bad macroeconomic news, resulting in significant optimism in earnings forecasts. Therefore, EUE-induced analyst optimism might be, at least, partly related to an underreaction to new economic information.

I expect that analysts tend to publish more (less) optimistic forecast for stocks with high EUE following bad (good) macroeconomic news due to their underreaction to news in earnings forecasts for such stocks. Consistent with Hann, Ogneva and Sapriza (2012) and Hugon, Kumar and Lim (2016), two measures are formed to distinguish the level of macroeconomic news to examine this prediction. The first measure is the difference between the actual real GDP growth and the median consensus real GDP growth forecast (News 1).[90] The second one is the difference between the actual real GDP growth and the actual real GDP growth for the same quarter last year (News 2).

Table 4.10 reports regression results estimated by Equation (4.4) following bad and good macro-news periods. I find that coefficients on Rank5 are positive following bad economic news. However, those results do not provide strong evidence in terms of their significance level. Furthermore, I do not observe any significant decrease in EUE-induced consensus optimism in a good news sample. Overall, those weak results do not help this

[89] Zhang (2006) measures forecast bias by taking the difference between actual earnings and analyst forecast divided by stock price.

[90] I take the first (advance) real GDP figures from Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/) then calculate the annualised growth rate for each quarter. Those figures are announced at the end of the month following the last month of each quarter. The median consensus real GDP forecasts is obtained from the Survey of Professional Forecasters (https://www.philadelphiafed.org/surveys-and-data).

study conclude that EUE-induced optimism might be, at least, partly related to analysts' underreaction to the news.

4.5.6 *Economic Uncertainty, Analyst Optimism and Mispricing*

In the stock market, the role of analysts is also to help investors investment decision with forecasts and recommendations, leading to improve market efficiency. However, recent studies have shown inconsistent results with this view. For instance, Engelberg, Mclean and Pontiff (2018) find that analysts issue positive (negative) earnings forecasts for overpriced (underpriced) stocks measured by using 97 anomaly signals. Moreover, Guo, Li and Wei (2020) show that analysts exhibit upward bias in stock recommendations for overpriced stocks, using 11 anomalies that are introduced in Chapter 2. Those findings are inconsistent with the price efficiency which impedes the correction of mispricing. Considering the main findings in Chapter 2, I interact EUE-induced mispricing in anomalies with EUE-induced analyst optimism in earnings forecasts. In this way, I further investigate whether their bias exacerbates anomaly mispricing in stocks with high EUE as a result of their incentive concerns. To test this conjecture, I form 18 portfolios by independently sorting stocks into two $OPTIM$, three EUE and three MIS groups.[91]

Table 4.11 reports risk-adjusted returns on 18 value-weighted OPTIM-EUE-MIS portfolios for high and low OPTIM groups in Panels A and B, respectively. The risk-risk adjusted returns are alphas estimated by an augmented Fama and French (2016) six-factor model introduced in Equation (2.3) of Chapter 2. I find that the EUE effect on mispricing is significantly apparent in the group with high consensus optimism. In Panel A, overpricing

[91] Due to data availability, portfolio formation starts from January 1983.

is pervasive in all EUE portfolios. The monthly alpha of the "Underpriced−Overpriced" portfolio in the high EUE quintile is significant (0.90%, $t = 3.37$), which is more than the average mispricing effect (monthly alpha of 0.65%, $t = 4.43$). The ambiguity-premium effect, furthermore, is only significantly observed in the group of stocks with low consensus optimism. The high-minus-low EUE portfolio in the non-mispricing group is significantly 0.44% per month with a t-statistic of 2.13. These results confirm that analysts issuing optimistic view for stocks with high EUE exacerbates mispricing in anomalies and their optimism impedes the price efficiency in the market.

Table 4.11 Triple sorts on OPTIM, EUE and MIS

This table reports risk-adjusted returns on 18 value-weighted portfolios formed by sorting independently stocks on the two OPTIM, the three EUE and the three MIS groups. The results among high and low OPTIM groups are reported in Panel A and Panel B, respectively. The risk-adjusted returns are estimates of alphas estimated in Equation (2.3). Variable definitions are listed in Appendix II. Portfolio returns are in percent and t-statistics are reported in parentheses using Newey-West (1987) robust standard errors with 3 lags. The sample period is from January 1983 to December 2018. ***, ** and * indicates significance at the 1%, 5% and 10% levels, respectively.

	Low EUE	2	High EUE	High - Low EUE	Average MIS
		Panel A: High OPTIM			
Overpriced	-0.98***	-1.59***	-1.77***	-0.79***	-1.44***
	(-6.15)	(-8.35)	(-8.03)	(-3.10)	(-11.43)
Non-Mispricing	-1.00***	-0.96***	-1.18***	-0.18	-1.05***
	(-6.27)	(-6.50)	(-4.56)	(-0.63)	(-7.88)
Underpriced	-0.73***	-0.80***	-0.86***	-0.13	-0.80***
	(-5.78)	(-5.48)	(-4.50)	(-0.59)	(-8.00)
Under-Overpriced	0.24	0.79***	0.90***	0.66**	0.65***
	(1.18)	(3.33)	(3.37)	(2.05)	(4.43)
Average EUE	-0.90***	-1.12***	-1.27***	-0.37**	
	(-10.90)	(-10.27)	(-8.25)	(-2.20)	
		Panel B: Low OPTIM			
Overpriced	0.84***	0.89***	1.45***	0.60***	1.06***
	(5.71)	(5.60)	(8.92)	(2.97)	(9.92)
Non-Mispricing	0.66***	0.88***	1.11***	0.44**	0.88***
	(5.69)	(6.57)	(6.00)	(2.13)	(9.66)
Underpriced	0.31***	0.68***	1.04***	0.74***	0.68***
	(3.08)	(5.89)	(5.93)	(3.76)	(8.71)
Under-Overpriced	-0.54***	-0.21	-0.41*	0.13	-0.39***
	(-3.03)	(-1.09)	(-1.87)	(0.48)	(-3.20)
Average EUE	0.60***	0.82***	1.20***	0.59***	
	(7.64)	(9.43)	(9.82)	(4.66)	

4.5.7 *Alternative Measure*

To verify whether my findings are unique due to the uncertainty measure, I repeat the main analyses considering another uncertainty measure which is the news-based economic uncertainty policy index (EPU) developed by Baker, Bloom and Davis (2016).[92] As in the main EUE estimation, I estimate EPU betas from a 60-month rolling regression for each stock with the model specified in Equation (4.3) by replacing ΔUNC_t with the change of EPU. Similar to the main analysis, I measure the exposure to EPU by the absolute value of the beta and form quintiles at the end of each month ($Rank5^{EPUE}$). Then, I re-perform all regression models in Equations (4.4), (4.5) and (4.6) by replacing $Rank5$ with $Rank5^{EPUE}$.

Table 4.12 provides additional evidence to support my main analyses, showing that stock exposure to EU measured by policy uncertainty induces optimism among analysts. Cross-section of earnings forecast optimism increases with firms' exposure to EPU in quintile ranks, controlling for the firm- and industry-fixed effects, respectively. Moreover, the percentage of buy recommendations increases with EPUE quintiles at a 1% significance level controlling for both firm and industry levels.

Finally, in Table 4.13 odds ratios on $Rank5^{EPUE}$ in the logistic regressions imply that analysts are more (less) likely to issue buy (sell) recommendations. Therefore, there is an increase(decrease) in the odds of issuing buy (sell) recommendation by firms' exposure to EPU in quintile ranks.

Collectively, those results further confirm that not only do stocks' exposure to

[92] This index is based on the uncertainty in regulatory and policy decisions captured in various newspapers. The monthly value of index is taken from https://www.policyuncertainty.com/

Table 4.12 Economic Policy Uncertainty and Analyst Optimism

This table reports panel predictive regressions of one-year earnings consensus optimism using Equation (4.4) and (4.6) replacing Rank5 with Rank5^{EPUE}. Variable definitions are listed in Appendix II. T-statistics are reported in parentheses. The sample periods are from January 1990 for OPTIM and from January 1994 for BUYPCT and SELLPCT to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	OPTIM		BUYPCT		SELLPCT	
	1	2	3	4	5	6
Rank5^{EPUE}	0.003**	0.001	0.004***	0.009***	-0.000	-0.000
	(2.189)	(0.836)	(3.655)	(6.070)	(-1.270)	(-0.855)
EXPER	0.010*	0.015**	-0.023***	-0.035***	0.005**	0.004**
	(1.783)	(2.712)	(-3.444)	(-5.091)	(2.616)	(2.376)
BRKSIZE	-0.005	-0.002	-0.063***	-0.082***	0.010***	0.022***
	(-0.749)	(-0.488)	(-10.212)	(-10.566)	(3.301)	(4.604)
COVER	0.003	0.007	-0.039***	-0.057***	0.004*	0.000
	(0.423)	(0.888)	(-5.912)	(-7.101)	(1.718)	(0.066)
IVOL	2.376***	2.497***	-1.123***	-0.463**	0.349***	0.359***
	(3.266)	(4.362)	(-7.380)	(-2.204)	(5.377)	(4.451)
DISP	0.001	0.002*	-0.005***	-0.005***	0.002***	0.002***
	(1.450)	(1.884)	(-4.417)	(-2.875)	(3.957)	(3.352)
BEME	0.018**	0.013**	-0.046***	-0.029***	0.006***	0.003*
	(2.404)	(2.514)	(-6.568)	(-4.888)	(3.186)	(1.820)
SIZE	-0.000	0.000**	0.000***	0.000***	-0.000***	-0.000**
	(-1.006)	(2.102)	(6.272)	(4.683)	(-3.819)	(-2.522)
MOM	-0.013***	-0.018***	0.055***	0.064***	-0.008***	-0.009***
	(-4.670)	(-5.143)	(5.668)	(5.421)	(-4.512)	(-4.391)
ILLIQ	0.001	0.000	0.000	0.001**	-0.000	-0.000***
	(1.312)	(0.691)	(0.773)	(2.200)	(-1.194)	(-3.607)
Constant	-0.055**	-0.084**	0.985***	1.109***	-0.025	-0.058***
	(-2.577)	(-2.124)	(32.526)	(35.755)	(-1.548)	(-3.115)
Observations	352,544	353,055	52,367	53,508	52,367	53,508
R-sq	0.062	0.005	0.521	0.202	0.390	0.084
Adj R-sq	0.0420	0.00489	0.461	0.201	0.313	0.0829
Firm FE	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Year	Yes	Yes	Yes	Yes	Yes	Yes

uncertainty in the real economy matter in analysts' optimism but also exposure to policy and regulatory uncertainty can affect analysts' bias in firms' earnings and stock recommendations.

Table 4.13 Economic Policy Uncertainty and Analyst Optimism: Stock Recommendations

This table reports binomial and multinomial logistic regressions of stock recommendations using Equation (4.5) replacing Rank5 with Rank5^{EPUE}. Variable definitions are listed in Appendix II. The slope coefficients are exponentiated and z-statistics are reported in parentheses. The sample period is from January 1994 to December 2018. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Sell	Buy	Rec		
			(Sell)	(Hold)	(Buy)
	1	2		3	
Rank5^{EPUE}	0.987	1.024***	0.987*	-	1.022***
	(-1.205)	(7.244)	(-1.919)		(6.639)
EXPER	1.011	1.013*	0.969*	-	1.009
	(0.311)	(1.783)	(-1.823)		(1.226)
BRKSIZE	0.713***	0.878***	1.137***	-	0.892***
	(-8.215)	(-14.919)	(4.584)		(-14.789)
COVER	1.134**	0.941***	1.001	-	0.942***
	(2.395)	(-5.733)	(0.029)		(-5.971)
IVOL	46.299***	3.795***	38.151***	-	6.783***
	(3.918)	(3.346)	(5.338)		(4.614)
DISP	1.016***	1.000	1.017**	-	1.005
	(2.952)	(0.056)	(2.225)		(0.718)
BM	1.082***	0.944***	1.077***	-	0.955***
	(3.411)	(-5.908)	(4.767)		(-4.893)
SIZE	1.000	1.000***	1.000*	-	1.000***
	(-0.568)	(10.384)	(-1.899)		(10.083)
MOM	0.630***	1.363***	0.728***	-	1.320***
	(-7.946)	(24.321)	(-10.182)		(22.036)
ILLIQ	0.489***	1.027	0.745***	-	1.019
	(-2.730)	(1.292)	(-3.348)		(1.176)
Constant	0.049***	1.795***	0.072***	-	1.882***
	(-13.460)	(9.720)	(-16.333)		(10.803)
Observation	247,897	247,897		247,897	
Pseudo R-sq	0.0414	0.0335		0.0319	
Industry FE	Yes	Yes		Yes	
Year FE	Yes	Yes		Yes	
Cluster by Analyst	Yes	Yes		Yes	

4.6 Conclusion

This study investigates the effect of economic uncertainty on analysts' decision process in earnings forecasts and stock recommendations. It shows that analyst optimism in their forecasts is larger for stocks with higher exposure to economic uncertainty. Additionally, this optimism is more pronounced with increasing macro-level uncertainty. The foundation of my conjecture relies on the rational framework where analysts face a dilemma when issuing optimistic forecasts: developing a better relationship with managers versus losing their reputation. Findings in Chapter 4 suggest that EUE-induced optimism is apparent when managers are more likely to hide information in financial reports or when market-level information is less likely to be available. I also show that analysts are less likely to lose their reputation with EUE-induced optimism. Therefore, EUE mitigates the dilemma faced by analysts. I, furthermore, find that the missing pessimistic view on stocks exposed to high macro uncertainty seems to feed this optimism. Lastly, I examine whether EUE-induced optimism in earnings forecasts might be driven by behavioural biases considering the underreaction hypothesis. However, there is no strong evidence supporting that EUE-induced optimism is, at least, partly related to analysts' underreaction to macroeconomic news.

As a result of analyst optimism for those assets, the mispricing effect of economic uncertainty is apparent in anomalies, inconsistent with the price efficiency which is expected to be improved by analysts in the market. Finally, my main findings are robust to the economic policy uncertainty index, indicating that uncertainty in regulations also matters to analyst optimism in earnings forecasts.

Chapter 5

5 Conclusion

5.1 Summary of the Thesis

This thesis aims to examine the effect of economic uncertainty on investors and security analysts in their decision-making processes. In the relevant literature, economic uncertainty has two seemingly contradicting predictions in asset pricing. It exacerbates heterogeneous beliefs among investors, making optimists more optimistic and pessimists more pessimistic and causing significant mispricing. However, it also affects the preference of investors facing uncertainty in the sense of the ambiguity-return trade-off. In Chapter 2, I reach a clear conclusion that both the ambiguity premium and the mispricing mechanisms are indeed at work. Such evidence can only be observed with my decomposition using an aggregate mispricing measure of Stambaugh, Yu and Yuan (2012; 2015) as two effects have been studied separately in the literature. I empirically show that the spread between underpriced and overpriced portfolios sorted by the mispricing measure is larger among stocks with higher exposures to macro uncertainty. The effect of EUE on the mispricing spread is mitigated when more elaborated multifactor models are used but remains significant in general. Moreover, I show that the high-minus-low EUE portfolio in the non-mispricing group, which is the middle portfolio sorted by the mispricing measure, generates a significant premium. This result is robust to all multifactor models, implying that it is different from existing risk factors. Considering the limits of arbitrage context, EUE is a new source of arbitrage frictions that is not captured by existing sources, such as idiosyncratic volatility. Empirical findings suggest that EUE can be a common source of mispricing and a candidate as a new risk factor.

Chapter 3 answers the question of whether market-wide sentiment has a significant role in two effects of EUE on cross-sectional returns. I show that the mispricing spread in stocks with high EUE following the high-sentiment period, suggesting that investors with optimistic view determine those stocks' value. By contrast, the high-minus-low EUE portfolio in the non-mispricing group yields a significant premium following a low-sentiment period where investors behave more rationally (Stambaugh, Yu and Yuan, 2012). Considering the presence of market-wide sentiment, I empirically provide further insights into those two opposite effects of economic uncertainty on cross-sectional returns from a behavioural perspective. Moreover, interacting market-wide sentiment with the macro-level uncertainty, the mispricing effect of EUE is significantly observed following periods with both high EU and high sentiment. This finding shows that economic uncertainty exacerbates investors' bias, leading to more irrational behaviours and larger disagreement. Second, the ambiguity premium in the non-mispricing group only exists following periods with high EU and low sentiment, confirming that rational investors demand an ambiguity premium when macro uncertainty intensifies as low market-wide sentiment reflects their preference.

Chapter 4 answers the question of whether economic uncertainty affects analyst optimism in earnings forecasts and stock recommendations. Existing studies have shown upward bias in forecasts and I show that this bias is even more pronounced for stocks with higher EUE relative to those with lower EUE. Considering the rational framework, analysts provide optimistic forecasts to develop a better relationship with managers. However, analyst optimism is constrained by their career concern as investors are able to detect it in the long term. I show that analysts with optimistic forecasts for stocks with high EUE are less likely to lose their position in a high-status brokerage house. Therefore, EUE-induced optimism is less likely to be penalised. These findings suggest that the dilemma of improving management access or losing their reputation faced by analysts are mitigated by EUE. Finally, interacting EUE-induced mispricing documented in Chapter 2 with EUE-induced optimism, I find that the mispricing spread in high EUE significantly apparent in the group of stocks with high consensus optimism. I suggest that analyst optimism for stocks with high EUE do not contribute to the price efficiency in the market, inconsistent with the role of analyst forecast and recommendation.

5.2 Key contributions of the Thesis

This study examines the role of economic uncertainty in asset pricing. It offers a new premise to the literature where economic uncertainty affects investors' beliefs and preferences that are not supposed to be mutually exclusive. They can be observed in markets and the strength varied with economic and investor sentiment conditions. Empirically, this observation can be made using firm-level mispricing characteristics, which offers a practical decomposition to disentangle those two effects in the literature. The divergence of opinion among investors is an important factor in asset pricing that has been examined extensively in relevant studies. This study complements the literature and provides further evidence suggesting that economic uncertainty is an important factor driving disagreement among investors, which is different from other existing factors.

This study unveils stock exposure to economic uncertainty as a new systematic factor to researchers and practitioners. First, it can be considered as a new common component across stocks and a new arbitrage risk which carries different information from existing ones such as idiosyncratic volatility (Nagel, 2005; Stambaugh, Yu and Yuan, 2015). Second, it can be exploited to evaluate fund managers' portfolio composition and performance (Song, 2020). Third, alongside macroeconomic risk factors, it can also be useful to develop benchmark models as macrolevel uncertainty is the unpredictable components of those risk factors (Barber, Huang and Odean, 2016). This study further confirms that investors have different attitudes towards stock exposure to economic uncertainty based on their beliefs and preferences considering the presence of market-wide sentiment (Stambaugh, Yu and Yuan, 2012; Shen, Yu and Zhao, 2017). Furthermore, it provides evidence showing that macro-level uncertainty matters for investors' irrationality as the strongest sentiment effect is observed when economic uncertainty is high (Garcia, 2013; Birru and Young, 2020).

This thesis contributes to security analyst literature by examining the effect of economic uncertainty on analyst optimism in forecasts and recommendations. It confirms that stock exposure to economic uncertainty affects analysts' trade-off between improving management access and losing their reputation, contributing to the rational bias framework (Chang and Choi, 2017). This study complements the relevant literature about analyst reputation concern limiting their optimism for incentives (Fama, 1980; Lim, 2001; Jackson, 2005). Analysts, however, can hide optimism for incentives as experiencing less career concern when issuing biased forecasts for stocks with high EUE. This study, therefore, unveils another important conditional variable to understand the determinant of analysts' optimism for incentives. Finally, this thesis contributes to analysts' research and price efficiency in stock markets (Engelberg, McLean and Pontiff, 2018; Goa, Li and Wei, 2020). It shows that analyst optimism in forecasts for stocks with high EUE tends to mislead investors in anomaly investment strategy and exacerbate mispricing.

5.3 Limitations and Future Research Suggestions

5.3.1 Measuring Good and Bad Economic Uncertainty

Economic uncertainty is unpredictable using available information and models (Jurado, Ludvigson and Ng, 2015). Time-varying shocks in it are linked to real economic activities and asset prices (Bloom, 2009). This study documents that it affects both preferences and beliefs in stock markets in Chapter 2. While there is a negative relationship between firms' economic uncertainty exposure and expected returns due to the mispricing effect, there is also a positive relationship between those due to the ambiguity premium effect. In the time-series analysis in Chapter 2, this thesis shows that those effects are more pronounced following periods with increasing economic uncertainty.

However, this study does not distinguish types of uncertainty in the economy as Segal, Shaliastovich and Yoran (2015) do in decomposing aggregate uncertainty into "good" and "bad" uncertainties. For instance, technological advancement in the real economy can be considered as good uncertainty providing growth opportunities, i.e., the high-tech revolution in the 90s (Segal, Shaliastovich and Yoran, 2015). By contrast, negative shocks into the economy lowering investments and consumptions can be classified as bad uncertainty, i.e., the recent outbreak of the COVID-19 pandemic. Although those types of macro uncertainty exacerbate the predictability of future outcomes for investors, the former matches with a positive view and the latter with a negative one (Segal, Shaliastovich and Yoran, 2015). In stock-level economic uncertainty beta estimation and time-variation analysis using these betas, distinguishing different types of aggregate uncertainty could give more insights into its effect on beliefs and preferences in stock markets.

To distinguish good and bad uncertainties in economy, one may follow the empirical method introduced by Segal, Shaliastovich and Yoran (2015). They decompose the usual realized variances into the positive and negative semi-variances which give information about the realized variation related to jumps in the right and left tails of the relevant state variables such as industrial production, consumption growth and dividend on market portfolio.[93]

5.3.2 *Economic Uncertainty, Mispricing and Ambiguity Premium: International Evidence*

In Chapter 2, the sample contains all common stocks traded on different markets in the United States. It can be extended to examine the effect of economic uncertainty in the US on global stock markets. For instance, Rapach, Strauss and Zhou (2013) show that macroeconomic indicators have significant predictive power on equity prices from various countries' markets, even stronger than those countries' fundamentals. They suggest that the US equity market is the largest, thus information on macro-indicators in the US is relevant for investors in different countries. In other words, investors give more attention to the US economy, leading to an informational diffusion on macroeconomic indicators across countries (Rapach, Strauss and Zhou, 2013). In this regard, the empirical setting in Chapter 2 could also be applied to international financial markets. Economic uncertainty in the US could affect investors' beliefs and preferences in other countries' stock markets.

[93] For more discussion on the both theoretical and empirical developments behind the methodology, see Segal, Shaliastovich and Yoran (2015).

5.3.3 *Economic Uncertainty Exposure and Fund Performance*

This study unveils economic uncertainty exposure as a new systematic factor in Chapter 2, which affects asset prices based on investors' beliefs and preferences. This new factor could be used in investment management applications in the relevant literature. Song (2020) shows that systematic factors are not taken into account in mutual fund flows, which lead investors to mismatch mutual fund skill and scale. Economic uncertainty is a relevant state variable affecting investment decisions alongside macro-risk factors (Bloom, 2009; Jurado, Ludvigson and Ng, 2015). Therefore, future research could focus on how to understand the composition of fund managers' portfolios and their exposures to macroeconomic uncertainty risk for achieving their longer-term investment objectives. This perspective could potentially inform practical investment management and might also be relevant to different asset classes in financial markets. Moreover, Barber, Huang and Odean (2016) show that sophisticated investors evaluate fund performance with more sophisticated benchmarks rather than the market model. For those investors, EUE could be taken into account for benchmark model advancement.

5.3.4 *Caveats in the Sentiment Index*

In Chapter 3, I examine the link between market-wide sentiment and investors' attitudes to assets with different levels of EUE to provide a behavioural explanation for two effects of economic uncertainty in a cross-section of stock returns. I use a sentiment index that measures the market-wide sentiment assuming that all industries face simultaneously the same sentiment state. However, this may not be the case. For instance, while the market is in a high sentiment state, the automotive industry might be facing a low sentiment period due to a supply crisis in steel. Therefore, investors may exhibit different attitudes to those companies in that industry. Chapter 3 could be extended considering an industry-specific sentiment measure.

Another limitation is with the construction of the market-wide sentiment index proposed by Baker and Wurgler (2006). They use six variables to construct the index, which is correlated with the business cycle. Although they remove this effect on the sentiment index by orthogonalizing these proxies with economic fundamentals, it might still be contaminated by those fundamentals (Baker and Wurgler, 2007). Therefore, it may not reflect investor sentiment in isolation though it has widely been used in empirical finance literature. To provide a robustness check, following the literature (Lemmon and Portniaguina, 2006; Bergman and Roychowdhury, 2008), I use a survey-based consumer sentiment index, such as the University of Michigan Consumer index. However, questions in the survey might not be responded to carefully.

5.3.5 Investor Mood and Two Tales of Economic Uncertainty Exposure

In behavioural finance literature, Hirshleifer, Jiang and DiGiovanni (2020) show that stocks with higher exposure to investor mood, called mood beta, generate significantly higher (lower) subsequent returns relative to those with lower mood beta during high (low) mood periods.[94] They define mood beta as variation in investor preferences, beliefs and risk tolerance induced by investors' emotion. They suggest that changes in seasonal mood cause periodic investor optimism or pessimism in evaluating common pricing factors, which induces seasonal variations in mispricing. This can be considered as a special case of

[94] Hirshleifer, Jian and DiGiovanni (2020) define January, March and Friday as high mood periods, while September, October and Monday are low mood periods. These classifications are made by following previous literature which is discussed extensively by Hirshleifer, Jian and DiGiovanni (2020). In their study, stock exposure to investor mood estimation are empirically explained in detail.

investor sentiment (Hirshleifer, Jian and DiGiovanni, 2020). Chapter 3 could be extended using the mood beta to examine whether investor mood has a significant role in those two effects of economic uncertainty exposure on cross-sectional expected returns during high and low mood periods.

5.3.6 Macroeconomic Disagreement and Analyst Optimism

In Chapter 4, this study shows that there is a significant effect of EUE on analyst optimism, and this effect is only observed following high economic uncertainty periods. In literature, Hong and Sraer (2016) and Li (2016) show that during such periods, macroeconomic disagreement is high. Therefore one may extend this chapter by examining its on analyst forecasts following the empirical setting of Li (2016) to identify the level of disagreement about different macroeconomic indicators. This examination may explore another channel which can drive the main results in Chapter 4 instead of analyst optimism.

5.3.7 Analyst Optimism and Earnings Management Quality

This thesis examines the effect of EUE on analyst optimism based on rational bias where analysts are in a compromise between their reputation and incentive concerns. To examine EUE-induced analyst optimism in the context of maintaining a relationship with managers, I identify firms based on their earnings management quality using the Modified Jones Model by Kothari et al. (2005). This is because Brown et al (2015) find that the quality of earnings management is an important factor for analysts to control in the forecast process. Although there are an extensive number of studies where researchers have developed different measures, such as persistence, accruals, smoothness and timeliness to identify earnings quality, discussing and evaluating each of those proxies are beyond the scope of this thesis.[95]

5.4 Conclusion

I study the role of economic uncertainty in the decision of investor and analysts by studying the asset pricing and analysts forecast in three empirical studies. The findings of this thesis further extend our understanding of this key state variable. It affects both investors belief formation and preference. It also exacerbates bias induced by the investor's sentiment and creates an information environment hiding analysts' optimistic biases. These new empirical facts would be a useful foundation for future theoretical and empirical studies but also relevant to practical investment management.

[95] For an extensive review of earnings quality proxies and its determinants, see Dechow, Ge and Schrand (2010) and DeFond (2010).

5.5 Appendix II: Description

Table A-II.1 Variable and Factor Descriptions

This table reports details of risk factors and stock-level variables used for the whole study. Panel A reports the details of market risk factors. Panel B reports the details of firm-level uncertainty exposures. Panel C and D report firm-level and analyst-level characteristics, respectively.

Variable Name	Description
	Panel A. Risk Factors
MKT	The excess market return is the value-weighted return of all firms listed on the NYSE, AMEX, and NASDAQ minus one-month Treasury-bill rate (Fama and French, 1993).
SMB	Small-minus-big is the average return on the three small-sized portfolios minus the average return on the three big-sized portfolios (Fama and French, 1993).
HML	High-minus-low is the average return on the two value portfolios minus the average return on the two growth portfolios (Fama and French, 1993).
UMD	Winner-minus-loser is previous 12-month return winner portfolios minus previous 12-month loser portfolios (Carhart, 1997).
IA	Conservative-minus-aggressive is the difference between the returns on portfolios of stocks with low and high investment (Fama and French, 2015).
ROE	Robust-minus-weak is the difference between the returns on portfolios of the stocks with high and low profitability (Fama and French, 2015).
LIQ	Liquidity is the level of aggregate market liquidity (Pastor and Stambaugh, 2003).
QIA	Investment factor is the difference between the mean returns on the six low I/A portfolios and on the six high I/A portfolios. I/A is the annual change in total assets scaled by previous year total assets (Hou, Xu and Zhang, 2015).
QROE	Profitability factor is the difference between the mean returns on the six low ROE portfolios and the six high ROE portfolios. ROE is income before extraordinary items scaled by previous quarter book equity (Hou, Xu, and Zhang, 2015).
QEG	The expected growth factor is the difference between the mean returns on two high EG portfolios and the low EG portfolios. EG is the product of operating cash flow-to-assets and the change in ROE (Hou et al, 2020).
MGMT	Management factor is pairwise cross-sectional correlations between stocks in net stock issues, composite issues, accruals, net operating asset, asset growth, and investment-to-assets groups (Stambaugh and Yuan, 2017).
PERF	The performance factor is pairwise cross-sectional correlations between stocks in distress, O-score, momentum, gross profitability and return on assets groups (Stambaugh and Yuan, 2017).
	Panel B. Firm Uncertainty Exposures
β^{EUE}	Economic uncertainty exposure is the absolute value of the coefficient of the change of economic uncertainty index (Jurado, Ludvigson, and Ng, 2015) estimated by a 60-month rolling regression for each stock with Equation (2.2).
β^{ADSM}	Macro-disagreement exposure is the absolute value of the coefficient of the change of dispersion in economic forecast estimated by a 20-quarter rolling regression for each stock with Equation (2.2) by replacing the log change of economic uncertainty index with the log change of those dispersions including GDP, industrial production (INPR), and nonresidential fixed investment (RNRSN) at the growth rates, and unemployment rate (UNEM), Treasury-bill (TBILL), and inflation rate (CPI). Those measures are from the Survey of Professional Forecasters
β^{EPUE}	Economic policy uncertainty exposure is the absolute value of the coefficient of the change of economic policy uncertainty index (Baker, Bloom, and Davis, 2016) estimated by a 60-month rolling regression for each stock with Equation (2.2) by replacing the log change of economic uncertainty index with the log change of the economic policy uncertainty index.
β^{VRE}	Variance risk exposure is the absolute value of the coefficient of variance risk index (Bali and Zhou, 2016) estimated by a 60-month rolling regression for each stock with Equation (2.2) by replacing the log change of economic uncertainty index with the variance risk index

β^{ADE}	Ambiguity degree exposure is the absolute value of the coefficient of the change of ambiguity index (Brenner and Izhakian, 2018) estimated by a 60-month rolling regression for each stock with Equation (2.2) the log change of economic uncertainty index with the log change of the ambiguity index.

Panel C. Firm Characteristics	
MIS	Mispricing measure is the mean of decile ranks of a stock based on 11 market anomalies (Stambaugh, Yu, and Yuan, 2015). These anomalies survive after adjusting for Fama and French's (1993) three factors. Those are accruals (Sloan, 1996), asset growth (Cooper, Gulen, and Schill, 2008), composite equity issuance (Daniel and Titman, 2006), gross profitability (Novy-Marx, 2013), investment-to-assets (Titman, Wei, and Xie (2004), 1-month momentum (Jegadeesh and Titman, 1993), 12-month momentum (Jegadeesh, 1990) net operating assets (Hirshleifer et al. (2004), net stock issues (Ritter, 1991), O-score (Ohlson, 1980) and return on assets (Fama and French, 2006). For each anomaly, the first decile has stocks with the highest abnormal return, while the 10th decile has stocks with the lowest abnormal return. For instance, Sloan (1996) documents that assets with high (low) accruals in the previous year have a low (high) return. Therefore, stocks with the highest (lowest) accruals have the highest (lowest) rank. Then, MIS is formed by computing the mean of each asset's decile rank based on those 11 market anomaly variables (Stambaugh, Yu, and Yuan, 2015).
β^{CAPM}	Market beta is the absolute value of the coefficient of the market excess return estimated by the market model.
SIZE	Size is defined as the price of the share multiplied by the number of share outstanding.
BM	Book-to-market is computed as the book value of equity at the end of fiscal year t-1 divided by the market value of equity at the end of fiscal year t-1.
MOM	Momentum (MOM) is the cumulative return of stock *i* from month t-12 to t-2.
REV	Reversal is defined as the stock return at the end of month t-1.
ILLIQ	Stock illiquidity is defined as the ratio of the daily absolute stock return to the daily dollar trading volume averaged within the month.
DISP	Analyst earnings forecast dispersion is measured as the standard value of the mean forecast deviation of long-term earnings forecasts divided by the absolute of the mean forecast.
IVOL	Following Ang et al. (2006), idiosyncratic volatility is defined as the standard deviation of the daily risk-adjusted return residuals computed by regressing each asset's daily return on four Fama and French market factors: MKT, SMB, HML, UMD.
ROE	The quarterly operating profitability is computed by income before extraordinary items divided by prior quarter book equity. Quarterly book equity is measured by aggregating shareholders' equity, balance-sheet deferred taxes, and investment tax credit if available, minus book value of preferred stock (Davis, Fama, and French, 2000).
I/A	The annual growth rate of total assets is calculated by the change in book assets divided by the prior fiscal year book asset (Hou, Xue, and Zhang 2015).
TO	Stock turnover is the total trading volume of stock *i* divided by the number of share outstanding.
IO	Institutional ownership is measured by total institutional ownership divided by shares outstanding, gathered quarterly from 13F filing on Thomson-Reuters, starting from the first quarter in 1980.
OPTIM	Consensus optimism is calculated as the difference between the mean value of all one-year earnings forecast made by all analysts in month and actual earnings divided by previous month's closing share price.
Rank5	Quintile ranks are formed by sorting all stocks on prior month's β^{EUE}. Top (bottom) quintile has stocks with highest (lowest) β^{EUE}.
$Rank5^{EPUE}$	Quintile ranks are formed by sorting all stocks on prior month's β^{EPUE}. Top (bottom) quintile has stocks with highest (lowest) β^{EPUE}.
DA	Absolute value of discretionary accruals is Modified Jones Model computed by Kothari et al. (2005).
RSQ	Monthly R-square is computed using the market-model regression of daily returns (Frankel, Kothari and Weber, 2006).
BUYPCT	Buy percentage is the mean of buy recommendation percentage for a firm during a year.

SELLPCT	Sell percentage is the mean of sell recommendation percentage for a firm during a year.
	Panel D. Analyst Characteristics
BUY	It is a binary variable which is 1 if analyst issues Buy or Strong Buy, and 0 otherwise.
SELL	It is a binary variable which is 1 if analyst issues Sell or Strong Sell or Underperform and 0 otherwise.
REC	It is a categorical variable where Buy or Strong Buy=3, Hold=2, and Sell or Strong Sell or Underperform=1.
OF	If an analyst issues a forecast greater than the actual value of a firm in a year, optimistic score is 1, and 0 otherwise. The mean of these dummy variables across the companies that the analyst covers gives the aggregate optimistic score for that analyst in that year. Next, analysts are sorted on their aggregate scores in five groups for each year to measure the level of their optimism. If that analyst is in the highest group, optimistic flag (OF) is 1 in that year, and 0 otherwise.
EUE^{score}	Aggregate EUE score is measured by taking the mean of monthly Rank5 for all stocks covered by an analyst in a year.
MOVEDOWN	If an analyst employed by a brokerage house having at least 25 analysts in previous year is observed in a brokerage house having less than 25 analysts in following year then it is 1, and 0 otherwise.
$Rank5^{OPTIM}$	Quintile optimistic ranks are measured by sorting all analysts on the mean of all OPTIMs of each analyst in a year.
Pessimists	It is 1 if an analyst in the bottom of $Rank5^{OPTIM}$, and 0 otherwise.
Optimists	It is 1 if an analyst in the top of $Rank5^{OPTIM}$, and 0 otherwise.
COVER	The number of companies covered by an analyst in a year in natural logarithm.
EXPER	The number of years from the starting year of an analyst in IBES sample in natural logarithm.
BRKSIZE	The number of analysts hired by a brokerage house in a year in natural logarithm.

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