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by

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Declarations

I declare that any material contained in this thesis has not been submitted for a degree to any other University. I further declare that one paper titled "Employee Satisfaction, Labor Market Flexibility, and Stock Returns Around the World", drawn from Chapter Two of this thesis, is co-authored with Alex Edmans and Chendi Zhang. It has been accepted by the National Bureau of Economic Research as a NBER Working Paper No. 20300 and by the European Corporate Governance Institute as ECFI Finance Working Paper No. 433/2014. A version of this chapter has been submitted to the Review of Financial Studies during the summer of 2015. Furthermore, the paper titled "Ambiguity, Earnings Surprises, and Asset Prices", drawn from Chapter Three of this thesis, is co-authored with Roman Kozhan.

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Abstract

This thesis consists of three essays in financial economics. Specifically, it focuses on financial market reactions to intangible information like employee satisfaction and tangible information like corporate earnings news. It examines the effects of factors including institutional contexts and quality of information environment on how financial markets incorporate those information.

The second chapter examines the relationship between employee satisfaction and abnormal stock returns around the world, using lists of the "Best Companies to Work For" in 14 countries. We show that employee satisfaction is associated with positive abnormal returns in countries with high labor market flexibility, such as the U.S. and U.K., but not in countries with low labor market flexibility, such as Germany. These results are consistent with high employee satisfaction being a valuable tool for recruitment, retention, and motivation in flexible labor markets, where firms face fewer constraints on hiring and firing. In contrast, in regulated labor markets, legislation already provides minimum standards for worker welfare and so additional expenditure may exhibit diminishing returns. The results have implications for differential profitability of socially responsible investing (SRI) strategies around the world. In particular, they emphasize the importance of taking institutional features into account when forming such strategies.

In the third chapter, we investigate the effect of ambiguity on return-earnings relation. Positive firm-level earnings news is informative about a firm's future cash flows, thereby increases its contemporaneous stock price. However, this positive relation does not translate into aggregate level. On the contrary, positive aggregate

earnings surprises lead to negative contemporaneous market returns. This puzzling finding could be explained by the diversification of firm-specific earnings surprises together with either high predictability of returns or high predictability of aggregate earnings changes. Motivated by the differential implications of the two explanations, this study constructs a theoretical model generating predictions in favour of the return-predictability explanation and provides empirical evidence supporting all the hypotheses. By interacting Knightian uncertainty with the return-earnings relation on both firm- and aggregate-level, the study shows that individual response coefficient increases with firm-level ambiguity. Firm-level ambiguity increases the aggregate earnings response coefficient. This increase is more pronounced when the degree of market-level ambiguity is high. The results conclude that the negative aggregate return-earnings relation results from the diversification effect as well as an amplifying effect of macroeconomic ambiguity on discount rate news and market-wide cash flow news.

In the fourth chapter, I examine the stylized fact that market reacts much more strongly to bad news than to good news. I show that the asymmetric reaction is due to the finding that investors are more surprised by bad earnings news. This stronger surprise can be explained by the interacting effects of two key elements in investors' decision making process: ambiguity and difference of opinion. Ambiguity reduces investors' reaction to good news while increases their reaction to bad news. Difference of opinion similarly reduces reaction to good news, but it has no discernible effect on bad news response. Combining both generates a "yes" tick shape for the earnings response coefficient. This asymmetry after controlling the amount of news explains away all the negative returns generated by leaked quarterly earnings news. To rationalize the findings, I build a simple model to capture the dynamics of the earnings-return relation. Multiple-prior ambiguity and difference of opinion regarding the center of priors range are incorporated and evaluated in a maxmin framework.

Abbreviations

ADRI Anti-director Rights Index

AMEX American Stock Exchange

BC Best Companies

BM Book to Market Ratio

CRSP Center for Research in Security Prices

CSR Corporate Social Responsibility

dEE Seasonally Differenced Earnings Changes Scaled by Lagged Earnings

dEB Seasonally Differenced Earnings Changes Scaled by Lagged Book Equity

dEP Seasonally Differenced Earnings Changes Scaled by Lagged Market Price

DM Decision Maker

DoO Difference of Opinion

EFW Economic Freedom of the World

EPL Employment Protection Legislation

ERC Earnings Response Coefficient

EUA Expert Uncertainty Aversion

FE Fixed Effect

FinDistress Financial Distress

FU Firm-level Uncertainty

HML High Minus Low (Value Premium)

IBES Institutional Brokers Estimate System

InfoAsymm Information Asymmetry

LitRisk Litigation Risk

Lsize Logarithmic Market Capitalization

MKT Market Premium

MOM Momentum

MU Macroeconomic Uncertainty

Neg Dummy Variable for Negative Earnings News

NASDAQ National Association of Securities Dealers Automated Quotations

NYSE New York Stock Exchange

OSOV One-share One-vote

PRC Market Price

RegFD Regulation Fair Disclosure

RET2-3 Cumulative return over months t-3 through t-2

RET4-6 Cumulative return over months t-6 through t-4

RET7-12 Cumulative return over months t-12 through t-7

SE Standard Error

SMB Small Minus Big (Size Premium)

SoCM Size of Capital Market

SRI Socially Responsible Investing

SUE Standardised Unexpected Earnings

VOL Dollar Trading Volume

WRDS Wharton Research Data Services

YLD Dividend Yield

Chapter 1

Introduction

1.1 Definitions of tangible and intangible information

In financial markets, investors make decisions based on value-relevant information. Those information can be broadly categorised as being either tangible or intangible. The *Oxford English Dictionary* defines tangible assets as "physical and material assets which can be precisely valued or measured" and intangibles as "assets which cannot easily or precisely be measured". Consistent with this, I define tangible information as tangible assets related performance information such as revenues, earnings, and cash flow growth, which are recorded in a structured manner in firms' financial statements. I define intangible information as other information relevant for firms' intangible assets such as goodwill, rights, employee satisfaction, etc.

This thesis studies financial market reactions to both tangible and intangible information. The second chapter investigates the efficiency of the stock markets across the world in terms of incorporating the value-relevant intangible information like employee satisfaction. Country-level factors including institutions and regulations are then examined for their impacts on the varied relation between employee satisfaction and stock returns in different economies. The third and fourth chapters move on to examine two puzzling empirical findings based on stock market reactions to tangible information like corporate earnings news. Specifically, the third chapter focuses on the negative aggregate return-earnings relation and explores the possibility whether Knightian uncertainty could shed some lights in explaining this puzzle. Chapter four discusses the stylized fact that market react asymmetrically to good versus bad earnings news and shows that both Knightian uncertainty and heterogeneous beliefs could explain the asymmetry. The following two sections present detailed accounts for each task.

1.2 Stock market reaction to employee satisfaction news

There is significant evidence in finance literature that intangible assets are not fully priced by the stock market. For instance, Chan, Lakonishok, and Sougiannis (2001) show that firms with high R&D and advertising both measured by expenditures are able to earn higher long-term returns. This positive relation with future returns can also be found in other intangible information including patent quality by citations (Deng, Lev, and Narin, 1999) and software quality measured by investments (Aboody and Lev, 1998). Consistently, Edmans (2011, 2012) shows that companies with high employee satisfaction, as measured by inclusion in the list of the "100 Best Companies to Work For in America", outperform their peers by 2-3% per year. These results suggest that satisfaction is positively correlated with firm value and that these benefits are not immediately capitalized by the market. However, these papers only study the U.S. - a country with particularly flexible labor markets - and so the external validity of their results is limited. It is unclear whether these results are generalizable to other countries, especially those with less flexible labor markets. The second chapter addresses this open question.

Chapter two examines the relationship between employee satisfaction and stock returns around the world. Existing theories yield conflicting predictions as to whether employee satisfaction is beneficial or harmful to firm value. On the positive side, employee welfare can be a valuable tool for recruitment, retention, and motivation. Modern human resources theory views a firm's workers as its key assets. Not only the senior management but also the rank-and-file employees are considered essential due to the growing importance of knowledge-based industries such as software, pharmaceuticals, and financial services. Non-managerial employees engage in product development and innovation, and build relationships with customers and suppliers, and mentor subordinates. Employee-friendly policies can attract high-quality workers to a firm and ensure that they remain within the firm, to form a source of sustainable competitive advantage.

In addition, the quantifiability of workers' tasks renders employee satisfaction a valuable motivational tool. The traditional manufacturing jobs can easily quantify the output of a worker by using the monetary "piece rates" (Taylor, 1911). In the knowledge-based industries, it is increasingly difficult to quantify the workers' tasks, such as innovation or building client relationships. The reduced effectiveness of extrinsic motivators increases the role for intrinsic motivators such as satisfaction. The efficiency wage theory of Akerlof and Yellen (1986) argues that employees view a positive working environment as a "gift" from the firm and respond with a "gift" of increased effort (Akerlof, 1982). Sociological theories argue that satisfied employees identify with the firm and internalize its objectives, thus inducing effort (McGregor, 1960).

On the negative side, employee satisfaction indicates unnecessary costs by the management. Traditional management theory views a firm's employees as part of its physical capital (Taylor, 1911). Heavy manufacturing based economy demands employees work in a rigid environment with tasks allocated mechanically. Employee satisfaction implies either workers are overpaid or underworked, both of which reduce the shareholders' value. It is optimal for managers to extract workers' maximum productivity while minimising their costs. Relatedly, agency problems may lead to managers tolerating insufficient effort and/or excessive pay, at shareholders' expense. The manager may enjoy more pleasant relationships with his subordinates by not holding them down to their reservation utility (Jensen and Meckling, 1976). Alternatively, high wages may constitute a takeover defense, as modeled by Pagano and Volpin (2005a). Cronqvist, Heyman, Nilsson, Svaleryd, and Vlachos (2009) find that salaries are higher when managers are more entrenched, which supports the view that high worker pay is inefficient.

Institutional context like the labor market regulations determines the relative importance of the above benefits and costs. In flexible labor market, firms are given more autonomy on the specifications of work contracts. Firms face fewer restrictions to recruit talents that they need and more easily dismiss underperforming workers and replace them with superior ones. On the hiring front, the recruitment benefit is clear. The retention benefits of employee satisfaction are also more important since the competitors also face few hiring constraints. On the firing side, easier dismissal of less productive employees makes the recruitment benefit even greater. In addition, the greater risk of firing means that employees invest in general rather than firm-specific skills, which also increases their ability to be recruited elsewhere (Hall and Soskice, 1998; Thelen, 2001). Easier firing indicates that employee satisfaction can also create motivational benefits. Shapiro and Stiglitz (1984)'s efficiency wage theory suggests that workers exert more effort to prevent from being fired when they are satisfied with their jobs. Comparing to senior managers who often hold shares of the firms, rank-and-file employees are not incentivised with equity hence the motivational benefits may be particularly stronger.

In regulated labor markets, strong regulations already impose a floor on worker welfare. The balance of benefits and costs for employee-friendly policies may shift over the optimal level. In other words, the marginal benefits of those policies may not justify the costs. In addition, in those markets the restrictions on hiring and firing are stronger. Thereby, following the logic of the above the recruitment, retention, and motivational benefits are lower. In short, both effects reduce the marginal benefit of employee satisfaction measures, rendering it potentially below the marginal cost.

The empirical section of this chapter examines the relationship between employee satisfaction and stock returns in multiple countries around the world, and investigate the effect of country-level labor market flexibility on the relationship. 14 countries are chosen due to data availability for Best Companies ("BC") lists. The lists are compiled by the Great Place to Work Institute in San Francisco and cover more than 45 countries. We use two measures of country-level labor market flexibility: the OECD Employment Protection Legislation ("EPL") index (Pagano and Volpin, 2005b; Simintzi, Vig, and Volpin, 2014) and the labor market flexibility categories of the Fraser Institute's Economic Freedom of the World ("EFW") index (Bernal-Verdugo, Furceri, and Guillaume, 2012ab,a; Freeman, Kruse, and Blasi, 2008; Haltiwanger, Scarpetta, and Schweiger, 2008).

We find that the alpha for the US (e.g. 22 basis points) documented by Edmans (2011, 2012) is merely the 10th highest out of the 14 countries that we study. For example, the monthly alpha is 77 basis points in Japan from 2007-2013 and (an insignificant) 81 basis points in the U.K. from 2001-2013. (The different time periods reflect the different years in which the BC list was initiated). On the negative territory, Germany exhibits a negative alpha of 45 basis points, albeit not significant due to the smaller sample size. These results indicate significant heterogeneity across countries' alpha.

Next, we show that labor market flexibility with either of the two measures can explain the cross country heterogeneity. Namely, the abnormal returns for the best companies are significantly increasing in their countries' labor market flexibility. Our main specification is a pooled panel regression controlling for firm-level characteristics relevant for stock returns, such as size, book-to-market, dividend yield, past returns, trading volume, and the stock price (Brennan, Chordia, and Subrahmanyam, 1998). To ensure that our labor market flexibility measure is not simply proxying for other differences between countries, we control for other country-level variables such as the rule of law, size of the capital market, and the existence of one-share-one-vote (all from La Porta, Lopez-de Silanes, Shleifer, and Vishny (1997)), GDP growth, and the anti-director rights index of Spamann (2010). We find that, a one standard deviation decrease in the EPL measure is associated with a 0.49% higher market-adjusted monthly return to being a BC. Similarly, a one standard deviation increase in the EFW measure is associated with a 0.67% higher market-adjusted monthly return to being a BC. The results are similar using a Fama and MacBeth (1973) analysis. Overall, our results suggest that the association between employee satisfaction and stock returns depends critically on the institutional context.

This chapter is related to several areas of research. Firstly, it deepens the understanding of the relationship between employee welfare and firms' financial performance. There are mixed messages regarding the link in the existing literature. Edmans (2011, 2012) document a positive relationship between employee satisfaction and future stock returns. In contrast, a negative link is established by Abowd (1989) between the announcements of pay rises and firms' market values in dollar term. Relatedly, stock returns are found to be uncorrelated with KLD's employee relations variable (Dhrymes, 1998) and the Council of Economic Priorities minority management and women in management variables, and negatively correlated with family benefits (Diltz, 1995). It is worth noting that all those studies focus on the US market and it is unclear whether those relationships either positive or negative can generalise into a wider international context.

Secondly, this study contributes to the literature in socially responsible investing ("SRI"). Employee welfare is one of main variables in SRI and often used by investors as an investment screening criteria (Renneboog, Ter Horst, and Zhang, 2008a, 2011). The SRI literature produces mixed results. A positive link between SRI and investor returns has been documented by Moskowitz (1972), Luck and Pilotte (1993), Derwall, Guenster, Bauer, and Koedijk (2005), and Edmans (2011, 2012). A negative link is found by Geczy, Stambaugh, and Levin (2005), Brammer, Brooks, and Pavelin (2006), Renneboog, Ter Horst, and Zhang (2008b), and Hong and Kacperczyk (2009). Insignificant links are shown in Hamilton, Jo, and Statman (1993), Kurtz and DiBartolomeo (1996), Gorton and Schmid (1997), Bauer, Koedijk, and Otten (2005), Schrder (2007), and Statman and Glushkov (2008). Again, the mentioned studies focus solely on the US and the generalisability of the documented links across countries is not clear. Our study shows that the relationship between employee satisfaction and future stock returns depends on the institutional context of labor market regulations. To our knowledge, this is the first study to explore the investing implications of a SRI variable in a global context. The results suggest that the investment values of other indicators of Corporate Social Responsibility ("CSR") such as gender diversity, animal rights, environmental protection, and whether the firm is in a "sin" industry (such as tobacco, alcohol, and gambling) are likely to depend on institutional context as well, such as regulations and cultural elements.

Lastly, this chapter adds value to the area of cross-country analysis of investment strategies. In Asness, Moskowitz, and Pedersen (2013), value premium inspired strategies are compared and shown to be profitable in major economies including the continental Europe, Japan, the U.K., and the U.S.. Momentum strategies in multiple countries are investigated by Chui, Titman, and Wei (2010) who conclude that the profitability discrepancy across countries can be explained by cultural elements, in particular individualism. That is, high level of individualism leads to more profits on the momentum strategy. This chapter builds on Edmans (2011, 2012)'s findings and shows that the profitability of employee satisfaction inspired strategies crucially depends on one country's labor market institution.

1.3 Stock market reaction to corporate earnings news

Corporate earnings news is arguably the most studied tangible information in accounting and finance literature. Theory suggests that earnings news is informative about future cash flows. Positive earnings news is indicative of more future cash flows resulting in high contemporaneous stock prices. Indeed, earlier studies like Ball and Brown (1968) and Beaver (1968) establish the stylized fact that firm-level stock returns are positively correlated with earnings surprises as measured by standardized seasonally differenced quarterly earnings. This intuitive relation, however, does not translate into aggregate level. Recent studies including Kothari, Lewellen, and Warner (2006) and Sadka and Sadka (2009) document a statistically indistinguishable contemporaneous relationship between aggregate stock returns and earnings surprises. This finding is puzzling since the current earnings on the aggregate level is no longer an indication for future profitability. Even more counter-intuitively, the contemporaneous relationship can be significantly negative under certain earnings surprises measures.

To explain the striking aggregate relationship, Kothari, Lewellen, and Warner (2006) and Sadka and Sadka (2009) employ the framework of return decomposition by Campbell and Shiller (1988a) and Campbell (1991). The decomposition states that the relationship between returns and earnings surprises is the relative dominance of the covariances between earnings surprises and each of the three components of returns, namely the current expected returns, the cash flow news component, and the discount rate news (or the future expected returns) component.

More detailedly, Kothari, Lewellen, and Warner (2006) argue that firm-level earnings surprises contains much more information about the future firm-specific cash flows than about the discount rate news. The positive firm-level relationship documented in the literature can be attributed to the dominance of the cash flow news component over the other two in the return decomposition. In contrast, on aggregate level the earnings surprises contains only information about the future aggregate cash flows and discount rate news due to diversification effect of the firm-specific news. Consequently, the discount rate news component becomes dominant and a possible negative correlation between earnings surprises and discount rates determines the negativity of the return-earnings relation. In other words, the negative aggregate relation requires the diversification argument and certain level of return predictability. It is worth noting that in Kothari, Lewellen, and Warner (2006)'s explanation, the earnings surprises are implicitly assumed to be independent of the first component - the current expected returns. Sadka and Sadka (2009) present in a simple and elegant derivation that this assumption might have ignored another if not the source of the negativity. They show that the covariance between the earnings surprises and current expected returns can be reduced to the negative covariance between the expected earnings surprises and the current expected returns due to their evidence that the earnings surprises are highly predictable on the aggregate level. The results of Sadka and Sadka (2009) compliment rather than contradict Kothari, Lewellen, and Warner (2006)'s story and the return-earnings relation could well be the outcomes of both the high predictability of earnings surprises and the predictability of returns.

The diversification effect of firm-specific earnings surprise is the center argument for Kothari, Lewellen, and Warner (2006). However, it is not required in Sadka and Sadka (2009)'s high predictability of earnings surprises argument. In fact, if the earnings surprises are highly predictable, then the "surprise" of the earnings changes does not exist any longer. This renders the diversification effect irrelevant in the context of aggregating firm-level earnings surprises. Thus, a clear identification of diversification effect in aggregation is a useful channel to differentiate the favourable explanation for the return-earnings relation puzzle.

A direct measure of diversification effect is not obvious. The idea behind this study is thereby to use an intermediary which not only has a direct link with the diversification effect but also measurably affects the return-earnings relation. Uppal and Wang (2003) shows that a high level of Knightian uncertainty regarding return distribution could result in a portfolio that is significantly under-diversified relative to the standard mean-variance portfolio. Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011) argue that asymmetric reaction to good versus bad news can arise due to the presence of Knightian uncertainty in the sense of Knight (1921) and Ellsberg (1961). Investors who are ambiguity averse choose the worst case scenario and consequently overvalue negative news and undervalue positive news. It is intuitive to see that high asymmetry leads to lower effect of diversification. Hereafter, I use terms Knightian uncertainty and ambiguity interchangeably.

Ambiguity refers to situations where objective probabilities are unknown or imperfectly known. It can arise due to lack of information and/or poor quality of information. Gilboa and Schmeidler (1989) axiomatize investors' acts of ambiguity aversion. Facing ambiguity, an agent chooses the worst case scenario and acts in a maxmin framework. That is, each possible course of action is evaluated with respect to the least favorable probability distribution from a given set of priors. The chosen action maximizes the minimum expected utility. Larger set of priors indicates higher level of ambiguity as well as more extreme type of ambiguity-aversion. Consequently, the agent tends to overweight the negative outcomes and underweight their positive counterparts.

Chapter 3 investigates how ambiguity affects the return-earnings relation on both firm- and aggregate-level. As argued above, high level of ambiguity leads to low level of diversification effect due to asymmetric reaction to good versus bad news. This will lead to relative dominance of cash flow news component over the discount rate news component, which in turns leads to a positive relationship between aggregate returns and earnings. For low level of ambiguity, however, the diversification effect is much more pronounced. Discount rate news plays a more dominant role resulting in a negative aggregate return-earnings relation. Therefore, if Kothari, Lewellen, and Warner (2006)'s argument is valid, the aggregate return-earnings relation should be negative for low ambiguity portfolios and positive for portfolios of high level of ambiguity. Alternatively, according to Sadka and Sadka (2009), the negativity of aggregate return-earnings relation comes from high predictability of earnings surprise. It is intuitive to state that earnings are less predictable when the information environment is highly ambiguous. Similarly, high level of ambiguity leads to less negative aggregate return-earnings relation. To understand the difference derived from both perspectives, we should be more specific about the type of ambiguity being employed.

Consistent with the dichotomous characterization of the return-earnings relation, this study categorises ambiguity into two levels: idiosyncratic or firm-level ambiguity and common or macroeconomic ambiguity. The arguments above are in fact based on the role of idiosyncratic ambiguity in diversification effect and the role of macroeconomic ambiguity in the predictability of earnings surprises. Macroeconomic ambiguity which measures the market-level information environment and affects only the discount rate news has little to do with the diversification effect. Its effect on firm-level return-earnings relations is unclear. Idiosyncratic ambiguity, on the other hand, has limited impact on the predictability of the aggregate earning surprises. This is a contradicting point for Kothari, Lewellen, and Warner (2006) and Sadka and Sadka (2009) theories when considering both firm-level and macroeconomic ambiguity altogether. If only the former is correct, then valid is that the aggregate return-earnings relation turns from negative to positive when the firm-level ambiguity increases. Since the market-level discount rate news has opposite effect on the response coefficient than cash-flow news, macroeconomic ambiguity amplifies its negative effect. Hence, for the portfolios of low firm-level ambiguity, we expect to observe a strong negative aggregate response coefficient. On the other hand for portfolios of highly ambiguous firms, the non-diversified effect of ambiguous cash-flow news dominates the negative effect of the discount rate news and we obtain a significantly positive aggregate response coefficient. If only the latter is correct, then the negativity of the aggregate response coefficient comes from purely the high predictability of aggregate earnings. Macroeconomic ambiguity is likely to decrease this predictability, while the firm-level ambiguity has little effect. Thereby, we expect to observe no clear trend on the effect of firm-level ambiguity on portfolio-level response coefficient. When adding the macroeconomic ambiguity, we expect to see positive coefficients for portfolios with all levels of firm-level ambiguity. This serves as our testable hypothesis.

To further develop our hypothesis in a rigorous manner, we build a simple model to capture the dynamics of earnings-return relation based on the return decomposition. There are one representative agent (i.e. the investor) and multiple firms in the economy. Upon receiving noisy signals of each firm, the investor forms her conditional expectations of the signals' informativeness about future cash flow and discount rate news. It is straightforward to generate a closed-form solution for the earnings response coefficient based on the covariances between returns and the two components. When the information environment becomes uncertain, the ambiguity-averse investor lacks confidence on the distribution of true part of a signal and hence consider a range of possible priors due to lack of information and/or poor quality of information. More specifically, we consider the noisy signals contain both firm-specific and market-wide cash flow components, which are orthogonal to each other. The ambiguity regarding the distribution of firm-specific cash flow component is purely idiosyncratic and we call it firm-level ambiguity. The ambiguity regarding the market-wide cash flow component represents the overall ambiguity about the market as whole and we name it macroeconomic ambiguity. We model both types of ambiguity using the multiple prior model of Gilboa and Schmeidler (1989). That is, the investor does not observe the variances of both cash flow components and can only provide their interval ranges, in a similar spirit to Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011). The investor's preferences are then described by the maxmin expected utility model of Gilboa and Schmeidler (1989). The resulting response coefficient is a function of return distribution parameters which in turn are a function of randomly generated noisy signals of normal distribution.

In order to quantify the effect of ambiguity on the earnings response coefficient, we perform a comparative statics analysis. Since the earnings response coefficients cannot be computed in the closed form with the presence of ambiguity, we employ Monte Carlo simulations to estimate the coefficients for various values of ambiguity parameters. To start with firm-level analysis, the model predicts that individual response coefficients strictly monotonically increase with firm-level ambiguity. This results also stands in the presence of market-level ambiguity. This pattern can be intuitively explained by the asymmetric reaction to bad versus good earnings news. Literature, such as Conrad, Cornell, and Landsman (2002) and Andersen, Bollerslev, Diebold, and Vega (2003), show that market reacts to negative news significantly more strongly than to positive news. Epstein and Schneider (2008) and the third chapter of this thesis argue that ambiguity plays an important role in explaining the asymmetry.

Moving to portfolio-level analysis, the aggregate responses increase with firm-level ambiguity similarly to that for the individual response coefficients. The effect of firm-specific cash flow news is diversified away during aggregation so that only the market-wide cash flow news prevail. However, ambiguity effect is not diversified away and always goes in the same direction. Positive cash flow effect remains in the response coefficients for portfolios of high firm-level ambiguity firms. The effect of macroeconomic ambiguity is similar to the case of individual firms because its effect on discount rate news is not dampened by aggregation of firms' signals. It is worth reiterating that high degree of market-level ambiguity leads to a decrease in the earnings response coefficient of low-ambiguity stocks and to an increase in the earnings response coefficient of high-ambiguity stocks, which means that the effect of market-level ambiguity is related to the degree of firm-level ambiguity. The overall firm-level ambiguity for the market portfolio is in between of the low and high degree that we have quantified in the portfolios. Thus, it is no surprise to see that the effect of market-wide ambiguity is less deterministic on the market level.

Using all firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4, we find strong empirical evidence consistent with all of our model predictions. The results are robust after controlling for size, different earnings surprise measures, different measures of ambiguity, and sample periods with/out the recent financial crisis. The results confirm that Kothari, Lewellen, and Warner (2006)'s explanation of the puzzling firm- and aggregate-level return-earnings relations is a viable approach. The combination of return decomposition and diversification effect explains the interacting behavior of earnings response coefficients with firm-level and macroeconomic ambiguity on firm-, portfolio-, and market-level analysis. The results also show that the earnings predictability explanation of Sadka and Sadka (2009) cannot stand alone.

Recent empirical literature employes the disagreement of professional forecasters to proxy the degree of ambiguity in firms and the market. Intuitively, if forecasters produce conflicting projections about the fundamentals, investors are likely to be uncertain about distributions of stock returns as they tend to condition their beliefs on professionals' forecasts. Thus, when dispersion among professionals' forecasts regarding the future performance is large, ambiguity is also likely to be high since investors might find it difficult to reduce their set of beliefs into a single prior. At the same time, dispersion of professionals' forecasts might not necessarily be the idea proxy for gauging the degree of ambiguity. Barron, Kim, Lim, and Stevens (1998) argue that the forecasts dispersion can be contaminated by the disagreement component that comes from information asymmetry. this can be a serious issue especially when proxies the degree of ambiguity at individual firm level. They propose a decomposition of the forecasts dispersion into uncertainty and disagreement. We argue that the decomposed uncertainty captures the degree of ambiguity embedded in the dispersion of professionals' forecasts. We construct the firm-level ambiguity by using analysts' forecasts of individual firm earnings and macroeconomic ambiguity by using individual analyst's forecasts for macroeconomic variables, e.g. next period real GDP growth or inflation growth.

Chapter 4 continues the examination of the return-earnings relation albeit exclusively on firm-level. Recall that in the second chapter, the argument has been used that firm-level ambiguity creates asymmetric market reaction to bad versus good news thereby leading to lesser extent of diversification effect. This chapter focuses on the asymmetry and investigates whether ambiguity can fully explain the stronger reaction to bad than to good earnings surprises. Another important element of decision making - difference of opinion - is also introduced to compliment (or discount) the effect of ambiguity in the case that a full explanation cannot be reached solely based on ambiguity.

Literature show that market reacts to firm-level news in an asymmetric fashion (Conrad, Cornell, and Landsman, 2002; Skinner and Sloan, 2002; Andersen, Bollerslev, Diebold, and Vega, 2003). That is, bad news has a greater impact than good news. The average negative return to negative news is significantly larger in magnitude than the average positive return to positive news. There are two possible explanations: 1) there is larger amount of negative news on the market; 2) investors react more strongly to bad news per se. The former refers to the practice that firms selectively release news to their own advantages. The latter states that the information content per unit of news is greater for bad news. Recent theories, such as Epstein and Schneider (2008) and Kelsey et al. (2011), argues that such asymmetric reaction can arise due to the presence of ambiguity. They show that investors who are ambiguity averse choose the worst case scenario and consequently overvalue negative news and undervalue positive news.

The initial empirical results confirm the existence of asymmetric reaction, even well before the actual news announcements due to information leakage. However, the extent of asymmetry is not linear with ambiguity. As a matter of fact, when the stock universe is divided into quintiles according to our measure of ambiguity, the return difference for bad versus good earnings news exhibit a "yes" tick shape for the five groups. This shows that whatever the cause of the asymmetry is, its impact has not been linearly reflected on the market. Thereby, another important element of decision making - difference of opinion - is introduced with the aim to fully explain this striking shape.

Studies in decision theory suggests that difference of opinion also creates reaction asymmetry (Gajdos and Vergnaud, 2009; Cres, Gilboa, and Vieille, 2011). Specifically, Cres, Gilboa, and Vieille (2011) consider a setting where experts are asked to provide their advice in a situation of Knightian uncertainty. The decision maker exhibits expert uncertainty aversion (EUA) when aggregating divergent opinions from the ambiguity-averse experts. They axiomatize that in face of different opinions the decision maker selects the minimal weighted valuation of experts valuations, which leads to consequential overvaluation of negative opinions and undervaluation of positive views in a similar vein to the case of ambiguity-aversion.

Note that unlike ambiguity large difference of opinion not necessarily implies high level of asymmetry. Baillon, Cabantous, and Wakker (2012) show in experiments that ambiguity reduces insensitivity to extreme events defined by Abdellaoui, Baillon, Placido, and Wakker (2011) and overweights the extreme events, hence amplifying financial phenomena found under risk. However, difference of opinion increases insensitivity and underweights the extremes. This underweighting generates consistent undervaluation of positive news due to EUA but not for negative news. Furthermore, the differential amounts of ambiguity and difference of opinions for any specific case could render their combined effect unclear. Together with risk, ambiguity and difference of opinion are considered as the sources of uncertainty (Baillon, Cabantous, and Wakker, 2012). Here, uncertainty is in the broadest sense and refers to any variation that causes forecast errors. In a mode based on experts' forecasts, Barron, Kim, Lim, and Stevens (1998) show that overall uncertainty is a linear combination of common uncertainty (for this matter ambiguity) shared by all experts attributable to their reliance on imprecise common information and idiosyncratic uncertainty (for this mater difference of opinion) that is due to information asymmetry among experts. For certain level of uncertainty, more fraction of ambiguity means less degree of divergence in experts' opinions. It is a matter of relative dominance between the two to form a combined effect on market reactions to bad versus good news.

Motivated by these questions, this study aims to model and test the combined effect of ambiguity and difference of opinion on market asymmetric reactions to bad versus good earnings news and propose justified measures for either. To test, I focus on the association-study framework adopted by Kothari, Lewellen, and Warner (2006) where the contemporaneous earnings-return relation is investigated on a quarterly basis before the earnings announcements, which are typically a couple of months after each fiscal quarter that the earnings cover[1]. This methodology is based on the reality of information leakage (Brunnermeier, 2005) and enables me to control for potentially differential amounts of news being leaked before the public announcements.

The data sample includes all US firms between 1984-2014 with the same screening criteria as Kothari, Lewellen, and Warner (2006). The empirical section starts by showing that the stylized fact holds even well before the actual news announcements due to information leakage. The average negative return to negative earnings news is around -4.9% over 20 years period, significantly higher than the 3.1% return for positive earnings news at 1% level. When I divide the stock universe

[1]Most studies use event-study framework which typically focus on limited period around the actual announcement dates. I do not adopt this framework due to 1) no apparent proxies for measuring differential amounts of good versus bad earnings news 2) that the announcement data in IBES is often effectively the date on which the information was recorded by IBES and, therefore, systematically delayed. Hoechle, Schaub, and Schmid (2013) show that the announcement day effect is underestimated in IBES while pre-announcement returns are overestimated as they often include the effective announcement day.

into quintiles according to our measure of ambiguity in ascending order, the return difference for bad versus good earnings news exhibit a ”yes” tick shape for the five groups.

Next, I include in the regressions the size of news and its interaction with a directional dummy variable with two purposes: 1) to exclude the proposition that the asymmetry is caused by differential amounts of information for good and bad news; 2) to focus on the interaction term where the combined effect of ambiguity and difference of opinion come into effect. The results show that the differential return between bad versus good news, -1.8%, completely disappeared. The positivity and high significance of the interaction term imply the asymmetry is entirely due to that investors are more surprised by bad earnings news. When applying to the quintiles, the coefficients of the interaction term exhibit a ”yes” tick shape matching that of the average returns difference, indicating that this stronger surprise from bad news could be explained by the combining effect of ambiguity and difference of opinion.

To ensure that the asymmetry is not due to the differential amounts of news leakage, I further control for proxies for managers' incentives to release bad news such as Regulation Fair Disclosure (thereafter RegFD) (Dong, Li, Ramesh, and Shen, 2011), litigation risk modeled by Rogers and Stocken (2005), information asymmetry following Kothari, Shu, and Wysocki (2009), and financial distress measured by Zmijewski (1984)'s Z-score. Those proxies explain away the rest of the negative returns by negative earnings news. Nevertheless, the ”yes” tick shape remains for the stronger reactions to negative earnings news.

Overall, the results suggest that the higher average negative return to negative news versus that to positive news is solely determined by the larger informational content of negative news per se. These results have important implications for understanding the roles of managers and investors in market reaction to financial news. Starting with the former, even if Kothari, Shu, and Wysocki (2009) results can be interpreted as causal, they do not suggest that managers should expect their "tactic" of selective release of news matters for the market on average. Moving to the latter, it suggests that investors' assessments of news under uncertainty determine the market reaction to financial news.

Similar to Chapter 3, the empirical measures for ambiguity and difference of opinion are drawn from decomposition proposed by Barron, Kim, Lim, and Stevens (1998). Uncertainty can be divided into common uncertainty and idiosyncratic uncertainty among experts. Common uncertainty is the average covariance between the belief of one analyst and the beliefs of the rest of the experts, while idiosyncratic uncertainty is the expected dispersion of experts' beliefs. The notable difference is that chapter two uses overall uncertainty as ambiguity, while this chapter employs ρ as a measure for ambiguity and $1-\rho$ as a measure for difference of opinion. ρ is the ratio of the average pair-wise covariance among experts' beliefs to overall uncertainty reflects the imprecision of common information shared by experts. $1-\rho$ is the ratio of expected dispersion of experts' beliefs to overall uncertainty captures the effect of two sources of information asymmetry on experts' beliefs - namely, the relative presence of private information and differential uncertainty. The new measures present an advantageous channel to investigate the combined effect of ambiguity and difference of opinion due to their perfectly negative correlation. Furthermore, the decomposition recognizes the well-established theoretical proposition that uncertainty consists of idiosyncratic and common components (Doukas, Kim, and Pantzalis, 2006; Sheng and Thevenot, 2012).

To validate the findings, I build a theoretical model to capture the dynamics of earnings-return relation based on one representative agent (i.e. the decision maker), multiple firms, and multiple experts. Ambiguity-averse experts are asked by the decision maker to provide advice on the informativeness of each firm's earnings signal and use the same utility function as the decision marker. Due to lack of information and/or poor quality of information, the ambiguity-averse experts lack confidence on the distribution of true part of a signal and hence consider a range of possible priors for the true signal, so does the decision marker. With the presence of private information, the center of the range of possible priors varies among experts resulting in their differential assessments of the signals even if the level of ambiguity is the same. Working independently, the decision maker and the experts maximize the minimal expected utility with respect to their own sets of priors. They act as if a positive signal is unreliable and a negative signal is reliable. Consequently, the price change of each firm triggered by a positive signal is less in magnitude than the price change triggered by a negative signal. The decision marker is averse to the uncertainty about the expert who "has access to truth", hence exhibits expert uncertainty aversion in her aggregation of experts' opinions. She chooses a weighting function among a set of weight vectors over the experts' priors such that it maximizes the minimal combination of experts minimal expected utility with their own sets of priors, or in a "maxminmin" way .

I firstly derive the return-earnings relation where the distribution of the signals is exactly known and there is consensus among all experts. Upon receiving a set of noise signals, experts form conditional expectations of the signals' informativeness about stock returns' cash flow news and discount rate news components (Campbell, 1991). By assuming zero-mean normal distributions for all the variables, I am able to obtain a beta coefficient showing the return-earnings relation as a function of the noisy signals' distribution parameters. To incorporate ambiguity, I then assume that experts do not observe the distribution of the true earnings (i.e. the variances) and hence assign interval ranges for the distribution. Facing ambiguity, experts minimize the expected market return generating an array of variances selected within the range. Using Bayesian updating with the chosen variances, I am able to obtain a new beta as a function of the chosen variances. Finally, I consider the difference of opinion by deviating the center of the distribution ranges across experts. After the experts minimize the expected market return with their own set of priors, the decision maker obtains an aggregated beta by allocating weights to the experts' betas such that 1) the decision maker's set of priors is precisely the weighted average of experts'; 2) the decision maker chooses the minimal weighted valuation of experts' betas over all possible weights (Cres, Gilboa, and Vieille, 2011).

Monte Carlo simulation for the model shows that ambiguity and difference of opinion have contrasted effects on investors' reactions on earnings surprises measured by earnings response coefficient (or beta in the model). For positive surprises, both ambiguity and difference of opinion reduce the beta. For negative news, ambiguity amplify investors' reaction while difference of opinion has a muted effect. Without differentiating the nature of news, high ambiguity leads to more positive beta, whereas high difference of opinion leads to less positive beta. By equating high ambiguity to low difference of opinion, I combine both effects and produce the differential reaction to negative versus positive news of a "yes" tick shape that matches the empirical finding.

The striking pattern for the effect of difference of opinion on good versus bad news can be explained, mathematically speaking, by the functional form of experts' betas to experts' priors. For positive news, the betas are a concave function of experts' priors. The minimum aggregate valuation is to assign most weights to experts with extreme priors. Hence the more dispersed experts' priors are, the lower is the aggregated beta for positive news. On the contrary for negative news, the betas are a convex function of the experts' priors due to the switching sign of the news. The minimal valuation allocates most weights to experts with priors of "centrality". As a result, the dispersion of priors does not matter significantly for the overall market reaction.

To conclude, Chapters 3 and 4 contribute to the literature of return-earnings relation. They build on the firm-, portfolio-, and market-level relationship between stock returns and earnings surprises and examine two existing anomalies, namely the negative aggregate return-earnings relation and asymmetric market reactions to bad versus good news. To start with the former, Ball and Brown (1968) and

Beaver (1968) establish the stylized fact that firm-level stock returns are positively correlated with earnings surprises. Kothari et al. (2006) and Cready and Gurun (2010) document a negative contemporaneous relationship between aggregate stock returns and earnings surprises. Chapter 3 reconciles this seemingly contradictory findings by bringing in the role of ambiguity. Note that some literature like Subasi (2011) finds that the magnitude of investors' reactions to aggregate earnings news decreases in macroeconomic ambiguity measured by cross-sectional dispersion in realized firm-level earnings surprises. With less controversial measure of ambiguity, we find the the relationship between ambiguity and aggregate return-earnings relation depends on the average level of firm-level ambiguity. For the second anomaly, Conrad, Cornell, and Landsman (2002), Skinner and Sloan (2002), and Andersen, Bollerslev, Diebold, and Vega (2003) show that market react to negative earnings news far stronger than to positive ones. Using news measures drawn from Barron, Kim, Lim, and Stevens (1998), Chapter 4 discovers that the differential firm-level return-earnings relations of bad versus good earnings news exhibits a striking "yes" tick shape with respective to our ambiguity measure. Its results show that it is the combining effects of both ambiguity and difference of opinion that explains this striking "yes" tick shape.

Chapter 2

Employee Satisfaction, Labor Market Flexibility, and Stock Returns Around the World

2.1 Introduction

This chapter studies the relationship between employee satisfaction and stock returns around the world. Theory provides conflicting predictions as to whether employee satisfaction is beneficial or harmful to firm value. On the one hand, employee welfare can be a valuable tool for recruitment, retention, and motivation. For the typical 20th-century firm, the bulk of its value stemmed from its physical capital. In contrast, most modern firms key assets are their workers - not only senior management, but also rank-and-file employees. For example, in knowledge-based industries such as software, pharmaceuticals, and financial services, non-managerial employees engage in product development and innovation, and build relationships with customers and suppliers, and mentor subordinates. Employee-friendly policies can attract high-quality workers to a firm and ensure that they remain within the firm, to form a source of sustainable competitive advantage.

Relatedly, employee satisfaction can be a valuable motivational tool. In traditional manufacturing firms, motivation was simple because workers output could be easily measured, allowing the use of monetary "piece rates" (Taylor, 1911). In the modern firm, workers tasks are increasingly difficult to quantify, such as innovation or building client relationships. The reduced effectiveness of extrinsic motivators increases the role for intrinsic motivators such as satisfaction. This role is microfounded in both economics and sociology. The efficiency wage theory of Akerlof and Yellen (1986) argues that employees view a positive working environment as a "gift" from the firm and respond with a "gift" of increased effort (Akerlof, 1982). Sociological theories argue that satisfied employees identify with the firm and internalize its objectives, thus inducing effort (McGregor, 1960).

On the other hand, employee satisfaction can represent wasteful expenditure by management. Taylor (1911) argued that workers should be treated like any input - managements goal is to extract maximum output from them while minimizing their cost. Under this view, satisfaction is an indicator that employees are overpaid or underworked, both of which reduce firm value. Indeed, agency problems may lead to managers tolerating insufficient effort and/or excessive pay, at shareholders expense. The manager may enjoy more pleasant relationships with his subordinates by not holding them down to their reservation utility (Jensen and Meckling, 1976). Alternatively, high wages may constitute a takeover defense, as modeled by Pagano and Volpin (2005a). Cronqvist, Heyman, Nilsson, Svaleryd, and Vlachos (2009) find that salaries are higher when managers are more entrenched, which supports the view that high worker pay is inefficient.

The relative importance of the above costs and benefits will depend on the institutional context. In flexible labor markets, firms face fewer restrictions on the contracts they can offer. When hiring constraints are weaker, the recruitment benefits of employee satisfaction are stronger. Since ones rivals also face few hiring constraints, the retention benefits of employee satisfaction are also more important.

Flexible labor markets also feature fewer firing constraints. Since it is easier for firms to dismiss underperforming workers and replace them with superior ones, the recruitment benefits of employee satisfaction are again greater. In addition, the greater risk of firing means that employees invest in general rather than firm-specific skills, which also increases their ability to be recruited elsewhere (Hall and Soskice, 1998; Thelen, 2001). Separately, the motivational benefits are also likely higher. Under the efficiency wage theory of Shapiro and Stiglitz (1984), workers exert effort to avoid being fired from a satisfying job, and thus employee satisfaction has greater motivational impact when the likelihood of firing is stronger. The motivational effect of employee satisfaction may be particularly important for rank-and-file employees, who are harder to incentivize with equity since they individually have a small effect on firm value.

In regulated labor markets, hiring and firing are harder, and thus the recruitment, retention, and motivational benefits are lower. In addition, expenditure on employee satisfaction is likely to exhibit diminishing marginal returns. When labor market regulations already ensure a minimum level of worker welfare, companies with high satisfaction relative to their peers may be exceeding the optimal level: the marginal benefit of their expenditure may not justify its cost.

Edmans (2011, 2012) shows that companies with high employee satisfaction, as measured by inclusion in the list of the "100 Best Companies to Work For in America", outperform their peers by 2-3% per year. The use of stock returns (rather than, say, accounting performance or Tobins Q) as the dependent variable mitigates concerns that causality runs from firm performance to employee satisfaction, since any publicly-observed performance measure should already be incorporated into the stock price at the start of the return compounding window. These results suggest that satisfaction is positively correlated with firm value and that these benefits are not immediately capitalized by the market. However, these papers only study the U.S. - a country with particularly flexible labor markets - and so the external validity of their results is limited. It is unclear whether these results are generalizable to other countries, especially those with less flexible labor markets.

This chapter addresses this open question. We study the link between employee satisfaction and stock returns in 14 countries around the world, and investigate how this relationship depends on the countrys level of labor market flexibility. The list of the "100 Best Companies to Work For in America" is published by the Great Place to Work Institute in San Francisco. The Institute produces similar Best Companies ("BC") lists in more than 45 countries, of which 15 have at least 10 publicly traded BCs. We use two measures of country-level labor market flexibility, which are available for 14 of these 15 countries. The first measure is the OECD Employment Protection Legislation ("EPL") index, also used by Pagano and Volpin (2005b) and Simintzi, Vig, and Volpin (2014). The second is the labor market flexibility categories of the Fraser Institutes Economic Freedom of the World index, also used by Bernal-Verdugo, Furceri, and Guillaume (2012ab,a), Freeman, Kruse, and Blasi (2008), and Haltiwanger, Scarpetta, and Schweiger (2008).

We find that the alphas documented by Edmans (2011, 2012) for the U.S. are not anomalous in a global context. An equal-weighted BC portfolio generates a Carhart (2001) 4-factor monthly alpha of 22 basis points in the U.S. from 1998-2013, statistically significant at the 1% level. This alpha is only the 10th highest out of the 14 countries that we study. High returns to Best Companies are not limited to the U.S., although the alphas for most other countries are not statistically significant due to the smaller sample size. For example, the monthly alpha is 77 basis points in Japan from 2007-2013 and (an insignificant) 81 basis points in the U.K. from 2001-2013. (The different time periods reflect the different years in which the BC list was initiated). However, we also document significant heterogeneity across countries. For example, Germany exhibits an insignificantly negative alpha of 45 basis points. Thus, while the previously-documented results generally hold out of sample, they do not extend to every country.

We next show that the abnormal returns to the BCs are significantly increasing in their countrys labor market flexibility, using both measures. We conduct a pooled panel regression controlling for other firm-level determinants of stock returns identified by Brennan, Chordia, and Subrahmanyam (1998), such as size, book-to-market, dividend yield, past returns, trading volume, and the stock price. To ensure that our labor market flexibility measure is not simply proxying for other differences between countries, we control for other country-level variables such as the rule of law, size of the capital market, and the existence of one-share-one-vote (all from La Porta, Lopez-de Silanes, Shleifer, and Vishny (1997)), GDP growth, and the anti-director rights index of Spamann (2010). We find that, a one standard deviation decrease in the EPL measure is associated with a 0.49% higher market-adjusted monthly return to being a BC. Similarly, a one standard deviation increase in the EFW measure is associated with a 0.67% higher market-adjusted monthly return to being a BC. The results are similar using a Fama and MacBeth (1973) analysis.

Overall, our results suggest that the association between employee satisfaction and stock returns depends critically on the institutional context. These results have important implications for both managers and investors. Starting with the former, even if the Edmans (2011, 2012) results can be interpreted as causal, they do not suggest that managers should necessarily increase expenditure on employee-friendly programs in countries with low labor market flexibility. Moving to the latter, it suggests that investors can only expect to earn alpha from investing in firms with high employee satisfaction in countries with high labor market flexibility.

This chapter contributes to a number of literature. First, it builds on the literature linking various measures of employee welfare to various measures of firm performance. Abowd (1989) shows that announcements of pay increases reduce market valuations dollar-for-dollar, Diltz (1995) finds that stock returns are uncorrelated with the Council of Economic Priorities minority management and women in management variables, and negatively correlated with family benefits, and Dhrymes

(1998) find no relationship with KLDs employee relations variable. In contrast, Edmans (2011, 2012) documents a positive relationship employee satisfaction and stock returns. However, the above studies only analyze the U.S. Given the importance of labor market institutions, it is unclear whether these relationships generalize more widely.

Second, since employee welfare is frequently used as a screen by socially responsible investors (Renneboog, Ter Horst, and Zhang, 2008a, 2011), this chapter contributes to research on the link between socially responsible investing ("SRI") and investor returns. This literature has mixed results. Hamilton, Jo, and Statman (1993), Kurtz and DiBartolomeo (1996), Gorton and Schmid (1997), Bauer, Koedijk, and Otten (2005), Schrder (2007), and Statman and Glushkov (2008) find no or a mixed relationship between various SRI screens and investment returns; Geczy, Stambaugh, and Levin (2005), Brammer, Brooks, and Pavelin (2006), Renneboog, Ter Horst, and Zhang (2008b), and Hong and Kacperczyk (2009) find a negative relationship; and Moskowitz (1972), Luck and Pilotte (1993), Derwall, Guenster, Bauer, and Koedijk (2005), and Edmans (2011, 2012) find a positive link. All of the above studies focus on U.S. data and their generalizability to other countries is again unclear. In particular, the value of various forms of Corporate Social Responsibility ("CSR") - employee welfare, gender diversity, animal rights, environmental protection, and whether the firm is in a "sin" industry (such as tobacco, alcohol, and gambling) - likely depends on the institutional context, such as regulations and cultural norms. To our knowledge, this is the first study to study the investment performance of a SRI screen in a global context.[1]

Finally, this chapter adds to the literature comparing the performance of investment strategies across countries. Asness, Moskowitz, and Pedersen (2013) find that value strategies are profitable not only in the U.S., but also in the U.K.,

[1] Ioannou and Serafeim (2012) and Cheng, Ioannou, and Serafeim (2014) study the determinants and consequences of corporate social responsibility in a cross-country context, but do not investigate stock returns.

continental Europe, and Japan. Momentum strategies are profitable in the first three regions, but not Japan. Chui, Titman, and Wei (2010) argue that cultural factors explain the differential profitability of momentum strategies across countries: in particular, countries with greater individualism exhibit higher momentum profits.

This chapter is organized as follows. Section 2.2 develops our hypotheses and Section 2.3 describes the data. Section 2.4 studies the abnormal returns to the BCs across different countries. Section 2.5 presents the core results of our chapter, relating these abnormal returns to measures of labor market flexibility. Section 2.6 concludes.

2.2 Hypothesis development

We first discuss whether we should expect to find any long-run abnormal returns to the Best Companies lists at all, either positive or negative. Our return compounding window starts at the beginning of the month after list publication. Thus, since these lists are public, we should find no abnormal returns if the market is semi-strong efficient. Regardless of the institutional context, and thus regardless of the direction of the link (if any) between employee welfare and firm value, the positive or negative value of list inclusion should be capitalized by the market before the start of the return compounding window.

However, there is significant prior evidence that intangible assets are not fully priced by the stock market. Firms with high R&D as measured by expenditure (Chan, Lakonishok, and Sougiannis, 2001; Lev and Sougiannis, 1996), advertising as measured by expenditure (Chan, Lakonishok, and Sougiannis, 2001), patent quality as measured by citations (Deng, Lev, and Narin, 1999), and software quality as measured by development costs Aboody and Lev (1998) all earn higher long-run returns. Consistent with these findings, Edmans (2011, 2012) documents that Best Companies in the U.S. outperform their peers by 2-3% per year, and that the value of list inclusion is not fully capitalized by the market until 4-5 years later. Indeed, equity analysts systematically under-predict the earnings announcements of these companies.

Thus, it is reasonable to hypothesize that the value of employee satisfaction will not be fully capitalized by the stock market immediately upon list inclusion, and thus that there will be long-horizon returns.[2] We now discuss our hypothesis for whether this value will be positive or negative, and why it may depend on a countrys level of labor market flexibility. Employee satisfaction has both benefits and costs. Starting with the benefits, worker welfare is likely to improve recruitment, retention, and motivation. For the reasons discussed in the introduction, these benefits are likely to be particularly strong in countries with flexible labor markets, in which hiring and firing are easier. Thus, in such countries, we hypothesize that expenditure on employee welfare is a value-creating investment that is underappreciated by the market.

However, as with any investment, the returns are likely decreasing. In regulated labor markets, regulations already impose a floor on worker welfare, leading to a downward movement along the marginal benefit curve. In addition, due to the increased restrictions in hiring and firing, labor mobility is less frequent and so the recruitment, retention, and motivational benefits are likely smaller, causing a downward shift in the marginal benefit curve. Both of these forces reduce the marginal benefit of further expenditure on worker welfare, potentially below its marginal cost. Indeed, firms may spend excessively on employee satisfaction due to an agency problem. The theory of Pagano and Volpin (2005a) argues that employee benefits such as high wages can be used as a takeover defense. Simintzi, Vig, and Volpin (2014) find employment protection increases labor costs and reduces firms profitability. Cronqvist, Heyman, Nilsson, Svaleryd, and Vlachos (2009) show that

[2] An alternative channel through which list inclusion can lead to long-run stock returns is through attracting demand from socially responsible investors. Edmans (2011) estimates this effect for the U.S. and found it to be very small compared to the magnitude of the abnormal returns.

entrenched managers pay their employees more. Similarly, countries with regulated labor markets tend to have more powerful labor unions (see, e.g., Nickell (1997)) - indeed, centralized collective bargaining is a component of the labor market flexibility categories of the Economic Freedom of the World database. Thus, high employee satisfaction may result from the influence of labor unions, rather being in shareholders interest. Gorton and Schmid (2004) find that, when labor has a voice in corporate governance, profitability and valuation are lower. Chen, Kacperczyk, and Ortiz-Molina (2011) hypothesize that labor unions protect wages in a downturn, and find that they increase a firms operating leverage and cost of equity. Unions also protect underperforming managers and reduce a firms value (Atanassov and Kim, 2009; Lee and Mas, 2012).

As a result, we predict that the BCs generate positive abnormal returns in countries with high labor market flexibility, and that the returns to list inclusion decrease with labor market rigidity.

2.3 Data and summary statistics

2.3.1 Measures of employee satisfaction

Our main data source is the Best Companies lists compiled by the Great Place to Work Institute. The first list focused on U.S. companies and was published in a 1984 book entitled the "The 100 Best Companies to Work for in America", which was later updated in 1993; from 1998 onwards it has been published every January in Fortune magazine. Two-thirds of the score comes from a 57-question survey that the Institute administers to 250 employees randomly selected in each firm. The remaining one-third comes from the Institutes evaluation of factors such as a companys demographic makeup, pay and benefits programs, and culture. The companies are scored in four areas: credibility (communication to employees), respect (opportunities and benefits), fairness (compensation, diversity), and pride/camaraderie (teamwork, philanthropy, celebrations), and the top 100 firms are publicly announced in rank order. According to the Institute, a Great Place to Work is a place in which "you can trust people you work for, have pride in what you do, and enjoy the people you work with". The list is highly regarded as a thorough measure of employee satisfaction, receiving significant attention from shareholders, management, employees and the media, and has since been extended to more than 45 countries around the world.

We include countries with more than five years history of BC listings, and exclude those where firm-level stock return and accounting data are unavailable, e.g. Colombia, Ecuador, Uruguay, and Venezuela. For each country, we only include BCs that are both headquartered and publicly listed in that country. Table 2.1 describes the 14 countries that have data on labor market flexibility (which we will describe in Section 2.2) and where at least 10 BCs are headquartered and publicly listed. Column (1) shows the start year of BC listings for each country. The numbers of public BCs per country are reported in column (3). Since the earliest start year for a non-U.S. country is 1998 (for Brazil), our sample period is from February 1998 to December 2013, although we will also study the U.S. from February 1984 to December 2013 to verify comparability with Edmans (2011, 2012).

To form BC portfolios, we use the beginning of the month immediately after the latest publication date of lists for each country as our portfolio formation date. For example, the U.S. list is typically published in mid-January, and so we use February 1 as the portfolio formation date. Thus, our analyses are joint tests of the value of employee satisfaction and the extent to which this value is immediately capitalized by the market. The constituents of BC portfolios are rebalanced once a year on the same day. Column (2) reports the portfolio formation dates for each country.

For the U.K. and U.S., the number of firms in the list has remained constant over time. For the other countries, this number has increased over time - for example, the first list in Germany (in 2003) contains 50 firms, while in 2013 it contains 100. Column (6) of Table 2.1 indicates the number of BCs selected in the initial list and the 2013 list for each country.

2.3.2 Measures of labor market flexibility

We use two measures of labor market flexibility. The first is the OECDs Employment Protection Legislation ("EPL") index, which is available for 34 OECD and 9 emerging countries. The index measures the procedures involved in hiring workers on either fixed-term or temporary contracts, and the procedures and costs involved in dismissing individuals and groups of workers. The index is based on statutory laws, collective bargaining agreements, case law, contributions from OECD member countries, and experts advice from each country. It has three components:

Individual dismissal of workers with regular contracts (category EPR) measures three aspects of dismissal protection: (i) procedural inconveniences of the dismissal process faced by employers, such as notification and consultation requirements; (ii) length of notice periods and conditions of severance pay; and (iii) difficulty of dismissal, such as the circumstances under which a dismissal can be made possible, and repercussions for the employer if an unfair dismissal is discovered. Additional costs for collective dismissals (category EPC) measures the extra costs faced by employers when they dismiss several workers simultaneously, over and above the costs applicable for individual dismissals.

Regulation of temporary contracts (category EPT) measures regulations for fixed-term and temporary work contracts in terms of job type and duration, requirements for such workers to receive equal pay and working conditions to permanent employees, and regulations for the setup and operations of work agencies.

The first two measures capture the ease of dismissal. As mentioned in the introduction, fewer constraints on firing increase the motivational benefits of employee satisfaction (as workers will exert greater effort to avoid being fired from a satisfying job), and also its recruitment benefits (since the ease of firing raises the number of vacancies the firm can create). The third measure captures constraints on hiring, which reduce the recruitment benefits of employee satisfaction. Separately, regulations on hiring and firing impose a minimum level of employee welfare, leading to a downward movement along the marginal benefit curve for expenditure on employee satisfaction. Thus, in regulated labor markets, firms with high satisfaction relative to their peers may be operating in the region in which the marginal benefit does not justify the cost.

The EPL index has been used in Pagano and Volpin (2005b) and Simintzi, Vig, and Volpin (2014). Following both papers, we calculate EPL as the average of the three sub-indicators scores; high EPL implies low labor market flexibility.[3] Column (1) of Table 2.1, Panel B reports the time series mean of EPL for each country from 1998-2013, and columns (2)-(4) of report the time series mean of each index. As a rough check that our EPL measure is linked to labor mobility, and thus the retention and recruitment benefits of employee satisfaction, we were able to collect data on labor turnover rates for seven countries in our sample from the OECD. Their correlation with our employment protection legislation index is -0.73. Similarly, the labor economics literature shows that employment protection is negatively associated with labor turnover (Bertola, 1999; Autor, Kerr, and Kugler, 2007; Messina and Vallanti, 2007; OECD, 2013).

Our second measure of labor market flexibility is calculated based on data from the Fraser Institutes Economic Freedom of the World (”EFW”) database. The database contains indices on labor market flexibility, which are also used by labor economics studies such as Bernal-Verdugo, Furceri, and Guillaume (2012ab,a), Freeman, Kruse, and Blasi (2008), and Haltiwanger, Scarpetta, and Schweiger (2008). The indices have been referred as a comprehensive measure of the ”de facto strict-

[3]The OECD reports EPL as a weighted average of the three broad categories, where the weights depend on the number of sub-indicators in each group. Our results are robust to this weighted measure of EPL.

ness of labor regulations" (Feldmann, 2009). We use the EFW indices across six policy categories. All indices are standardized on a 0-10 scale, with higher values indicating more flexible labor markets:

Hiring regulations and minimum wage (category 5Bi) is based on the World Banks Doing Business Difficulty of Hiring Index. The index measures three areas: (i) whether fixed-term contracts are prohibited for permanent tasks; (ii) the maximum cumulative duration of fixed-term contracts; and (iii) the ratio of the minimum wage for a trainee or first-time employee to the average value added per worker.

Hiring and firing regulations (category 5Bii) is derived from the World Economic Forums Global Competitiveness Reports survey question "'How would you characterize the hiring and firing of workers in your country?" Respondents assign a score from 1 ("impeded by regulations") to 7 ("flexibly determined by employers") which are then standardized onto a 0-10 scale.

Centralized collective bargaining (category 5Biii) is based on the World Economic Forums Global Competitiveness Reports survey question "How are wages generally set in your country?". Respondents assign a score from 1 ("by a centralized bargaining process by regulations") to 7 ("up to each individual company") which are then standardized onto a 0-10 scale.

Hours regulations (category 5Biv, previously called "mandated cost of hiring a worker") is based on the World Banks Doing Business Rigidity of Hours Index, which measures (i) whether there are restrictions on night work; (ii) whether there are restrictions on weekly holiday work; (iii) whether the work-week can consist of 5.5 days; (iv) whether the work-week can extend to 50 hours or more (including overtime) for 2 months a year to respond to a seasonal increase in production; and (v) whether paid annual vacation is 21 working days or fewer.

Mandated cost of worker dismissal (category 5Bv) is based on the World Banks Doing Business data. It includes the cost of the advance notice requirements, severance payments, and penalties due when dismissing a redundant worker.

Conscription (category 5Bvi) is based on the use and duration of military conscription. Lower ratings of labor market flexibility are assigned to countries with longer conscription periods. Columns (6)-(11) of Table 2.1, Panel B report the time series mean of each index across the sample period.

Categories 5Bi, 5Bii and 5Biv capture the ease of hiring (similar to category EPT in the EPL index, although the latter focuses on temporary contracts), and category 5Bv captures the ease of firing (similar to categories EPR and EPC in the EPL index). Category 5Biii measures the power of labor unions. Labor unions impose restrictions on contracts which hinder both hiring and firing, and may press for higher employee satisfaction even if not in shareholders interest. Category 5Bvi captures a regulatory intervention to the supply-side. Where conscription is greater, the recruitment benefits of employee satisfaction are smaller since individuals have less freedom to join firms.

The current form of the EFW data is available annually from 2002 to 2013.[4] We construct a composite measure of labor market flexibility (EFW) that equals the average of the six indices in each country-year. Column (5) of Table 2.1, Panel B reports the mean of the composite indicator for each country.

2.4 Empirical results

2.4.1 Country-level alphas

We first calculate the Carhart (2001) four-factor alphas to the BC portfolios in each country:

$$R_{ct} = \alpha + \beta_{MKT} MKT_{ct} + \beta_{HML} HML_{ct} + \beta_{SMB} SMB_{ct} + \beta_{MOM} MOM_{ct} + \epsilon_{ct} \quad (2.1)$$

[4]The EFW also provided labor market flexibility data in 2000 and 2001 but on different components, which are not comparable to the data from 2002 onwards.

where R_{ct} is the U.S. dollar returns to a BC portfolio (either equal-weighted or value-weighted) in month t for country c in excess of the U.S. one-month treasury rate. Stock returns are taken from the Center for Research in Security Prices ("CRSP") for U.S. firms and Datastream for other firms. Both active and inactive firms are included to avoid survivorship bias. We winsorize stock returns at the 0.5% and 99.5% level in each country. Results are very similar without winsorization.

α is an intercept that captures the abnormal risk-adjusted return. MKT_{ct}, HML_{ct}, SMB_{ct}, and MOM_{ct}, are, respectively, the Fama and French (2012) regional factors on market, value, size, and momentum, collected from Kenneth Frenchs website. We use the Europe factors for all European countries, the North American factors for Brazil, Chile, Canada and the U.S., the Japan factors for Japan, and the Asia-Pacific Excluding Japan factors for Korea and India.

ϵ_{ct} is an error term. Standard errors are corrected for heteroscedasticity and autocorrelation using Newey and West (1987) estimator with four lags.

Table 2.2 reports results for equal-weighted portfolios. Three of the 14 countries (Denmark, Germany, and Greece) have insignificantly negative alphas. The remaining 11 countries have positive alphas, which are significant at the 10% level or better for Chile, Japan, Sweden, and the U.S. In terms of economic significance, the U.S. has the tenth highest alpha out of the fourteen countries, suggesting that it is not an outlier. Table 2.3 reports results for value-weighted portfolios. Denmark, France, Germany, and Greece have negative alphas, with Denmarks being significant at the 10% level. The alphas for Chile, the U.K., and the U.S., are significantly positive at the 10% level or better.

It should be noted that the joint-hypothesis problem applies here: to test whether the market is efficient in conjunction with the soundness of the asset pricing model. Thus, the above (and the following) results depend on the maintained specification for the economic risk premium. Relevant asset pricing models that have recently appeared in the literature subsequent to this research include Fama and French (2015a), Fama and French (2015b), Hou et al. (2014a), and Hou et al. (2014b).

2.4.2 Characteristics controls

While above section controls for the BCs covariance with risk factors, this section controls for firm characteristics that may also affect stock returns. We first run the following pooled panel regression across all firms (both BCs and non-BCs) within a country, at the firm-month level:

$$R_{it} = \alpha_0 + \alpha_1 BC_{it} + \alpha_2 FirmControls_{it} + \alpha_3 FE_t + \epsilon_{it} \tag{2.2}$$

R_{it} is the return on stock i in month t. BC_{it} is a dummy variable that equals one if firm i was included in the most recent BC list prior to month t, and zero otherwise. $FirmControls_{it}$ include the control variables used in Brennan, Chordia, and Subrahmanyam (1998), calculated using CRSP and Compustat for U.S. firms and Datastream and Worldscope for non-U.S. firms. $SIZE$ is the log of firm is market capitalization at the end of month t-2. BM is the log of firm is book-to-market ratio at the end of month t-2. YLD is firm is dividend yield as measured by the sum of all dividends paid over the previous 12 months prior to month t, divided by the share price at the end of month t-2. $RET2-3$ is the log of one plus firm is cumulative return over months t-3 through t-2. $RET4-6$ and $RET7-12$ are defined similarly. VOL is the log of firm is dollar trading volume in month t-2. PRC is the log of firm is price at the end of month t-2. FE_t are month fixed effects to control for macroeconomic cycles. Standard errors are clustered by firm.

Results for each country are reported in Table 2.4. The coefficient on the BC dummy is significantly positive for Canada, Chile, Greece, India, Japan, Korea, and the U.S. For example, in the U.S., being a BC is associated with an additional monthly return of 28 basis points. Denmark, Finland, France, Germany, and Sweden have insignificantly negative coefficients on the BC dummy. We next run Fama and MacBeth (1973) cross-sectional regressions for each country in a given month t:

$$R_i = \alpha_0 + \alpha_1 BC_i + \alpha_2 FirmControls_i + \epsilon_i \tag{2.3}$$

where R_i is the return on stock i. BC_i is a dummy variable that equals one if firm i has been included in the most recent BC list, and zero otherwise. $FirmControls_i$ include the control variables used in Brennan, Chordia, and Subrahmanyam (1998). Standard errors are adjusted for heteroscedasticity and autocorrelation using Newey and West (1987) estimator with four lags. We then take the time-series average of the monthly coefficients for each country. While the pooled panel regression weights each firm-month observation equally, the Fama and MacBeth (1973) approach weights each month equally.

Results for each country are reported in Table 2.5. Consistent with prior results, the BC coefficient is significantly positive at the 5% level or better in Canada, India, Japan, Korea, and the U.K. The coefficients are negative and insignificant for Denmark, Finland, Germany, and Greece. Overall, the results suggest that the positive returns to Best Companies in the U.S. do extend to other countries, but there is significant heterogeneity between countries. In the next section, we study how this heterogeneity is related to labor market flexibility.

2.5 The role of labor market flexibility

This section examines how the relationship between employee satisfaction and stock returns depends on the degree of labor market flexibility. Holderness (2014a,b) argues that international empirical analyses should be conducted at the firm level, rather than at the country level, as the latter approach ignores between-firm, within-country variation. In our context, using country averages (e.g. regressing country-level alpha on labor market flexibility) will ignore other firm-specific determinants of stock returns. We thus study the impact of labor market flexibility using firm-level analyses that take into account firm characteristics.

We start by enhancing the pooled panel regression in equation 2.2 with measures of labor market flexibility and country-level controls, and estimating it across the full sample of all countries:

$$\begin{aligned} Return_{cit} &= \beta_0 + \beta_1 BC_{cit} + \beta_2 BC_{cit} EPL_{ct}(EFW_{ct}) + \beta_3 BC_{cit} CountryControls_{ct} \quad (2.4) \\ &+ \delta_1 EPL_{ct}(EFW_{ct}) + \delta_2 CountryControls_{ct} + \delta_3 FirmControls_{cit-2} \\ &+ \delta_4 FE_t + \epsilon_{cit} \end{aligned}$$

where $Return_{cit}$ is either the raw return (R_{cit}) or the market-adjusted return (i.e. the raw return in excess of the local country market return) for firm i in country c in month t.[5] The local market return is measured using the MSCI market index for each country, collected from Datastream. EPL_{ct} is the employment protection legislation indicator for country c in month t and EFW_{ct} is the labor market flexibility indicator. To ensure that our EPL and EFW variables are not simply proxying for other country-level differences, we include $CountryControls_{ct}$, a vector of other country-level control variables: $RuleofLaw_c$ measures the rule of law from La Porta, Lopez-de Silanes, Shleifer, and Vishny (1997); $Gdpg_{ct}$ measures GDP growth for country c in month t taken from the World Bank; $SoCM_c$ measures the size of capital market, specifically the number of listed domestic firms per (million) capita from La Porta, Lopez-de Silanes, Shleifer, and Vishny (1997); $ADRI_c$ measures the anti-director rights index corrected by Spamann (2010); and $OSOV_c$ measures the presence of one-share one-vote from La Porta, Lopez-de Silanes, Shleifer, and Vishny (1997). In particular, the returns to Best Companies capture not only the value of employee satisfaction, but the extent to which this value is not immediately capitalized by the market. Thus, we include a control for the size of the capital market as a proxy for market efficiency. Standard errors are clustered by firm.

[5] We also use the abnormal return (AR_{cit}) for firm i in country c at month t as the dependent variable. AR_{cit} is calculated as the CAPM-adjusted abnormal return using either a 5- or 3-year rolling-window beta. Results are similar.

Panel A of Table 2.6 presents the results using EPL as the measure of labor market flexibility. Columns (1) − (3) use raw returns as the dependent variable. In column (1), which contains no measures of labor market flexibility or country controls, BC has a positive coefficient of 0.760, which is significant at the 1% level. However, in column (3) when interactions with EPL and the country controls are added, the coefficient on BC is no longer significant. Instead, the coefficient on BC*EPL is a significantly negative -0.693. Thus, BCs are associated with significantly higher returns in countries with weak employment protection legislation. Columns (4) - (6) use the market-adjusted return (i.e. the raw return minus the market return) as the dependent variable. The results are slightly stronger, with the coefficient on BC*EPL falling to -0.790. A one standard deviation decrease in EPL is associated with a 0.49% increase in the monthly market-adjusted return to being a BC.

Panel B presents the results using EFW as the measure of labor market flexibility, which are similar to Panel A. For both raw returns and market-adjusted returns in columns (3) and (6), the coefficient on BC is insignificant, but the coefficient on BC*EFW is positive and significant at the 1% level. For example, the coefficient of 0.394 in column (6) indicates that a one standard deviation increase in EFW is associated with a 0.67% increase in the monthly market-adjusted return to being a BC.

Table 2.7 presents the results of Fama-MacBeth cross-sectional regressions for the full sample, which includes country-level controls and measures of labor market flexibility. The results are very similar to Table 2.6, with the coefficients on BC*EPL being significantly negative and those on BC*EFW being significantly positive.

2.6 Conclusions

This chapter studies how the relationship between employee satisfaction and stock returns depends critically on the level of a countrys labor market flexibility. The alphas documented by Edmans (2011, 2012) for the U.S. are not anomalous in a global context, in terms of economic significance, and do extend to several other countries. However, they do not automatically generalize to every country - being listed as a Best Company to Work For is associated with superior returns only in countries with high labor market flexibility. These results are consistent with the idea that the recruitment, retention, and motivational benefits of employee satisfaction are most valuable in countries in which firms face fewer constraints on hiring and firing. These benefits are lower in countries with inflexible labor markets, leading to a downward shift in the marginal benefit of expenditure on employee welfare. Moreover, in such countries, regulations already provide a floor for worker welfare, leading to a movement down the marginal benefit curve. Both forces reduce the marginal benefit of investing in worker satisfaction, and thus being listed as a Best Company may reflect an agency problem.

The results emphasize the importance of the institutional context for both managers and investors. Edmans (2011, 2012) uses long-run stock returns as the dependent variable to mitigate concerns about reverse causality from firm performance to employee satisfaction - any publicly-available performance measure should be incorporated into the stock price at the start of the return compounding window. However, these papers do not make strong claims about causality, as it may be that a third, unobservable variable (e.g. management quality) drives both employee satisfaction and stock returns. Even if their results are interpreted as causal, it is not the case that managers can hope to increase stock returns by investing in employee satisfaction, as a positive link only exists in countries with high labor market flexibility. Turning to investors, a strategy of investing in firms with high employee satisfaction will only generate superior returns in countries with high labor market flexibility. Given that the vast majority of empirical asset pricing studies that uncover alpha are based on U.S. data, the results emphasize caution in applying these strategies overseas. This caution is especially warranted for strategies that are likely to be dependent on the institutional or cultural environment, such as socially responsible investing strategies. Just as the value of employee satisfaction depends on the flexibility of labor markets and existing regulations on worker welfare, the value of other SRI screens such as gender diversity, animal rights, environmental protection, and operating in an ethical industry also likely depend on the context.

Table 2.1: *Summary statistics*

Panel A reports the list of countries in which at least ten publicly-listed Best Companies (BCs) are headquartered and publicly listed. Column (1) presents the years of BC lists that we use for each country. Column (2) reports our portfolio formation date for each country. Column (3) gives the number of listed BC per country. Column (4) presents the total number of listed firms in each country including BCs. Column (5) records the total number of firm-month observations for each country. Column (6) indicates for each country the number of BCs in the year the list was initiated and also in 2013. The last row summarizes data of all countries except the US(84-). Our sample period is from February 1998 to December 2013. For the US we also extend the sample period from February 1984 to December 2013.

Panel A: Publicly-listed Best Companies to Work For							
	(1)	(2)	(3)	(4)	(5)	(6)	
	Listing years	Formation date	Total No. of Public BCs	Total no. of firms	Total no. of Obs.	Size of BC lists Initial	2013
Brazil	1998 – 2013	01 – *Sep*	70	652	30,883	50	100
Canada	2006 – 2013	01 – *May*	15	4,405	172,724	30	50
Chile	2001 – 2013	01 – *Dec*	11	304	22,050	25	50
Denmark	2001 – 2013	01 – *Dec*	23	461	26,960	50	75
Finland	2003 – 2013	01 – *Mar*	14	241	19,448	20	50
France	2002 – 2013	01 – *Apr*	18	1,765	92,813	25	49
Germany	2003 – 2013	01 – *Mar*	24	1,646	84,252	50	100
Greece	2003 – 2013	01 – *May*	12	443	39,570	10	25
India	2003 – 2013	01 – *Jun*	46	2,578	131,432	25	100
Japan	2007 – 2013	01 – *Apr*	38	4,981	510,977	20	40
Korea	2002 – 2013	01 – *Nov*	49	2,019	128,687	20	100
Sweden	2003 – 2013	01 – *May*	11	823	44,418	25	38
UK	2001 – 2013	01 – *May*	33	4,943	199,276	50	50
US(98-)	1998 – 2013	01 – *Feb*	188	11,478	1,209,671	100	100
US(84-)	1984 – 2013	01 – *Feb*	259			100	100
All			552	39,239	2,713,161	500	840

Table 2.1 continued.

Panel B summarizes the employment protection legislation (EPL) indicators from OECD and the labor market flexibility index (EFW) based on the Fraser Institutes Economic Freedom of the World database. Column (1) presents the average scores of employment protection legislation index for each country. They are based on the average of three components, namely the individual dismissal of workers with regular contracts (EPR), additional costs for collective dismissals (EPC), and regulation of temporary contracts (EPT). Columns (2) - (4) report the average per country for these components, respectively. Column (5) presents the average scores of the aggregate labor market flexibility index calculated as the average of its six components. Column (6) presents the average score of hiring regulations and minimum wage per country (5Bi). Column (7) presents the average score of hiring and firing regulations (5Bii). Column (8) presents the average score of centralized collective bargaining (5Biii). Column (9) presents the average score of hours regulations. Column (10) presents the average score of mandated cost of worker dismissal (5Bv). Column (11) presents the average score of military conscription (5Bvi). The sample period is from 1998 to 2013 for EPL and from 2002 to 2013 for EFW.

Panel B: Employment protection legislation and labor market flexibility											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	EPL	Individual dismissals (regular contracts) EPR	Collective dismissals (additional costs) EPC	Temporary contracts EPT	EFW	Hiring regulations and min. wage 5Bi	Hiring and firing regulations 5Bii	Centralized collective bargaining 5Biii	Hours regulations 5Biv	Mandated cost of worker dismissal 5Bv	Conscription 5Bvi
Brazil	2.159	1.452	0.900	4.125	4.643	3.620	4.410	5.335	5.175	6.315	3.000
Canada	1.380	0.921	2.969	0.250	7.916	7.740	6.055	7.485	8.430	7.785	10.000
Chile	1.876	2.627	0.000	3.000	5.766	6.120	4.900	7.965	8.625	6.215	0.769
Denmark	2.257	2.147	3.250	1.375	6.753	7.795	7.580	5.490	6.650	10.000	3.000
Finland	1.849	2.203	1.781	1.563	4.931	4.625	4.335	3.635	5.280	8.708	3.000
France	3.134	2.402	3.375	3.625	5.528	3.245	2.885	5.870	3.570	7.600	10.000
Germany	2.591	2.798	3.625	1.352	4.515	5.500	2.870	3.410	5.045	4.800	5.462
Greece	3.117	2.680	3.250	3.422	4.472	5.405	3.655	4.010	4.360	7.015	2.385
India	1.846	3.286	0.438	1.813	6.990	8.370	3.335	6.940	7.850	5.446	10.000
Japan	1.920	1.556	3.250	0.953	8.085	8.250	3.785	8.005	8.685	9.785	10.000
Korea	2.144	2.369	1.875	2.188	4.376	6.600	4.110	7.135	6.475	1.938	0.000
Sweden	2.109	2.333	2.500	2.945	5.285	5.535	3.080	3.975	4.725	8.708	5.692
UK	1.459	1.159	2.860	0.338	7.968	7.920	6.045	7.555	7.825	8.462	10.000
US	1.127	0.257	2.875	0.250	8.673	8.355	7.015	7.790	8.875	10.000	10.000
Average	2.069	1.937	2.852	1.681	6.396	6.363	4.576	6.043	6.541	7.341	5.951
Std. Dev.	0.623	0.767	1.016	1.201	1.711	2.459	1.754	1.763	2.479	1.891	3.993

Table 2.2: *Risk-adjusted returns of equal-weighted BC portfolios*

This table reports regression results of monthly returns of equal-weighted portfolios of Best Companies using Carhart (2001) four-factor model:

$R_{ct} = \alpha + \beta_{MKT}MKT_{ct} + \beta_{HML}HML_{ct} + \beta_{SMB}SMB_{ct} + \beta_{MOM}MOM_{ct} + \epsilon_{ct}$,

where R_ct is the return on equal-weighted portfolio of listed BCs in month t for country c in excess of the risk-free rate. α is the intercept that captures the abnormal risk-adjusted return. MKT_{ct}, HML_{ct}, SMB_{ct}, and MOM_{ct}, are, respectively, the Fama and French (2012)s regional factors on market, value, and size, and momentum. Coefficient estimates standard errors are displayed in parentheses below, adjusted for heteroscedasticity and autocorrelation (Newey and West, 1987). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from February 1998 to December 2013. For the US we also extend the sample period from February 1984 to December 2013.

	α	β_{MKT}	β_{HML}	β_{SMB}	β_{MOM}	$Adj.R^2$	Obs. No.
Brazil	0.942	0.969***	0.349**	0.535**	−0.057	0.312	183
	(0.606)	(0.135)	(0.147)	(0.211)	(0.142)		
Canada	0.091	1.280***	−0.209	−0.320	−0.113	0.648	90
	(0.485)	(0.113)	(0.217)	(0.277)	(0.142)		
Chile	0.971*	0.716***	−0.264	0.464**	0.003	0.280	143
	(0.503)	(0.146)	(0.211)	(0.216)	(0.109)		
Denmark	−0.629	0.934***	0.074	0.788***	0.095	0.685	143
	(0.403)	(0.076)	(0.160)	(0.154)	(0.077)		
Finland	0.957	0.947***	0.295	0.501	−0.232	0.471	92
	(0.715)	(0.165)	(0.390)	(0.359)	(0.156)		
France	0.346	0.891***	−0.415*	−0.366	−0.240	0.592	127
	(0.453)	(0.093)	(0.242)	(0.252)	(0.101)		
Germany	−0.445	1.028***	0.310	−0.167	−0.193**	0.642	128
	(0.437)	(0.092)	(0.301)	(0.189)	(0.096)		
Greece	−0.584	1.143***	−0.275	0.282	−0.462	0.488	96
	(0.791)	(0.227)	(0.630)	(0.461)	(0.180)		
India	1.076	1.029***	0.274	0.089	−0.413***	0.533	113
	(0.670)	(0.099)	(0.269)	(0.224)	(0.141)		
Japan	0.768**	0.985***	−0.083	0.623***	0.008	0.701	79
	(0.332)	(0.076)	(0.156)	(0.156)	(0.096)		
Korea	0.602	1.037***	0.000	−0.194	−0.159	0.552	132
	(0.570)	(0.082)	(0.209)	(0.229)	(0.200)		
Sweden	0.870*	1.136***	−0.623**	0.377	0.129	0.497	127
	(0.497)	(0.106)	(0.262)	(0.328)	(0.159)		
UK	0.812	0.835***	−0.617***	0.405*	−0.279**	0.446	150
	(0.569)	(0.081)	(0.195)	(0.216)	(0.126)		
US(98-)	0.222***	1.028***	0.134***	0.117***	0.008	0.895	280
	(0.080)	(0.028)	(0.036)	(0.040)	(0.008)		
US(84-)	0.262***	1.076***	0.030	0.192***	−0.148***	0.927	359
	(0.080)	(0.022)	(0.033)	(0.043)	(0.020)		

Table 2.3: *Risk-adjusted returns of value-weighted BC portfolios*

This table reports regression results of monthly returns of equal-weighted portfolios of Best Companies using Carhart (2001) four-factor model:

$R_{ct} = \alpha + \beta_{MKT}MKT_{ct} + \beta_{HML}HML_{ct} + \beta_{SMB}SMB_{ct} + \beta_{MOM}MOM_{ct} + \epsilon_{ct}$,

where R_ct is the return on value-weighted portfolio of listed BCs in month t for country c in excess of the risk-free rate. α is the intercept that captures the abnormal risk-adjusted return. MKT_{ct}, HML_{ct}, SMB_{ct}, and MOM_{ct}, are, respectively, the Fama and French (2012)s regional factors on market, value, and size, and momentum. Coefficient estimates standard errors are displayed in parentheses below, adjusted for heteroscedasticity and autocorrelation (Newey and West, 1987). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from February 1998 to December 2013. For the US we also extend the sample period from February 1984 to December 2013.

	α	β_{MKT}	β_{HML}	β_{SMB}	β_{MOM}	$Adj.R^2$	Obs. No.
Brazil	0.591	0.944***	0.228	0.420**	−0.119	0.306	183
	(0.580)	(0.134)	(0.168)	(0.204)	(0.123)		
Canada	0.203	1.148***	0.093	−0.227	−0.137	0.757	90
	(0.326)	(0.089)	(0.197)	(0.162)	(0.092)		
Chile	1.039*	0.762***	−0.288	0.580*	0.070	0.240	143
	(0.563)	(0.144)	(0.230)	(0.337)	(0.148)		
Denmark	−1.020*	1.045***	−0.220	0.442*	0.151	0.490	143
	(0.572)	(0.105)	(0.288)	(0.230)	(0.136)		
Finland	0.739	0.960***	0.135	0.325	−0.298**	0.455	92
	(0.717)	(0.169)	(0.395)	(0.374)	(0.149)		
France	−0.200	0.891***	−0.129	0.161	0.083	0.478	127
	(0.424)	(0.081)	(0.257)	(0.212)	(0.100)		
Germany	−0.453	0.957***	0.338	−0.285	−0.106	0.509	128
	(0.549)	(0.092)	(0.289)	(0.205)	(0.101)		
Greece	−0.582	1.216***	−0.050	−0.219	−0.734**	0.542	96
	(0.843)	(0.229)	(0.685)	(0.503)	(0.243)		
India	0.861	1.022***	−0.085	0.172	−0.264*	0.559	113
	(0.608)	(0.097)	(0.222)	(0.200)	(0.149)		
Japan	0.365	0.938***	−0.276**	−0.011	−0.015	0.721	79
	(0.308)	(0.074)	(0.130)	(0.155)	(0.103)		
Korea	0.135	1.121***	0.107	−0.384	−0.158	0.527	132
	(0.623)	(0.092)	(0.262)	(0.284)	(0.247)		
Sweden	0.212	1.165***	−0.761***	0.313	0.140	0.475	127
	(0.517)	(0.127)	(0.280)	(0.358)	(0.138)		
UK	0.988**	0.727***	−0.400**	−0.243	−0.010	0.360	150
	(0.475)	(0.081)	(0.156)	(0.202)	(0.096)		
US(98-)	0.194*	1.032***	−0.302***	−0.237***	0.007	0.834	280
	(0.106)	(0.031)	(0.060)	(0.051)	(0.007)		
US(84-)	0.191*	1.019***	−0.334***	−0.153***	−0.063*	0.862	359
	(0.107)	(0.028)	(0.049)	(0.046)	(0.033)		

Table 2.4: *Pooled panel regressions by country*

This table reports results of monthly firm-level pooled panel regressions:

$R_{it} = \alpha_0 + \alpha_1 BC_{it} + \alpha_2 FirmControls_{it} + \alpha_3 FE_t + \epsilon_{it}$,

where R_{it} is the raw return for firm i in month t. BC_{it} is a dummy variable that equals one if firm i has been included in the most recent BC list prior to month t, and zero otherwise. The firm characteristics control variables, $FirmControls_{it-2}$, include the following variables: $SIZE$ is the log of firm is market capitalization at the end of month t-2. BM is the log of firm is book-to-market ratio at the end of month t-2. YLD is firm is dividend yield as measured by the sum of all dividends paid over the previous 12 months prior to month t, divided by the share price at the end of month t-2. $RET2-3$ is the log of one plus firm is cumulative return over months t-3 through t-2. $RET4-6$ and $RET7-12$ are defined similarly. VOL is the log of firm is dollar trading volume in month t-2. PRC is the log of firm is price at the end of month t-2. FEt refers to month fixed effect. Coefficient estimates standard errors are clustered by firm and are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1998 to December 2013.

	BC	$SIZE$	BM	$YIELD$	$RET2-3$	$RET4-6$
Brazil	0.159	−0.110	0.531***	−0.009***	−0.693	0.791*
	(0.530)	(0.068)	(0.106)	(0.002)	(0.568)	(0.450)
Canada	2.724***	−0.272***	1.172***	−0.010	0.182	−0.113
	(0.339)	(0.060)	(0.061)	(0.033)	(0.225)	(0.178)
Chile	0.352*	0.019	0.373***	0.029	0.887	1.565***
	(0.207)	(0.059)	(0.088)	(0.020)	(0.538)	(0.437)
Denmark	−0.547	−0.048	0.871***	0.095	1.907***	1.842***
	(0.344)	(0.063)	(0.131)	(0.063)	(0.682)	(0.474)
Finland	−0.454	−0.241***	0.925***	0.008	1.180*	1.773***
	(0.489)	(0.075)	(0.116)	(0.009)	(0.678)	(0.411)
France	−0.332	−0.100**	0.790***	0.064***	0.834**	1.533***
	(0.426)	(0.040)	(0.069)	(0.017)	(0.347)	(0.229)
Germany	−0.365	0.110***	0.974***	0.000	1.596***	1.851***
	(0.350)	(0.032)	(0.069)	(0.007)	(0.306)	(0.232)
Greece	1.518***	−0.187**	0.854***	−0.008	0.808*	0.181
	(0.547)	(0.083)	(0.115)	(0.010)	(0.449)	(0.380)
India	1.434**	−0.110***	0.688***	0.151*	0.596**	0.841***
	(0.589)	(0.041)	(0.054)	(0.083)	(0.240)	(0.177)
Japan	1.075***	−0.134***	0.882***	0.002***	0.480***	−0.688***
	(0.269)	(0.017)	(0.031)	0.000	(0.135)	(0.104)
Korea	1.407***	−0.004	1.430***	0.002**	−1.341***	0.490**
	(0.443)	(0.045)	(0.077)	(0.001)	(0.297)	(0.216)
Sweden	−0.039	−0.199***	0.851***	−0.003	1.282***	1.927***
	(0.473)	(0.066)	(0.082)	(0.006)	(0.435)	(0.327)
UK	0.432	−0.311***	0.847***	0.000	0.626***	1.452***
	(0.319)	(0.035)	(0.041)	(0.001)	(0.201)	(0.154)
US(98-)	0.284***	0.055***	−0.178***	0.207***	0.493***	0.669***
	(0.099)	(0.015)	(0.019)	(0.062)	(0.099)	(0.080)

Table 2.4 continued.

	$RET7-12$	VOL	PRC	Constant	R^2	Obs. No.
Brazil	-0.356	0.065^{*}	0.000	2.200^{***}	0.00	$30,883.00$
	(0.301)	(0.034)	(0.049)	(0.170)		
Canada	0.764^{***}	0.195^{***}	0.000	1.526^{***}	0.01	$172,724.00$
	(0.131)	(0.033)	(0.061)	(0.194)		
Chile	0.610^{**}	0.029	-0.104^{**}	1.382^{***}	0.00	$22,050.00$
	(0.306)	(0.027)	(0.042)	(0.087)		
Denmark	1.598^{***}	0.198^{***}	-0.307^{***}	0.300	0.01	$26,960.00$
	(0.340)	(0.037)	(0.068)	(0.252)		
Finland	0.932^{***}	0.230^{***}	-0.442^{***}	0.210	0.01	$19,448.00$
	(0.349)	(0.046)	(0.085)	(0.260)		
France	0.786^{***}	0.098^{***}	0.000	1.050^{***}	0.01	$92,813.00$
	(0.166)	(0.023)	(0.051)	(0.184)		
Germany	0.483^{***}	-0.026	0.000	1.032^{***}	0.07	$84,252.00$
	(0.166)	(0.026)	(0.050)	(0.144)		
Greece	-0.179	0.001	-0.316^{***}	(0.03)	0.01	$39,570.00$
	(0.257)	(0.051)	(0.112)	(0.314)		
India	0.620^{***}	0.064^{**}	-0.259^{***}	1.365^{***}	0.00	$131,432.00$
	(0.128)	(0.027)	(0.045)	(0.139)		
Japan	-0.047	0.164^{***}	-0.110^{***}	0.351^{***}	0.05	$510,977.00$
	(-0.077)	(0.011)	(0.018)	(0.050)		
Korea	0.361^{**}	0.097^{***}	0.131^{**}	1.879^{***}	0.01	$128,687.00$
	(0.161)	(0.029)	(0.053)	(0.214)		
Sweden	0.226	0.165^{***}	-0.367^{***}	0.586^{***}	0.01	$44,418.00$
	(0.243)	(0.043)	(0.071)	(0.220)		
UK	0.831^{***}	0.280^{***}	-0.387^{**}	-0.387^{***}	0.01	$199,276.00$
	(0.116)	(0.021)	(0.033)	(0.033)		
US(98-)	1.161^{***}	-0.069^{***}	0.188^{***}	0.279^{***}	0.00	$1,209,671.00$
	(0.104)	(0.012)	(0.017)	(0.094)		

Table 2.5: *Fama-MacBeth regressions by country*

This table reports results of firm-level cross-sectional regressions based on Fama and MacBeth (1973) method in a given month t:

$R_i = \alpha_0 + \alpha_1 BC_i + \alpha_2 FirmControls_i + \epsilon_i,$

where R_i is the raw return for firm i in the given month t. BC_i is a dummy variable that equals one if firm i has been included in the most recent BC list prior to the given month t, and zero otherwise. The firm characteristics control variables, $FirmControls_i$, include the following variables: $SIZE$ is the log of firm is market capitalization at the end of month t-2. BM is the log of firm is book-to-market ratio at the end of month t-2. YLD is firm is dividend yield as measured by the sum of all dividends paid over the previous 12 months prior to month t, divided by the share price at the end of month t-2. $RET2-3$ is the log of one plus firm is cumulative return over months t-3 through t-2. $RET4-6$ and $RET7-12$ are defined similarly. VOL is the log of firm is dollar trading volume in month t-2. PRC is the log of firm is price at the end of month t-2. Coefficient estimates are calculated as the time-series average of the monthly coefficients for each country and shown in bold, and their standard errors are displayed in parentheses below, adjusted for heteroscedasticity and autocorrelation (Newey and West, 1987). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1998 to December 2013.

	BC	$SIZE$	BM	$YIELD$	$RET2-3$	$RET4-6$
Brazil	0.196	−0.090	0.465***	−0.179*	0.047	0.611
	(0.386)	(0.096)	(0.111)	(0.098)	(0.621)	(0.668)
Canada	0.895***	−0.380***	1.095***	−0.027	0.521	0.117
	(0.250)	(0.102)	(0.128)	(0.115)	(0.443)	(0.420)
Chile	0.101	−0.012	0.494***	0.453***	2.132***	2.601***
	(0.215)	(0.064)	(0.137)	(0.150)	(0.750)	(0.585)
Denmark	−0.313	−0.100	0.807***	0.276	3.061***	1.371**
	(0.278)	(0.089)	(0.141)	(0.173)	(0.799)	(0.536)
Finland	−0.088	−0.322***	0.768***	0.016	3.375***	1.547**
	(0.113)	(0.093)	(0.187)	(0.181)	(0.748)	(0.691)
France	0.231	−0.133*	0.650***	0.068	1.630**	2.020***
	(0.257)	(0.071)	(0.118)	(0.114)	(0.651)	(0.445)
Germany	−0.425	−0.016	0.734***	−0.334	1.457***	1.107***
	(0.292)	(0.072)	(0.134)	(0.245)	(0.539)	(0.406)
Greece	−0.078	−0.269	1.159***	−0.078	−0.341	−0.323
	(0.352)	(0.231)	(0.239)	(0.099)	(0.798)	(0.587)
India	0.742**	−0.173	0.799***	0.163	1.446**	1.724***
	(0.332)	(0.111)	(0.152)	(0.120)	(0.620)	(0.455)
Japan	0.526***	−0.234**	0.847***	−0.388***	−0.330	−0.168
	(0.193)	(0.116)	(0.080)	(0.144)	(0.434)	(0.357)
Korea	0.844***	−0.181	1.402***	−0.006	−1.193***	0.668
	(0.280)	(0.133)	(0.170)	(0.070)	(0.419)	(0.468)
Sweden	0.222	−0.309***	0.709***	0.077	1.757***	2.400***
	(0.281)	(0.096)	(0.170)	(0.171)	(0.621)	(0.560)
UK	0.769***	−0.250***	0.707***	0.098	1.261***	1.797***
	(0.261)	(0.095)	(0.122)	(0.087)	(0.477)	(0.364)
US(98-)	0.193	0.048	−0.263***	0.369	1.047***	0.851**
	(0.147)	(0.087)	(0.096)	(0.294)	(0.382)	(0.341)

Table 2.5 continued.

	$RET7-12$	VOL	PRC	Constant	R^2	Obs. No.
Brazil	-0.184	0.044	0.070	1.755**	0.124	30,883
	(0.528)	(0.045)	(0.095)	(0.776)		
Canada	0.565*	0.243***	0.470**	1.487*	0.058	172,724
	(0.312)	(0.072)	(0.189)	(0.804)		
Chile	0.344	0.042	-0.027	1.046**	0.160	22,050
	(0.465)	(0.038)	(0.041)	(0.482)		
Denmark	1.635***	0.205***	0.003	0.517	0.146	26,960
	(0.493)	(0.045)	(0.064)	(0.611)		
Finland	1.431***	0.238***	-0.087	0.069	0.179	19,448
	(0.505)	(0.068)	(0.092)	(0.499)		
France	1.072***	0.070	0.153**	1.425**	0.092	92,813
	(0.384)	(0.054)	(0.076)	(0.562)		
Germany	0.534	0.049	0.047	1.216*	0.092	84,252
	(0.332)	(0.069)	(0.087)	(0.652)		
Greece	0.152	-0.018	-0.226	0.337	0.148	39,570
	(0.439)	(0.092)	(0.204)	(1.173)		
India	0.920*	0.023	-0.058	1.535*	0.103	131,432
	(0.518)	(0.061)	(0.108)	(0.804)		
Japan	-0.198	0.179**	-0.025	0.118	0.079	510,977
	(0.334)	(0.074)	(0.096)	(0.292)		
Korea	0.626**	0.137**	0.133	0.819	0.062	128,687
	(0.279)	(0.058)	(0.129)	(1.077)		
Sweden	0.704	0.229***	0.057	0.690	0.112	44,418
	(0.512)	(0.067)	(0.107)	(0.562)		
UK	1.154***	0.230***	0.111*	0.281	0.057	199,276
	(0.310)	(0.053)	(0.065)	(0.441)		
US(98-)	1.591***	-0.086	0.144	-0.357	0.060	1,209,671
	(0.509)	(0.088)	(0.173)	(0.949)		

Table 2.6: *Pooled panel regressions across countries*

Panel A: Measuring labor market flexibility with EPL

This table reports the results of pooled panel regressions across countries:

$Return_{cit} = \beta_0 + \beta_1 BC_{cit} + \beta_2 BC_{cit} EPL_{ct} + \beta_3 BC_{cit} CountryControls_{ct} + \delta_1 EPL_{ct} + \delta_2 CountryControls_{ct} + \delta_3 FirmControls_{cit} + \delta_4 FE_t + \epsilon_{cit}$,

where $Return_{cit}$ is either the raw return (R_{cit}) or the market-adjusted return (i.e. the raw return in excess of the local country market return) for firm i in country c in month t. BC_{cit} is a dummy variable that equals one if firm i has been included in the most recent BC list in country c prior to month t, and zero otherwise. EPL_{ct} is the Employment Protection Legislation (EPL) indicator from OECD for country c at time t and is based on the legislation in three broad categories: individual dismissal of workers with regular contracts, collective dismissals, and temporary contracts. $CountryControls_{ct}$ indicate the following country-level control variables for country c at time t: $RuleofLaw_c$ measures the law and order tradition from LLSV(1997); $Gdpg_{ct}$ measures the GDP growth taken from the World Bank; $SoCM_c$ measures the size of capital market, specifically the number of listed domestic firms per (million) capita from LLSV(1997); $ADRI_c$ measures anti-director rights index corrected by Spamann (2010); OSOVc measures one-share one-vote from LLSV (1997). $FirmControls_{cit}$ include the following variables: $SIZE$ is the log of firm is market capitalization at the end of month t-2. BM is the log of firm is book-to-market ratio at the end of month t-2. YLD is firm is dividend yield as measured by the sum of all dividends paid over the previous 12 months prior to month t, divided by the share price at the end of month t-2. $RET2-3$ is the log of one plus firm is cumulative return over months t-3 through t-2. $RET4-6$ and $RET7-12$ are defined similarly. VOL is the log of firm is dollar trading volume in month t-2. PRC is the log of firm is price at the end of month t-2. FEt refers to month fixed effect. Standard errors are clustered by firm and are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample is from January 1998 to December 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables		Raw returns			Market-adjusted returns	
BC_{cit}	0.760***	0.964***	0.814	0.719***	1.167***	0.30
	(0.086)	(0.218)	(0.913)	(0.107)	(0.245)	(0.915)
$BC_{cit} * EPL_{ct}$		−0.171	−0.693***		−0.302*	−0.790***
		(0.140)	(0.155)		(0.160)	(0.177)
$BC_{cit} * RuleofLaw_c$			0.081			0.059
			(0.115)			(0.140)
$BC_{cit} * Gdpgct$			0.138***			0.123**
			(0.045)			(0.048)
$BC_{cit} * SoCM_c$			−0.026**			−0.020
			(0.011)			(0.012)
$BC_{cit} * ADRI_c$			0.077			0.225
			(0.203)			(0.245)
$BC_{cit} * OSOV_c$			0.906**			1.353***
			(0.359)			(0.396)
EPL_{ct}		−0.067***	0.236***		−0.014	−0.008
		(0.025)	(0.037)		(0.036)	(0.060)
$RuleofLaw_c$			−0.049***			−0.121***
			(0.015)			(0.020)
$Gdpg_{ct}$			0.066***			−0.066***
			(0.008)			(0.010)
$SoCM_c$			0.018***			0.005*
			(0.002)			(0.003)
$ADRI_c$			0.355***			0.342***
			(0.031)			(0.041)
$OSOV_c$			−0.554***			−0.517***
			(0.034)			(0.041)

$SIZE$	-0.092^{***}	-0.080^{***}	-0.110^{***}	-0.055^{***}	-0.061^{***}	-0.091^{***}
	(0.005)	(0.006)	(0.006)	(0.009)	(0.010)	(0.011)
BM	0.562^{***}	0.528^{***}	0.569^{***}	0.545^{***}	0.515^{***}	0.531^{***}
	(0.015)	(0.015)	(0.016)	(0.027)	(0.029)	(0.033)
$YIELD$	0.000	0.000	0.000	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$RET2-3$	0.414^{***}	0.329^{***}	0.320^{***}	0.020	0.006	-0.009
	(0.066)	(0.068)	(0.069)	(0.101)	(0.105)	(0.107)
$RET4-6$	0.311^{***}	0.207^{***}	0.183^{***}	-0.195^{***}	-0.263^{***}	-0.288^{***}
	(0.052)	(0.054)	(0.055)	(0.070)	(0.073)	(0.074)
$RET7-12$	0.772^{***}	0.677^{***}	0.573^{***}	0.803^{***}	0.835^{***}	0.780^{***}
	(0.039)	(0.042)	(0.043)	(0.069)	(0.061)	(0.063)
VOL	0.081^{***}	0.073^{***}	0.091^{***}	0.046^{***}	0.048^{***}	0.065^{***}
	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.011)
PRC	0.174^{***}	0.145^{***}	0.150^{***}	0.300^{***}	0.292^{***}	0.305^{***}
	(0.008)	(0.008)	(0.009)	(0.021)	(0.023)	(0.024)
Constant	1.296^{***}	1.291^{***}	-0.845^{***}	1.096^{***}	1.086^{***}	0.818^{***}
	(0.021)	(0.045)	(0.213)	(0.063)	(0.078)	(0.256)
Month fixed effects	Y	Y	Y	Y	Y	Y
R^2	0.002	0.002	0.002	0.001	0.001	0.002
Number of obs. (in million)	2.713	2.607	2.532	2.635	2.544	2.474

Panel B: Measuring labor market flexibility with EFW

This table reports the results of pooled panel regressions across countries:

$Return_{cit} = \beta_0 + \beta_1 BC_{cit} + \beta_2 BC_{cit} EFW_{ct} + \beta_3 BC_{cit} CountryControls_{ct} + \delta_1 EFW_{ct} + \delta_2 CountryControls_{ct} + \delta_3 FirmControls_{cit} + \delta_4 FE_t + \epsilon_{cit}$,

where $Return_{cit}$ is either the raw return (R_{cit}) or the market-adjusted return (i.e. the raw return in excess of the local country market return) for firm i in country c in month t. BC_{cit} is a dummy variable that equals one if firm i has been included in the most recent BC list in country c prior to month t, and zero otherwise. EFW_{ct} is the labor market flexibility indicator for country c at time t and is calculated as the average score of six indicators on hiring regulations and mini wage, hiring and firing regulations, centralized collective bargaining, hours regulations, mandated cost of worker dismissal and military conscription obtained from the Fraser Institutes Economic Freedom of the World database. $CountryControls_{ct}$ indicate the following country-level control variables for country c at time t: $RuleofLaw_c$ measures the law and order tradition from LLSV(1997); $Gdpg_{ct}$ measures the GDP growth taken from the World Bank; $SoCM_c$ measures the size of capital market, specifically the number of listed domestic firms per (million) capita from LLSV(1997); $ADRI_c$ measures anti-director rights index corrected by Spamann (2010); OSOVc measures one-share one-vote from LLSV (1997). $FirmControls_{cit}$ include the following variables: $SIZE$ is the log of firm is market capitalization at the end of month t-2. BM is the log of firm is book-to-market ratio at the end of month t-2. YLD is firm is dividend yield as measured by the sum of all dividends paid over the previous 12 months prior to month t, divided by the share price at the end of month t-2. $RET2-3$ is the log of one plus firm is cumulative return over months t-3 through t-2. $RET4-6$ and $RET7-12$ are defined similarly. VOL is the log of firm is dollar trading volume in month t-2. PRC is the log of firm is price at the end of month t-2. FEt refers to month fixed effect. Standard errors are clustered by firm and are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample is from January 1998 to December 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables		Raw returns			Market-adjusted returns	
BC_{cit}	0.629***	−0.157	−0.890	0.620***	−0.543	−0.546
	(0.096)	(0.434)	(0.799)	(0.121)	(0.531)	(0.727)
$BC_{cit} * EFW_{ct}$		0.088*	0.232***		0.140**	0.394***
		(0.053)	(0.084)		(0.063)	(0.097)
$BC_{cit} * RuleofLaw_c$			−0.187			−0.144
			(0.114)			(0.140)
$BC_{cit} * Gdpgct$			−0.050			−0.051
			(0.040)			(0.043)
$BC_{cit} * SoCM_c$			−0.016			−0.021
			(0.012)			(0.014)
$BC_{cit} * ADRI_c$			0.358*			−0.043
			(0.213)			(0.260)
$BC_{cit} * OSOV_c$			0.262			0.861**
			(0.370)			(0.413)
EFW_{ct}		−0.147***	−0.153***		−0.066***	−0.075***
		(0.008)	(0.012)		(0.011)	(0.022)
$RuleofLaw_c$			0.152***			−0.035
			(0.016)			(0.025)
$Gdpg_{ct}$			0.296***			0.020*
			(0.008)			(0.011)
$SoCM_c$			0.006***			0.006**
			(0.002)			(0.003)
$ADRI_c$			0.113***			0.399***
			(0.034)			(0.043)
$OSOV_c$			−0.284***			−0.400***
			(0.046)			(0.064)

$SIZE$	-0.123^{***}	-0.086^{***}	-0.132^{***}	-0.071^{***}	-0.055^{***}	-0.098^{***}
	(0.006)	(0.006)	(0.007)	(0.011)	(0.012)	(0.013)
BM	0.591^{***}	0.593^{***}	0.672^{***}	0.629^{***}	0.632^{***}	0.662^{***}
	(0.017)	(0.017)	(0.018)	(0.036)	(0.036)	(0.040)
$YIELD$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$RET2-3$	0.367^{***}	0.371^{***}	0.231^{***}	0.092	0.094	0.056
	(0.078)	(0.078)	(0.079)	(0.105)	(0.105)	(0.107)
$RET4-6$	-0.512^{***}	-0.510^{***}	-0.657^{***}	-0.780^{***}	-0.779^{***}	-0.821^{***}
	(0.061)	(0.061)	(0.062)	(0.079)	(0.079)	(0.081)
$RET7-12$	0.845^{***}	0.895^{***}	0.645^{***}	0.806^{***}	0.830^{***}	0.737^{***}
	(0.045)	(0.045)	(0.047)	(0.065)	(0.065)	(0.068)
VOL	0.083^{***}	0.074^{***}	0.093^{***}	0.038^{***}	0.035^{***}	0.053^{***}
	(0.005)	(0.005)	(0.006)	(0.012)	(0.012)	(0.013)
PRC	0.145^{***}	0.182^{***}	0.137^{***}	0.241^{***}	0.259^{***}	0.273^{***}
	(0.009)	(0.009)	(0.009)	(0.025)	(0.026)	(0.027)
Constant	1.388^{***}	2.598^{***}	0.115	1.049^{***}	1.596^{***}	0.160
	(0.024)	(0.073)	(0.159)	(0.078)	(0.130)	(0.188)
Month fixed effects	Y	Y	Y	Y	Y	Y
R^2	0.002	0.003	0.003	0.001	0.002	0.002
Number of obs. (in million)	2.058	2.058	1.977	2.007	2.007	1.931

Table 2.7: *Fama-MacBeth regressions across countries*

Panel A: Measuring labor market flexibility with EPL

This table reports the results of pooled panel regressions across countries:

$Return_{ci} = \beta_0 + \beta_1 BC_{ci} + \beta_2 BC_{ci} EPL_c + \beta_3 BC_{ci} CountryControls_c + \delta_1 EPL_c + \delta_2 CountryControls_c + \delta_3 FirmControls_{ci} + \epsilon_{ci}$,

where $Return_{ci}$ is either the raw return (R_{ci}) or the market-adjusted return (i.e. the raw return in excess of the local country market return) for firm i in country c in the given month t. BC_{ci} is a dummy variable that equals one if firm i has been included in the most recent BC list in country c prior to month t, and zero otherwise. EPL_c is the Employment Protection Legislation (EPL) indicator from OECD for country c at time t and is based on the legislation in three broad categories: individual dismissal of workers with regular contracts, collective dismissals, and temporary contracts. $CountryControls_c$ indicate the following country-level control variables for country c at time t: $RuleofLaw_c$ measures the law and order tradition from LLSV(1997); $Gdpg_c$ measures the GDP growth taken from the World Bank; $SoCM_c$ measures the size of capital market, specifically the number of listed domestic firms per (million) capita from LLSV(1997); $ADRI_c$ measures anti-director rights index corrected by Spamann (2010); OSOVc measures one-share one-vote from LLSV (1997). $FirmControls_{ci}$ include the following variables: $SIZE$ is the log of firm is market capitalization at the end of month t-2. BM is the log of firm is book-to-market ratio at the end of month t-2. YLD is firm is dividend yield as measured by the sum of all dividends paid over the previous 12 months prior to month t, divided by the share price at the end of month t-2. $RET2-3$ is the log of one plus firm is cumulative return over months t-3 through t-2. $RET4-6$ and $RET7-12$ are defined similarly. VOL is the log of firm is dollar trading volume in month t-2. PRC is the log of firm is price at the end of month t-2. FEt refers to month fixed effect. Standard errors are clustered by firm and are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample is from January 1998 to December 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Raw returns			Market-adjusted returns		
BC_{cit}	0.679***	0.513	−0.239	0.676***	0.818**	1.553
	(0.123)	(0.387)	(1.730)	(0.147)	(0.382)	(6.173)
BCcit*EPLct		0.157	−0.522**		−0.041	−0.754**
		(0.312)	(0.213)		(0.295)	(0.371)
$BC_{cit} * RuleofLaw_c$			0.279			0.428
			(0.296)			(1.234)
$BC_{cit} * Gdpgct$			0.038			0.037
			(0.169)			(0.265)
$BC_{cit} * SoCM_c$			−0.001			0.003
			(0.014)			(0.016)
$BC_{cit} * ADRI_c$			−0.227			−0.859
			(0.394)			(1.516)
$BC_{cit} * OSOV_c$			2.259			1.596*
			(1.477)			(0.961)
EPLct		−0.036	0.245		0.040	0.008
		(0.196)	(0.241)		(0.140)	(0.204)
$RuleofLaw_c$			0.269*			0.033
			(0.146)			(0.288)
$Gdpg_{ct}$			0.321**			0.184
			(0.149)			(0.165)
$SoCM_c$			0.014			0.004
			(0.010)			(0.010)
$ADRI_c$			0.339			0.611**
			(0.216)			(0.309)
$OSOV_c$			−0.058			0.184
			(0.447)			(0.455)

$SIZE$	-0.087^{*}	-0.086^{*}	-0.112^{**}	-0.070	-0.080^{*}	-0.109^{*}
	(0.047)	(0.044)	(0.049)	(0.049)	(0.047)	(0.056)
BM	0.438^{***}	0.365^{***}	0.359^{***}	0.422^{***}	0.366^{***}	0.352^{***}
	(0.088)	(0.093)	(0.090)	(0.101)	(0.106)	(0.108)
$YIELD$	0.248	0.146	0.144	0.261	0.151	0.155
	(0.161)	(0.117)	(0.125)	(0.168)	(0.126)	(0.134)
$RET2-3$	0.842^{**}	0.817^{**}	0.701^{*}	0.559	0.610	0.410
	(0.398)	(0.385)	(0.373)	(0.448)	(0.451)	(0.453)
$RET4-6$	0.812^{**}	0.691^{*}	0.592^{*}	0.396	0.305	0.253
	(0.399)	(0.379)	(0.348)	(0.394)	(0.389)	(0.387)
$RET7-12$	0.939^{***}	0.963^{***}	0.819^{***}	0.787^{***}	0.909^{***}	0.746^{**}
	(0.269)	(0.273)	(0.269)	(0.249)	(0.257)	(0.295)
VOL	0.046	0.046	0.065	0.024	0.033	0.046
	(0.042)	(0.042)	(0.045)	(0.044)	(0.045)	(0.050)
PRC	0.114	0.107	0.107	0.251^{**}	0.267^{**}	0.273^{**}
	(0.082)	(0.090)	(0.096)	(0.110)	(0.113)	(0.126)
Constant	0.806	0.795	-4.609^{***}	0.595^{*}	0.502	-3.020
	(0.541)	(0.604)	(1.764)	(0.325)	(0.441)	(2.400)
Month fixed effects	Y	Y	Y	Y	Y	Y
Avg. R^2	0.048	0.051	0.084	0.039	0.041	0.060
Number of obs. (in million)	2.713	2.607	2.532	2.635	2.544	2.474

Panel B: Measuring labor market flexibility with EFW

This table reports the results of pooled panel regressions across countries:

$Return_{ci} = \beta_0 + \beta_1 BC_{ci} + \beta_2 BC_{ci} EFW_c + \beta_3 BC_{ci} CountryControls_c + \delta_1 EFW_c + \delta_2 CountryControls_c + \delta_3 FirmControls_{ci} + \epsilon_{ci}$,

where $Return_{ci}$ is either the raw return (R_{ci}) or the market-adjusted return (i.e. the raw return in excess of the local country market return) for firm i in country c in the given month t. BC_{ci} is a dummy variable that equals one if firm i has been included in the most recent BC list in country c prior to month t, and zero otherwise. EFW_c is the labor market flexibility indicator for country c at time t and is calculated as the average score of six indicators on hiring regulations and mini wage, hiring and firing regulations, centralized collective bargaining, hours regulations, mandated cost of worker dismissal and military conscription obtained from the Fraser Institutes Economic Freedom of the World database. $CountryControls_c$ indicate the following country-level control variables for country c at time t: $RuleofLaw_c$ measures the law and order tradition from LLSV(1997); $Gdpg_{ct}$ measures the GDP growth taken from the World Bank; $SoCM_c$ measures the size of capital market, specifically the number of listed domestic firms per (million) capita from LLSV(1997); $ADRI_c$ measures anti-director rights index corrected by Spamann (2010); OSOVc measures one-share one-vote from LLSV (1997). $FirmControls_{ci}$ include the following variables: $SIZE$ is the log of firm is market capitalization at the end of month t-2. BM is the log of firm is book-to-market ratio at the end of month t-2. YLD is firm is dividend yield as measured by the sum of all dividends paid over the previous 12 months prior to month t, divided by the share price at the end of month t-2. $RET2-3$ is the log of one plus firm is cumulative return over months t-3 through t-2. $RET4-6$ and $RET7-12$ are defined similarly. VOL is the log of firm is dollar trading volume in month t-2. PRC is the log of firm is price at the end of month t-2. FEt refers to month fixed effect. Standard errors are clustered by firm and are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The sample is from January 1998 to December 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Raw returns			Market-adjusted returns		
BC_{cit}	0.647***	−0.548	−0.788	0.627***	−0.595	−0.539
	(0.105)	(0.467)	(0.628)	(0.145)	(0.595)	(0.685)
$BC_{cit} * EFW_{ct}$		0.137**	0.338**		0.148**	0.760***
		(0.061)	(0.147)		(0.074)	(0.222)
$BC_{cit} * RuleofLaw_c$			−0.324			−0.399
			(0.254)			(0.325)
$BC_{cit} * Gdpgct$			−0.116			−0.417**
			(0.155)			(0.200)
$BC_{cit} * SoCM_c$			−0.013			−0.036**
			(0.018)			(0.018)
$BC_{cit} * ADRI_c$			0.436			0.119
			(0.395)			(0.412)
$BC_{cit} * OSOV_c$			0.150			1.607*
			(0.763)			(0.866)
EFW_{ct}		−0.090	−0.131		−0.040	−0.025
		(0.089)	(0.116)		(0.060)	(0.116)
$RuleofLaw_c$			0.224			0.159
			(0.145)			(0.144)
$Gdpg_{ct}$			0.249**			0.061
			(0.120)			(0.118)
$SoCM_c$			0.005			−0.003
			(0.015)			(0.015)
$ADRI_c$			0.128			0.312
			(0.187)			(0.292)
$OSOV_c$			−0.056			0.055
			(0.414)			(0.339)

$SIZE$	-0.118^{***}	-0.095^{**}	-0.119^{***}	-0.088^{**}	-0.076^{*}	-0.079^{*}
	(0.045)	(0.048)	(0.043)	(0.044)	(0.043)	(0.042)
BM	0.509^{***}	0.499^{***}	0.505^{***}	0.551^{***}	0.544^{***}	0.544^{***}
	(0.069)	(0.067)	(0.058)	(0.072)	(0.071)	(0.073)
$YIELD$	0.030	0.026	0.022	0.012	0.008	0.000
	(0.021)	(0.020)	(0.016)	(0.021)	(0.018)	(0.014)
$RET2-3$	0.670	0.642	0.562	0.443	0.410	0.303
	(0.426)	(0.404)	(0.382)	(0.452)	(0.446)	(0.453)
$RET4-6$	0.291	0.331	0.271	0.040	0.057	-0.041
	(0.397)	(0.379)	(0.350)	(0.406)	(0.405)	(0.416)
$RET7-12$	0.953^{***}	0.964^{***}	0.705^{**}	0.762^{***}	0.777^{***}	0.616^{**}
	(0.322)	(0.314)	(0.287)	(0.264)	(0.271)	(0.302)
VOL	0.054^{*}	0.048^{*}	0.057^{*}	0.028	0.024	0.016
	(0.030)	(0.029)	(0.033)	(0.035)	(0.034)	(0.033)
PRC	0.085	0.106	0.077	0.190^{*}	0.196^{*}	0.202^{*}
	(0.086)	(0.096)	(0.091)	(0.110)	(0.110)	(0.115)
Constant	0.950	1.708	-1.197	0.578^{*}	0.920^{*}	-2.091
	(0.612)	(1.098)	(1.672)	(0.302)	(0.529)	(1.492)
Month fixed effects	Y	Y	Y	Y	Y	Y
Avg. R^2	0.048	0.051	0.084	0.039	0.041	0.060
Number of obs. (in million)	2.058	2.058	1.977	2.007	2.007	1.931

Chapter 3

Ambiguity, Earnings Surprises, and Asset Prices

3.1 Introduction

The price of an asset is equal to its expected discounted cash flows. Positive earnings news is informative about future cash flows, which in turn elevates the concurrent stock price, and vice versa for negative earnings news. Earlier studies like Ball and Brown (1968) and Beaver (1968) establish the stylized fact that firm-level stock returns are positively correlated with earnings surprises. This intuitive relation, however, does not translate into aggregate level. Recent studies including Kothari, Lewellen, and Warner (2006) and Sadka and Sadka (2009) document a negative contemporaneous relationship between aggregate stock returns and earnings surprises. This finding is puzzling since the current earnings on the aggregate level is no longer an indication for future profitability. Even more counter-intuitively, the contemporaneous relationship can be negative under certain earnings surprises measures. To explain the striking relationship, the two studies employ the framework of return decomposition by Campbell and Shiller (1988a) and Campbell (1991) so that the relationship between returns and earnings surprises is the relative dominance of the relationships between earnings surprises and each of the three components of returns, namely the current expected returns, the cash flow news component, and the discount rate news (or the future expected returns) component. This chapter attempts to shed some lights on the puzzle by interacting ambiguity with the return-earnings relation on both firm- and aggregate-level.

Specifically, Kothari, Lewellen, and Warner (2006) argue that firm-level earnings news contains much more information about the future firm-specific cash flows than about the discount rate. Therefore, the firm-level relationship between returns and earning news is positive due to the dominance of the cash flow news component in the return decomposition. However, on aggregate level, the earnings news contains only information about the future aggregate cash flows and discount rate news due to diversification effect of the firm-specific news. As a result, the discount rate news component becomes dominant and a possible negative correlation between earnings surprises and discount rates determines the negativity of the return-earnings relation. This negative correlation is based on certain level of return predictability. It is worth noting that in Kothari, Lewellen, and Warner (2006), the earnings surprises are implicitly assumed to be independent of the first component - the current expected returns. Sadka and Sadka (2009) present in a simple and elegant derivation that this assumption might have ignored another if not the source of the negativity. They show that the covariance between the earnings surprises and current expected returns can be reduced to the negative covariance between the expected earnings surprises and the current expected returns due to that the earnings surprises are highly predictable on the aggregate level. The results of Sadka and Sadka (2009) compliment rather than contradict Kothari, Lewellen, and Warner (2006) story and the return-earnings relation could well be the outcomes of both the high predictability of earnings surprises and the predictability of returns.

The diversification effect of firm-specific earnings surprise is the center argument for Kothari, Lewellen, and Warner (2006). However, it is not required in

Sadka and Sadka (2009) high predictability of earnings surprises argument. In fact, if the earnings surprises are highly predictable, then the "surprise" of the earnings changes does not exist any longer. This renders the diversification effect irrelevant in the context of aggregating firm-level earnings surprises. Thus, a clear identification of diversification effect in aggregation is a useful channel to differentiate the favorable explanation for the return-earnings relation puzzle.

The diversification effect could be distorted by the asymmetry between good and bad news reactions (Grier, Henry, Olekalns, and Shields, 2004). Recent studies, such as Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011), argue that asymmetric reaction can arise due to the presence of Knightian uncertainty in the sense of Knight (1921) and Ellsberg (1961). They show that investors who are ambiguity averse choose the worst case scenario and consequently overvalue negative news and undervalue positive news. Hereafter, I use terms Knightian uncertainty and ambiguity interchangeably. Ambiguity refers to situations where objective probabilities are unknown or imperfectly known. It can arise due to lack of information and/or poor quality of information. Gilboa and Schmeidler (1989) axiomatize investors' acts of ambiguity aversion. Facing ambiguity, an agent chooses the worst case scenario and acts in a maxmin framework. That is, each possible course of action is evaluated with respect to the least favorable probability distribution from a given set of priors. The chosen action maximizes the minimum expected utility. Larger set of priors indicates higher level of ambiguity as well as more extreme type of ambiguity-aversion. Consequently, the agent tends to overweight the negative outcomes and underweight their positive counterparts.

This chapter investigates how ambiguity affects the return-earnings relation on both firm- and aggregate-level. As argued above, high level of ambiguity leads to low level of diversification effect due to asymmetric reaction to good versus bad news. This will lead to relative dominance of cash flow news component over the discount rate news component, which in turns leads to a positive relationship between aggregate returns and earnings. For low level of ambiguity, however, the diversification effect is much more pronounced. Discount rate news plays a more dominant role resulting in a negative aggregate return-earnings relation. Therefore, if the argument of Kothari, Lewellen, and Warner (2006) is valid, the aggregate return-earnings relation should be negative for low ambiguity portfolios and positive for portfolios of high level of ambiguity. Alternatively, according to Sadka and Sadka (2009), the negativity of aggregate return-earnings relation comes from high predictability of earnings surprise. It is intuitive to state that earnings are less predictable when the information environment is highly ambiguous. Similarly, high level of ambiguity leads to less negative aggregate return-earnings relation. From both perspectives, we could preliminarily conclude that the return-earnings relation turns from negative to positive when the level of ambiguity increases.

There are two level of ambiguity: idiosyncratic or firm-level ambiguity and common or macroeconomic ambiguity. To be precise, the above conclusion is based on the role of idiosyncratic ambiguity in diversification effect and the role of macroeconomic ambiguity in the predictability of earnings surprises. Macroeconomic ambiguity which measures the market-level information environment and affects only the discount rate news has little to do with the diversification effect. Its effect on firm-level return-earnings relations is unclear. Idiosyncratic ambiguity, on the other hand, has limited impact on the predictability of the aggregate earning surprises. This is a contradicting point for Kothari, Lewellen, and Warner (2006) and Sadka and Sadka (2009) theories when considering both firm-level and macroeconomic ambiguity altogether. If only the former is correct, then valid is that the aggregate return-earnings relation turns from negative to positive when the firm-level ambiguity increases. Since the market-level discount rate news has opposite effect on the response coefficient than cash-flow news, macroeconomic ambiguity amplifies its negative effect. Hence, for the portfolios of low firm-level ambiguity, we expect to observe a strong negative aggregate response coefficient. On the other hand for portfolios of highly ambiguous firms, the non-diversified effect of ambiguous cash-flow news dominates the negative effect of the discount rate news and we obtain a significantly positive aggregate response coefficient. If only the latter is correct, then the negativity of the aggregate response coefficient comes from purely the high predictability of aggregate earnings. Macroeconomic ambiguity is likely to decrease this predictability, while the firm-level ambiguity has little effect. Thereby, we expect to observe no clear trend on the effect of firm-level ambiguity on portfolio-level response coefficient. When adding the macroeconomic ambiguity however, we expect to see negative response coefficient for low level of macroeconomic ambiguity but a positive coefficient for the high level counterpart.[1]

To further develop our hypotheses in a rigorous manner, we build a simple model to capture the dynamics of earnings-return relation based on the return decomposition. There are one representative agent (i.e. the investor) and multiple firms. Upon receiving noisy signals of each firm, the investor forms her conditional expectations of the signals' informativeness about future cash flow and discount rate news. It is straightforward to generate a closed-form solution for the earnings response coefficient based on the covariances between returns and the two components. When the information environment becomes uncertain, the ambiguity-averse investor lacks confidence on the distribution of true part of a signal and hence consider a range of possible priors due to lack of information and/or poor quality of information. More specifically, we consider the noisy signals contain both firm-specific and market-wide cash flow components, which are orthogonal to each other. The ambiguity regarding the distribution of firm-specific cash flow component is purely idiosyncratic and we call it firm-level ambiguity. The ambiguity regarding the market-wide cash flow component represents the overall ambiguity about the

[1]If both theories are correct, we should observe the same pattern consistent with Kothari, Lewellen, and Warner (2006) theory. That is, the portfolio-level response coefficient is strictly increase as the firm-level ambiguity increase. And this increasing trend is further enhanced by the effect of macroeconomic ambiguity on the predictability of aggregate earnings as well as on the discount rate news.

market as whole and we name it macroeconomic ambiguity. We model both types of ambiguity using the multiple prior model of (Gilboa and Schmeidler, 1989). That is, the investor does not observe the variances of both cash flow components and can only present their interval ranges, in a similar spirit to Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011). The investor's preferences are then described by the maxmin expected utility model of Gilboa and Schmeidler (1989). The resulting response coefficient is a function of distribution parameters which in turn are a function of randomly generated noisy signals.

In order to quantify the effect of ambiguity on the earnings response coefficient, we perform a comparative statics analysis. Since the earnings response coefficients cannot be computed in the closed form with the presence of ambiguity, we employ Monte Carlo simulations to estimate the coefficients for various values of ambiguity parameters. To start with firm-level analysis, the model predicts that individual response coefficients strictly monotonically increase with firm-level ambiguity. This results also stands in the presence of market-level ambiguity. This pattern can be intuitively explained by the asymmetric reaction to bad versus good earnings news. Literature, such as Conrad, Cornell, and Landsman (2002) and Andersen, Bollerslev, Diebold, and Vega (2003), show that market reacts to negative news significantly more strongly than to positive news. Epstein and Schneider (2008) argue that ambiguity plays an important role in explaining the asymmetry. When the firm-level ambiguity is high, the response to negative news is particularly amplified due to investor's aversion to ambiguity. This leads to an overall larger reaction to earnings news. Market-wide ambiguity amplifies the negative contribution of the discount rate news. Hence, for earnings response coefficient with low firm-level ambiguity, we observe that high macroeconomic ambiguity decrease the coefficients, and vice versa for coefficient with high firm-level ambiguity.

Moving to portfolio-level analysis, the aggregate responses increase with firm-level ambiguity similarly to that for the individual response coefficients. The effect of firm-specific cash flow news is diversified away during aggregation so that only the market-wide cash flow news prevail. However, ambiguity effect is not diversified away and always goes in the same direction. Positive cash flow effect remains in the response coefficients for portfolios of high firm-level ambiguity firms. The effect of macroeconomic ambiguity is similar to the case of individual firms because its effect on discount rate news is not dampened by aggregation of firms' signals. It is worth reiterating that high degree of market-level ambiguity leads to a decrease in the earnings response coefficient of low-ambiguity stocks and to an increase in the earnings response coefficient of high-ambiguity stocks, which means that the effect of market-level ambiguity is related to the degree of firm-level ambiguity. The overall firm-level ambiguity for the market portfolio is in between of the low and high degree that we have quantified in the portfolios. Thus, it is no surprise to see that the effect of market-wide ambiguity is less deterministic on the market level. A more structured version of our hypotheses is presented at the end of the model section.

Using all firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4, we find strong empirical evidence consistent with all of our hypotheses. The results are robust after controlling for size, different earnings surprise measures, different measures of ambiguity, and sample periods with/out the recent financial crisis. The results confirm that Kothari, Lewellen, and Warner (2006) explanation of the puzzling firm- and aggregate-level return-earnings relations is a viable approach. The combination of return decomposition and diversification effect explains the interacting behavior of earnings response coefficients with firm-level and macroeconomic ambiguity on firm-, portfolio-, and market-level analysis. These also show that the earnings predictability explanation of Sadka and Sadka (2009) can not stand alone.

New measures of ambiguity are proposed. Recent empirical literature employes the disagreement of professional forecasters to proxy the degree of ambiguity in firms and the market. Intuitively, if forecasters produce conflicting projections about the fundamentals, investors are likely to be uncertain about distributions of stock returns as they tend to condition their beliefs on professionals' forecasts. Thus, when dispersion among professionals' forecasts regarding the future performance is large, ambiguity is also likely to be high since investors might find it difficult to reduce their set of beliefs into a single prior. At the same time, dispersion of professionals' forecasts might not necessarily be the idea proxy for gauging the degree of ambiguity. Barron, Kim, Lim, and Stevens (1998) argue that the forecasts dispersion can be contaminated by the disagreement component that comes from information asymmetry. this can be a serious issue especially when proxies the degree of ambiguity at individual firm level. They propose a decomposition of the forecasts dispersion into uncertainty and disagreement. We argue that the decomposed uncertainty captures the degree of ambiguity embedded in the dispersion of professionals' forecasts. We construct the firm-level ambiguity by using analysts' forecasts of individual firm earnings and macroeconomic ambiguity by using individual analyst's forecasts for macroeconomic variables, e.g. next period real GDP growth or inflation growth.

This chapter contributes to a number of literature. First, it builds on the literature on the firm-, portfolio-, and market-level relationship between stock returns and earnings surprises. Ball and Brown (1968) and Beaver (1968) establish the stylized fact that firm-level stock returns are positively correlated with earnings surprises. Kothari, Lewellen, and Warner (2006) and Cready and Gurun (2010) document a negative contemporaneous relationship between aggregate stock returns and earnings surprises. Our chapter reconciles this seemingly contradictory findings by bringing in the role of ambiguity. Second, it adds values to the literature of the role of ambiguity in explaining investors' asymmetric reaction on good versus bad news. Epstein and Schneider (2008), Hansen and Sargent (2008) and Williams (2009) state that facing ambiguity investors always choose the worst-case scenario. This ambiguity averse behaviour induce stronger reaction to bad news than to good news on the firm-level. Subasi (2011) finds that macroeconomic ambiguity reduces the magnitude of investors' reactions to aggregate earnings news. Our study is different from Subasi (2011) in a couple of ways. Firstly, our uses of uncertainty measure are different. He uses the cross-sectional dispersion in realized firm-level earnings surprises to measure uncertainty. This measure is questionable because it is ex post dispersion based on realized earnings surprise. Secondly, we consider the separate effects of micro- and macro-uncertainty. The two impact on different components of return-earnings relation. Subasi (2011) uses cross-sectional uncertainty and does not differentiate the level of ambiguity.

This chapter is organized as follows. Section 3.2 develop our model and present the model predictions as our testable hypotheses. Section 3.3 describes the data and present our measures for both firm-level and macroeconomic ambiguity. Section 3.4 present the core empirical results of our chapter, relating the earnings response coefficients in three levels to measures of firm-level and market-wide ambiguity. Section 3.5 concludes.

3.2 The model

In this section we construct a simple model which captures the main intuition on how ambiguous information affects the responses of returns to earnings announcements. Assume there are n firms that together make up the market portfolio. For simplicity, we assume all firms are equal in size. At the end of period t, investors observe earnings announcements e_{it} of each of the firm i. Firm's earnings consist of two components: $e_{it} = c_{it} + m_t$, where c_{it} is a firm-specific "cash-flow" component of the earnings and m_t is a market-wide component common for all firms. We assume that $cov[c_{it}, c_{jt}] = 0$ for $i \neq j$, $cov[c_{it}, m_t] = 0$ for any i. In addition, at the end of period t, investors can observe the realization of some market wide shock to returns ("discount rate news") d_t which is common for all stocks. We assume that the discount rate news correlates with the market-wide component of earnings news:

$d_t = m_t + \eta_t$ with $cov[c_{it}, \eta_t] = 0$ for any i.

At the end of period $t-1$, investors observe noisy signals s_{it} about the future cash flow and discount news

$$s_{it} = e_{it} + u_{it},$$

where u_{it} is idiosyncratic noise with $cov[u_{it}, c_{jt}] = 0$ and $cov[u_{it}, \eta_{jt}] = 0$ for all i, j and t. Denote by $\mathbf{s}_t = \{s_{1t}, ..., s_{nt}\}$, $\mathbf{e}_t = \{e_{1t}, ..., e_{nt}\}$, $\Sigma_{\mathbf{se}} = cov[\mathbf{s}, \mathbf{s}]$ and $\Sigma_{\mathbf{s}} = var[\mathbf{s}]$.

Firm i's period t return is given by

$$R_{it} = E_{t-1}[R_{it}] + \varepsilon_{it} - \omega_t,$$

where ε_{it} is the revision to expected earnings of firm i and ω_t is an additional shock to firm i's return associated with common for each firm discount rate news.

3.2.1 Case of no ambiguity

In order to establish benchmark, we start by considering the case with no ambiguity in information and signals. This implies that investors know exactly the probabilistic distributions of all the variables in the model. Hence, $c_{it} \sim N(0, \sigma_c^2)$ for any i and t, $m_t \sim N(0, \sigma_m^2)$, $\eta_{it} \sim N(0, \sigma_\eta^2)$ and $u_{it} \sim N(0, \sigma_u^2)$.

We are interested in computing the responses of individual firms' returns to earnings announcements as well as the response of the market return to the aggregate announcement. We start with the former one.

Individual firms responses

Given the set of signals s_{it}, the investors' expectation about the realization of variables e_{it} and d_t are:

$$\begin{aligned} E_{t-1}[e_{it}|\mathbf{s}] &= \gamma_i \mathbf{s}_t = \sum_{j=1}^{n} \gamma_i^j s_{jt} \\ E_{t-1}[d_t|\mathbf{s}] &= \delta \bar{s}_t, \end{aligned}$$

where $\gamma_{\mathbf{i}} = \{\gamma_i^1, ..., \gamma_i^n\} = \Sigma_{\mathbf{se}} \Sigma_{\mathbf{s}}^{-1}$ and $\delta = \frac{cov[d_t, \bar{s}_t]}{var[d_t]} = \frac{n\sigma_m^2}{\sigma_c^2 + n\sigma_m^2 + \sigma_u^2}$ (see Appendix A.1 for detailed derivation). Hence, the announcement surprises ε_{it} and ω_t are

$$\varepsilon_{it} = e_{it} - E_{t-1}[e_{it}|\mathbf{s}] = e_{it} - \sum_{j=1}^{n} \gamma_i^j s_{jt}, \tag{3.1}$$

$$\omega_t = d_t - E_{t-1}[d_t|\mathbf{s}] = d_t - \gamma_d \bar{s}_t. \tag{3.2}$$

The earnings response coefficient of firm i's return to its earnings surprise is equal to the beta coefficient:

$$\beta_i = \frac{cov[R_{it}, \Delta e_{it}]}{var[\Delta e_{it}]}, \tag{3.3}$$

where the covariance between the returns of the stock and the changes in the earnings announcements,

$$cov[R_{it}, \Delta e_{it}] = cov[\varepsilon_{it}, e_{it}] - cov[\omega_t, e_{it}].$$

Given that

$$\begin{aligned} cov[\varepsilon_{it}, e_{it}] &= var[e_{it}] - \sum_{j=1}^{n} \gamma_i^j cov[s_{jt}, e_{it}] = (\sigma_c^2 + \sigma_m^2)(1 - \gamma_i^i) - (n-1)\gamma_i^j \sigma_m^2, \\ cov[\omega_t, e_{it}] &= cov[d_t, e_{it}] - \delta cov[\bar{s}_t, e_{it}] = \sigma_m^2 - \frac{\delta}{n}(\sigma_c^2 + n\sigma_m^2) \end{aligned}$$

we get

$$cov[R_{it}, \Delta e_{it}] = (\sigma_c^2 + \sigma_m^2)\left(1 - \gamma_i^i + \frac{\delta}{n}\right) - \sigma_m^2\left(1 + (n-1)\gamma_i^j - \delta + \frac{\delta}{n}\right).$$

Aggregate responses

In order to look at the reaction of the market portfolio returns to the aggregate earnings, we define the aggregate market return as

$$R_{mt} = \frac{1}{n}\sum_{i=1}^{n} R_{it} = E_{t-1}[R_{mt}] + \bar{\varepsilon}_t - \omega_t$$

where $E_{t-1}[R_{mt}] = \frac{1}{n}\sum_{i=1}^{n} E_{t-1}[R_{it}]$ and $\bar{\varepsilon}_t = \frac{1}{n}\sum_{i=1}^{n}\varepsilon_{it} = \bar{e}_t - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_i^j s_{jt}$ with the aggregate earning being defined as $\bar{e}_t = \frac{1}{n}\sum_{i=1}^{n} e_{it} = \frac{1}{n}\sum_{i=1}^{n} c_{it} + m_t$.

The earnings response coefficient of the portfolio returns to the aggregate earnings is given by

$$\beta_m = \frac{cov[R_{mt}, \Delta\bar{e}_t]}{var[\Delta\bar{e}_t]}, \tag{3.4}$$

where the covariance between the aggregate returns of the the changes in aggregate earnings is

$$cov[R_{mt}, \Delta\bar{e}_t] = cov[\bar{\varepsilon}_t, \bar{e}_t] - cov[\omega_t, \bar{e}_t].$$

Since $cov[s_{jt}, \bar{e}_t] = \sigma_m^2 + \frac{\sigma_c^2}{n}$ we have

$$\begin{aligned} cov[\bar{\varepsilon}_t, \bar{e}_t] &= var[\bar{e}_t] - \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{n}\gamma_i^j cov[s_{jt}, \bar{e}_t]\right) = var[\bar{e}_t] - \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{n}\gamma_i^j\left(\sigma_m^2 + \frac{\sigma_c^2}{n}\right)\right) &(3.5)\\ &= \frac{(\sigma_c^2 + n\sigma_m^2)}{n}\left(1 - \gamma_i^i - (n-1)\gamma_i^j\right). &(3.6) \end{aligned}$$

It is also straightforward to compute

$$cov[\omega_t, \bar{e}_t] = cov[d_t, \bar{e}_t] - \delta cov[\bar{s}_t, \bar{e}_t] = \sigma_m^2 - \frac{\delta(\sigma_c^2 + n\sigma_m^2)}{n}. \tag{3.7}$$

Hence, taking into account the fact that $var[\Delta \bar{e}_t] = \frac{\sigma_c^2 + n\sigma_m^2}{n}$, the covariance

$$cov[R_{mt}, \Delta \bar{e}_t] = \frac{\sigma_c^2 + n\sigma_m^2}{n} \left(1 - \gamma_i^i - (n-1)\gamma_i^j) + \delta - \frac{n\sigma_m^2}{\sigma_c^2 + n\sigma_m^2} \right). \quad (3.8)$$

3.2.2 Case of ambiguous information

Let us consider now an extension of the model where the investors face ambiguity regarding the variance of firm-specific and market-wide cash flow components. The ambiguity of the firm specific component is purely idiosyncratic and represents the quality of information environment around firm-specific cash flows news. We will call it firm-specific ambiguity hereafter. The ambiguity about the market-wide represents the overall ambiguity about the market as whole. It refers to the quality of information environment around market-level cash flow news as well as discount rate news. We will call it market-wide ambiguity.

We model both types of ambiguity using the multiple prior model of Gilboa and Schmeidler (1989). More specifically, the investors do not observe the variances of c_{it} and m_t and know only their interval ranges: $\sigma_{ci}^2 \in [\underline{\sigma}_c^2, \overline{\sigma}_c^2]$ and $\sigma_m^2 \in [\underline{\sigma}_m^2, \overline{\sigma}_m^2]$. Similar approach has been adopted by Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011).

Investor's preferences exhibit ambiguity aversion and are described by the max-min expected utility model (see Gilboa and Schmeidler (1989)) for the preference specification of the model). We assume that the investor chooses parameters σ_{ci}^2 and σ_m^2 through the minimization problem

$$\min_{\substack{\sigma_{ci}^2 \in [\underline{\sigma}_c^2, \overline{\sigma}_c^2] \\ \sigma_m^2 \in [\underline{\sigma}_m^2, \overline{\sigma}_m^2]}} E\left[R_{mt}(\sigma_{c1}^2, ..., \sigma_{cn}^2, \sigma_m^2)|\mathbf{s}\right], \quad (3.9)$$

where

$$E\left[R_{mt}(\sigma_{c1}^2,...,\sigma_{cn}^2,\sigma_m^2)|\mathbf{s}\right] = \frac{1}{n}\sum_{i=1}^{n}\sum_{i=1}^{n}\gamma_i^j(\mathbf{s})\mathbf{s_{jt}} + \delta(\mathbf{s})\bar{\mathbf{s}}_\mathbf{t}$$

where $\gamma_i^j \equiv \gamma_i^j\left(\sigma_{c1}^2,...,\sigma_{cn}^2,\sigma_m\right)$ and $\delta \equiv \delta\left(\sigma_{c1}^2,...,\sigma_{cn}^2,\sigma_m\right)$ (see Appendix A.2 for detailed representations).

Denote by $\sigma^{2*} = \underset{\substack{\sigma_{ci}^2 \in [\underline{\sigma}_c^2,\overline{\sigma}_c^2] \\ \sigma_m^2 \in [\underline{\sigma}_m^2,\overline{\sigma}_m^2]}}{\operatorname{argmin}} E\left[R_{mt}(\sigma_{c1}^2,...,\sigma_{cn}^2,\sigma_m^2)|\mathbf{s}\right]$

Similarly to the case with no ambiguity, we compute two response coefficients: individual firms' returns responses to earnings surprises and the market return response to the aggregate earnings. We start with the former one.

Individual firms responses

Given the realizations of signals $\mathbf{s}$ and the choice of parameters determined by the representative investor preferences, the return if asset i is given by

$$R_{it} = E_{t-1}[R_{it}] + \varepsilon_{it} + \omega_t = E_{t-1}[R_{it}] + (e_{it} - \sum_{j=1}^{n}\gamma_i^j\left(\sigma^{2*}\right)s_{it}) - (d_t - \delta\left(\sigma^{2*}\right)\bar{s}_t).$$

The beta coefficient is $\beta_i = \frac{cov[R_{it},\Delta e_{it}]}{var[\Delta e_{it}]}$. The covariance between the returns of the stock and the changes in the earnings announcements is

$$cov[R_{it},\Delta e_{it}] = cov[\varepsilon_{it},e_{it}] - cov[\omega_t,e_{it}],$$

where

$$\begin{aligned} cov[\varepsilon_{it},e_{it}] &= var[e_{it}] - \sum_{j=1}^{n}cov[\gamma_i^j(\sigma_\mathbf{s})s_{jt},e_{it}] = \sigma_c^2+\sigma_m^2 - \sum_{j=1}^{n}E[\gamma_i^j(\sigma_\mathbf{c})s_{jt}e_{it}] \\ &= \sigma_c^2+\sigma_m^2 - \sum_{j=1}^{n}E[\gamma_i^j(\sigma_\mathbf{c})s_{jt}E[e_{it}|\mathbf{s}]] = \sigma_c^2+\sigma_m^2 - \sum_{j=1}^{n}\sum_{\iota=1}^{n}\gamma_i^\iota E[\gamma_i^j\left(\sigma_\mathbf{c}\right)s_{jt}s_{\iota t}] \end{aligned}$$

and

$$\begin{aligned} cov[\omega_t, e_{it}] &= cov[d_t, e_{it}] - cov[\delta\left(\mathbf{s}\right)\bar{s}_t, e_{it}] = \sigma_m^2 - E[\delta\left(\mathbf{s}\right)\bar{s}_t e_{it}] \\ &= \sigma_m^2 - E[\delta\left(\sigma_\mathbf{c}\right)\bar{s}_t E[e_{it}|\mathbf{s}]] = \sigma_m^2 - \sum_{j=1}^{n}\gamma_i^j E[\delta\left(\sigma_\mathbf{c}\right)\bar{s}_t s_{jt}]. \end{aligned}$$

Aggregate responses

As before, we compute the response coefficient of the market returns to the aggregate change in earnings as $\beta_m = \frac{cov[R_{mt}, \Delta e_{mt}]}{var[\Delta e_{mt}]}$. The covariance between the market return response and the aggregate change in earnings is given by $cov[R_{mt}, \Delta\bar{e}_t] = cov[\bar{\varepsilon}_t, \bar{e}_t] - cov[\omega_t, \bar{e}_t]$, where $\bar{\varepsilon}_t = \bar{e}_t - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_i^j(\sigma_\mathbf{c})s_{jt}$ as the response coefficients $\gamma_i(\sigma^*)$ are not constant across firms any more and are functions of the variances σ^*. Thus,

$$\begin{aligned} cov[\bar{\varepsilon}_t, \bar{e}_t] &= var[\bar{e}_t] - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}cov[\gamma_i^j(\mathbf{s})s_{jt}, \bar{e}_t] = var[\bar{e}_t] - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}E[\gamma_i^j(\mathbf{s})s_{jt}\bar{e}_t] \\ &= var[\bar{e}_t] - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}E[\gamma_i^j(\mathbf{s})s_{jt}E[\bar{e}_t|\mathbf{s}]] = \frac{\sigma_c^2 + n\sigma_m^2}{n} - \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{\iota=1}^{n}\sum_{k=1}^{n}\gamma_\iota^k E[\gamma_i^j(\mathbf{s})s_{jt}s_{kt}] \end{aligned}$$

and

$$\begin{aligned} cov[\omega_t, \bar{e}_t] &= cov[d_t, \bar{e}_t] - cov[\delta(\mathbf{s})\bar{s}_t, \bar{e}_t] = \sigma_m^2 - E[\delta(\mathbf{s})\bar{s}_t\bar{e}_t] = \sigma_m^2 - \frac{1}{n}\sum_{i=1}^{n}E[\delta(\mathbf{s})\bar{s}_t E[e_{it}|\mathbf{s}]] \\ &= \sigma_m^2 - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_i^j E\left[\delta(\mathbf{s})\bar{s}_t s_{jt}\right]. \end{aligned}$$

3.2.3 Simulations and hypotheses development

In order to quantify the effect of ambiguity on the earnings response coefficients we perform a comparative statics analysis. However, the earnings response coefficients cannot be computed in the closed form. To circumvent this difficulty we fix the values of σ_v^2, σ_u^2, σ_c^2, σ_d^2 and n and use Monte Carlo simulations to estimate the earnings response coefficients for different values of the ambiguity parameters $\Delta_c =$

$\bar{\sigma}_c^2 - \sigma_c^2$ and $\Delta_d = \bar{\sigma}_d^2 - \sigma_d^2$. To do this we simulate 100,000 repetitions of variables $\mathbf{c}$, $\mathbf{m}$, $\mathbf{v}$ and $\mathbf{u}$ for each of n firms with $n = 50, 100, 500$.

We assume the actual parameters are as follows: $\sigma_v^2 = 4.0 \times 10^{-4}$, $\sigma_u^2 = 5.3 \times 10^{-4}$, $\sigma_c^2 = 2.94 \times 10^{-4}$ and $\sigma_d^2 = 1.22 \times 10^{-5}$. Those coefficients are computed using back-envelope method using actual response coefficients.[2] We consider six different degrees of firm-level ambiguity: $\Delta_c = 0, 0.2\sigma_c^2, 0.4\sigma_c^2, 0.6\sigma_c^2, 0.8\sigma_c^2, 0.99\sigma_c^2$ and six different degrees of market-level ambiguity: $\Delta_d = 0, 0.2\sigma_d^2, 0.4\sigma_d^2, 0.6\sigma_d^2, 0.8\sigma_d^2, 0.99\sigma_d^2$.

Figure 3.1 plots individual response coefficients for different degrees of firm-level and market-level ambiguity. Three different panels exhibit cases for different number of cross-section. The earnings response coefficient clearly increases with firm-level ambiguity. This is true for each degree of market-level ambiguity. The intuition is as follows. Investors react asymmetrically to good versus bad news under firm-level ambiguity. The higher the ambiguity, the stronger the reaction is to bad than to good news. As a result, the average reaction to firm-specific news is stronger with high level of firm-level ambiguity. Similarly, market reacts stronger to market-wide bad than to good news under macroeconomic ambiguity. At the same time, market-wide ambiguity amplifies the effect of discount rate news. Under low macroeconomic ambiguity, discount rate news effect seems to exceed that of market-wide cash flows news. Under high macroeconomic ambiguity, the overreaction to common cash flows news seems to dominate. Hence, we observe macroeconomic ambiguity decreases the earnings response coefficient under low firm-level ambiguity while increases the coefficient under high firm-level ambiguity.

Figure 3.2 contains plots of the aggregate responses of the market returns to the aggregate earnings. Similarly to the individual response coefficients, the aggregate responses increase with firm-level ambiguity. When forming portfolios firm-specific cash-flow news and their effects diversify away so that only market-wide news prevails (see Campbell and Shiller (1988b), Kothari, Lewellen, and Warner

[2]See the following section how we estimate the earnings response coefficients empirically.

(2006)). However, ambiguity effect is not diversified away and always goes in the same direction (see Epstein and Schneider (2008)). Therefore, positive cash-flow effect remains in the response coefficient for portfolios of high firm-level ambiguity firms. However, the market-level ambiguity has different effects on the aggregate response coefficient depending on the degree of the firm-level ambiguity. Specifically, the market-level ambiguity increases the aggregate response coefficient for portfolios of highly ambiguous firms while it decreases the aggregate response coefficient for portfolios of low-ambiguity firms. Since market-level discount news has opposite effect on the response coefficient than cash-flow news, market-wide ambiguity amplifies its negative effect. Hence, for the portfolios of low firm-level ambiguity cash-flow news are diversified while the discount rate news effect is amplified, we expect to observe a strong negative aggregate response coefficient. However, for portfolios of highly ambiguous firms, the non-diversified effect of ambiguous cash-flow news dominates the negative effect of the discount rate news and we obtain a positive aggregate response coefficient.

When forming market portfolio, the effect of market-wide ambiguity is determined by three factors: the undiversified firm-specific cash flow news, the market-wide cash flows news, and the discount rate news. Macroeconomic ambiguity affects the latter two with opposite signs. It increases the effect of market-side cash flow news while amplifying that of discount rate news. Depending on the average firm-level ambiguity level, the market wide effect of macroeconomic ambiguity could vary in nature.

Hence, based on the theoretical predictions we formulate our empirical hypotheses.

H 1. *Individual response coefficient increases with firm-level ambiguity.*

H 2. *Firm-level ambiguity increases the aggregate earnings response coefficient. Moreover, this increase is more pronounced when the degree of market-level ambiguity is high.*

H 3. *High degree of market-level ambiguity leads to an increase in the earnings response coefficient of high-ambiguity stocks and to a decrease in the earnings response coefficient of the low-ambiguity stocks.*

3.3 Data and variable definition

Our sample selection starts from all firms with March, June, September, or December fiscal year-end from 1984 to 2013, with available accounting data in the Compustat quarterly database. We use earnings per share (basic) excluding extraordinary items (Compustat item EPSPXQ) adjusted by stock splits (Compustat item AJEXQ). In case this data is not available, we use earnings per share (diluted) excluding extraordinary items (Compustat item EPSFXQ) adjusted. Following Daniel and Titman (2006), we define book value as book equity to be shareholders' equity numbers (Compustat item SEQQ) minus total preferred/preference stock (Compustat item PSTKQ) plus the deferred taxes and investment tax credit (Compustat item TXDITCQ) and divided by common shares outstanding (Compustat item CSHOQ) adjusted. If book equity is missing, we use total common/ordinary equity (Compustat CEQQ) or total assets (Compustat item ATQ) minus total liabilities (Compustat item LTQ).

Following literature (e.g., Kothari, Lewellen, and Warner (2006), Sadka and Sadka (2009)), earnings surprise dES_{it} of firm i in quarter t is defined as

$$dES_{it} = \frac{E_{i,t} - E_{i,t-4}}{S_{i,t-4}},$$

where $E_{i,t} - E_{i,t-4}$ is seasonally differenced quarterly earnings and S_{it} is either market price ($S_{it} = P_{it}$), book equity ($S_{it} = B_{it}$), or earnings ($S_{it} = E_{it}$).

For market- and portfolio-level estimates of earnings surprises, we use value-weighted cross-sectional averages of individual stock earnings surprises where value weights are calculated as the beginning-of-period market capitalization. Stock returns R_{it} are calculated using adjusted prices (Compustat items PRCCQ / AJEXQ). In each period we exclude firms with beginning-of-quarter price below \$1. Also, we exclude the top and bottom 0.5% ranked on the distribution of the corresponding measures of earnings surprise each quarter.

We calculate earnings surprises for portfolios as well as the overall market using aggregate data. The aggregate series is simply the cross-sectional sum of earnings changes multiplied by the number of shares outstanding for all firms in the sample, subsequently scaled by the sum of lagged market equity, lagged book equity, or lagged multiplication of earnings and the number of shares outstanding for the same group of firms.[3]

Analysts' earnings forecasts data are from the Institutional Brokers Estimate System (IBES) U.S. Summary History dataset via WRDS. The data is available on a monthly basis; the forecasts are provided on Thursday before the third Friday of the month. We only consider forecasts that we within the fiscal quarter. We also use individual forecasts from the IBES U.S. Detail History dataset to mitigate the problematic rounding procedure and the results are similar. We exclude firms that in the current quarter has less than two analysts' earnings per share forecasts.

3.3.1 Measures of the degree of ambiguity

Recent empirical literature uses the disagreement of professional forecasters to proxy the degree of ambiguity in the market (see Anderson, Ghysels, and Juergens (2009) and Drechsler (2013)). Intuitively, if forecasters produce very different and conflicting forecasts about the fundamentals (either of a firm or the economy in general), investors are likely to be unsure about the distributions of stock returns as they tend to condition their beliefs on the analysts' forecasts. Thus, when dispersion among analysts' opinion regarding the future performance of stock markets is high,

[3] We also use the value-weighted data based on per share numbers, where the per share earnings surprises $dE_{it}/S_{i,t-4}$ are weighted using the number of shares outstanding of quarter t. Results are qualitatively similar and can be available upon the request.

ambiguity is also likely to be high since investors cannot confidently narrow down the set of their beliefs to a single prior.

At the same time, dispersion of analysts' forecasts might not necessarily be the ideal proxy for measuring the degree of ambiguity. Barron, Kim, Lim, and Stevens (1998) argue that the ambiguity component of the dispersion of analysts forecasts can be contaminated by the disagreement component that comes from the asymmetric information. This can be a serious issue especially when proxies the degree of ambiguity at individual firm level. Barron, Kim, Lim, and Stevens (1998) propose a decomposition of the forecasts dispersion into uncertainty and disagreement in the following way. Define the consensus measure ρ as

$$\rho = \frac{C}{V}, \tag{3.10}$$

where V is overall uncertainty defined as a simple average of individual uncertainty (i.e. variance of forecast errors) over N analysts. C is common uncertainty defined as the average pair-wise covariance among analysts' beliefs. Thus, ρ measures the degree to which analysts' beliefs covary relative to the overall uncertainty, in other words, the ratio of common uncertainty to the overall uncertainty.

To compute the consensus among the analysts, we use a special case of above formula where the private information is of equal precision[4]:

$$\rho = \frac{H}{H+Z}, \tag{3.11}$$

where $H = \frac{(SE - \frac{V}{N})}{(SE - \frac{V}{N} + V)^2}$ measures the precision of common information and $Z = \frac{V}{(SE - \frac{V}{N} + V)^2}$ measures the precision of idiosyncratic information. Here, SE is the mean squared error of forecasts scaled by the absolute value of the actual forecasted variable, V is the variance of forecasts scaled by the absolute value of the actual

[4] Please refer to Barron, Kim, Lim, and Stevens (1998) for detailed explanation regarding the relation with common and private information

forecasted variable, and N is the number of forecasts. Thus, the variable ρ measures the uncertainty attributable to experts' reliance on imprecise common information. We argue that this measure captures the degree of ambiguity embedded in the dispersion of analysts' forecasts: that is, the more information uncertainty is, the more likely that investors form multiple beliefs about fundamentals of stocks and the economy as a whole. The results using dispersion of analyst forecasts as an alternative measure of ambiguity are similar.

We construct firm-level ambiguity by using analysts' forecasts of individual firm earnings. They reflect news about individual firms' news on cash flows. The higher is the uncertainty component in the dispersion of analysts' earnings forecasts, the more ambiguous is signals about the firm's cash flow news. Thus, we denote by FU_i the uncertainly measure ρ constructed on the basis of analysts' earnings forecasts for firm i from IBES data. Specifically, SE will correspond to the mean squared *earnings* forecasts error and V corresponds to the variance of *earnings* forecasts. Hence, we argue that FU_i is a good measure for the degree of ambiguity in the market for two reasons. First, because it is based on the dispersion of experts' forecasts about the fundamentals, it nicely measures the set of reasonable models considered by the representative investor. Secondly, it is free of the impact of asymmetric information component that can possibly contaminate the effect of ambiguity. In fact, Doukas, Kim, and Pantzalis (2006) has demonstrated that uncertainty and asymmetric information component have indeed opposite effects on stock returns.

In order to examine the cross-sectional effect of firm-level ambiguity on the earnings response coefficient we categorize stocks into five different groups based on the degree of firm-level ambiguity. Specifically, every quarter we group stocks into quintiles of firm-level ambiguity variable FU_i. We define dummy variable D^j_{it}, $j = 1, ..., 5$ to be equal to 1 if stock i falls into firm-level ambiguity quintile j in quarter t. In this way, dummy variable D^1 corresponds to the stocks with the least ambiguous cash-flow information and D^5 correspond to the most ambiguous stocks.

In order to proxy the degree of market-level ambiguity we use individual analyst's forecasts for macroeconomic variables, e.g. real GDP growth or inflation growth, that comes from the Survey of Professional Forecasters managed by the Federal Reserve Bank of Philadelphia. Similar to the firm-level ambiguity measure, we obtained the decomposed uncertainty from the dispersion of analysts' forecasts for the next period real GDP growth rate[5]. That is, we denote by MU the uncertainly measure ρ constructed on the basis of experts' forecasts of the GDP growth. Specifically, SE corresponds now to the mean squared *GDP* forecasts' error and V corresponds to the variance of *GDP* growth forecasts. Finally, in order to estimate the differential effect of market-level ambiguity on the earnings response coefficient, we define a dummy variable D_t^M that is equal to 1 if the market-level ambiguity MU_t is above its historical mean value, and zero otherwise.

The choice of the realized value, needed for calculating the mean squared forecasts' error, depends on the version of data that professional forecasters are trying to predict. Survey of Professional Forecasters database offers five vintages of the realized value, ranging from the initial-release numbers to the values that we understand today. The reliability of the historical values increases in time while the availability decreases in time. We use the latter four vintages on the ground that they suffer less measurement error yet are close enough to what the professionals are try to forecast[6]. The results are similar for each of the four.

3.3.2 Summary statistics

Table 3.1 reports summary statistics for stock returns, earnings surprises and ambiguity measures. Panel A shows the mean, standard deviation, and quintile values for firm and market level variable. The average number of stocks per quarter is 1498. The average return across firms is around 3.3% per quarter, with a standard devi-

[5]Other studies, for instance Anderson, Ghysels, and Juergens (2009) and Drechsler (2013), have used the raw dispersion of next period RGDP growth rate to gauge macroeconomic uncertainty.

[6]The middle three measures of historical numbers are, respectively, the revised values as they appear one, five, and nine quarters after the initial release.

ation 25.4%. The mean for earnings surprise measure dEP is 0.2%. The mean for dEB and dEE are 0.3% and 8.7% respectively. The average firm-level uncertainty is around 0.141 with standard deviation 0.603. The average market-level uncertainty is around 3.069 with standard deviation 4.675. The total number of observation stands at 179,913. Panel B presents the mean and standard deviation for portfolio level variables.

Table 3.2 describe the correlation between our main variables, namely return, earnings surprises measures, and ambiguity. Firm-level returns and earnings surprises are highly significantly correlated at 10% (indicated in bold). It is interesting to observe that aggregate earnings surprises at portfolio level is highly significantly correlated with firm-level ambiguity at 10%. For all three level of analysis, our three earnings surprises measures are all highly significantly correlated with each other.

Figure 3.3 plots the time-series of the market-level ambiguity measure for our sample period. The series has several big spikes, particularly in 1985-1986, 1990-1991, 1994-1995, 1999-2001, the recent crisis and the second half of 2010.

3.4 Empirical analysis

Our main tests explore how firm- and market-level ambiguity affect the stocks reaction to earnings surprises. We start our analysis with the individual firms responses.

3.4.1 Firm-level analysis

We test our hypothesis 1 by estimating the following pooled panel regression:

$$\begin{aligned} R_{it} &= \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{it}^j + \alpha_6 D_t^M + \beta_1 dES_{it} + \sum_{j=2}^{5} \beta_j dES_{it} \times D_{it}^j \\ &+ \gamma_1 dES_{it} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{it} \times D_{it}^j \times D_t^M + \alpha_7 MV_{it} + \epsilon_{it}, \end{aligned} \tag{3.12}$$

MV_{it} denotes the log market capitalization for firm i at the beginning of quarter t. The estimation results are given in Table 3.3.

The results are consistent with our theoretical predictions. The individual stock prices react positively to earnings surprises dEP. The earnings response coefficient β_1 is 0.841 and is statistically significant at 1% level when we do not control for ambiguity. The earnings response coefficient is also positive and highly significant when earnings sunrises are proxied by dEB and dEE.

When firm-level ambiguity variables included in the regression, the earnings response coefficient for the least ambiguous firms is 0.455 and remains statistically significant at 1% level. The coefficient increases monotonically with the degree of firm-level ambiguity. The earnings response coefficient for the most ambiguous firms $\beta_1 + \gamma_5$ is 0.861 (i.e. 0.455+0.406) and is statistically larger than the one for the least ambiguous firms β_1. This pattern remains unchanged for the other two proxies of earnings surprise dEB and dEE.

Finally, the earnings response coefficient is significantly positive and increases with firm-level ambiguity even when we control for market-level ambiguity. Overall, the results show that investors respond to corporate earnings news more strongly when the information environment around the firm is highly ambiguous. This confirms our hypothesis 1.

3.4.2 Portfolio-level analysis

In order to test Hypotheses 2 and 3 and estimate the effect ambiguity on the aggregate response coefficient we form portfolio of stocks ranked on the degree of firm-level ambiguity. That is, each quarter we group stocks into five quintiles based on FU_i and form value-weighted portfolios. For each portfolio we compute the aggregated earnings surprises. To perform our tests we estimate the following panel regression:

$$\begin{aligned} R_{pt} &= \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{pt}^{j} + \alpha_6 D_t^M + \beta_1 dES_{pt} + \sum_{j=2}^{5} \beta_j dES_{pt} \times D_{pt}^{j} \\ &+ \gamma_1 dES_{pt} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{pt} \times D_{pt}^{j} \times D_t^M + \alpha_7 MV_{pt} + \epsilon_{pt}, \end{aligned} \tag{3.13}$$

where p denotes the corresponding quintile portfolio, R_{pt} is the value-weighted return on portfolio p, dES_{pt} is the aggregate earnings surprise of portfolio p in quarter t and MV_{pt} is the log of aggregate market capitalization of portfolio p. The results are provided in Table 3.4.

Similarly to the firm-level case, the earnings response coefficient increases with the degree of firm-level ambiguity. In the case when earnings surprise are measured by dEP, the coefficients β_4 and β_5 are positive and statistically significant at 5% and 10% levels respectively. This means that the earnings response coefficient for the portfolio of the most ambiguous firms is significantly higher than for the least ambiguous portfolio. This result is weaker, however, when dEB and dEE variables are used as proxies for earnings surprise – only β_4 is statistically significant at 10% in the case of $S = B$ (see columns (2), (5) and (8) of Table 3.4). When we control for market-level ambiguity (columns (3), (6) and (9)), the coefficients β_2 to β_5 are statistically insignificant. That is, the increase of the earnings response coefficient is insignificant for the period of low market-level ambiguity. However, the earnings response coefficient increases dramatically with firm-level ambiguity when the market-level ambiguity is high. Indeed, coefficient γ_5 is positive and statistically significant at 5% level when dEP is used as the proxy of earnings surprises (the significance levels of γ_5 is 5% for dEE respectively). This is consistent with our theoretical results and confirms our Hypothesis 2. Indeed, the pale grey line on Figure 3.2 is almost flat suggesting that earnings response coefficient increases with firm-level ambiguity very slowly when the degree of market-level ambiguity is low. At the same time, the black line is steep suggesting that when the information about discount rates is very ambiguous the earnings response coefficient increases with firm-level ambiguity at much higher rate.

The estimation results of Equation 3.13 provide evidence in favour of Hypothesis 3. The coefficient of $dEP_{pt} \times D_t^M$ term, γ_1, is negative and statistically significant at the 5% level. This means that an increase in market-level ambiguity significantly decreases the earnings response coefficient of the portfolio of low ambiguity firms as suggested by our theoretical prediction. In contrast, we observe increases in the earnings response coefficient for high ambiguity portfolios. For example, high market-level ambiguity increases the response coefficient for the second-to-last highest ambiguity portfolios (the sum of the coefficients of $dEP_{pt} \times D_t^M$ and $dEP_{pt} \times D_{pt}^4 \times D_t^M$ is equal to -0.788 (e.g. -4.556+3.768), although the increase measured by γ_4 is statistically insignificant at the 10% level (the corresponding t-statistics is around 1.40). For the last quintile of the highest firm-level ambiguity portfolio, the increase is significant at the 5% level measured by γ_5. The results are similar when dEB and dEE are used as the proxies of earnings surprises.

Lastly, the coefficient for dEP_{pt} of Equation 3.13 is small and statistically insignificant at the 10% level (column (1) of Table 3.4). This is what the most of the existing literature finds: an insignificant aggregate earnings response coefficient. Out results show that the insignificance is due to the interacting effects of firm-level and market-level ambiguities on earnings surprises. High market ambiguity decreases the response coefficients for low ambiguity firms (i.e. γ_1) and increases the response coefficients for high ambiguity counterparts (i.e. γ_5). Those two contrasting forces cancel each other on average and consequently produce an insignificant aggregate earnings response coefficient.

3.4.3 Aggregate-level analysis

Our theoretical model implies that the sign of the aggregate earnings response coefficient depends on the overall level of ambiguity about cash flow news on the market.

That is, if low ambiguity firms prevail in the market we can expect a negative price responses to the aggregate earnings. On the other hand if the overall level of chase flow ambiguity is high, the earnings response coefficient is expected to be positive. Finally, if the market is populated by firms with both high and low degree of firm-level ambiguity then both effects would cancel each other and we expect to see small and insignificant market reaction. In this section we verify empirically which of those statements is true. To do this we estimate the following time series regression:

$$R_t^M = \beta_0 + \beta_1 dES_t + \beta_2 D_t^M + \beta_3 dES_t \times D_t^M + \epsilon_t, \tag{3.14}$$

where R_t^M is the market return at time t, dES_t is the aggregate earnings surprises at time t. Table 3.5 show the estimation results.

When market-level ambiguity is not included in the regression, the results are similar that is found in the existing literature (see Kothari, Lewellen, and Warner (2006), Sadka and Sadka (2009)). The aggregate earnings response coefficient is insignificant regardless of which proxy of earnings surprises is used (see columns (1), (4) and (7) of Table 3.5). When we control for market-level ambiguity, the coefficient β_1 remains insignificant. Furthermore, coefficient β_3 is positive but also statistically insignificant. Thus, the results are in line with the third statement. Aggregate earnings response coefficient is insignificant both for low and high level of market-level ambiguity. This again confirms our previous point that taking into account both firm- and market-level ambiguity is important for correct and unbiased estimation of the earnings response coefficient.

To check the robustness of our results, we employ different measures of ambiguity. Firstly, we try using higher criterion for creating high ambiguity dummy variable. The value of the dummy variable is set to one if the macroeconomic uncertainty is above it's 80% value. The results are consistent and present in Tables 3.6, 3.7, and 3.8. Secondly, we try the uncertainty measured constructed by Anderson, Ghysels, and Juergens (2009). The results are consistent and present in Tables 3.9, 3.10, and 3.11.

3.5 Conclusions

In this chapter we investigate how ambiguity affects return-earnings relation on both firm- and aggregate-level. Literature shows that positive firm-level earnings news is informative about a firm's future cash flows, thereby increases its contemporaneous stock price. However, this positive return-earnings relation does not translate into aggregate level. In fact, a negative contemporaneous relationship between market returns and aggregate earnings surprises has been documented in recent literature (Kothari, Lewellen, and Warner, 2006; Sadka and Sadka, 2009). The puzzling finding could be explained by the diversification of firm-specific earnings surprises together with either high predictability of returns or high predictability of aggregate earnings changes. On firm-level, distortion of diversification effect (of firm-specific cash flows news) by firm-level ambiguity implies that portfolio-level ERC is expected to increase in firm-level ambiguity. On aggregate-level, the effect of microeconomic ambiguity depends on which of the above two explanations is favoured. If expected returns are highly predictable, then for the lowest firm-level ambiguity portfolio, high macroeconomic ambiguity should decreases the response coefficient thanks for the dominance of discount rate news. For the highest firm-level ambiguity portfolio where cash flows news dominates, high macroeconomic ambiguity amplifies the distorting diversification effect thereby increases the response coefficient. If aggregate earnings are highly predictable, then for both the lowest and the highest firm-level ambiguity portfolios, high macroeconomic ambiguity intuitively resulting in low predictability is expected to increase the response coefficients. Motivated by the differential implications of the two explanations, this chapter constructs a theoretical model generating predictions in favour of the former explanation and provides empirical evidence supporting all the hypotheses.

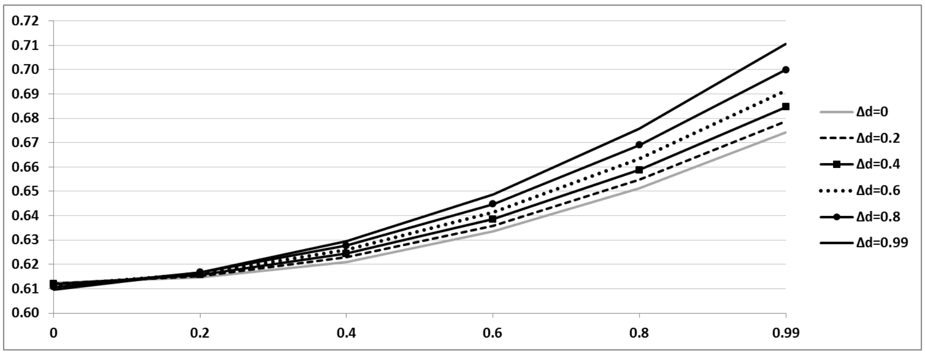
Our results show that individual response coefficient increases with firm-level ambiguity. Firm-level ambiguity increases the aggregate earnings response coefficient. Moreover, this increase is more pronounced when the degree of market-level ambiguity is high. High degree of market-level ambiguity leads to an increase in the earnings response coefficient of high-ambiguity stocks and to a decrease in the earnings response coefficient of the low-ambiguity stocks. We conclude that the negative aggregate relation comes from the diversification effect as well as an amplifying effect of macroeconomic ambiguity on discount rate news and market-wide cash flow news.

This chapter indicates several directions for future research. Firstly, the results assume high predictability of future expected returns and a negative correlation between earnings surprises and future expected returns. Empirical evidence on these points is weak due to the difficulty of finding appropriate discount rate proxies and lack of consistent methodologies to test them. It will be a good contribution to provide further robust evidence to support this assumption. Secondly, the results preclude the explanation based on high predictability of aggregate earnings changes. In particular, the study assumes high level macroeconomic ambiguity reduces the predictability of aggregate earnings changes. Although this is intuitive, the rigour of this subject requires a thorough investigation in this matter.

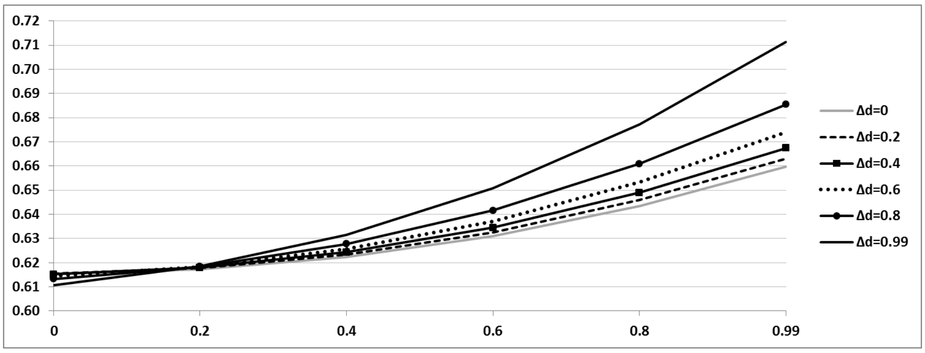
Figure 3.1: Individual responses

This figure plots individual response coefficients for different degrees of firm-level and market-level ambiguity. Three different panels exhibit cases for different number of cross-section: 50, 200, and 500. The horizontal axis refers to the degree of firm-level ambiguity. The vertical axis refers to the earnings response coefficient. The legend refers to each degree of market-level ambiguity. We consider six different degrees of firm- as well as market-level ambiguity, starting with no ambiguity, to 20%, 40%, 60%, 80%, and 99% each side.

Panel A: N=50



Panel B: N=200



Panel C: N=500

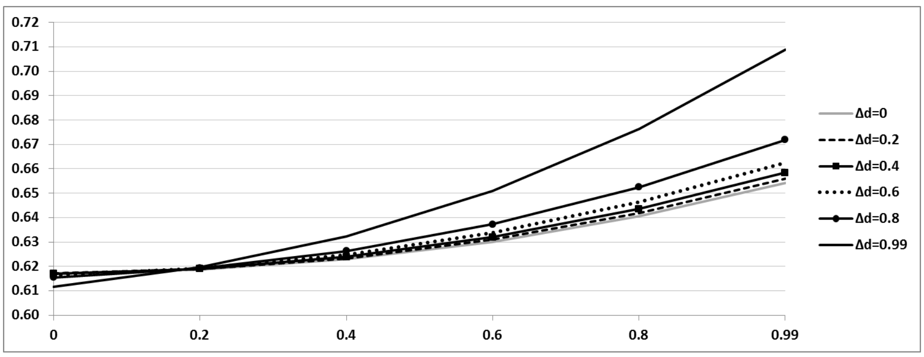
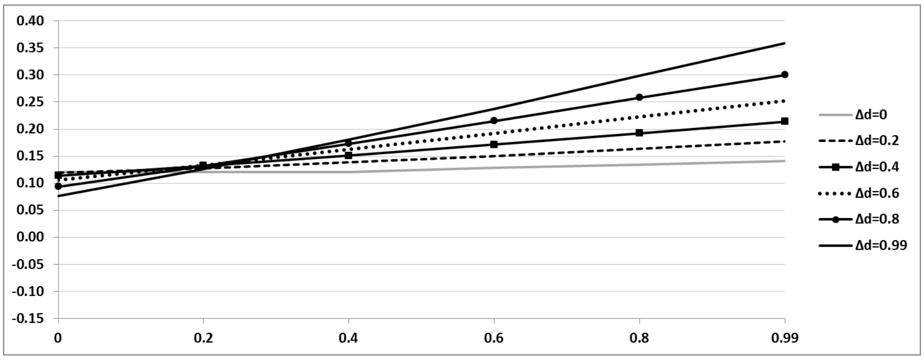


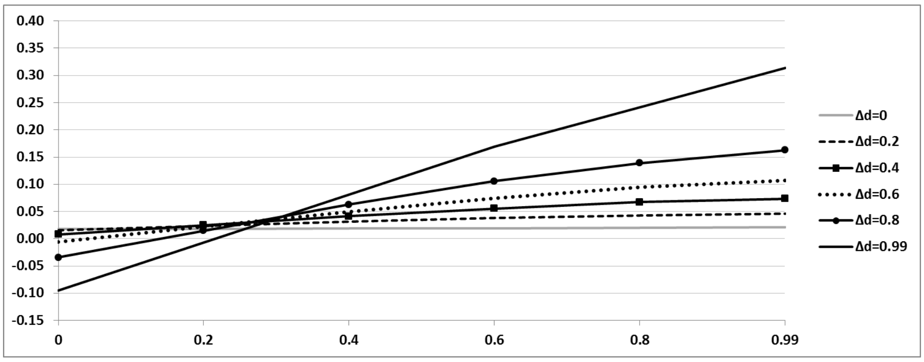
Figure 3.2: Aggregate responses

This figure illustrates earnings response coefficients of portfolio for different degrees of firm-level and market-level ambiguity. Three different panels exhibit cases for different number of cross-section: 50, 200, and 500. The horizontal axis refers to the degree of firm-level ambiguity. The vertical axis refers to the earnings response coefficient. The legend refers to each degree of market-level ambiguity. We consider six different degrees of firm- as well as market-level ambiguity, starting with no ambiguity, to 20%, 40%, 60%, 80%, and 99% each side.

Panel A: N=50



Panel B: N=200



Panel C: N=500

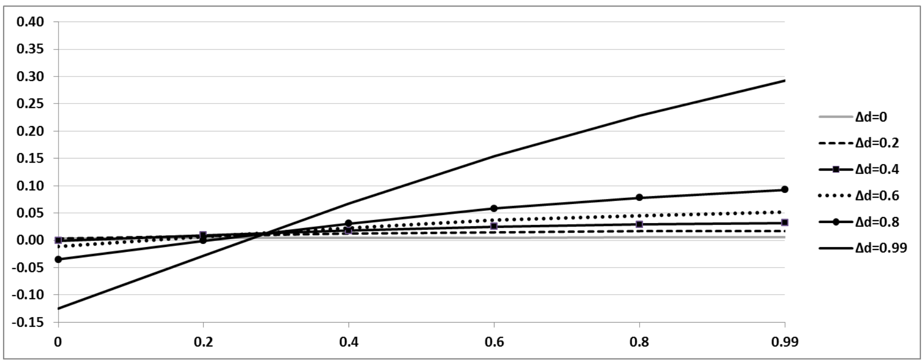


Figure 3.3: Market-level ambiguity

This figure plots the time series of the market-level ambiguity MU_t (black line) for the period from 1984 to 2012. MU_t is computed as the decomposed uncertainty part of the analysts' next-period GDP growth forecasts dispersion. Grey lines indicate periods when MU_t is above it historic mean value. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia.

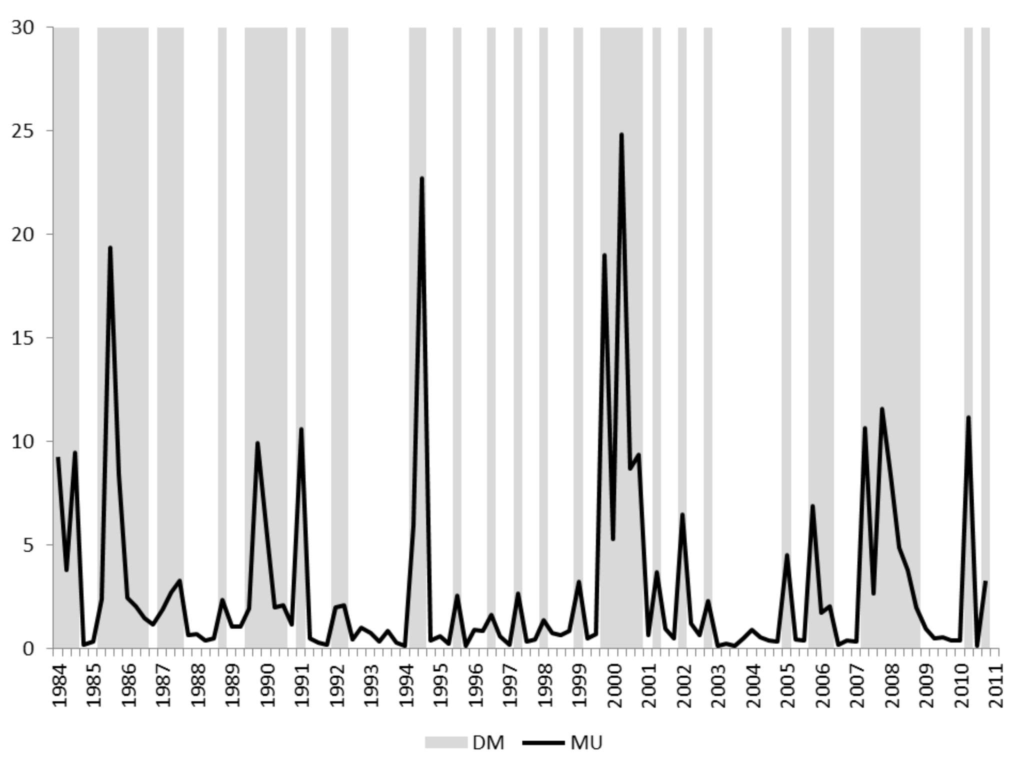


Table 3.1: *Summary statistics*

This table reports the summary statistics of the sample. Panel A describes the mean, standard deviation, and quintiles of the firm and market level variables. R_{it} is the quarterly return for firm i at quarter t. dEP_{it}, dEB_{it}, and dEE_{it} are, respectively, the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book value (B), or earnings (E) for firm i at quarter t. FU_{it} is the firm-level uncertainty for firm i at quarter t, calculated as the decomposed uncertainty part of the analysts' earnings forecasts dispersion. MU_t is the macroeconomic uncertainty for quarter t, calculated as the decomposed uncertainty part of the analysts' next-period GDP growth forecasts dispersion. N is the number of observations in our sample. Panel B describes the mean and standard deviation of the portfolio variables under 5 levels of firm-level uncertainty. MV_{pt} is the average market value in millions. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dEP, dEB, or dEE. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

Panel A: Firm and market level variables					
	Mean	Std.Dev.	Q1	Median	Q3
R_{it}	0.034	0.254	-0.093	0.022	0.139
R_t^M	0.033	0.108	-0.035	0.039	0.094
dEP_{it}	0.002	0.031	-0.005	0.001	0.007
dEB_{it}	0.003	0.068	-0.011	0.003	0.016
dEE_{it}	0.087	1.870	-0.315	0.095	0.500
FU_{it}	0.141	0.603	0.002	0.009	0.044
MU_t	3.069	4.675	0.451	1.046	3.260
N			179,913		
Panel B: Portfolio level variables					
	Low	2	3	4	High
R_{pt}	0.040	0.046	0.044	0.038	-0.001
	0.090	0.103	0.109	0.118	0.130
dEP_{pt}	-0.004	-0.002	0.003	0.004	-0.372
	0.006	0.008	0.011	0.015	1.559
dEB_{pt}	-0.008	-0.003	0.006	0.008	-0.891
	0.124	0.019	0.036	0.033	3.114
dEE_{pt}	-0.002	-0.001	0.002	0.002	-0.174
	0.003	0.004	0.007	0.007	0.667
$MV_{pt}(mil)$	5785.65	4211.282	3865.363	3600.74	2783.748
	3187.11	2076.798	1822.682	1852.623	1615.116

Table 3.2: *Correlations*

This table reports the correlations of important variables. Panel A describes the correlations of the firm level variables. R_{it} is the quarterly return for firm i at quarter t. dEP_{it}, dEB_{it}, and dEE_{it} are, respectively, the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book value (B), or earnings (E) for firm i at quarter t. FU_{it} is the firm-level uncertainty for firm i at quarter t, calculated as the decomposed uncertainty part of the analysts' earnings forecasts dispersion. Panel B and C describe the correlations of portfolio and market level variables, respectively.MU_t is the macroeconomic uncertainty for quarter t, calculated as the decomposed uncertainty part of the analysts' next-period GDP growth forecasts dispersion. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than $1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dEP, dEB, or dEE. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

Panel A: Firm level variables					
	R_{it}	dEP_{it}	dEB_{it}	dEE_{it}	FU_{it}
R_{it}	1	**0.100**	**0.089**	**0.100**	0.003
dEP_{it}		1	**0.667**	**0.547**	0.003
dEB_{it}			1	**0.493**	**0.004**
dEE_{it}				1	0.001
FU_{it}					1
Panel B: Portfolio level variables					
	R_{pt}	dEP_{pt}	dEB_{pt}	dEE_{pt}	FU_{pt}
R_{pt}	1	-0.036	-0.013	-0.012	-0.006
dEP_{pt}		1	**0.970**	**0.958**	**-0.104**
dEB_{pt}			1	**0.958**	**-0.106**
dEE_{pt}				1	**-0.105**
FU_{pt}					1
Panel C: Market level variables					
	R_t^M	dEP_t	dEB_t	dEE_t	MU_t
R_t^M	1	-0.046	-0.009	-0.024	-0.066
dEP_t		1	**0.965**	**0.975**	0.051
dEB_t			1	**0.961**	-0.008
dEE_t				1	0.052
MU_t					1

Table 3.3: *Quarterly returns and earnings surprises: firm-level regressions*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty:

$$R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{it}^j + \alpha_6 D_t^M + \beta_1 dES_{it} + \sum_{j=2}^{5} \beta_j dES_{it} \times D_{it}^j + \gamma_1 dES_{it} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{it} \times D_{it}^j \times D_t^M + \epsilon_{it},$$

where dES_{it} is seasonally differenced earnings scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for firm i at time t. R_{it} is the return for firm i at time t. D_t^M is a dummy variable assigned with 1 if the market-level ambiguity is above its historic mean, and zero otherwise. The market-level ambiguity is defined as the uncertainty part of the dispersion of forecasts for next-period real GDP Growth. D_{it}^j is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D_{it}^5 is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than $1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$		
dES_{it}	0.841***	0.455***	0.656***	0.367***	0.192***	0.288***	1.543***	0.742***	0.935***
	(0.027)	(0.094)	(0.118)	(0.013)	(0.036)	(0.046)	(0.153)	(0.115)	(0.155)
$dES_{it} \times D_{it}^2$		0.236*	0.239		0.072	0.025		0.242	0.250
		(0.124)	(0.163)		(0.049)	(0.064)		(0.155)	(0.207)
$dES_{it} \times D_{it}^3$		0.309***	0.188		0.085*	0.054		0.451***	0.428**
		(0.112)	(0.145)		(0.046)	(0.060)		(0.148)	(0.195)
$dES_{it} \times D_{it}^4$		0.361***	0.094		0.128***	0.025		0.460***	0.311
		(0.111)	(0.141)		(0.047)	(0.062)		(0.152)	(0.199)
$dES_{it} \times D_{it}^5$		0.406***	0.259**		0.245***	0.126**		1.289***	1.637*
		(0.103)	(0.130)		(0.042)	(0.056)		(0.457)	(0.994)
D_t^M			-0.020***			-0.021***			-0.023***
			(0.001)			(0.001)			(0.003)
$dES_{it} \times D_t^M$			-0.486**			-0.217***			-0.490**
			(0.189)			(0.071)			(0.232)
$dES_{it} \times D_{it}^2 \times D_t^M$			0.046			0.106			0.002
			(0.246)			(0.097)			(0.303)
$dES_{it} \times D_{it}^3 \times D_t^M$			0.282			0.073			0.085
			(0.224)			(0.092)			(0.290)
$dES_{it} \times D_{it}^4 \times D_t^M$			0.587***			0.219**			0.360
			(0.222)			(0.093)			(0.299)
$dES_{it} \times D_{it}^5 \times D_t^M$			0.370*			0.254***			-0.478
			(0.207)			(0.084)			(0.991)
D_{it}^2		0.009***	0.010***		0.009***	0.010***		0.009***	0.010***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^3		0.005***	0.006***		0.006***	0.007***		0.006***	0.007***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^4		0.002	0.004**		0.003*	0.005***		0.004**	0.005***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^5		-0.034***	-0.032***		-0.033***	-0.031***		-0.018**	-0.016**
		(0.002)	(0.002)		(0.002)	(0.002)		(0.008)	(0.008)
Const	0.032***	0.036***	0.045***	0.033***	0.036***	0.046***	0.034***	0.036***	0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
adj. R^2	0.011	0.015	0.017	0.010	0.014	0.017	0.003	0.004	0.005

Table 3.4: *Quarterly returns and earnings surprises: portfolio-level regressions*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly portfolio returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty::

$$R_{pt} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{pt}^j + \alpha_6 D_t^M + \beta_1 dES_{pt} + \sum_{j=2}^{5} \beta_j dES_{pt} \times D_{pt}^j + \gamma_1 dES_{pt} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{pt} \times D_{pt}^j \times D_t^M + \epsilon_{pt},,$$

where dES_{pt} is aggregate seasonally differenced earnings (dE) scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for portfolio p at time t. R_{pt} is the return for portfolio p at time t. D_t^M is a dummy variable assigned with 1 if the macroeconomic uncertainty is above its mean, and zero otherwise. The macroeconomic uncertainty is defined as the uncertainty part of the dispersion of forecasts for next-period real GDP Growth. D_{pt}^j is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D_{pt}^5 is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$	
dES_{pt}	-0.002	-2.322*	0.156	0.001	-0.711	-0.019	0.005	-3.523	1.035
	(0.006)	(1.300)	(1.568)	(0.003)	(0.599)	(0.639)	(0.015)	(2.601)	(2.793)
$dES_{pt} \times D_{pt}^2$		0.884	-0.093		0.233	-0.136		1.522	0.180
		(1.217)	(1.524)		(0.688)	(0.862)		(2.615)	(2.940)
$dES_{pt} \times D_{pt}^3$		1.851	0.574		0.533	0.040		2.588	0.467
		(1.420)	(1.694)		(0.606)	(0.705)		(2.714)	(3.098)
$dES_{pt} \times D_{pt}^4$		3.085**	0.858		1.128*	0.549		4.649	1.079
		(1.480)	(1.877)		(0.685)	(0.810)		(3.013)	(3.580)
$dES_{pt} \times D_{pt}^5$		2.317*	-0.160		0.710	0.017		3.520	-1.038
		(1.301)	(1.568)		(0.599)	(0.639)		(2.601)	(2.793)
D_t^M			-0.020			-0.017			-0.018
			(0.015)			(0.014)			(0.015)
$dES_{pt} \times D_t^M$			-4.556**			-1.425			-9.553**
			(2.153)			(1.031)			(4.393)
$dES_{pt} \times D_{pt}^2 \times D_t^M$			1.604			0.917			3.834
			(2.005)			(1.216)			(4.790)
$dES_{pt} \times D_{pt}^3 \times D_t^M$			2.069			0.956			5.055
			(2.587)			(1.152)			(4.992)
$dES_{pt} \times D_{pt}^4 \times D_t^M$			3.768			1.124			6.781
			(2.699)			(1.232)			(5.487)
$dES_{pt} \times D_{pt}^5 \times D_t^M$			4.558**			1.429			9.558**
			(2.154)			(1.031)			(4.398)
D_{pt}^2		0.008	0.008		0.008	0.009		0.008	0.010
		(0.007)	(0.007)		(0.007)	(0.007)		(0.007)	(0.007)
D_{pt}^3		0.006	0.005		0.003	0.004		0.005	0.004
		(0.009)	(0.009)		(0.009)	(0.009)		(0.010)	(0.009)
D_{pt}^4		-0.002	-0.003		-0.006	-0.006		-0.003	-0.003
		(0.010)	(0.010)		(0.010)	(0.010)		(0.011)	(0.011)
D_{pt}^5		-0.021	-0.021		-0.023*	-0.022*		-0.022*	-0.021
		(0.013)	(0.013)		(0.013)	(0.013)		(0.013)	(0.013)
Const	0.021***	0.019**	0.029***	0.021***	0.022***	0.030***	0.021***	0.022***	0.030***
	(0.007)	(0.008)	(0.010)	(0.007)	(0.008)	(0.010)	(0.007)	(0.008)	(0.010)
adj. R^2	-0.002	0.010	0.028	-0.002	0.007	0.016	-0.001	0.004	0.023

Table 3.5: *Quarterly returns and earnings surprises: market level regressions*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of macroeconomic forecasts dispersion measure: $R_t^M = \beta_0 + \beta_1 dES_t + \beta_2 D_t^M + \beta_3 dES_t \times D_t^M + \epsilon_t$,
where dES_t is aggregate seasonally differenced earnings (dE) scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) at time t. R_t^M is the market return at time t. D_t^M is a dummy variable assigned with 1 if the macroeconomic uncertainty is above its mean, and zero otherwise. The macroeconomic uncertainty is defined as the uncertainty part of the dispersion of forecasts for next-period real GDP Growth. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than $1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$	
dES_{it}	-0.001	0.005	-0.011	0.005	0.006	-0.004	0.013	0.023	-0.004
	(0.043)	(0.044)	(0.022)	(0.016)	(0.016)	(0.008)	(0.069)	(0.070)	(0.035)
D_t^M		-0.016	-0.014		-0.017	-0.013		-0.017	-0.014
		(0.018)	(0.017)		(0.017)	(0.016)		(0.018)	(0.016)
$dES_{it} \times D_t^M$			0.050			0.024			0.093
			(0.112)			(0.027)			(0.217)
Const	0.022***	0.031***	0.029***	0.023***	0.032***	0.029***	0.023***	0.032***	0.030***
	(0.007)	(0.011)	(0.011)	(0.007)	(0.010)	(0.011)	(0.007)	(0.011)	(0.011)
adj. R^2	-0.009	-0.004	-0.010	-0.007	-0.002	-0.005	-0.008	-0.003	-0.009

Table 3.6: *Quarterly returns and earnings surprises: firm-level regressions with alternative dummy*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty:

$$R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{it}^j + \alpha_6 D_t^M + \beta_1 dES_{it} + \sum_{j=2}^{5} \beta_j dES_{it} \times D_{it}^j + \gamma_1 dES_{it} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{it} \times D_{it}^j \times D_t^M + \epsilon_{it},$$

where dES_{it} is seasonally differenced earnings scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for firm i at time t. R_{it} is the return for firm i at time t. D_t^M is a dummy variable assigned with 1 if the market-level ambiguity is historically in the top quintile, and zero otherwise. The market-level ambiguity is defined as the uncertainty part of the dispersion of forecasts for next-period real GDP Growth. D_{it}^j is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D_{it}^5 is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$		
dES_{it}	0.841***	0.455***	0.457***	0.367***	0.192***	0.246***	1.543***	0.742***	0.784***
	(0.027)	(0.094)	(0.107)	(0.013)	(0.036)	(0.040)	(0.153)	(0.115)	(0.130)
$dES_{it} \times D_{it}^2$		0.236*	0.388***		0.072	0.054		0.242	0.267
		(0.124)	(0.148)		(0.049)	(0.058)		(0.155)	(0.180)
$dES_{it} \times D_{it}^3$		0.309***	0.432***		0.085*	0.084		0.451***	0.478***
		(0.112)	(0.131)		(0.046)	(0.053)		(0.148)	(0.170)
$dES_{it} \times D_{it}^4$		0.361***	0.400***		0.128***	0.099*		0.460***	0.474***
		(0.111)	(0.128)		(0.047)	(0.054)		(0.152)	(0.177)
$dES_{it} \times D_{it}^5$		0.406***	0.483***		0.245***	0.231***		1.289***	1.587**
		(0.103)	(0.118)		(0.042)	(0.049)		(0.457)	(0.629)
D_t^M			-0.015***			-0.015***			-0.019***
			(0.001)			(0.001)			(0.003)
$dES_{it} \times D_t^M$			-0.041			-0.228***			-0.221
			(0.218)			(0.083)			(0.269)
$dES_{it} \times D_{it}^2 \times D_t^M$			-0.483*			0.092			-0.072
			(0.270)			(0.106)			(0.339)
$dES_{it} \times D_{it}^3 \times D_t^M$			-0.408			0.030			-0.072
			(0.252)			(0.103)			(0.327)
$dES_{it} \times D_{it}^4 \times D_t^M$			-0.118			0.141			0.005
			(0.252)			(0.104)			(0.339)
$dES_{it} \times D_{it}^5 \times D_t^M$			-0.248			0.091			-0.930
			(0.237)			(0.096)			(0.673)
D_{it}^2		0.009***	0.009***		0.009***	0.010***		0.009***	0.010***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^3		0.005***	0.006***		0.006***	0.007***		0.006***	0.007***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^4		0.002	0.003		0.003*	0.004**		0.004**	0.005***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^5		-0.034***	-0.033***		-0.033***	-0.033***		-0.018**	-0.017**
		(0.002)	(0.002)		(0.002)	(0.002)		(0.008)	(0.008)
$Const$	0.032***	0.036***	0.040***	0.033***	0.036***	0.040***	0.034***	0.036***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
adj. R^2	0.011	0.015	0.017	0.010	0.014	0.017	0.003	0.004	0.005

Table 3.7: *Quarterly returns and earnings surprises: portfolio-level regressions with alternative dummy*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly portfolio returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty::

$$R_{pt} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{pt}^j + \alpha_6 D_t^M + \beta_1 dES_{pt} + \sum_{j=2}^{5} \beta_j dES_{pt} \times D_{pt}^j + \gamma_1 dES_{pt} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{pt} \times D_{pt}^j \times D_t^M + \epsilon_{pt},,$$

where dES_{pt} is aggregate seasonally differenced earnings (dE) scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for portfolio p at time t. R_{pt} is the return for portfolio p at time t. D_t^M is a dummy variable assigned with 1 if the macroeconomic uncertainty is historically in the top quintile, and zero otherwise. The macroeconomic uncertainty is defined as the uncertainty part of the dispersion of forecasts for next-period real GDP Growth. D_{pt}^j is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D_{pt}^5 is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$		
dES_{pt}	-0.002	-2.322*	-0.890	0.001	-0.711	-0.111	0.005	-3.523	-0.695
	(0.006)	(1.300)	(1.580)	(0.003)	(0.599)	(0.668)	(0.015)	(2.601)	(2.877)
$dES_{pt} \times D_{pt}^2$		0.884	0.136		0.233	-0.002		1.522	0.240
		(1.217)	(1.407)		(0.688)	(0.719)		(2.615)	(2.694)
$dES_{pt} \times D_{pt}^3$		1.851	1.363		0.533	0.156		2.588	1.605
		(1.420)	(1.808)		(0.606)	(0.728)		(2.714)	(3.199)
$dES_{pt} \times D_{pt}^4$		3.085**	2.012		1.128	0.718		4.649	2.575
		(1.480)	(1.761)		(0.685)	(0.750)		(3.013)	(3.347)
$dES_{pt} \times D_{pt}^5$		2.317*	0.881		0.710	0.107		3.520	0.685
		(1.301)	(1.580)		(0.599)	(0.668)		(2.601)	(2.877)
D_t^M			-0.012			-0.010			-0.011
			(0.015)			(0.015)			(0.015)
$dES_{pt} \times D_t^M$			-5.115**			-2.996***			-13.10***
			(2.159)			(1.083)			(4.612)
$dES_{pt} \times D_{pt}^2 \times D_t^M$			0.956			0.872			3.394
			(2.100)			(1.221)			(5.234)
$dES_{pt} \times D_{pt}^3 \times D_t^M$			1.641			2.097*			7.774
			(2.595)			(1.205)			(5.128)
$dES_{pt} \times D_{pt}^4 \times D_t^M$			1.576			1.437			7.163
			(2.719)			(1.260)			(5.472)
$dES_{pt} \times D_{pt}^5 \times D_t^M$			5.153**			3.010***			13.190***
			(2.156)			(1.082)			(4.607)
D_{pt}^2		0.008	0.006		0.008	0.007		0.008	0.007
		(0.007)	(0.007)		(0.007)	(0.007)		(0.007)	(0.007)
D_{pt}^3		0.006	0.004		0.003	0.002		0.005	0.002
		(0.009)	(0.009)		(0.009)	(0.009)		(0.010)	(0.010)
D_{pt}^4		-0.002	-0.005		-0.006	-0.009		-0.003	-0.007
		(0.010)	(0.010)		(0.010)	(0.010)		(0.011)	(0.011)
D_{pt}^5		-0.021	-0.023*		-0.023*	-0.025*		-0.022*	-0.023*
		(0.013)	(0.013)		(0.013)	(0.013)		(0.013)	(0.013)
Const	0.021***	0.019**	0.025***	0.021***	0.022***	0.027***	0.021***	0.022***	0.026***
	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)
adj. R^2	-0.002	0.010	0.028	-0.002	0.007	0.016	-0.001	0.004	0.023

Table 3.8: *Quarterly returns and earnings surprises: market level regressions with alternative dummy*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty:
$$R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{it}^j + \alpha_6 D_t^M + \beta_1 dES_{it} + \sum_{j=2}^{5} \beta_j dES_{it} \times D_{it}^j + \gamma_1 dES_{it} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{it} \times D_{it}^j \times D_t^M + \epsilon_{it},$$
where dES_{it} is seasonally differenced earnings scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for firm i at time t. R_{it} is the return for firm i at time t. D_t^M is a dummy variable assigned with 1 if the market-level ambiguity is historically in the top quintile, and zero otherwise. The market-level ambiguity is defined as the uncertainty part of the dispersion of forecasts for next-period real GDP Growth. D_{it}^j is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D_{it}^5 is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$		
dES_{it}	-0.001	-0.000	-0.029	0.005	0.005	-0.008	0.013	0.016	-0.020
	(0.043)	(0.041)	(0.030)	(0.016)	(0.016)	(0.012)	(0.069)	(0.066)	(0.048)
D_t^M		-0.012	-0.005		-0.011	-0.004		-0.011	-0.005
		(0.015)	(0.015)		(0.015)	(0.015)		(0.015)	(0.015)
$dES_{it} \times D_t^M$			0.168^{***}			0.040^{***}			0.261^{***}
			(0.040)			(0.013)			(0.067)
$Const$	0.022^{***}	0.025^{***}	0.023^{***}	0.023^{***}	0.026^{***}	0.024^{***}	0.023^{***}	0.026^{***}	0.024^{***}
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
adj. R^2	-0.009	-0.004	-0.010	-0.007	-0.002	-0.005	-0.008	-0.003	-0.009

Table 3.9: *Quarterly returns and earnings surprises: firm-level regressions with Anderson, Ghysels, and Juergens (2009) uncertainty measure*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty: $R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{it}^j + \alpha_6 D_t^M + \beta_1 dES_{it} + \sum_{j=2}^{5} \beta_j dES_{it} \times D_{it}^j + \gamma_1 dES_{it} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{it} \times D_{it}^j \times D_t^M + \epsilon_{it}$, where dES_{it} is seasonally differenced earnings scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for firm i at time t. R_{it} is the return for firm i at time t. D_t^M is a dummy variable assigned with 1 if the market-level ambiguity is above its historic mean, and zero otherwise. The market-level ambiguity is calculated following Anderson, Ghysels and Juergens (2009). D_{it}^j is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D_{it}^5 is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$		
dES_{it}	0.841***	0.455***	0.642***	0.367***	0.192***	0.239***	1.543***	0.742***	0.912***
	(0.027)	(0.094)	(0.114)	(0.013)	(0.036)	(0.041)	(0.153)	(0.115)	(0.141)
$dES_{it} \times D_{it}^2$		0.236*	0.198		0.072	0.029		0.242	0.233
		(0.124)	(0.151)		(0.049)	(0.056)		(0.155)	(0.184)
$dES_{it} \times D_{it}^3$		0.309***	0.204		0.085*	0.081		0.451***	0.425**
		(0.112)	(0.139)		(0.046)	(0.055)		(0.148)	(0.178)
$dES_{it} \times D_{it}^4$		0.361***	0.387***		0.128***	0.150***		0.460***	0.574***
		(0.111)	(0.136)		(0.047)	(0.055)		(0.152)	(0.175)
$dES_{it} \times D_{it}^5$		0.406***	0.351***		0.245***	0.229***		1.289***	0.838***
		(0.103)	(0.126)		(0.042)	(0.049)		(0.457)	(0.171)
D_t^M			-0.022***			-0.022***			-0.017***
			(0.001)			(0.001)			(0.004)
$dES_{it} \times D_t^M$			-0.470**			-0.137*			-0.500**
			(0.196)			(0.080)			(0.244)
$dES_{it} \times D_{it}^2 \times D_t^M$			0.131			0.129			0.023
			(0.255)			(0.106)			(0.325)
$dES_{it} \times D_{it}^3 \times D_t^M$			0.275			0.025			0.113
			(0.232)			(0.099)			(0.304)
$dES_{it} \times D_{it}^4 \times D_t^M$			0.013			-0.018			-0.192
			(0.229)			(0.100)			(0.322)
$dES_{it} \times D_{it}^5 \times D_t^M$			0.207			0.074			1.104
			(0.214)			(0.091)			(0.941)
D_{it}^2		0.009***	0.010***		0.009***	0.010***		0.009***	0.010***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^3		0.005***	0.006***		0.006***	0.007***		0.006***	0.007***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^4		0.002	0.004**		0.003*	0.005***		0.004**	0.005***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
D_{it}^5		-0.034***	-0.032***		-0.033***	-0.031***		-0.018**	-0.016**
		(0.002)	(0.002)		(0.002)	(0.002)		(0.008)	(0.007)
Const	0.032***	0.036***	0.044***	0.033***	0.036***	0.044***	0.034***	0.036***	0.041***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
adj. R^2	0.011	0.015	0.017	0.010	0.014	0.017	0.003	0.004	0.005

Table 3.10: *Quarterly returns and earnings surprises: portfolio-level regressions with Anderson, Ghysels, and Juergens (2009) uncertainty measure*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly portfolio returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty::

$$R_{pt} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{pt}^j + \alpha_6 D_t^M + \beta_1 dES_{pt} + \sum_{j=2}^{5} \beta_j dES_{pt} \times D_{pt}^j + \gamma_1 dES_{pt} \times D_t^M + \sum_{j=2}^{5} \gamma_j dES_{pt} \times D_{pt}^j \times D_t^M + \epsilon_{pt},,$$

where dES_{pt} is aggregate seasonally differenced earnings (dE) scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for portfolio p at time t. R_{pt} is the return for portfolio p at time t. D_t^M is a dummy variable assigned with 1 if the macroeconomic uncertainty is above its mean, and zero otherwise. The macroeconomic uncertainty is calculated following Anderson, Ghysels and Juergens (2009). D_{pt}^j is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D_{pt}^5 is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$	
dES_{pt}	-0.002	-2.322*	-0.354	0.001	-0.711	-0.273	0.005	-3.523	-0.428
	(0.006)	(1.300)	(1.764)	(0.003)	(0.599)	(0.718)	(0.015)	(2.601)	(3.212)
$dES_{pt} \times D_{pt}^2$		0.884	0.085		0.233	0.155		1.522	0.552
		(1.217)	(1.779)		(0.688)	(0.811)		(2.615)	(3.230)
$dES_{pt} \times D_{pt}^3$		1.851	1.063		0.533	0.607		2.588	1.406
		(1.420)	(1.879)		(0.606)	(0.783)		(2.714)	(3.425)
$dES_{pt} \times D_{pt}^4$		3.085**	1.599		1.128	0.950		4.649	3.336
		(1.480)	(1.969)		(0.685)	(0.830)		(3.013)	(3.738)
$dES_{pt} \times D_{pt}^5$		2.317*	0.356		0.710	0.275		3.520	0.434
		(1.301)	(1.764)		(0.599)	(0.718)		(2.601)	(3.212)
D_t^M			-0.027*			-0.025			-0.024
			(0.016)			(0.016)			(0.016)
$dES_{pt} \times D_t^M$			-3.640			-0.872			-5.858
			(2.292)			(1.056)			(4.638)
$dES_{pt} \times D_{pt}^2 \times D_t^M$			1.038			-0.484			-0.059
			(2.101)			(1.105)			(4.304)
$dES_{pt} \times D_{pt}^3 \times D_t^M$			0.631			-0.091			0.567
			(2.801)			(1.130)			(5.351)
$dES_{pt} \times D_{pt}^4 \times D_t^M$			2.384			0.287			1.777
			(2.894)			(1.305)			(5.783)
$dES_{pt} \times D_{pt}^5 \times D_t^M$			3.628			0.867			5.841
			(2.292)			(1.056)			(4.639)
D_{pt}^2		0.008	0.006		0.008	0.005		0.008	0.005
		(0.007)	(0.007)		(0.007)	(0.007)		(0.007)	(0.007)
D_{pt}^3		0.006	0.004		0.003	-0.000		0.005	0.003
		(0.009)	(0.009)		(0.009)	(0.009)		(0.010)	(0.009)
D_{pt}^4		-0.002	-0.002		-0.006	-0.006		-0.003	-0.004
		(0.010)	(0.011)		(0.010)	(0.010)		(0.011)	(0.011)
D_{pt}^5		-0.021	-0.021		-0.023*	-0.023*		-0.022*	-0.022*
		(0.013)	(0.013)		(0.013)	(0.013)		(0.013)	(0.013)
Const	0.021***	0.019**	0.031***	0.021***	0.022***	0.033***	0.021***	0.022***	0.032***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
adj. R^2	-0.002	0.010	0.028	-0.002	0.007	0.016	-0.001	0.004	0.023

Table 3.11: *Quarterly returns and earnings surprises: market level regressions with Anderson, Ghysels, and Juergens (2009) uncertainty measure*

This table reports the coefficient, t-statistic, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of firm-level and macroeconomic uncertainty:
$$R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D^j_{it} + \alpha_6 D^M_t + \beta_1 dES_{it} + \sum_{j=2}^{5} \beta_j dES_{it} \times D^j_{it} + \gamma_1 dES_{it} \times D^M_t + \sum_{j=2}^{5} \gamma_j dES_{it} \times D^j_{it} \times D^M_t + \epsilon_{it},$$
where dES_{it} is seasonally differenced earnings scaled by beginning-of-period market price ($S = P$), book value ($S = B$), or earnings ($S = E$) for firm i at time t. R_{it} is the return for firm i at time t. D^M_t is a dummy variable assigned with 1 if the market-level ambiguity is above its historic mean, and zero otherwise. The market-level ambiguity is calculated following Anderson, Ghysels and Juergens (2009). D^j_{it} is the uncertainty part of analyst earnings forecast dispersion measuring firm-specific uncertainty for uncertainty quintile j at time t. D^5_{it} is the quintile with highest uncertainty and so forth. The first quintile is embedded in the no-dummy variable. Earnings are excluding extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. Analysts' forecasts are from IBES. Individual forecasts for real GDP growth are from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. The firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and four quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) at least two analysts' forecasts for EPS; 5) not in the top and bottom 1 percentile of firms ranked by dES. Standard errors are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Our sample includes all the firms on NYSE, AMEX, and NASDAQ from 1984 Q1 to 2013 Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$S_{it} = P_{it}$			$S_{it} = B_{it}$			$S_{it} = E_{it}$		
dES_{it}	-0.001	-0.003	0.027	0.005	0.004	0.011	0.013	0.007	0.049
	(0.043)	(0.044)	(0.021)	(0.016)	(0.016)	(0.008)	(0.069)	(0.069)	(0.038)
D^M_t		-0.022	-0.025		-0.022	-0.024		-0.023	-0.025
		(0.016)	(0.017)		(0.016)	(0.016)		(0.016)	(0.017)
$dES_{it} \times D^M_t$			-0.052			-0.013			-0.069
			(0.073)			(0.025)			(0.105)
Const	0.022***	0.032***	0.033***	0.023***	0.032***	0.034***	0.023***	0.032***	0.034***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
adj. R^2	-0.009	-0.004	-0.010	-0.007	-0.002	-0.005	-0.008	-0.003	-0.009

Chapter 4

Asymmetric Asset Price Reaction to Earnings News: the Roles of Ambiguity and Difference of Opinion

4.1 Introduction

Market reacts to news in an asymmetric fashion. That is, bad news has a greater impact than good news. The average negative return to negative news is significantly larger in magnitude than the average positive return to positive news (Conrad, Cornell, and Landsman, 2002; Skinner and Sloan, 2002; Andersen, Bollerslev, Diebold, and Vega, 2003). There are two possible explanations: 1) there is larger amount of negative news on the market; 2) investors react more strongly to bad news per se. The former refers to the practice that firms selectively release news to their own advantages. For example, Aboody and Kasznik (2000) show that managers accelerate bad news and/or withhold good news in the period immediately preceding option grant dates to lower the exercise price o the options. The latter states that the information content per unit of news is greater for bad news. Much of the literature focuses on the latter. Earlier studies, for instance Daniel, Hirshleifer, and Subrahmanyam (1998) and Barberis, Shleifer, and Vishny (1998), interpret the evidence on the asymmetry in the context of value/glamor effect as a result of investors' psychological behaviour. Specifically, investors expect stocks to continue on the positive trends following a string of shocks. When good news is announced, the market response is relatively small since the positive shock is anticipated. Bad news, however, generates a much larger contemporaneous return since the negative shock is more of a surprise. This chapter contributes to this strand of literature and provide explanation by examining the characteristics of investors' decision making under uncertainty.

Recent theories, such as Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011), argues that asymmetric reaction to bad versus good news can arise due to the presence of Knightian uncertainty. Investors who are ambiguity averse choose the worst case scenario and consequently overvalue negative news and undervalue positive news (see Chapter 3 for the definition of ambiguity).

Studies in decision theory indicate that difference of opinion - another important characteristic of decision making under uncertainty - might also contribute to the asymmetry (Gajdos and Vergnaud, 2009; Cres, Gilboa, and Vieille, 2011). Specifically, Cres, Gilboa, and Vieille (2011) consider a setting where experts are asked to provide their advice in a situation of Knightian uncertainty. The decision maker exhibits expert uncertainty aversion (EUA) when aggregating divergent opinions from the ambiguity-averse experts. They axiomatize that in face of different opinions the decision maker selects the minimal weighted valuation of experts valuations, which leads to consequential overvaluation of negative opinions and undervaluation of positive views in a similar vein to the case of ambiguity-aversion. This chapter contributes to both strands of literature by showing that rationalized investors' behavior when facing ambiguity and difference of opinion generates asymmetric market response to bad versus good news even after controlling for the differential amounts (if any) of good and bad news leaked prior to announcement and the news magnitude.

The differential amounts of ambiguity and difference of opinions for any specific case could render their combined effect unclear. Together with risk, ambiguity and difference of opinion are considered as the sources of uncertainty (Baillon, Cabantous, and Wakker, 2012). Here, uncertainty is in the broadest sense and refers to any variation that causes forecast errors. In a mode based on experts' forecasts, Barron, Kim, Lim, and Stevens (1998) show that overall uncertainty is a linear combination of common uncertainty (for this matter ambiguity) shared by all experts attributable to their reliance on imprecise common information and idiosyncratic uncertainty (for this mater difference of opinion) that is due to information asymmetry among experts. For certain level of uncertainty, more fraction of ambiguity means less degree of divergence in experts' opinions. It is a matter of relative dominance between the two to form a combined effect on market reactions to bad versus good news.

This chapter aims to model and test the combined effect of ambiguity and difference of opinion on market asymmetric reactions to bad versus good earnings news and propose justified measures for either. This asymmetry is possibly due to either larger amount of negative news on the market or that investors react more strongly to bad news per se (or both). I hypothesize that it is solely the combining effect of ambiguity and difference of opinion on investors' reactions that leads to all the asymmetry. To test, I focus on the association-study framework adopted by Kothari, Lewellen, and Warner (2006) where the contemporaneous earnings-return relation is investigated on a quarterly basis before the earnings announcements, which are typically a couple of months after each fiscal quarter that the earnings cover[1]. This methodology is based on the reality of information leakage (Brunnermeier, 2005) and enables me to control for potentially differential amounts of news

[1]Most studies use event-study framework which typically focus on limited period around the actual announcement dates. I do not adopt this framework due to 1) no apparent proxies for measuring differential amounts of good versus bad earnings news 2) that the announcement data in IBES is often effectively the date on which the information was recorded by IBES and, therefore, systematically delayed. Hoechle, Schaub, and Schmid (2013) show that the announcement day effect is underestimated in IBES while pre-announcement returns are overestimated as they often include the effective announcement day.

being leaked before the public announcements.

Uncertainty can be divided into common uncertainty and idiosyncratic uncertainty among experts as shown in Barron, Kim, Lim, and Stevens (1998). Common uncertainty is the average covariance between the belief of one analyst and the beliefs of the rest of the experts, while idiosyncratic uncertainty is the expected dispersion of experts' beliefs. They further show that the ratio of expected dispersion of experts' beliefs to overall uncertainty captures the effect of two sources of information asymmetry on experts' beliefs - namely, the relative presence of private information and differential uncertainty, denoted as $1-\rho$. The ratio of the average pair-wise covariance among experts' beliefs to overall uncertainty reflects the imprecision of common information shared by experts, denoted as ρ. In this chapter, I employ ρ as a measure for ambiguity and $1-\rho$ as a measure for difference of opinion. The new measures present an advantageous channel to investigate the combined effect of ambiguity and difference of opinion due to their perfectly negative correlation. The decomposition recognizes the well-established theoretical proposition that uncertainty consists of idiosyncratic and common components (Doukas, Kim, and Pantzalis, 2006; Sheng and Thevenot, 2012).

With all the US firms which has more than two analyst' earnings forecasts, I start by showing that the stylized fact holds even well before the actual news announcements due to information leakage. The average negative return to negative earnings news is around -4.9% over 20 years period, significantly higher than the 3.1% return for positive earnings news at 1% level. When I divide the stock universe into quintiles according to ρ in ascending order, the return difference for bad versus good earnings news exhibit a "yes" tick shape for the five groups. This shows that whatever the cause of the asymmetry is, its impact has not been linearly reflected on the market and conforms the motivation to investigate the combined effect of ambiguity and difference of opinion.

To illustrate the combined effect, I include the size of news and its interaction with a directional dummy variable. I find that the differential return between bad versus good news, -1.8%, completely disappeared. The positivity and high significance of the interaction term imply that investors are more surprised by bad earnings news. When applying to the quintiles, the coefficients of the interaction term exhibit a "yes" tick shape matching that of the average returns difference, indicating that this stronger surprise from bad news could be explained by the combining effect of ambiguity and difference of opinion. To ensure that the asymmetry is not due to the differential amounts of news leakage, I further control for proxies for managers' incentives to release bad news such as Regulation Fair Disclosure (thereafter RegFD) (Dong, Li, Ramesh, and Shen, 2011), litigation risk modelled by Rogers and Stocken (2005), information asymmetry following Kothari, Shu, and Wysocki (2009), and financial distress measured by Zmijewski (1984)'s Z-score. Those proxies explain away the rest of the negative returns by negative earnings news. Nevertheless, the "yes" tick shape remains for the stronger reactions to negative earnings news.

Overall, the results suggest that the higher average negative return to negative news versus that to positive news is solely determined by the larger informational content of negative news per se. These results have important implications for understanding the roles of managers and investors in market reaction to financial news. Starting with the former, even if Kothari, Shu, and Wysocki (2009) results can be interpreted as causal, they do not suggest that managers should expect their "tactic" of selective release of news matters for the market overall. Moving to the latter, it suggests that investors' assessments of news under uncertainty determine the market reaction to financial news.

To validate the findings, I build a simple model to capture the dynamics of earnings-return relation based on one representative agent (i.e. the decision maker), multiple firms, and multiple experts. Ambiguity-averse experts are asked by the decision maker to provide advice on the informativeness of each firm's earnings signal and use the same utility function as the decision marker. Due to lack of information and/or poor quality of information, the ambiguity-averse experts lack confidence on the distribution of true part of a signal and hence consider a range of possible priors for the true signal, so does the decision marker. With the presence of private information, the center of the range of possible priors varies among experts resulting in their differential assessments of the signals even if the level of ambiguity is the same. Working independently, the decision maker and the experts maximize the minimal expected utility with respect to their own sets of priors. They act as if a positive signal is unreliable and a negative signal is reliable. Consequently, the price change of each firm triggered by a positive signal is less in magnitude than the price change triggered by a negative signal. The decision marker is averse to the uncertainty about the expert who "has access to truth", hence exhibits expert uncertainty aversion in her aggregation of experts' opinions. She chooses a weighting function among a set of weight vectors over the experts' priors such that it maximizes the minimal combination of experts minimal expected utility with their own sets of priors, or in a "maxminmin" way.

I firstly derive the return-earnings relation where the distribution of the signals is exactly known and there is consensus among all experts. Upon receiving a set of noise signals, experts form conditional expectations of the signals' informativeness about stock returns' cash flow news and discount rate news components (Campbell, 1991). By assuming zero-mean normal distributions for all the variables, I am able to obtain a beta coefficient showing the return-earnings relation as a function of the noisy signals' distribution parameters. To incorporate ambiguity, I then assume that experts do not observe the distribution of the true earnings (i.e. the variances) and hence assign interval ranges for the distribution. Facing ambiguity, experts minimize the expected market return generating an array of variances selected within the range. Using Bayesian updating with the chosen variances, I am able to obtain a new beta as a function of the chosen variances. Finally, I consider the difference of opinion by deviating the center of the distribution ranges across experts. After the experts minimize the expected market return with their own set of priors, the decision maker obtains an aggregated beta by allocating weights to the experts' betas such that 1) the decision maker's set of priors is precisely the weighted average of experts'; 2) the decision maker chooses the minimal weighted valuation of experts' betas over all possible weights.

Monte Carlo simulation for the model shows that ambiguity and difference of opinion have contrasted effects on investors' reactions on earnings surprises measured by earnings response coefficient (or beta in the model). For positive surprises, both ambiguity and difference of opinion reduce the beta. For negative news, ambiguity amplify investors' reaction while difference of opinion has a muted effect. Without differentiating the nature of news, high ambiguity leads to more positive beta consistent with Chapter 3, whereas high difference of opinion leads to less positive beta. By equating high ambiguity to low difference of opinion, I combine both effects and produce the differential reaction to negative versus positive news of a "yes" tick shape that matches the empirical finding.

The striking pattern for the effect of difference of opinion on good versus bad news can be explained, mathematically speaking, by the functional form of experts' betas to experts' priors. For positive news, the betas are a concave function of experts' priors. The minimum aggregate valuation is to assign most weights to experts with extreme priors. Hence the more dispersed experts' priors are, the lower is the aggregated beta for positive news. On the contrary for negative news, the betas are a convex function of the experts' priors due to the switching sign of the news. The minimal valuation allocates most weights to experts with priors of "centrality". As a result, the dispersion of priors does not matter significantly for the overall market reaction.

This chapter is related to several strands of literature. Firstly, the asymmetry in responses to negative versus positive information is well documented in various areas. Skinner (1994) studies the stock market reaction to corporate earnings news. Defond and Zhang (2014) examine the bond market reaction to earning news. Andersen, Bollerslev, Diebold, and Vega (2003) investigate the foreign exchange market reaction to macroeconomic news. And Soroka (2006) and Barbara and Lanoue (1991) look into attitudes toward economic news and voting behaviour in politics. Secondly, the process behind the asymmetric responsiveness has been explored in both psychology and behavioural economics literature. In psychology, Ronis and Lipinski (1985) propose a possible explanation named perspective theory under which impressions are formed based on an expectation, or reference point. The reference point tends to be slightly positive on average due to generally mildly optimistic individuals, and this leads to a shift in perspective. Fiske (1980) suggests that cognitive weighting creates the asymmetry. Individuals give more attention to extreme information, which tends to be negative. Both perspective and cognitive weighting theories suggest that individuals have an average expectation of a reasonable state of economy, which leads to very negative reaction to mildly negative information. In behavioural economics, Kahneman and Tversky (1979) propose an alternative theory of choice under uncertainty called prospect theory. Under this theory, the value function is assigned to the gains and losses rather than to the final wealth, and its shape is normally concave for gains and convex for losses and the slope is generally larger for losses than for gains. The probabilities of the gains and losses are replaced by the decision weights. Except in the range of low probabilities, the decision weights are generally beneath the corresponding probabilities. As a result of the particular designs of the value and weighting functions, individuals react asymmetrically stronger to the negative information than to the good ones, as if they are loss-averse.

Prospect theory takes a different conceptual approach to explain the asymmetry. It is specific to consumption and focuses on the process of reacting differently to positive and negative perceptions. The value function and decision weights are pre-determined by human nature in order to exert more weights on the negative information. In contrast, the ambiguity approach, notably popularized by Epstein and Schneider (2008) and adopted by this chapter, is specific to ambiguity or ambiguous information environment. It focuses on a well-defined investors' behavioural trait called ambiguity aversion (Gilboa and Schmeidler, 1989). The asymmetry is a result of ambiguity-averse investors choosing the worst-case scenario when facing ambiguous information, which is different from the prospect theory cognitive process on perspective or attitude. In each narrative though, reactions to bad news are greater than reactions to good ones.

The chapter is structured as follows. Section 4.2 describes the sample. In particular, I show the constructions of the three earnings surprises, the new proxies for ambiguity and difference of opinion, and the variables for measuring managers' incentives to selectively release news. In Section 4.3, I firstly present the empirical finding of the "yes" tick shape of differential average returns to bad versus good news. Then, I move on to test the validity of the measures for ambiguity and difference of opinion by running pooled panel firm-level regression of quarterly returns on earnings surprises with dummy variables. Section 4.4 develops and calibrates a model based on return-earnings relation and presents its predictions. Section 4.5 summarizes and concludes.

4.2 Data and variable definition

The sample includes all the firms on NYSE, AMEX, and NASDAQ from Q1 1984 to Q4 2013. The starting date for the study is determined by the availability of data in the IBES Summary History dataset. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and the quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) there are at least two experts' forecasts for EPS; 5) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case.[2]

Similar to Chapter 3, I define earnings surprises as seasonally differenced quarterly earnings scaled by lagged market price (P), book equity (B), and earnings (E), using per share numbers. Scaling by lagged variables eliminates or substantially reduces the cross-sectional and temporal dispersion of earnings differences. I use earnings per share (basic) - excluding extraordinary items (Compustat item EPSPXQ).

Stock returns are calculated using adjusted prices (Compustat items PRCCQ / AJEXQ). Market values are the multiplication of market closing price and common shares outstanding (Compustat item CSHOQ). Historical data are adjusted accordingly to ensure comparisons on the same basis. All accounting data are from Compustat quarterly files.

4.2.1 Proxies for ambiguity and difference of opinion

Analysts' earnings forecasts data are from the Institutional Brokers Estimate System (IBES) U.S. Summary History dataset via WRDS. In this module of IBES the forecasts of the individual analysts are summarized to create "snapshots". The data is available on a monthly basis; the snapshots are made the Thursday before the third Friday of the month. I prefer the summary statistics with IBES statistical period within and close to the end of each fiscal quarter with the aim to balance the accuracy of forecasts as well as to ensure that they capture the uncertainty within the fiscal quarter when investors make decisions. I also use individual forecasts from the IBES U.S. Detail History dataset to mitigate the problematic rounding procedure and the results are similar.

The ambiguity measure employed here is the same as in the previous chapter. For the sake of completeness, I reiterate the definition here. Define V as the overall uncertainty level averaged over N analysts' individual uncertainty, C as the pair-

[2]Following Brown, Fazzari, and Petersen (2009) I also tried trimming 0.25% and 1% for each tail, the results are similar.

wise covariance among analysts' beliefs, and D as expected dispersion of analysts' forecast. Barron, Kim, Lim, and Stevens (1998) show that

$$V = C + D$$

which can be interpreted as the overall uncertainty of analysts' information environment V is the sum of common uncertainty C attributable to imprecise common information and dispersion D reflecting idiosyncratic uncertainty among analysts.

They further show that a consensus measure defined as

$$\rho = \frac{C}{V}$$

captures the extent of how much analysts' beliefs reflect common versus private information. In other words, ρ measures the ratio of common uncertainty to the overall uncertainty.

When analysts' private information is of equal precision, the consensus measure can be computed in the following way

$$\rho = \frac{h}{h + s}$$

where h is the precision of common information and s is the precision of idiosyncratic information. Both precisions are calculated as

$$h = \frac{(SE - \frac{D}{N})}{(SE - \frac{D}{N} + D)^2}$$

and

$$s = \frac{D}{(SE - \frac{D}{N} + D)^2}$$

where SE is the mean squared error (MSE) of the earnings forecasts deflated by the absolute value of the actual EPS (ACTUAL), D is the variance (STDEV squared) of forecasts deflated by the absolute value of the actual EPS, and N is the number of forecasts (NUMEST).

I argue in this chapter that ρ as a better measure of ambiguity than the widely used D and $1-\rho=\frac{D}{V}$ as a valid measure of difference of opinion. Barron, Kim, Lim, and Stevens (1998) show in Appendix B that $1-\rho$ captures two sources of information asymmetry on experts' belief: the relative presence of private information and differential uncertainty due to differential quality of private information, and ρ captures the sources of forecasting uncertainty that is due to poor quality of non-private information, or ambiguity.

4.2.2 Proxies for firms' incentives to leak negative news

In this section I discuss the empirical proxies of the factors that are predicted to influence firm's disclosure choices for bad news.

Effective on October 23, 2000, the Securities and Exchange Commission in the US passed Regulation Fair Disclosure that prohibits selective disclosure of material information to experts and other investment professionals. Under the regulation, any intentional disclosure of material non-public information by firms to experts or other parties must be simultaneously released to the general public. RegFD reduces the amount of asymmetric information in the securities markets by forcing firms to either disclose information to everyone or disclose no information (Eleswarapu, Thompson, and Venkataraman, 2004). RegFD delays price discovery to quarterly earnings release by stifling information leakage (Dong, Li, Ramesh, and Shen, 2011). I argue that passage of RegFD reduces managers' incentives to leak bad news well before the mandatory quarterly earnings announcements.

The litigation reduction hypothesis proposed by Skinner (1994) states that firms reveal bad news to lower the likelihood of litigation. Donlson, McInnis, Mergenthaler, and Yu (2012) study bad earnings news and conclude that litigation risk measured by predicted litigation probability is negatively associated with the amount of bad news leaked. I argue that firms with low litigation risk benefit from revealing more bad mandatory earnings news and are thereby more likely to continue the practice. Despite firms with high litigation risk might have incentive to withhold bad news in relation to discretionary announcements, they may release more bad earnings news in the run-up to disappointing mandatory earnings announcements. The measure of litigation risk is calculated using the coefficient estimates obtained from Rogers and Stocken (2005). The explanatory variables used in their model are primarily stock return-based variables such as market value, stock turnover, beta, and volatility (see Rogers and Stocken, 2005 appendix B for more details). Same as Kothari, Shu, and Wysocki (2009), I only include the independent variables that are significant into the prediction. All the variables are computed at the end of the last fiscal quarter.

Information asymmetry between management and investors affects news disclosure. In the traditional setting, high information asymmetry tends to provide incentives for managers to disclose all types of news to avoid market penalties from investors. Thus, higher information asymmetry corresponds to larger amount of bad news released. Following Kothari, Shu, and Wysocki (2009), I construct a factor that potentially measure information asymmetry based on five variables, namely market-to-book ratio, stock volatility, leverage ratio, membership in high-tech industries, and regulatory status. The market-to-book ratio is computed by dividing the market value of equity by the book value of equity. Stock volatility is calculated as the standard deviation of daily stock returns within a quarter. Leverage is measured as long-term debt scaled by total assets. High-tech firms are firms with the Standard Industrial Classification (SIC) codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, and 8731-8734. Regulated industries excluding the financial institutions are considered with SIC codes 4812-4813, 4833, 4841, 4891-4899, 4922-4924, 4931, and 4941. The factor analysis is conducted to extract an underlying information asymmetry factor. I define firms with above-median asymmetry factor score as high information asymmetry firms and vice versa for low information asymmetry firms. All the ratios are measured at the end of the previous fiscal quarter.

Finally, managers' reputation may affect the news release. Managers face an asymmetric loss function in choosing their voluntary disclosure policies. That is, managers behave as if they bear large costs when investors are surprised by large negative earnings news, but not when other types of news are announced (Skinner, 1994). Both litigation risk and reputation costs possibly create this asymmetric loss function. The costs borne by managers as a result of large negative earnings surprises further increase when firms are in distress (Gilson, 1989). I argue that the career concern incentivizes managers to release more bad news. To capture these incentives, I classify a firm quarter as being financially distressed if the Zmijewski (1984) Z-score financial distress rank is in the top decile of all firms in that quarter.

Our predications are the opposite of those of Kothari, Shu, and Wysocki (2009). The reasons are mainly twofold. Firstly, this chapter investigates the stock market reaction to mandatory quarterly earnings announcement while Kothari, Shu, and Wysocki (2009) look at stock price behaviour surrounding discretionary corporation information including dividend change and voluntary management earnings forecasts. Secondly, the association study framework is adopted to examine the stock return-news relation. With this framework, the return calculation windows are the fiscal quarters for which the mandatory earnings announcements cover, and the public announcements are typically two to three months after the fiscal quarter. This framework works based on the assumption that earnings news is leaked well before the actual announcements. Due to these two characteristics, the overall prediction is that firms may release more bad news in the run-up to disappointment mandatory earnings announcements even if they have a general incentive to withhold bad news in relation to discretionary announcements. The release increases with lower litigation risk and high information asymmetry, and decreases after the passage of RegFD.

4.2.3 Summary statistics

Table 4.1 Panel A reports summary statistics for some of the important variables. There are 9345 firms in the final sample. The average log return across firms is around 0.3% per quarter, with a standard deviation 25.6%. The earnings surprise measure, dEP, has a mean 0.2% and a standard deviation 0.045. the measure for difference of opinion, DoO, has a average of 0.450 and a standard deviation of 0.467. Ambiguity which is equal to $1 - DoO$ has a average of 0.550 and the same precision. From IBES, the number of experts ($NUMEST$) following each firm ranges from 2 to 50 with an average around 7. This range is used as a measure of difference of opinion in the model. The rational is that more experts coverage leads to lower standard deviation of forecasts. The correlations between those variables are presented in the Panel B of Table 4.1.

4.3 Empirical analysis

In this section, I firstly show the role of ambiguity and difference of opinion in explaining the differential reactions to good versus bad news. Then, using quintile analysis I present a more vigorous explanation on the combining effect of ambiguity and difference of opinion on earnings news responses.

4.3.1 Asymmetric reactions to bad versus good news

I start by investigating whether there is asymmetry even well before the news being publicly released.

Asymmetric average returns generated by good versus bad news

Following Kothari, Shu, and Wysocki (2009), I run the following baseline regression:

$$R_{it} = \alpha_0 + \beta_0 Neg_{it} + \epsilon_{it}, \tag{4.1}$$

where R_{it} is the quarterly excess return over Fama and French (1993) market, size, book-to-market factors and Carhart (2001) momentum factor, or the residuals of running a Carhart four-factor model in quarter t for firm i. Neg_{it} is a dummy variable for firm i in quarter t that equals one for negative earnings surprises, and zero otherwise. I also conduct the F-test to examine whether stock market reactions to negative versus good earnings surprises are the same. Specifically, we test if $2^*|\alpha_0|=|\beta_0|$. Since the magnitude for stock returns to negative earnings surprises is $|\alpha + \beta|$ with the β being negative, so testing $2^*|\alpha_0|=|\beta_0|$ is equivalent to test $|\alpha + \beta|=|\alpha|$.

Table 4.2 presents the results. For dE/P, positive earnings surprises generate average stock return of +3.1% around the fiscal quarter the earnings cover. Negative surprises capture average return of −4.2% (= 0.031 − 0.073). The F-test confirms that the market's reaction to earnings decreases is significantly at 1% level larger in magnitude than the reaction to earnings increases, with a difference of −1.1%. When I divide the firms into quintiles according to ascending ρ, the higher average returns for negative news remain for each of the quintile. The estimates of the model are presented in panel A columns 3-7. A1/D5 means the lowest quintile for ambiguity also the fifth quintile for DoO, and so forth. Then, I plot the difference between the average negative returns by negative news and average positive returns by positive news. Figure 4.1 shows that the differential returns exhibit a "yes" tick shape with respect to ρ, with the lowest point in either second or third quintile. The results are the same for all three earnings surprises measures.

The market reaction to earnings decreases might be more pronounced because (1) the amount of total news revealed is greater for bad news disclosures and/or (2) the information content per unit of news is greater because investors are more surprised by the bad news disclosures. I firstly examine the former that how information amount contributes to the asymmetric reaction to bad and good news. I use the measures for managers' incentives to release bad news. First, Reg FD arguably has limited the ability of managers to informally leak news either good or bad to experts and institutional investors prior to the announcements of quarterly earnings. This implies that firms before the passage of Reg FD are more incentivized to release (bad) news. Second, to mitigate litigation risk, firms are more likely to disclose bad news before it becomes public. Third, firms with high information asymmetry tend to release earlier all kinds of news to avoid market penalties from investors. Fourth, reputation risks limit the ability of managers to withhold bad news particularly when the firms are in financial distress. I examine the effects of those factors using the following regression:

$$\begin{aligned} R_{it} &= \alpha_0 + \beta_0 Neg_{it} + \beta_1 RegFD_{it} + \beta_2 RegFD_{it} * Neg_{it} + \beta_3 LitRisk_{it} \quad (4.2) \\ &+ \beta_4 LitRisk_{it} * Neg_{it} + \beta_5 InfoAsymm_{it} + \beta_6 InfoAsymm_{it} * Neg_{it} \\ &+ \beta_7 FinDistress_{it} + \beta_7 FinDistress_{it} * Neg_{it} + \epsilon_{it}, \end{aligned}$$

where $RegFD$ is a dummy variable equal to one if the announcement occurs before the passage of Regulation FD in October 2000, and zero otherwise. $LitRisk$ is a dummy variable that equals one if the firm has less than median litigation risk calculated using Rogers and Stocken (2005) predictive regression, and zero otherwise. $InfoAsymm$ is a dummy variable that equals one if the firm is above the median value of a single information asymmetry factor, and zero otherwise. The information asymmetry factor is derived from a factor analysis based on the information asymmetry proxies: market-to-book ratio, stock volatility, high-tech firms, financial leverage, and regulatory status. $FinDistress$ is a dummy variable that equals one if the firm's Z-score (Zmijewski, 1984) financial distress rank is in the top decile of all firms in a given year, and zero otherwise. I present the F-tests of whether the estimated intercept coefficient is equal in magnitude to coefficient for the dummy variable Neg. Note that this is different from the F-test for equation 4.1, which is to examine the asymmetric reaction (in magnitude) to good versus bad earnings surprises. Here, I test whether the identified asymmetry could be explained entirely by the information amount of news proxied by the managerial incentives to release or withheld bad news. If the explanation is in full, then $|\alpha_0 + \beta_0|$ should be statistically indifferent from zero, in other words $|\alpha_0|$ should be statistically indifferent from $|\beta_0|$. Thus, I test $|\alpha_0|$=$|\beta_0|$.

Panel A Column 2 of table 4.3 reports the estimates of regression model (4.3) for earnings surprise measure dE/P. $RegFD * Neg$, $InfoAsymm * Neg$, and $LitRisk * Neg$ have the anticipated negative signs and are significant at 1% level. $FinDistress * Neg$ is indistinguishable from zero. The coefficient for Neg drops to -0.043 from -0.073 of the baseline regression. The rest is captured by the interaction terms mentioned above. There is -1.2% of average return for negative news unaccounted for and significant at 1% level shown by the F-test at the bottom of column 2. This return is not significantly different from the -1.1% differential return recorded in table 4.2 (not tabulated).

Secondly, I examine the explanatory power of the informational content of the news per se by including the size of the news as well as its interaction with the directional dummy variable in the baseline equation 4.1:

$$R_{it} = \alpha_0 + \beta_0 Neg_{it} + \delta_1 sue_{it} + \delta_2 sue_{it} * Neg_{it} + \epsilon_{it}, \tag{4.3}$$

where sue_{it} is the standardised unexpected earnings and refers to one of the three earnings surprises measures. Panel A of table 4.4 presents the regression results for model (4.3) with $sue = dE/P$. As can been seen, the average negative return generated by negative earnings surprises is around -2.8%, computed as the sum of the estimated intercept and Neg_{it} coefficients. This is indistinguishable in magnitude from the average positive returns by positive news 2.9%: the p-value for the F-test of their equal magnitude stands at 0.217. Here, the F-test is the same as in equation 4.1. The interaction variable $sue_{it} * Neg_{it}$ is positive and highly significant at 1% level. It shows that for a given percentage change in earnings, investors' reaction to earnings decrease is much more pronounced than to earnings increases. This implies that investors are more surprised by bad news. In other words, the informational content of per unit of bad news is higher than that of good news. The F-test shows that this surprise explains the differential average firm-level stock returns of bad versus good news in its entirety. The results are similar for each of quintiles.

Figure 4.2 plots the differential returns of each quintile after controlling the informational contents of news per se. The "yes" tick shape disappears and more importantly those differential returns are insignificant at 5% level. Figure 4.3 plots the coefficients for interaction term $sue_{it} * Neg_{it}$, which generally matches the "yes" tick shape. It further enhances the explanation that it is the larger information content of bad news per se explains the differential average returns generated by bad versus good news.

Finally, I include both the information content per unit of news and the fthe proxies for managerial incentives as controls and run the following regression:

$$\begin{aligned} R_{it} &= \alpha + \beta_0 Neg_{it} + \delta_1 sue_{it} + \delta_2 sue_{it} * Neg_{it} + \beta_1 RegFD_{it} \\ &+ \beta_2 RegFD_{it} * Neg_{it} + \beta_3 LitRisk_{it} + \beta_4 LitRisk_{it} * Neg_{it} + \beta_5 InfoAsymm_{it} \\ &+ \beta_6 InfoAsymm_{it} * Neg_{it} + \beta_7 FinDistress_{it} + \beta_7 FinDistress_{it} * Neg_{it} + \epsilon_{it}, \end{aligned} \tag{4.4}$$

Panel A of table 4.5 reports the estimates of the model (4.5) for dE/P. $sue_{it} * Neg$ is significantly positive at 1% level for all firms and for each quintile. For the regression with all firms, the reaction to per unit of bad news is more than 4.5 times (i.e. $\frac{0.491}{0.108}$) of that to per unit of good news measured by the coefficient of sue_{it}. p_{value} of 0.299 for the F-test confirms that all the differential average return of -1.1% of the baseline model comes from the differential reactions to the information contents of bad versus good news. Figure 4.4 plots the differential earnings response coefficients for bad versus good news. The "yes" tick shape remains.

4.3.2 Quintile analysis

In this subsection, I further the analysis to focus on the role of ambiguity and difference of opinion of earnings response coefficient, with the aim to provide more rigorous empirical foundations for the modeling later.

Individual stock returns and earnings surprises

The analysis starts with the replication of the stylized fact that a positive contemporaneous relation exists between returns and earnings surprises at firm level (Ball and Brown, 1968). The contemporaneous relation is examined with pooled panel data using the following regression:

$$r_{it} = \alpha + \beta sue_{it} + \lambda lsize_{it} + \epsilon_{it} \tag{4.5}$$

where r_{it} is the return for firm i in quarter t. sue_{it} is the individual earnings surprise for firm i in quarter t. $lsize_{it}$ is the natural log of beginning-of-period market capitalization for firm i in quarter t. The size proxy is included to control for risk differences not already reflected in the return (Fama and French, 1992, 1993) and for potential scale differences (Barth and Kallapur, 1996).

Table 4.6 column 2 confirms that individual stock prices react positively to earnings news measured by dE/P. The ERC is around 0.711 with standard error 0.020. The size control variable, $lsize$, is significantly negative at 1%, consistent with Conrad, Cornell, and Landsman (2002). Both variables explain 1.64% of total variation of the returns. The results of using alternative surprises measures including dE/B and dE/E are similar.

As a robustness check, I run both time series and cross section regressions as in Sadka and Sadka (2009). The untabulated results are similar for all measures of earnings surprises. The interpretations for the time series and cross sectional results are different. A positive time series return-earnings relation suggests that a firm with better-than-expected (firm-level expected) earnings figures has higher concurrent stock prices. A cross sectional relation indicates that a firm with better-than-expected (cross-section average expected) earnings has positive stock returns. Time series analysis does not take into account the correlation between firms; while cross sectional analysis implicitly assumes either the firm-level ERCs or the variances of earnings surprises are the same for all firms Teets and Wasley (1996).

Firm-level ERC with ascending ambiguity

Now I interact the earnings surprises with the ambiguity measure. I run the following regression:

$$\begin{aligned} r_{it} &= \alpha + \alpha_1 A_{it}^2 + \alpha_2 A_{it}^3 + \alpha_3 A_{it}^4 + \alpha_4 A_{it}^5 + \beta sue_{it} + \delta_1 sue_{it} A_{it}^2 \\ &+ \delta_2 sue_{it} A_{it}^3 + \delta_3 sue_{it} A_{it}^4 + \delta_4 sue_{it} A_{it}^5 + \lambda lsize_{it} + \epsilon_{it} \end{aligned} \tag{4.6}$$

where r_{it} is the return for firm i in quarter t. sue_{it} is the individual earnings surprise for firm i in quarter t. As are dummy variables indicating each quintile level of ambiguity. In descending order, A^5 is the top quintile with highest ambiguity, while A^1 is the bottom quintile with the lowest level, which is reflected in the constant term. $lsize_{it}$ is the natural log of beginning-of-period market capitalization for firm i in quarter t. ERCs of the second to fifth quintile are split into two parts. For example, for the fifth quintile, the coefficient is equal to $(\beta + \delta_4 D_{it}^5)$, which is a function of the level of ambiguity. The same calculation works for ERCs of other quintiles.

Table 4.6 column 3 shows that the ERC is monotonically increasing with the level of ambiguity for dE/P. ERC for the bottom quintile is 0.467 with standard error 0.043. For the second quintile, the ERC increases by 0.016 albeit insignificant at 10% level. For the middle quintile, the ERC increases an insignificant (at 10%) 0.105 over the first quintile. For the fourth quintile, a significant increase of 0.377 from the non-interacting term achieves a ERC of 0.844 (i.e. 0.377+0.467). The trend remains for the the top quintile with a ERC of 0.908 (i.e. 0.377+0.531). This strictly monotonically increasing trend is consistent with model generated figure 4.10. The results are similar with/out the size control variable. All variables explain a total of 1.84% of the variation of returns. The results of using alternative surprises measures including dE/B and dE/E are consistent. Note that although I focus the explanation of the results using ascending ambiguity, the measure ρ also has the effect of descending level of difference of opinion.

Differential reactions of quarterly returns to positive and negative earnings surprises under ambiguity and difference of opinion

I firstly run the regression 4.5 on positive and negative earnings surprises, respectively. Table 4.7 show the average earnings response coefficients for positive and negative earnings news for each of the three surprise measures. Column (2) shows that for given 1% earnings increase measured by dE/P, the quarterly return increases 0.126%. Column (3) shows that if the earnings decrease by 1%, the quarterly return drops by 0.814% which is significantly larger in magnitude. This asymmetry also appears evidently for the other two surprise measures.

Then, I run the equation 4.7 for positive and negative news separately. Table 4.8 presents the differential effects that the ascending ambiguity has on positive and negative news. There is a strictly monotonically positive contemporaneous relation between ambiguity and ERCs for negative surprises as shown in column 3, consistent with the model prediction shown on the right panel of figure 4.11. Nevertheless, the effects on positive news in column 2 present a picture with no discernible pattern. For example, ERC for dE/P in the first quintile is 0.087 insignificant at 10% level. Then, it increases by 0.162 for the second quintile, increase 0.059 for the third albeit decrease from the second quintile, increase 0.193 for the fourth, and increases 0.066 for the fifth quintile albeit decrease from the fourth quintile, although the changes are insignificant at 10% level. These results for positive news are consistent with the model prediction presented in figure 4.11. Note that these results are in fact the combined effect of both ambiguity and difference of opinion due to the proxies.

4.4 The model

In this section I construct a simple model which captures the main intuition on how ambiguous information and difference of opinion among experts affect the responses of returns to earnings announcements. I will start with the baseline model setup similar in nature to that of Chapter 3 and add a layer of experts in the decision making process following Cres, Gilboa, and Vieille (2011). Ambiguity is then introduced into the signals. Finally, I introduce the role of experts with difference of opinion into the setting. Assume there are N experts and n firms that together make up the market portfolio. Experts are asked by the decision maker to provide assessment of the informativeness of the signals. Each experts makes judgment of the probability distribution of the signals independently, so does the decision maker. When aggregating experts' opinions, the decision maker exhibits expert uncertainty aversion towards different opinions.

For simplicity, I assume all firms are equal in size. At the end of period t, the decision maker and experts observe earnings announcements e_{it} of each of the firm i. Firm's earnings consist of two components: $e_{it} = c_{it} + m_t$, where c_{it} is a firm-specific "cash-flow" component of the earnings and m_t is a market-wide component common for all firms. I assume that $cov[c_{it}, c_{jt}] = 0$ for $i \neq j$, $cov[c_{it}, m_t] = 0$ for any i. At the end of period t, the decision maker and experts can observe the realization of some market wide shock to returns ("discount rate news") d_t which is common for all stocks. I assume that the discount rate news correlates with the market-wide component of earnings news: $d_t = m_t + \eta_t$ with $cov[c_{it}, \eta_t] = 0$ for any i.

At the end of period $t-1$, the decision maker and experts observe noisy signals s_{it} about the future cash flow and discount news

$$s_{it} = e_{it} + u_{it},$$

where u_{it} is idiosyncratic noise with $cov[u_{it}, c_{jt}] = 0$ and $cov[u_{it}, \eta_{jt}] = 0$ for all i, j

and t. Denote by $\mathbf{s} = \{s_1, ..., s_n\}$.

Firm i's period t return is given by

$$R_{it} = E_{t-1}[R_{it}] + \varepsilon_{it} - \omega_t,$$

where ε_{it} is the revision to expected earnings of firm i and ω_t is an additional shock to firm i's return associated with common for each firm discount rate news. The negative sign captures the idea Campbell (1991).

4.4.1 Case of no uncertainty

In order to establish benchmark, I start by considering the case with no ambiguity in information and signals and no difference of opinion among experts. Since all experts and the decision maker have exactly the same opinion regarding the signals, I remove the layer of experts without loss of generality. Hence, $c_{it} \sim N(0, \sigma_{ci}^2)$ for any i and t, $m_t \sim N(0, \sigma_m^2)$, $\eta_t \sim N(0, \sigma_\eta^2)$ and $u_{it} \sim N(0, \sigma_u^2)$.

Denote in matrix form,

$$Z = \begin{pmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{nt} \end{pmatrix}, X = \begin{pmatrix} s_{1t} \\ s_{2t} \\ \vdots \\ s_{nt} \end{pmatrix}$$

where $Z \sim N(0, \sum_Z)$, $X \sim N(0, \sum_X)$, $\sum_{ZX} = Cov(Z, X)$, and $\sum_{dX} = Cov(d, X)$.

I am only interested in computing the responses of individual firms' returns to earnings announcements. Given the set of signals s_{it}, the decision maker's expectations about the realization of variables e_{it} and d_t are:

$$E(Z|X) = \Sigma_{ZX}\Sigma_X^{-1}X$$
$$E(d|X) = \Sigma_{dX}\Sigma_X^{-1}X$$

Specifically (see Appendix A.1 for detailed derivation),

$$\begin{aligned} E_{t-1}[e_{it}|\mathbf{s}] &= \sum_{j=1}^{n} \gamma_i^j s_{jt} \\ E_{t-1}[d_t|\mathbf{s}] &= \delta \bar{s}_t, \end{aligned}$$

where

$$\begin{aligned} \gamma_i^j &= \frac{\Delta}{\sigma_c^2 + \sigma_u^2} \quad \text{for } i \neq j \\ \gamma_i^i &= \frac{\sigma_c^2 + \Delta}{\sigma_c^2 + \sigma_u^2}, \\ \delta &= \frac{n\sigma_m^2}{\sigma_c^2 + n\sigma_m^2 + \sigma_u^2}. \end{aligned}$$

Hence, the announcement surprises ε_{it} and ω_t are

$$\begin{aligned} \varepsilon_{it} = e_{it} - E_{t-1}[e_{it}|\mathbf{s}] = e_{it} - \sum_{j=1}^{n} \gamma_i^j s_{jt}, \\ \omega_t = d_t - E_{t-1}[d_t|\mathbf{s}] = d_t - \delta \bar{s}_t. \end{aligned}$$

The covariance between the returns of the stock and the changes in the earnings announcements,

$$cov[R_{it}, \Delta e_{it}] = cov[\varepsilon_{it}, e_{it}] - cov[\omega_t, e_{it}].$$

Given that

$$\begin{aligned} cov[\varepsilon_{it}, e_{it}] &= var[e_{it}] - \sum_{j=1}^{n} \gamma_i^j cov[s_{jt}, e_{it}] = (\sigma_c^2 + \sigma_m^2)(1 - \gamma_i^i) - (n-1)\gamma_i^j \sigma_m^2, \\ cov[\omega_t, e_{it}] &= cov[d_t, e_{it}] - \delta cov[\bar{s}_t, e_{it}] = \sigma_m^2 - \frac{\delta}{n}(\sigma_c^2 + n\sigma_m^2) \end{aligned}$$

I get

$$cov[R_{it}, \Delta e_{it}] = (\sigma_c^2 + \sigma_m^2)\left(1 - \gamma_i^i + \frac{\delta}{n}\right) - \sigma_m^2 \left(1 + (n-1)\gamma_i^j - \delta + \frac{\delta}{n}\right).$$

The response coefficient of the return if firm i to its earnings surprise is equal to the beta coefficient:

$$\beta_i = \frac{cov[R_{it}, \Delta e_{it}]}{var[\Delta e_{it}]} = 1 - \gamma_i^i + \frac{\delta}{n} - \left(1 + (n-1)\gamma_i^j - \delta + \frac{\delta}{n}\right) \frac{\sigma_m^2}{\sigma_c^2 + \sigma_m^2}. \qquad (4.7)$$

4.4.2 Case of ambiguous information

Let us consider now an extension of the model where the experts and decision maker face ambiguity regarding the variance of firm-specific and market-wide cash flow components. The ambiguity of the firm specific component is purely idiosyncratic. I will call it firm-specific ambiguity hereafter. The ambiguity about the market represents the overall ambiguity about the market as whole. I will call it market-wide ambiguity. I consider both level of ambiguity altogether as a whole.

I model both types of ambiguity using the multiple prior model of Gilboa and Schmeidler (1989). More specifically, the experts and decision maker do not observe the variances of c_{it} and m_t and know only their interval ranges: $\sigma_{ci}^2 \in [\underline{\sigma}_c^2, \overline{\sigma}_c^2]$ and $\sigma_m^2 \in [\underline{\sigma}_m^2, \overline{\sigma}_m^2]$. Similar approach has been adopted by Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011). In this case, there is no difference of opinion. Hence the variance ranges will be the same for experts and the decision maker. without loss of generality, the layer of experts in the modelling setup is omitted in this subsection.

Following similar steps as in previous section (refer to Appendix A.2 for detailed derivation), we have

$$\begin{aligned} E_{t-1}[e_{it}|\mathbf{s}] &= \sum_{j=1}^{n} \gamma_i^j s_{jt} \\ E_{t-1}[d_t|\mathbf{s}] &= \sum_{i=1}^{n} \delta_i s_{it}, \end{aligned}$$

where

$$
\begin{aligned}
\gamma_i^i &= \frac{1}{\Gamma}\left[\frac{[\Gamma(\sigma_{ci}^2+\sigma_u^2)-\sigma_m^2](\sigma_{ci}^2+\sigma_m^2)}{(\sigma_{ci}^2+\sigma_u^2)^2} - \sum_{k=1,k\neq i}^{n} \frac{\sigma_m^2\sigma_m^2}{(\sigma_{ck}^2+\sigma_u^2)(\sigma_{ci}^2+\sigma_u^2)}\right] \quad \text{for } i=j \\
\gamma_i^j &= \frac{1}{\Gamma}\left[\frac{[\Gamma(\sigma_{cj}^2+\sigma_u^2)-\sigma_m^2]\sigma_m^2}{(\sigma_{cj}^2+\sigma_u^2)^2} - \frac{(\sigma_{ci}^2+\sigma_m^2)\sigma_m^2}{(\sigma_{ci}^2+\sigma_u^2)(\sigma_{cj}^2+\sigma_u^2)} - \sum_{k=1,k\neq i,j}^{n} \frac{\sigma_m^2\sigma_m^2}{(\sigma_{ck}^2+\sigma_u^2)(\sigma_{cj}^2+\sigma_u^2)}\right] \quad \text{for } i\neq j, \\
\delta_i &= \frac{\sigma_m^2}{\Gamma}\left[\frac{\Gamma}{\sigma_{ci}^2+\sigma_u^2} - \sum_{k=1}^{n} \frac{\sigma_m^2}{(\sigma_{ck}^2+\sigma_u^2)(\sigma_{ci}^2+\sigma_u^2)}\right].
\end{aligned}
$$

Hence, the announcement surprises ε_{it} and ω_t are

$$
\varepsilon_{it} = e_{it} - E_{t-1}[e_{it}|\mathbf{s}] = e_{it} - \sum_{j=1}^{n}\gamma_i^j s_{jt},
$$

$$
\omega_t = d_t - E_{t-1}[d_t|\mathbf{s}] = d_t - \sum_{i=1}^{n}\delta_i s_{it}.
$$

The decision maker's preferences exhibit ambiguity aversion and are described by the max-min expected utility model (see Gilboa and Schmeidler (1989) for the preference specification of the model). I assume that the decision maker chooses parameters σ_{ci}^2 and σ_m^2 through the minimization problem

$$
\min_{\substack{\sigma_{ci}^2 \in [\underline{\sigma}_c^2, \overline{\sigma}_c^2] \\ \sigma_m^2 \in [\underline{\sigma}_m^2, \overline{\sigma}_m^2]}} \quad E\left[R_{mt}(\sigma_{c1}^2, ..., \sigma_{cn}^2, \sigma_m^2)|\mathbf{s}\right], \tag{4.8}
$$

where

$$
E\left[R_{mt}(\sigma_{c1}^2, ..., \sigma_{cn}^2, \sigma_m^2)|\mathbf{s}\right] = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_i^j(\mathbf{s})s_{jt} - \sum_{i=1}^{n}\delta_i(\mathbf{s})s_{it}
$$

with $\gamma_i^i(\mathbf{s})$, $\gamma_i^j(\mathbf{s})$, and $\delta_i(\mathbf{s})$ defined the same way as above.

Next, I compute individual firms' returns responses to earnings surprises. Given the realizations of signals $\mathbf{s}$ and the choice of parameters determined by the decision maker's preferences, the return of asset i is given by

$$
R_{it} = E_{t-1}[R_{it}] + \varepsilon_{it} - \omega_t = E_{t-1}[R_{it}] + (e_{it} - \sum_{j=1}^{n}\gamma_i^j\,(\mathbf{s})\,s_{jt}) - (d_t - \sum_{i=1}^{n}\delta_i(\mathbf{s})s_{it}).
$$

The covariance between the returns of the stock and the changes in the earnings announcements is

$$cov[R_{it}, \Delta e_{it}] = cov[\varepsilon_{it}, e_{it}] - cov[\omega_t, e_{it}],$$

where

$$\begin{aligned} cov[\varepsilon_{it}, e_{it}] &= var[e_{it}] - \sum_{j=1}^{n} cov[\gamma_i^j(\mathbf{s})s_{jt}, e_{it}] = \sigma_c^2 + \sigma_m^2 - \sum_{j=1}^{n} E[\gamma_i^j(\mathbf{s})s_{jt}e_{it}] \\ &= \sigma_c^2 + \sigma_m^2 - \sum_{j=1}^{n} E[\gamma_i^j(\mathbf{s})s_{jt}E[e_{it}|\mathbf{s}]] = \sigma_c^2 + \sigma_m^2 - \sum_{j=1}^{n}\sum_{\iota=1}^{n}\gamma_i^\iota E[\gamma_i^j(\mathbf{s})\, s_{jt}s_{\iota t}] \end{aligned}$$

and

$$\begin{aligned} cov[\omega_t, e_{it}] &= cov[d_t, e_{it}] - \sum_{j=1}^{n} cov[\delta_j(\mathbf{s})s_{jt}, e_{it}] = \sigma_m^2 - \sum_{j=1}^{n} E[\delta_j(\mathbf{s})s_{jt}e_{it}] \\ &= \sigma_m^2 - \sum_{j=1}^{n} E[\delta_j(\mathbf{s})s_{jt}E[e_{it}|\mathbf{s}]] = \sigma_m^2 - \sum_{j=1}^{n}\sum_{\iota=1}^{n}\gamma_i^\iota E[\delta_j(\mathbf{s})s_{jt}s_{\iota t}]. \end{aligned}$$

The beta coefficient is

$$\begin{aligned} \beta_i &= \frac{cov[R_{it}, \Delta e_{it}]}{var[\Delta e_{it}]} \qquad (4.9) \\ &= 1 - \frac{1}{\sigma_c^2 + \sigma_m^2}\left(\sum_{j=1}^{n}\sum_{\iota=1}^{n}\gamma_i^\iota E[\gamma_i^j(\mathbf{s})\, s_{jt}s_{\iota t}] - \sigma_m^2 - \sum_{j=1}^{n}\sum_{\iota=1}^{n}\gamma_i^\iota E[\delta_j(\mathbf{s})s_{jt}s_{\iota t}]\right) \\ &- \frac{\sigma_m^2}{\sigma_c^2 + \sigma_m^2}. \end{aligned}$$

4.4.3 Case of difference of opinion among experts

Let us consider now an extension of the model where the investors face only difference of opinion. There are N experts, each of whom observes signals of all firms. Each expert has different but precise judgment of the probability distribution of the signals. There is a decision maker who aggregates experts' observations of the signals. In essence, this extension is N replications of the baseline model with experts possessing distinct priors and then the decision maker aggregates the signal assessments of the N experts within a maxmin framework.

Individual firms responses

Under difference of opinion, for each expert denoted as e, $\sigma_{c1}^{2(e)} = \sigma_{c2}^{2(e)} = \ldots = \sigma_{cn}^{2(e)} = \sigma_c^{2(e)}, e = 1 \ldots N$. Given the set of signals s_{it}, the expert's expectation about the realization of variables e_{it} and d_t are:

$$
\begin{aligned}
E_{t-1}^{(e)}[e_{it}|\mathbf{s}] &= \sum_{j=1}^{n} \gamma_i^{j(e)} s_{jt} \\
E_{t-1}^{(e)}[d_t|\mathbf{s}] &= \delta^{(e)} \bar{s}_t,
\end{aligned}
$$

where

$$
\begin{aligned}
\gamma_i^{j(e)} &= \frac{\Delta}{\sigma_c^{2(e)} + \sigma_u^2} \qquad \text{for } i \neq j \\
\gamma_i^{i(e)} &= \frac{\sigma_c^{2(e)} + \Delta}{\sigma_c^{2(e)} + \sigma_u^2}, \\
\delta^{(e)} &= \frac{n\sigma_m^{2(e)}}{\sigma_c^{2(e)} + n\sigma_m^{2(e)} + \sigma_u^2}.
\end{aligned}
$$

Hence, the announcement surprises $\varepsilon_{it}^{(e)}$ and $\omega_t^{(e)}$ are

$$
\begin{aligned}
\varepsilon_{it}^{(e)} = e_{it} - E_{t-1}^{(e)}[e_{it}|\mathbf{s}] = e_{it} - \sum_{j=1}^{n} \gamma_i^{j(e)} s_{jt}, \\
\omega_t^{(e)} = d_t - E_{t-1}^{(e)}[d_t|\mathbf{s}] = d_t - \delta^{(e)} \bar{s}_t.
\end{aligned}
$$

The decision maker's (DM) preferences exhibit aversion to expert uncertainty and are described by the "maxminmin" expected utility model (see Cres, Gilboa, and Vieille (2011) for the preference specification of the model). The weights allocated to each of the experts are determined as following two sets of rules:

1. the decision maker's set of priors is the weighted averages of experts' priors;
2. the decision maker's valuation is the the minimum of all weighted valuations of the experts' independent valuations.

$$\min_{\lambda \in \Lambda} \quad E\left[R_{mt}(\sigma_{c1}^2, ..., \sigma_{cn}^2, \sigma_m^2)|\mathbf{s}\right], \tag{4.10}$$

where

$$E\left[R_{mt}(\sigma_{c1}^2, ..., \sigma_{cn}^2, \sigma_m^2)|\mathbf{s}\right] = \sum_{e=1}^{N} \lambda_e(\mathbf{s}) (\frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_i^{j(e)} s_{jt} - \delta^{(e)} \bar{s}_t)$$

subject to

$$\begin{aligned}
\sigma_c^{2(DM)} &= \sum_{\substack{e=1 \\ \lambda \in \Lambda}}^{N} \lambda_e(\mathbf{s}) \sigma_c^{2(e)} \\
\sigma_m^{2(DM)} &= \sum_{\substack{e=1 \\ \lambda \in \Lambda}}^{N} \lambda_e(\mathbf{s}) \sigma_m^{2(e)} \\
\sum_{e=1}^{N} \lambda_e(\mathbf{s}) &= 1
\end{aligned}$$

with

$$\begin{aligned}
\gamma_i^{j(e)} &= \frac{\Delta}{\sigma_c^{2(e)} + \sigma_u^2} \quad \text{for } i \neq j \\
\gamma_i^{i(e)} &= \frac{\sigma_c^{2(e)} + \Delta}{\sigma_c^{2(e)} + \sigma_u^2}, \\
\delta^{(e)} &= \frac{n\sigma_m^{2(e)}}{\sigma_c^{2(e)} + n\sigma_m^{2(e)} + \sigma_u^2}.
\end{aligned}$$

Hence, the announcement surprises ε_{it} and ω_t are

$$\varepsilon_{it}^{(DM)} = e_{it} - \sum_{e=1}^{N} \lambda_e(\mathbf{s}) (E_{t-1}^{(e)}[e_{it}|\mathbf{s}]) = e_{it} - \sum_{e=1}^{N} \lambda_e(\mathbf{s}) (\sum_{j=1}^{n} \gamma_i^{j(e)} s_{jt}),$$

$$\omega_t^{(DM)} = d_t - \sum_{e=1}^{N} \lambda_e(\mathbf{s}) (E_{t-1}^{(e)}[d_t|\mathbf{s}]) = d_t - \delta^{(e)} \bar{s}_t.$$

The covariance between the returns of the stock and the changes in the earnings announcements,

$$cov[R_{it}, \Delta e_{it}] = cov[\varepsilon_{it}^{(DM)}, e_{it}] - cov[\omega_t^{(DM)}, e_{it}].$$

Given that

$$\begin{aligned}
cov[\varepsilon_{it}^{(DM)}, e_{it}] &= var[e_{it}] - \sum_{e=1}^{N}\lambda_e(\mathbf{s})\sum_{j=1}^{n}\gamma_i^{j(e)} cov[s_{jt}, e_{it}] \\
&= \sigma_c^2 + \sigma_m^2 - \sum_{e=1}^{N}\lambda_e(\mathbf{s})\left((\sigma_c^2+\sigma_m^2)\gamma_i^{i(e)} + (n-1)\gamma_i^{j(e)}\sigma_m^2\right), \\
&= \sum_{e=1}^{N}\lambda_e(\mathbf{s})\left((\sigma_c^2+\sigma_m^2)(1-\gamma_i^{i(e)}) - (n-1)\gamma_i^{j(e)}\sigma_m^2\right), \\
cov[\omega_t^{(DM)}, e_{it}] &= cov[d_t, e_{it}] - \sum_{e=1}^{N}\lambda_e(\mathbf{s})\left(\delta^{(e)} cov[\bar{s}_t, e_{it}]\right) \\
&= \sum_{e=1}^{N}\lambda_e(\mathbf{s})\left(\sigma_m^2 - \frac{\delta^{(e)}}{n}(\sigma_c^2 + n\sigma_m^2)\right)
\end{aligned}$$

I get

$$cov[R_{it}, \Delta e_{it}] = \sum_{e=1}^{N}\lambda_e(\mathbf{s})\left((\sigma_c^2+\sigma_m^2)\left(1-\gamma_i^{i(e)}+\frac{\delta^{(e)}}{n}\right) - \sigma_m^2\left(1+(n-1)\gamma_i^{j(e)} - \delta^{(e)} + \frac{\delta^{(e)}}{n}\right)\right).$$

The response coefficient of the return if firm i to its earnings surprise is equal to the beta coefficient:

$$\beta_i = \frac{cov[R_{it}, \Delta e_{it}]}{var[\Delta e_{it}]} = \sum_{e=1}^{N}\lambda_e(\mathbf{s})\left(1-\gamma_i^{i(e)}+\frac{\delta^{(e)}}{n} - \left(1+(n-1)\gamma_i^{j(e)}-\delta^{(e)}+\frac{\delta^{(e)}}{n}\right)\frac{\sigma_m^2}{\sigma_c^2+\sigma_m^2}\right). \quad (4.11)$$

4.4.4 Case of both ambiguity and difference of opinion

Now I consider the case when experts face both ambiguity and difference of opinion. A range of priors reflect ambiguity and different levels of the midpoints of the range reflect difference of opinion. The assessment of the signals by the decision maker proceed in two steps. Firstly, Experts choose the worst-case scenario under ambiguity. Secondly, decision maker aggregates experts' observations under difference of opinion.

Under both ambiguity and difference of opinion, $\sigma_{c1}^{2(e)} \neq \sigma_{c2}^{2(e)} \neq \ldots \neq \sigma_{cn}^{2(e)}$. As a result,

$$\begin{aligned} E_{t-1}^{(e)}[e_{it}|\mathbf{s}] &= \sum_{j=1}^{n} \gamma_i^{j(e)} s_{jt} \\ E_{t-1}^{(e)}[d_t|\mathbf{s}] &= \sum_{i=1}^{n} \delta_i^{(e)} s_{it}, \end{aligned}$$

with $\gamma_i^{j(e)}$, and $\delta_i^{(e)}$ defined in the same manner as in the section with only ambiguous information.

Hence, the announcement surprises $\varepsilon_{it}^{(e)}$ and $\omega_t^{(e)}$ are

$$\varepsilon_{it}^{(e)} = e_{it} - E_{t-1}^{(e)}[e_{it}|\mathbf{s}] = e_{it} - \sum_{j=1}^{n} \gamma_i^{j(e)} s_{jt},$$
$$\omega_t^{(e)} = d_t - E_{t-1}^{(e)}[d_t|\mathbf{s}] = d_t - \sum_{i=1}^{n} \delta_i^{(e)} s_{it}.$$

Experts' preferences exhibit ambiguity aversion and are described by the max-min expected utility model (see Gilboa and Schmeidler (1989) for the preference specification of the model). The decision maker's preferences exhibit aversion to expert uncertainty and are described by the "maxminmin" expected utility model (see Cres, Gilboa, and Vieille (2011) for the preference specification of the model). The weights allocated to each of the experts are determined following two sets of rules:

1. the decision maker's set of priors is the weighted averages of experts' priors;

2. the decision maker's valuation is the the minimum of all weighted valuations of the experts' independent valuations.

I assume that the investor chooses parameters σ_{ci}^2 and σ_m^2 through the double minimization problem

$$\min_{\lambda \in \Lambda} \sum_{e=1}^{N} \lambda_e(\mathbf{s}) \left(\min_{\substack{\sigma_{ci}^{2(e)} \in [\underline{\sigma}_c^{2(e)}, \overline{\sigma}_c^{2(e)}] \\ \sigma_m^{2(e)} \in [\underline{\sigma}_m^{2(e)}, \overline{\sigma}_m^{2(e)}]}} E\left[R_{mt}(\sigma_{c1}^{2(e)}, ..., \sigma_{cn}^{2(e)}, \sigma_m^{2(e)}) | \mathbf{s} \right] \right), \quad (4.12)$$

where

$$E\left[R_{mt}(\sigma_{c1}^{2(e)}, ..., \sigma_{cn}^{2(e)}, \sigma_m^{2(e)}) | \mathbf{s} \right] = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_i^{j(e)}(\mathbf{s}) s_{jt} - \sum_{i=1}^{n} \delta_i^{(e)}(\mathbf{s}) s_{it}$$

subject to

$$\begin{aligned} \sigma_{ci}^{2(DM)} &= \sum_{\substack{e=1 \\ \lambda \in \Lambda}}^{N} \lambda_e(\mathbf{s}) \sigma_{ci}^{2(e)}, \quad i = 1 \dots n \\ \sigma_m^{2(DM)} &= \sum_{\substack{e=1 \\ \lambda \in \Lambda}}^{N} \lambda_e(\mathbf{s}) \sigma_m^2 \\ \sum_{e=1}^{N} \lambda_e(\mathbf{s}) &= 1 \end{aligned}$$

Given the realizations of signals $\mathbf{s}$ and the choice of parameters determined by the representative investor preferences, the return of asset i is given by

$$\begin{aligned} R_{it}^{(DM)} &= E_{t-1}[R_{it}] + \sum_{e=1}^{N} \lambda_e(\mathbf{s}) \left(\varepsilon_{it}^{(e)} - \omega_t^{(e)} \right) \\ &= E_{t-1}[R_{it}] + \left(e_{it} - \sum_{e=1}^{N} \lambda_e(\mathbf{s}) \left(\sum_{j=1}^{n} \gamma_i^{j(e)}(\mathbf{s})\, s_{jt} \right) \right) - \left(d_t - \sum_{e=1}^{N} \lambda_e(\mathbf{s}) \left(\sum_{i=1}^{n} \delta_{i(e)}(\mathbf{s}) s_{it} \right) \right). \end{aligned}$$

The covariance between the returns of the stock and the changes in the earnings announcements is

$$cov[R_{it}^{(DM)}, \Delta e_{it}] = \sum_{e=1}^{N} \lambda_e(\mathbf{s}) \left(cov[\varepsilon_{it}^{(e)}, e_{it}] - cov[\omega_t^{(e)}, e_{it}] \right),$$

where

$$\begin{aligned} cov[\varepsilon_{it}^{(e)}, e_{it}] &= var[e_{it}] - \sum_{j=1}^{n} cov[\gamma_i^{j(e)}(\mathbf{s}) s_{jt}, e_{it}] = \sigma_c^2 + \sigma_m^2 - \sum_{j=1}^{n} E[\gamma_i^{j(e)}(\mathbf{s}) s_{jt} e_{it}] \\ &= \sigma_c^2 + \sigma_m^2 - \sum_{j=1}^{n} E[\gamma_i^{j(e)}(\mathbf{s}) s_{jt} E^{(e)}[e_{it}|\mathbf{s}]] \\ &= \sigma_c^2 + \sigma_m^2 - \sum_{j=1}^{n} \sum_{\iota=1}^{n} \gamma_i^{\iota(e)} E[\gamma_i^{j(e)}(\mathbf{s}) s_{jt} s_{\iota t}] \end{aligned}$$

and

$$\begin{aligned} cov[\omega_t^{(e)}, e_{it}] &= cov[d_t, e_{it}] - \sum_{i=1}^{n} cov[\delta_i(\mathbf{s}) s_{it}, e_{it}] = \sigma_m^2 - \sum_{i=1}^{n} E[\delta_i^{(e)}(\mathbf{s}) s_{it} e_{it}] \\ &= \sigma_m^2 - \sum_{i=1}^{n} E[\delta_i^{(e)}(\mathbf{s}) s_{it} E^{(e)}[e_{it}|\mathbf{s}]] = \sigma_m^2 - \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_i^{j(e)} E[\delta_i^{(e)}(\mathbf{s}) s_{it} s_{jt}]. \end{aligned}$$

The beta coefficient is

$$\begin{aligned} \beta_i &= \frac{cov[R_{it}, \Delta e_{it}]}{var[\Delta e_{it}]} \\ &= \sum_{e=1}^{N} \lambda_e(\mathbf{s}) \left(1 - \frac{1}{\sigma_c^2 + \sigma_m^2} \left(\sum_{j=1}^{n} \sum_{\iota=1}^{n} \gamma_i^{\iota(e)} E[\gamma_i^{j(e)}(\mathbf{s}) s_{jt} s_{\iota t}] - \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_i^{j(e)} E[\delta_i^{(e)}(\mathbf{s}) s_{it} s_{jt}] \right) - \frac{\sigma_m^2}{\sigma_c^2 + \sigma_m^2} \right). \end{aligned} \tag{4.13}$$

4.4.5 Calibration and simulations

In order to quantify the effects of ambiguity and difference of opinion on earnings response coefficients I perform a comparative statics analysis. However, the earnings response coefficients cannot be computed in the closed form. To circumvent this difficulty I fixed the values of σ_u^2, σ_c^2, σ_m^2 and n and use Monte Carlo simulations to estimate the earnings response coefficients for different values of the ambiguity parameters $\Delta_c = \bar{\sigma}_c^2 - \sigma_c^2$ and $\Delta_d = \bar{\sigma}_d^2 - \sigma_d^2$. I consider five different degrees of firm-level ambiguity: $\Delta_c = 0.2\sigma_c^2, 0.4\sigma_c^2, 0.6\sigma_c^2, 0.8\sigma_c^2, 0.99\sigma_c^2$ and six different degrees of market-level ambiguity: $\Delta_m = 0.2\sigma_m^2, 0.4\sigma_m^2, 0.6\sigma_m^2, 0.8\sigma_m^2, 0.99\sigma_m^2$. To do this I simulate 10,000 repetitions of signals for each of n firms with $n = 50$. Signals are generated following a normal probability distribution with $N(0, \sigma_c^2 + \sigma_m^2 + \sigma_u^2)$.

Parameter Values

I now parameterize and calibrate a version of the model framework with ambiguity and difference of opinion to quantitatively match the empirical earnings response coefficients which can be found in empirical results section.

For computing variance of m - the market-wide component of firms' earnings, I firstly take the cross-sectional average for earnings and then calculate the variance of of the time series for EP, EB, and EE, respectively. The rational is that firms' idiosyncratic components of earnings cancel out during cross-sectional averaging thus leaving only the common market-wide component.

For computing variance of c - the firm-specific "cash flow" component of firms' earnings, I firstly divide data into quintiles in terms of uncertainty (V) and then calculate the variance of the pooled data for each earnings surprise measure for each quintile. Subtraction of σ_m^2 from the calculated variances gives σ_c^2 for each quintile. The "aggregate" σ_c^2 is computed in the same way without splitting the data into quintiles.

For computing variance of u - the idiosyncratic noise of signals, I put σ_c^2 and σ_m^2 back to beta equation under no uncertainty with beta equal to 0.7 from table 4.2. σ_u^2 is around 0.00053.

Difference of opinion is measured by the number of experts following each firm. The correlation between the measure of difference of opinion (i.e. $1 - \rho$) and the number of experts is -0.010 significant at 1% level. I use five level of difference of opinion where the number of experts ranges from 2 to 10 with equal intervals.

Table 4.9 lists the calibrated parameter values that I employ in producing the results below.

Simulation results

ERCs are estimated using calibrated variable values and five levels of ambiguity and difference of opinions indicated above. The simulations results are exhibited via graphs. Figure 4.8 illustrates the effects of ambiguity and difference of opinion on reactions to positive signals. Panel A shows that as ambiguity level increases, the ERC decreases. The decreases are more pronounced for high levels of difference of opinion. Panel B shows that high difference of opinion similarly decreases ERC for positive news. The negative relation is more pronounced for high levels of ambiguity. Note that the slope of the ERC curve is much steeper as DoO increases. Hence, both ambiguity and difference of opinion decrease the positive signals' response coefficients in a largely similar magnitude. Figure 4.9 illustrates the effects of ambiguity and difference of opinion on reactions to negative signals. Panel A shows that ambiguity increases ERC in a linear manner. The ERC for 0.99 level of ambiguity is 60% larger than that of 0.2 level of ambiguity. The level of DoO shows little impact on the slope of ERC curve, which means the effect of ambiguity dominates that of DoO for negative signals. Panel B confirms that DoO has no discernible impact on ERC, while there is clear differences of ERCs for various levels of ambiguity. Hence, ambiguity increases the negative signals' response coefficients while DoO has a muted effect. These results correspond to the predictions 6 and 7.

I argue in this chapter that ambiguity is negatively correlated to DoO. Therefore, it is empirically informational to look at the combined effects of ambiguity and DoO on firstly signals without differentiating their nature and secondly positive and negative signals separately. Figure 4.10 shows the signal response coefficients with ascending ambiguity. Ascending ambiguity is equivalent to descending DoO for this case. It is evident that ambiguity (DoO) amplifies (reduces) the response to signals. These results correspond to the predictions 4 and 5. Next, I look at positive and negative signals separately. I add up the ERCs of high ambiguity and corresponding low DoO and plot the aggregated ERC. To be more precise, I aggregate the ERCs of the fifth ambiguity quintile and the first DoO quintile, the ERCs of fourth ambiguity quintile and second DoO quintile, and so forth. Figure 4.11 panel A shows the aggregate effect on positive signals. There is no clear trend and the ERC varies mostly between 1.330 and 1.346, around 1% interval. The variation of ERCs for different quintiles is insignificant. Figure 4.11 panel B shows the aggregate effect on negative signals. There is an unambiguous increasing trend and the ERC ranges between 1.33 to 1.61, around 20% interval and much significant. These results correspond to the predictions 8.

Lastly, I look at the differential reactions of negative versus positive signals under the combined effect of ambiguity and DoO. I generate the ERCs in two steps. Firstly, I add up the ERCs for positive and negative signals under ambiguity and the ERCs for positive and negative signals under DoO. Essentially, I compute the aggregate of data from panel As of figure 4.8 and 4.9 for ambiguity and the aggregate of data from panel Bs of figure 4.8 and 4.9 for DoO. Secondly, I add up the aggregated ERCs from the first step according to high ambiguity and low DoO order. Figure 4.12 shows a "yes" tick shape. Specifically, the ERC of the second ambiguity (fourth DoO) quintile has the lowest ERC. This particular shape is precisely captured in the empirical results.

4.4.6 Model predictions

H 4. *Higher firm-level ambiguity leads to more positive firm-level ERC.*

H 5. *Higher difference of opinion leads to less positive firm-level ERC.*

H 6. *For positive news, higher firm-level ambiguity leads to less positive firm-level ERC. For negative news, higher firm-level ambiguity leads to more positive firm-level ERC.*

H 7. *For positive news, higher difference of opinion leads to less positive firm-level ERC. For negative news, difference of opinion has an indiscernible effect on the firm-level ERC.*

H 8. *Ambiguity and DoO are negatively correlated. For ascending ambiguity (or descending DoO) quintiles, there is indiscernible trend of market reaction to positive news since the effect of ambiguity cancel out that of difference of opinion. There* *is strictly increasing trend of ERC for negative news since the effect of ambiguity dominates that of difference of opinion.*

4.5 Conclusions

The average negative return generated by bad news is larger in magnitude than the average positive return generated by good news. The asymmetric reaction could be due to either larger amount of negative news on the market or stronger reaction to bad news per se. This chapter shows that it is the latter that causes the differential average return between good and bad news. Literature provides two channels for explaining this asymmetric reaction. Firstly, Epstein and Schneider (2008) show in their model that Knightian uncertainty or ambiguity can lead to stronger reaction to bad news versus good news. Kelsey, Kozhan, and Pang (2011) show that this asymmetric reaction to bad versus good news causes asymmetric profitability of momentum strategy. Secondly, recent studies in decision theory raise the question that difference of opinion among experts could contribute to the decision maker's asymmetric assessment of the good versus bad news. Cres, Gilboa, and Vieille (2011), for instance, develop an axiomatized framework of incorporate ambiguity and difference of opinion altogether in the decision maker's assessment of signals. Based on those two strands of literature, this chapter sets out to empirically test and model the effects of both ambiguity and difference of opinion on firm-level return-earnings relation.

The results are striking. I show empirically that both ambiguity and difference of opinion are related to the differential reactions to bad versus good news and their combining effects generate a "yes" tick shape of differential earnings response coefficients in quintile portfolios. To verify the finding, I build a model to capture the return-earnings relation with one decision maker, multiple experts, and multiple firms. Due to lack of information, the ambiguity-averse experts and decision maker lack confidence on the distribution of firms' signals and hence assign a variance internal for the distributions of the signals. In the presence of private information, the gravity center of experts' set of priors differs, resulting in differential assessments of the signals even if the level of ambiguity is the same. Experts's preference exhibit ambiguity aversion and are described by the maxmin expected utility model proposed by Gilboa and Schmeidler (1989). The decision maker exhibits aversion to expert uncertainty and her preferences follow the "maxminmin" expected utility model axiomatized by Cres, Gilboa, and Vieille (2011). Monte Carlo simulation of the model shows that ambiguity and difference of opinion have contrasted effects on investors' reactions on earnings surprises measured by earnings response coefficient. Ambiguity increases the ERC for negative news. Difference of opinion, however, has a muted effect. For positive news, both decrease the response coefficients. By combining ambiguity with difference of opinion, the model generates a "yes" tick shape of differential reactions to negative versus positive news that matches the empirical finding.

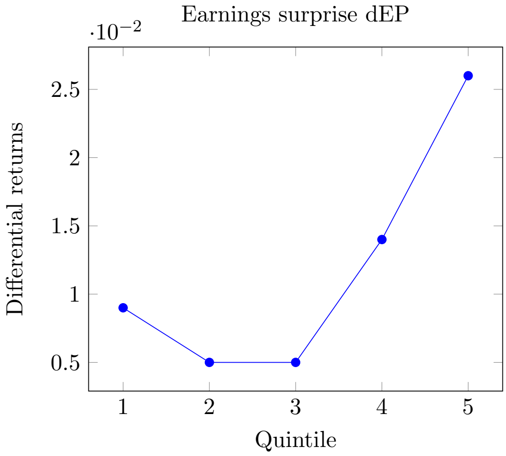
The results support our hypothesis that both ambiguity and difference of opinion contribute to the asymmetric market reaction to bad versus good news. The implication for investors is clear. When designing trading strategies based on news, it is important to consider the quality of information environment and the extent of private information on the market. Since ambiguity and difference of opinion generates asymmetric reactions to news, it is interesting to explore for future research that whether both could contribute to other asymmetric phenomena found on the financial markets. There are no independent proxies for ambiguity and difference of opinion available in the literature according to my knowledge, although a clearly separate measure for each will be ideal for the existing research design. The proposed consensus measure employed in this chapter thereby is the next best thing that I can find to disentangle those two concepts to a certain degree. I suggest that it would be instructive if future research can produce separate measures for ambiguity and difference of opinion that better capture the intuition of my mathematical model and would allow me to identify the separate empirical effects of the two variables on the return-earnings relation.

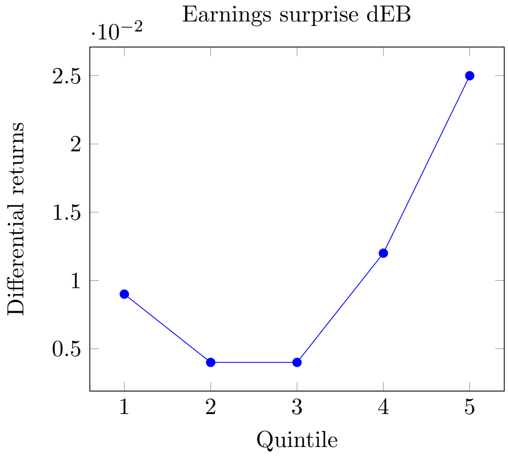
Figure 4.1: Asymmetric market reaction of bad versus good earnings surprises

This figure exhibits the difference between the average negative return generated by negative earnings surprises and the average positive return generated by positive earnings surprises:

$Diff.Ret = \|Neg\| - 2 \times \|Const\|$

where $\|Neg\|$ and $\|Const\|$ are the second and first rows of each panel from table 4.2. The vertical axis refers to the differential return. The horizontal axis refers to the quintile groups according to level of the ambiguity measure ρ. Quintile 1 indicates the group with the lowest level of ρ. Quintile 5 indicates the group with the highest level of ρ. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E).





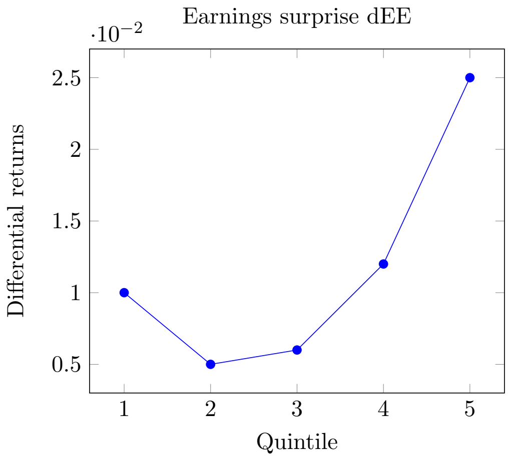


Figure 4.2: Asymmetric market reaction to bad versus good earnings surprises after controlling for the informational content of news

This figure exhibits the difference between the average negative return generated by negative earnings surprises and the average positive return generated by positive earnings surprises:

$Diff.Ret = \|Neg\| - 2 \times \|Const\|$

where $\|Neg\|$ and $\|Const\|$ are the second and first rows of each panel from table 4.3. The vertical axis refers to the differential return. The horizontal axis refers to the quintile groups according to level of the ambiguity measure ρ. Quintile 1 indicates the group with the lowest level of ρ. Quintile 5 indicates the group with the highest level of ρ. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E).

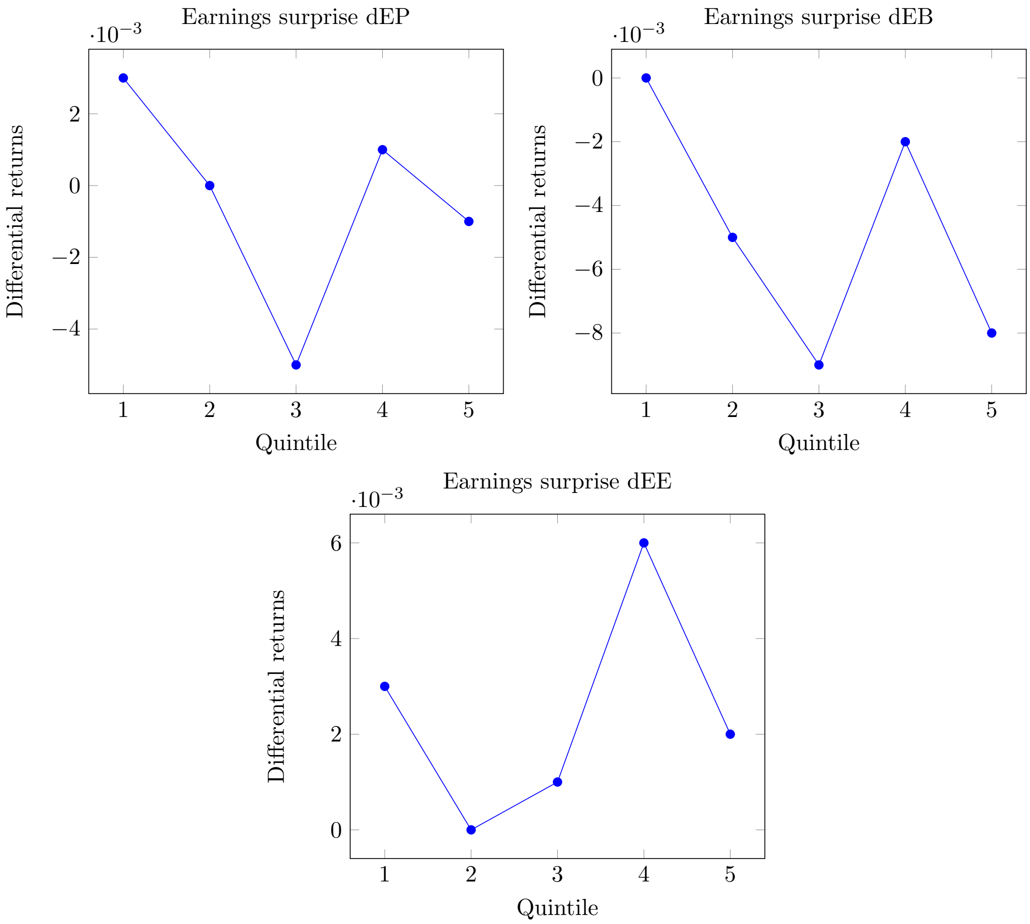


Figure 4.3: Asymmetric investors' reaction to bad versus good earnings surprises per se

This figure exhibits the differential investors' reaction to bad versus good news per se. The numbers are obtained from the fourth rows of each panel of table 4.3. The vertical axis refers to the investor's stronger reaction to bad news versus good news measured by the coefficient of the interaction term between news and dummy variable Neg. The horizontal axis refers to the quintile groups according to level of the ambiguity measure ρ. Quintile 1 indicates the group with the lowest level of ρ. Quintile 5 indicates the group with the highest level of ρ. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E).

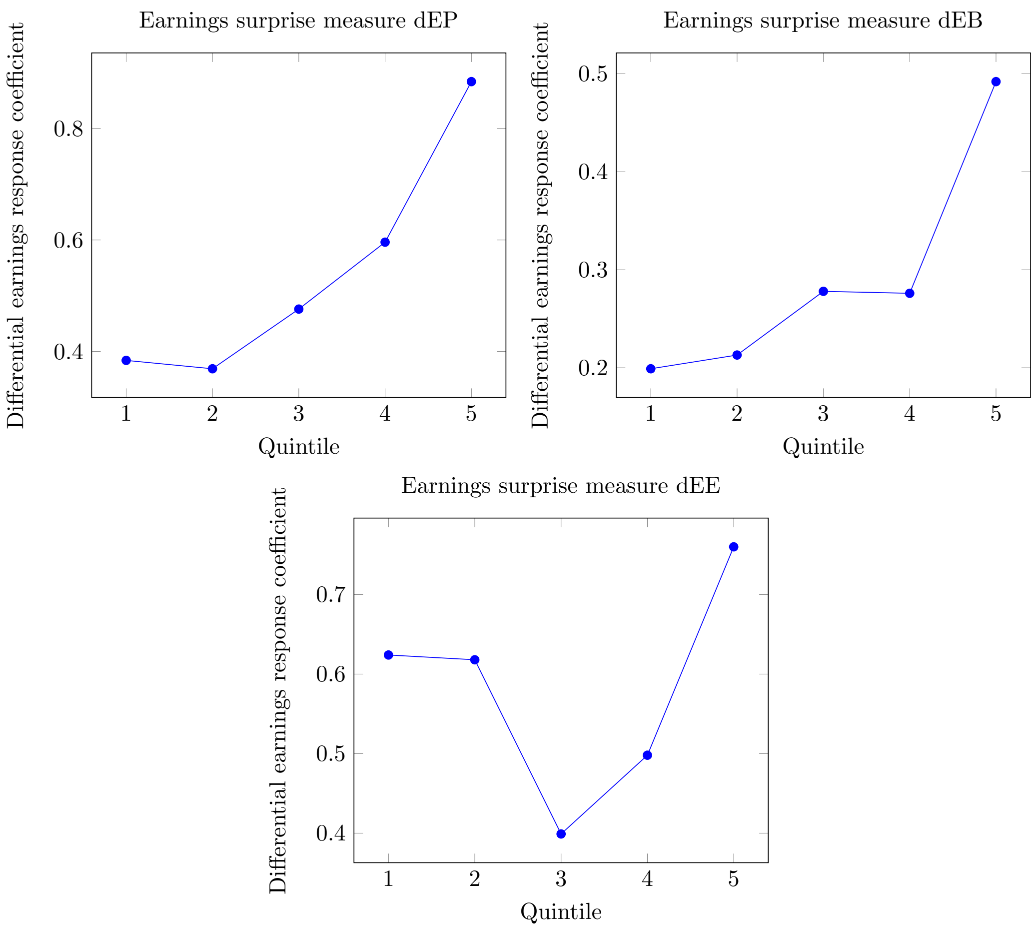


Figure 4.4: Asymmetric investors' reaction to bad versus good earnings surprises per se after controlling for managers' incentives

This figure exhibits the differential investors' reaction to bad versus good news per se after controlling for managers' incentives to selectively release relevant information about news. The numbers are obtained from the fourth rows of each panel of table 4.5. The vertical axis refers to the investor's stronger reaction to bad news versus good news measured by the coefficient of the interaction term between news and dummy variable Neg. The horizontal axis refers to the quintile groups according to level of the ambiguity measure ρ. Quintile 1 indicates the group with the lowest level of ρ. Quintile 5 indicates the group with the highest level of ρ. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E).

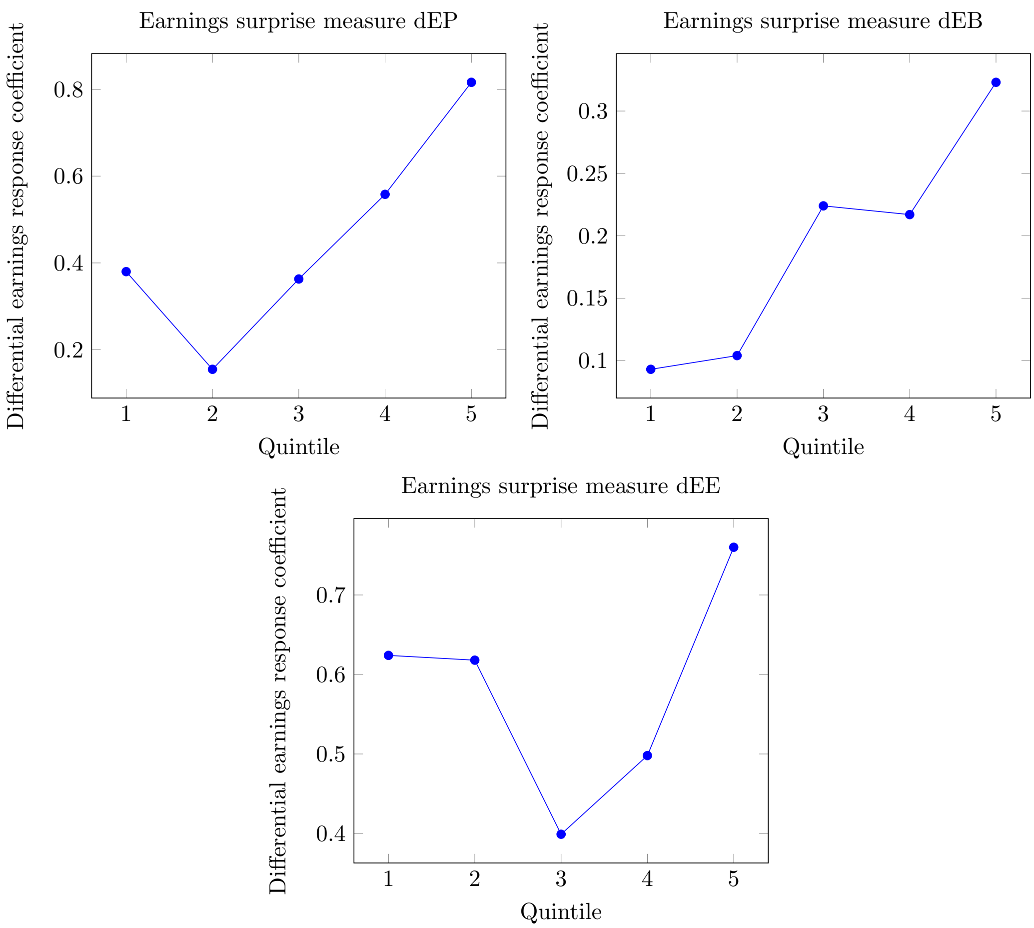


Figure 4.5: Reaction of quarterly returns to earnings surprises under different levels of ambiguity and difference of opinion

This figure exhibits investors' reaction to earnings surprises under different levels of ambiguity and difference of opinion, including both positive and negative surprises. The numbers are obtained from the sixth to tenth rows of each panel of table 4.6. The vertical axis refers to the investor's reaction to earnings news measured by the earnings response coefficient. The horizontal axis refers to the quintile groups according to level of the ambiguity measure ρ. Quintile 1 indicates the group with the lowest level of ρ. Quintile 5 indicates the group with the highest level of ρ. For quintile 1, the earnings response coefficients are shown in the 3, 5, 7 columns of the sixth row. For quintile 2, the earnings response coefficients are calculated as sum of the coefficient for *sue* and the coefficient for the the second interaction term $sue \times A^2$, and so forth. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E).

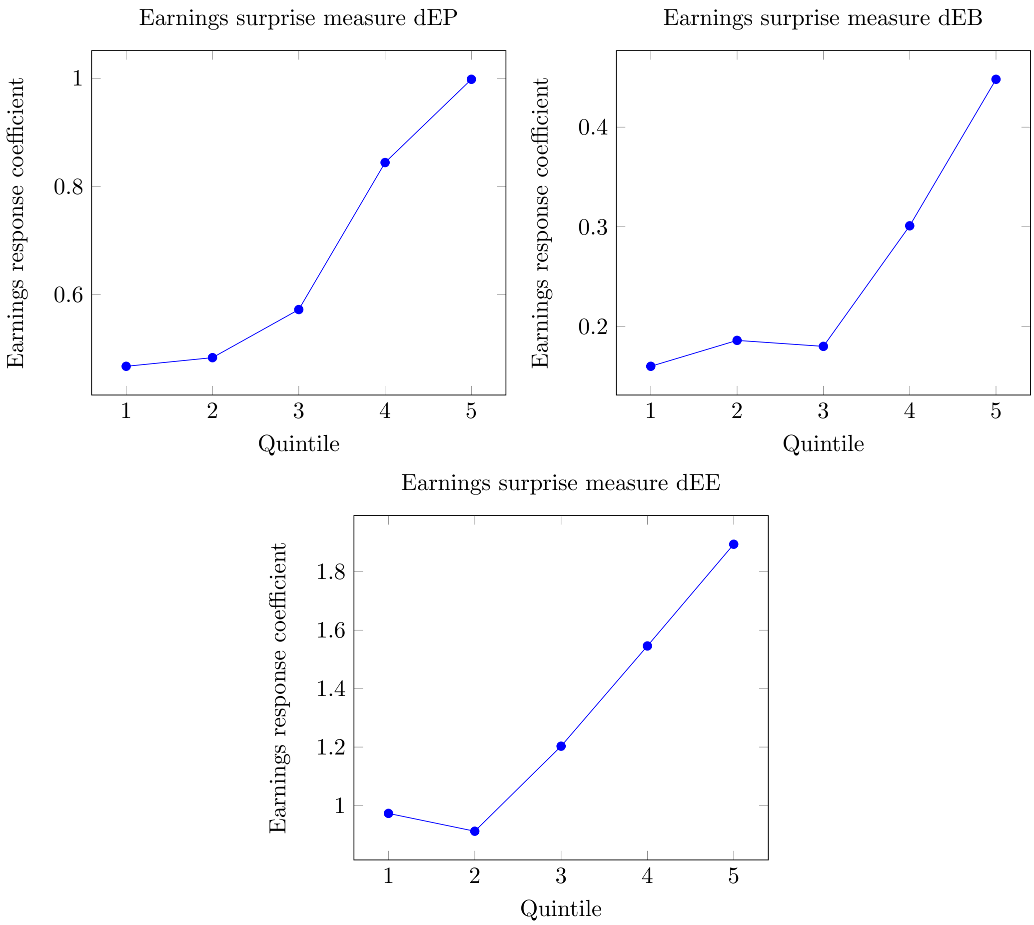


Figure 4.6: Reaction of quarterly returns to positive and negative earnings surprises under different levels of ambiguity and difference of opinion

This figure exhibits investors' reaction to, respectively, the positive and negative earnings surprises under different levels of ambiguity and difference of opinion. The figures on the left panel are based on positive surprises, while the ones on the right panel are based on negative surprises. The numbers are obtained from the sixth to tenth rows of each panel of table 4.8. The vertical axis refers to the investor's reaction to earnings news measured by the earnings response coefficient. The horizontal axis refers to the quintile groups according to level of the ambiguity measure ρ. Quintile 1 indicates the group with the lowest level of ρ. Quintile 5 indicates the group with the highest level of ρ. For quintile 1, the earnings response coefficients for positive earnings surprises are shown in the 2, 4, 6 columns of the sixth row. The earnings response coefficients for negative earnings surprises are shown in the 3, 5, 7 columns of the sixth row. For quintile 2, the earnings response coefficients are calculated as sum of the coefficient for *sue* and the coefficient for the the second interaction term $sue \times A^2$, and so forth. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E).

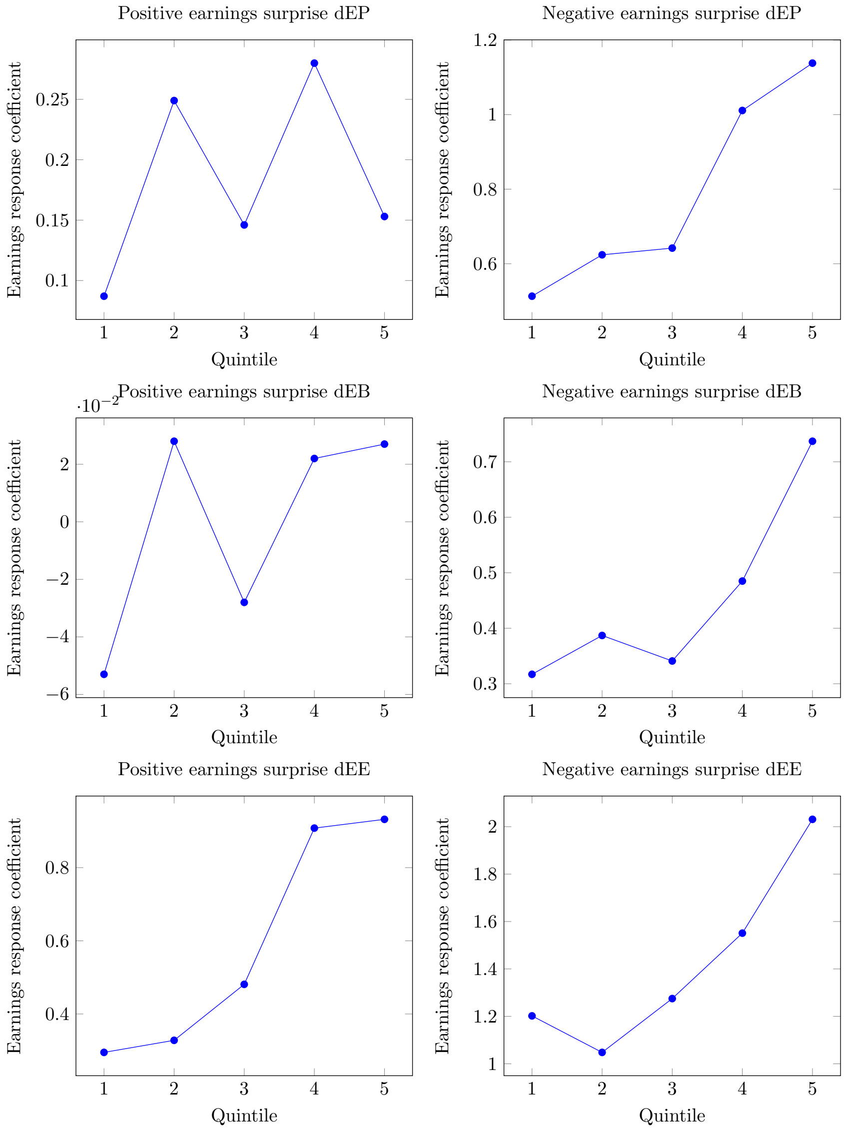


Figure 4.7: Difference in magnitude of investors' reaction of quarterly returns to negative versus positive earnings surprises under different levels of ambiguity and difference of opinion

This figure exhibits the difference in magnitude of investors' reaction to, respectively, the positive and negative earnings surprises under different levels of ambiguity and difference of opinion. The figures on the left panel are based on positive surprises, while the ones on the right panel are based on negative surprises. The numbers are obtained from the sixth to tenth rows of each panel of table 4.8. The vertical axis refers to the investor's differential reaction to bad versus good earnings news calculated as the subtraction of the earnings response coefficient for positive news from that for negative news. The horizontal axis refers to the quintile groups according to level of the ambiguity measure ρ. Quintile 1 indicates the group with the lowest level of ρ. Quintile 5 indicates the group with the highest level of ρ. For quintile 1, the differential earnings response coefficients are calculate using the numbers on the right panel of figure 4.6 minus those on the left panel. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E).

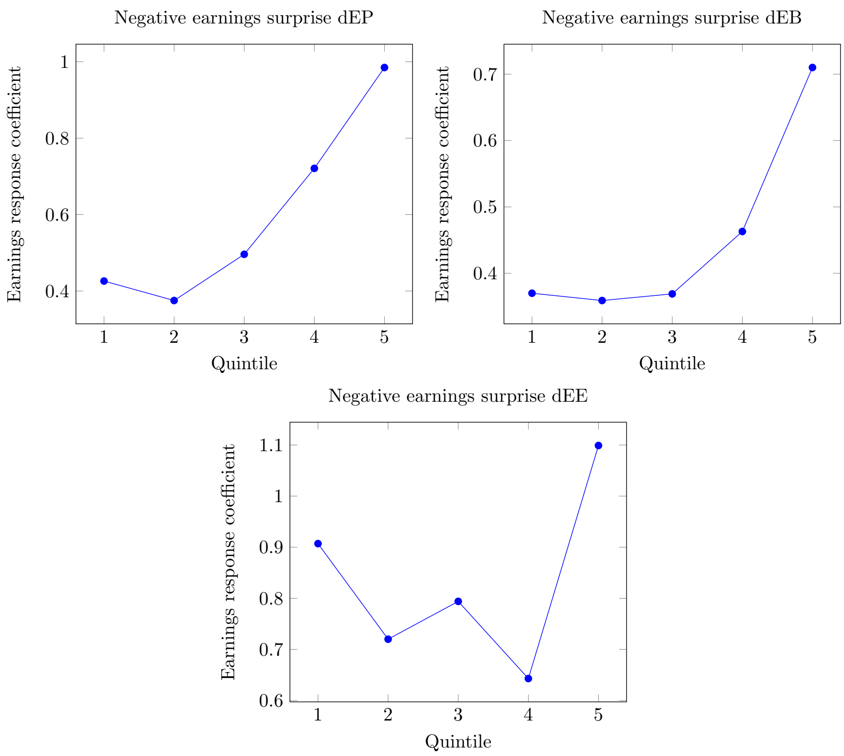


Figure 4.8: The effects of ambiguity and difference of opinion on response to positive signals

This figure exhibits the model generated effects of ambiguity and difference of opinion on positive signals reaction. Panel A shows the effect of ambiguity on positive signals under different layers of difference of opinion. Panel B shows the effect of difference of opinion on positive signals under different layers of ambiguity. $D = 1$ refers to the lowest level of difference of opinion while $D = 5$ refers the highest level. The range indicator 0.2 indicates the lowest level of ambiguity while 0.99 refers to the highest ambiguity. The vertical axis is the signal response coefficient.

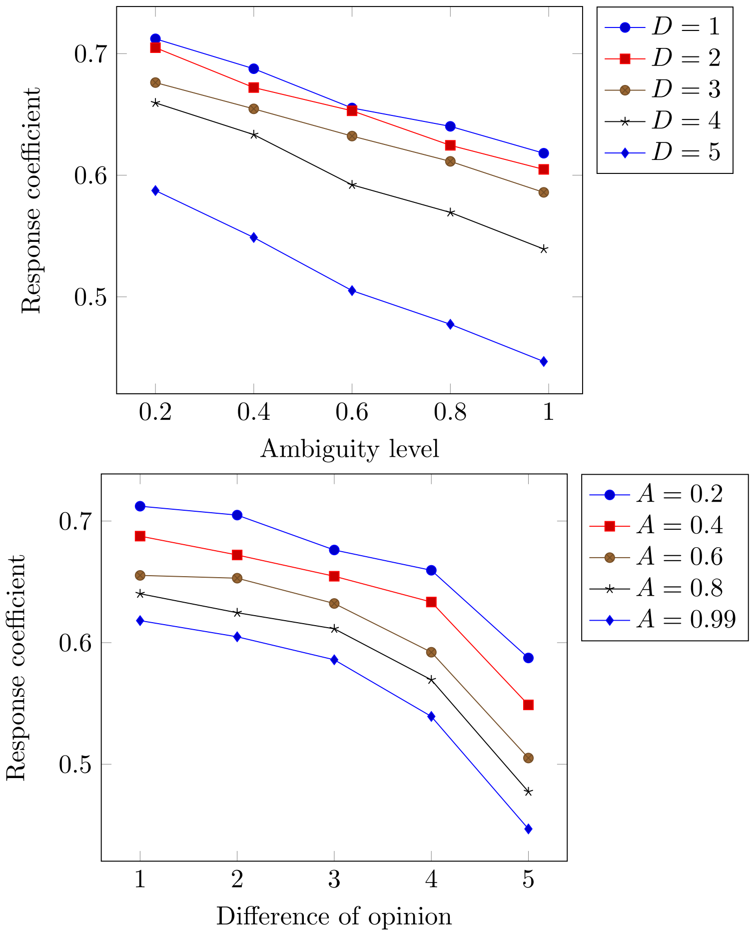


Figure 4.9: The effects of ambiguity and difference of opinion on response to negative signals

This figure exhibits the model generated effects of ambiguity and difference of opinion on negative signals reaction. Panel A shows the effect of ambiguity on negative signals under different layers of difference of opinion. Panel B shows the effect of difference of opinion on negative signals under different layers of ambiguity. $D = 1$ refers to the lowest level of difference of opinion while $D = 5$ refers the highest level. 0.2 indicates the lowest level of ambiguity while 0.99 refers to the highest ambiguity. The vertical axis is the signal response coefficient.

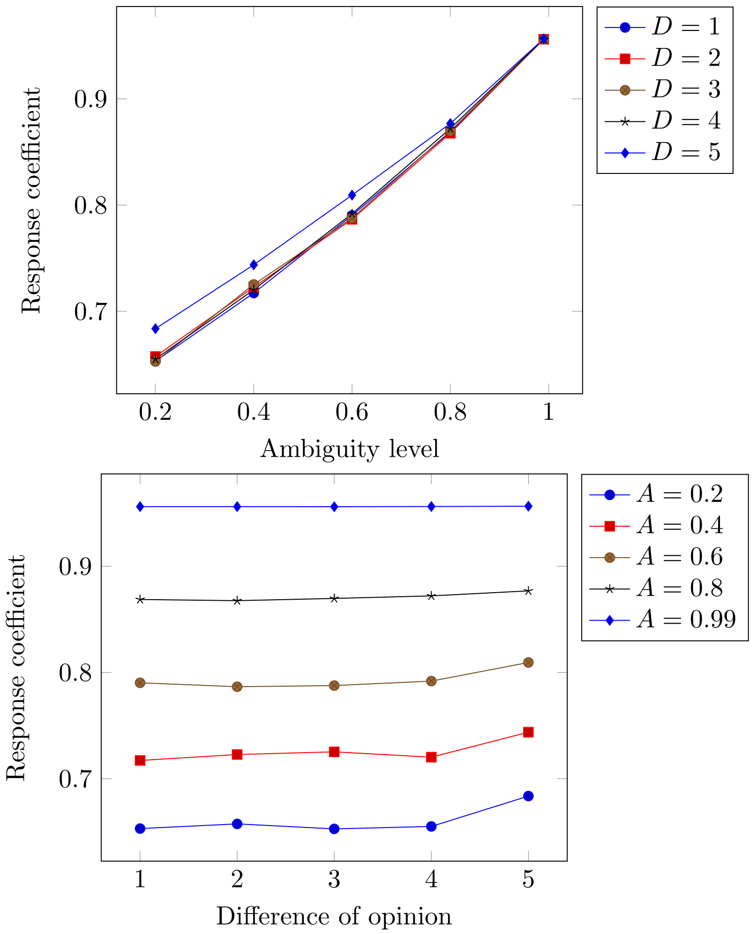


Figure 4.10: The aggregate effect of ambiguity and difference of opinion on signals response

This figure exhibits the model generated effect of ambiguity on signals reaction. The horizontal axis indicates the quintile groups with the combination of increasing ambiguity level and decreasing difference of opinion level. Quintile 1 indicates the lowest level of ambiguity at the same time the highest level of difference of opinion while Quintile 5 refers to the highest level of ambiguity while the lowest level of difference of opinion. The vertical axis is the signals response coefficient.

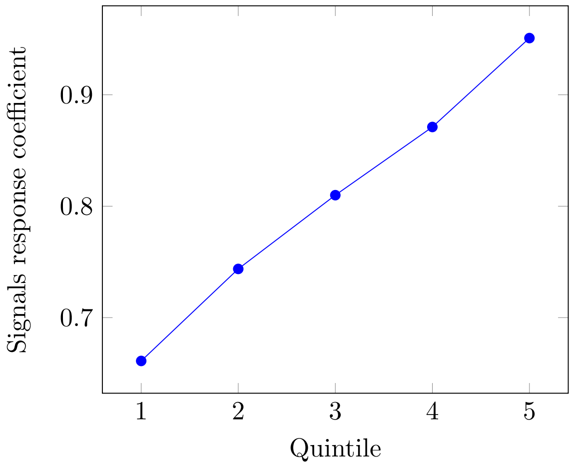


Figure 4.11: Aggregate reactions to positive versus bad signals

This figure exhibits the model generated aggregate effects of ambiguity and difference of opinion on the responses to positive versus negative news. The left panel shows the response to positive signals. I recalibrate the parameters only using the firm-quarter observations with only positive surprises and run the same simulations as before. The aggregate response for bad news shown on the right panel is conducted similarly. The horizontal axis indicates the quintile groups with the combination of increasing ambiguity level and decreasing difference of opinion level. Quintile 1 indicates that the coefficient is calculated using the data from the lowest level of ambiguity and highest level of difference of opinion, and so forth.

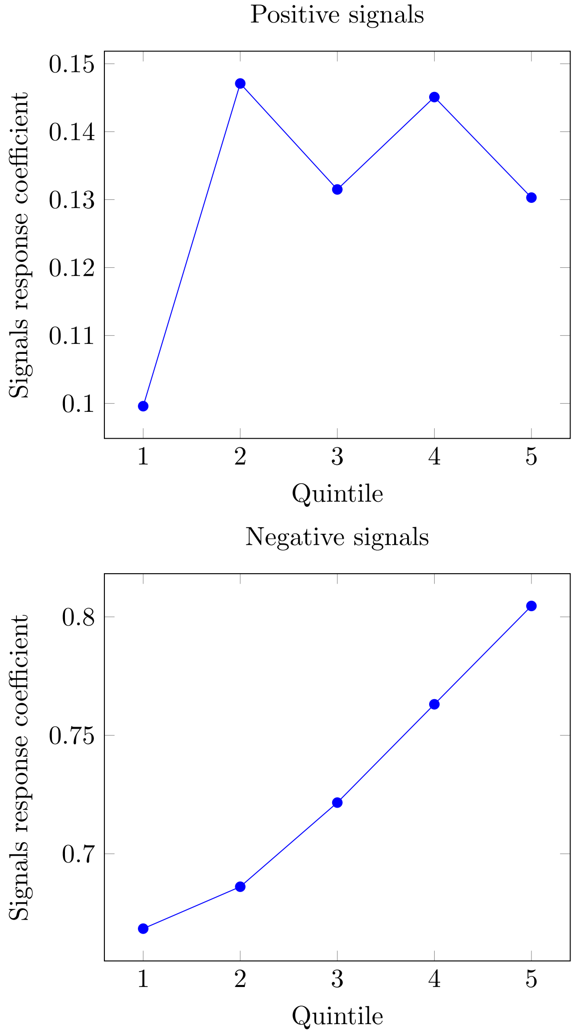


Figure 4.12: Differential reactions to bad versus good signals

This figure exhibits the model generated effect of the differential reactions to bad versus good news. The graph is generated by subtracting the response coefficients of the top panel of figure 4.11 from those from the bottom panel of figure 4.11. The horizontal axis indicates the quintile groups with the combination of increasing ambiguity level and decreasing difference of opinion level. Quintile 1 indicates that the coefficient is calculated using the data from the lowest level of ambiguity and highest level of difference of opinion, and so forth.

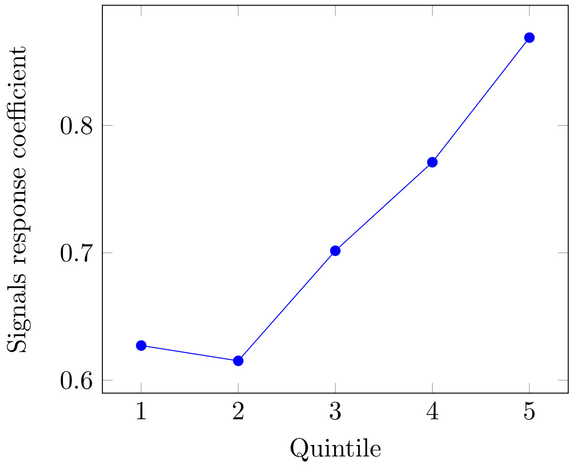


Table 4.1: *Summary statistics*

This table reports the summary statistics of the pooled panel individual firm data. *Return* is the quarterly return. *dEP*, *dEP*, and *dEE* are, respectively, the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), and earnings (E). *Log size* is the natural log of beginning-of-period market capitalization (in millions). *Analyst no.* is the number of experts following each firm. *Dispersion* is the dispersion of experts' earnings forecasts calculated by IBES. *Total unc* is the total uncertainty defined by Barron, Kim, Lim, and Stevens (1998) that equals to the sum of idiosyncratic uncertainty - *Idiosy unc*, and common uncertainty - *Common unc*. *Ambiguity* is refers to the version of ambiguity measured by $1 - \rho$ equal to common uncertainty divided by total uncertainty. *DoO* is the version of difference of opinion measured by ρ equal to idiosyncratic uncertainty divided by total uncertainty. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' earnings forecasts are from IBES Summary History - Summary Statistics. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. The sample period is from Q4/1983 to Q4/2013. The sample period is from Q4/1983 to Q4/2013.

Panel A: Summary statistics							
	Mean	Std. Dev.	Minimum	P25	Median	P75	Maximum
Return (qtr)	0.003	0.256	−3.098	−0.102	0.022	0.134	2.487
Log size	0.067	0.017	−0.024	0.055	0.066	0.077	0.133
dEP	0.002	0.045	−0.395	−0.005	0.002	0.007	0.531
dEB	0.002	0.109	−1.125	−0.011	0.003	0.016	1.274
dEE	0.013	2.643	−27.667	−0.316	0.105	0.500	18.667
Analyst no.	7.076	5.473	2.000	3.000	5.000	9.000	50.000
Dispersion	28.416	3793.732	0.000	0.010	0.020	0.040	1060660.200
Total unc	49.934	6304.870	0.000	0.002	0.010	0.050	2178125.002
Idiosy unc	11.630	2064.058	0.000	0.000	0.002	0.008	785454.291
Common unc	36.827	5783.835	−349090.781	0.000	0.004	0.031	2100000.000
Ambiguity	0.550	0.467	−1.000	0.231	0.733	0.952	1.000
DoO	0.450	0.467	0.000	0.048	0.267	0.769	2.000
Firm no.	9345						
N	227095						

Table 4.1 continued.

Panel B: Pearson correlation												
	Return	Log size	dEP	dEB	dEE	Analyst no.	Dispersion	Total unc	Idiosy unc	Common unc	Ambiguity	DoO
Return (qtr)	1.000											
Log size	−0.008	1.000										
	(0.000)											
dEP	0.067	−0.031	1.000									
	(0.000)	(0.000)										
dEB	0.002	−0.001	0.030	1.000								
	(0.356)	(0.721)	(0.000)									
dEE	0.143	0.027	0.186	0.016	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)								
Analyst no.	0.011	0.651	−0.002	0.001	0.031	1.000						
	(0.000)	(0.000)	(0.372)	(0.556)	(0.000)							
Dispersion	−0.005	−0.007	−0.000	0.009	−0.001	−0.005	1.000					
	(0.027)	(0.001)	(0.835)	(0.000)	(0.693)	(0.011)						
Total unc	−0.000	−0.007	−0.000	0.005	−0.001	−0.004	0.392	1.000				
	(1.000)	(0.001)	(0.979)	(0.044)	(0.575)	(0.046)	(0.000)					
Idiosy unc	−0.003	−0.005	0.000	0.005	0.001	−0.004	0.758	0.402	1.000			
	(0.164)	(0.013)	(0.908)	(0.028)	(0.791)	(0.048)	(0.000)	(0.000)				
Common unc	0.001	−0.006	−0.000	0.003	−0.002	−0.003	0.140	0.938	0.059	1.000		
	(0.614)	(0.011)	(0.943)	(0.158)	(0.471)	(0.163)	(0.000)	(0.000)	(0.000)			
Ambiguity	−0.003	−0.009	−0.004	−0.001	−0.032	0.014	−0.005	0.004	−0.007	0.007	1.000	
	(0.139)	(0.000)	(0.046)	(0.697)	(0.000)	(0.000)	(0.013)	(0.061)	(0.000)	(0.001)		
DoO	0.003	0.009	0.004	0.001	0.032	−0.014	0.005	−0.004	0.007	−0.007	−1.000	1.000
	(0.139)	(0.000)	(0.046)	(0.697)	(0.000)	(0.000)	(0.013)	(0.061)	(0.000)	(0.001)	(0.000)	

Standard errors in parentheses

Table 4.2: *Asymmetric stock price reaction to good vs. bad earnings news*

This table reports the coefficient, t-statistic, the number of observations used, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and within each quintile group regarding the level of rho:

$R_{it} = \alpha_0 + \beta_0 Neg_{it} + \epsilon_{it}$,

where R_{it} is the quarterly excess return over Fama and French (1993) market, size, book-to-market factors and Carhart (2001) momentum factor for firm i in quarter t. Neg is a categorical variable that equals one for negative earnings surprises, and zero otherwise. *A1/D5* refers to the lowest level of ambiguity yet the highest level of difference of opinion, and so forth. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), or earnings (E) for firm i at time t. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' forecasts are from IBES. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. Standard errors are given in parentheses. The standard errors are corrected for both heteroscedasticity and autocorrelation (Newey and West, 1987). I present the F-tests of whether twice the estimated intercept coefficient is equal in magnitude to coefficient for the dummy variable Neg. The sample period is from Q4/1983 to Q4/2013.

	Panel A: dE/P					
	All	$A1/D5$	$A2/D4$	$A3/D3$	$A4/D2$	$A5/D1$
$Const$	0.031***	0.019***	0.021***	0.030***	0.035***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neg_{it}	−0.073***	−0.047***	−0.047***	−0.065***	−0.084***	−0.124***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
N	227612	45609	45427	45533	45527	45516
adj. R^2	0.025	0.012	0.012	0.021	0.032	0.056
F-test:						
$2 * \lvert Const \rvert = \lvert Neg \rvert$	0.000	0.000	0.001	0.015	0.000	0.000
	Panel B: dE/B					
	All	$A1/D5$	$A2/D4$	$A3/D3$	$A4/D2$	$A5/D1$
$Const$	0.030***	0.018***	0.021***	0.029***	0.035***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neg_{it}	−0.072***	−0.045***	−0.046***	−0.062***	−0.082***	−0.123***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
N	227438	45507	45449	45523	45485	45474
adj. R^2	0.024	0.011	0.011	0.019	0.031	0.056
F-test:						
$2 * \lvert Const \rvert = \lvert Neg \rvert$	0.000	0.000	0.015	0.027	0.000	0.000
	Panel C: dE/E					
	All	$A1/D5$	$A2/D4$	$A3/D3$	$A4/D2$	$A5/D1$
$Const$	0.030***	0.018***	0.021***	0.029***	0.035***	0.048***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neg_{it}	−0.072***	−0.046***	−0.047***	−0.064***	−0.082***	−0.121***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
N	226774	45479	45225	45371	45348	45351
adj. R^2	0.024	0.011	0.012	0.020	0.031	0.054
F-test:						
$2 * \lvert Const \rvert = \lvert Neg \rvert$	0.000	0.000	0.005	0.005	0.000	0.000

Standard errors in parentheses

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

Table 4.3: *Cross-sectional variations in market reactions to earnings news after controlling for news leakage*

This table reports the coefficient, t-statistic, the number of observations used, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of either difference of opinion or ambiguity:

$R_{it} = \alpha_0 + \beta_0 Neg_{it} + \beta_1 RegFD_{it} + \beta_2 RegFD_{it} * Neg_{it} + \beta_3 LitRisk_{it} + \beta_4 LitRisk_{it} * Neg_{it} + \beta_5 InfoAsymm_{it} + \beta_6 InfoAsymm_{it} * Neg_{it} + \beta_7 FinDistress_{it} + \beta_7 FinDistress_{it} * Neg_{it} + \epsilon_{it}$,

where R_{it} is the quarterly excess return over Fama and French (1993) market, size, book-to-market factors and Carhart (2001) momentum factor for firm i in quarter t. *A1/D5* refers to the lowest level of ambiguity yet the highest level of difference of opinion, and so forth. Neg_{it} is a categorical variable that equals one for Negative earnings surprises, and zero otherwise. $RegFD_{it}$ is a dummy variable equal to one if the announcement occurs before the passage of Regulation FD in October 2000, and zero otherwise. $LitRisk_{it}$ is a dummy variable that equals one if the firm has less than median litigation risk calculated using Rogers and Stocken (2005) predictive regression, and zero otherwise. $InfoAsymm_{it}$ is a dummy variable that equals one if the firm is above the median value of a single information asymmetry factor, and zero otherwise. The information asymmetry factor is derived from a factor analysis based on the information asymmetry proxies: market-to-book ratio, stock volatility, high-tech firms, financial leverage, and regulatory status. $FinDistress_{it}$ is a dummy variable that equals one if the firm's Z-score (Zmijewski, 1984) financial distress rank is in the top decile of all firms in a given year, and zero otherwise. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), or earnings (E) for firm i at time t. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' forecasts are from IBES. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. Standard errors are given in parentheses. The standard errors are corrected for both heteroscedasticity and autocorrelation (Newey and West, 1987). I present the F-tests of whether the estimated intercept coefficient is equal in magnitude to coefficient for the dummy variable Neg_{it}. The sample period is from Q4/1983 to Q4/2013.

	Panel A: dE/P					
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
Const	0.031^{***}	0.018^{***}	0.023^{***}	0.034^{***}	0.038^{***}	0.044^{***}
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Neg_{it}	-0.043^{***}	-0.028^{***}	-0.032^{***}	-0.042^{***}	-0.053^{***}	-0.070^{***}
	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)
$RegFD_{it}$	0.001	0.002	0.003	0.001	0.002	−0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
$RegFD_{it} \times Neg_{it}$	-0.023^{***}	−0.008	-0.014^{**}	-0.020^{***}	-0.038^{***}	-0.029^{***}
	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
$LitRisk_{it}$	0.009^{***}	0.014^{**}	0.009	−0.003	0.011^{*}	0.010^{*}
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$LitRisk_{it} \times Neg_{it}$	-0.026^{***}	-0.031^{***}	-0.038^{***}	−0.014	−0.014	-0.027^{***}
	(0.004)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
$InfoAsymm$	-0.004^{**}	-0.010^{**}	−0.006	-0.012^{***}	−0.001	0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$InfoAsymm \times Neg_{it}$	-0.014^{***}	−0.008	−0.004	-0.013^{*}	-0.014^{**}	-0.023^{***}
	(0.003)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
$FinDistress$	0.000	−0.006	−0.011	0.001	0.000	0.010
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$FinDistress \times Neg_{it}$	0.001	0.021^{*}	0.016	−0.019	−0.005	−0.001
	(0.006)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)
N	99084	19404	21097	20855	21001	16727
adj. R^2	0.022	0.010	0.013	0.020	0.031	0.046
F-test:						
$\lvert Const\rvert = \lvert Neg\rvert$	0.000	0.006	0.009	0.024	0.000	0.000

Table 4.3 continued.

Panel B: dE/B						
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
$Const$	0.030^{***}	0.018^{***}	0.023^{***}	0.031^{***}	0.037^{***}	0.044^{***}
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Neg_{it}	-0.041^{***}	-0.026^{***}	-0.031^{***}	-0.037^{***}	-0.051^{***}	-0.071^{***}
	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)
$RegFD_{it}$	0.001	0.001	0.003	0.002	0.002	-0.003
	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
$RegFD_{it} \times Neg_{it}$	-0.022^{***}	-0.008	-0.012^{**}	-0.020^{***}	-0.038^{***}	-0.024^{***}
	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
$LitRisk_{it}$	0.008^{***}	0.013^{**}	0.006	-0.004	0.012^{*}	0.010
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$LitRisk_{it} \times Neg_{it}$	-0.026^{***}	-0.029^{***}	-0.032^{***}	-0.012	-0.018^{*}	-0.030^{***}
	(0.004)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
$InfoAsymm$	-0.003	-0.009^{**}	-0.004	-0.008^{*}	-0.001	0.002
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$InfoAsymm \times Neg_{it}$	-0.017^{***}	-0.009	-0.009	-0.020^{***}	-0.013^{**}	-0.023^{***}
	(0.003)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
$FinDistress$	0.001	-0.007	-0.010	0.002	0.001	0.011
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$FinDistress \times Neg_{it}$	0.001	0.020^{*}	0.016	-0.018	-0.007	0.000
	(0.006)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)
N	98976	19360	21103	20853	20995	16665
adj. R^2	0.021	0.010	0.012	0.019	0.030	0.047
F-test:						
$\|Const\| = \|Neg\|$	0.000	0.014	0.018	0.127	0.000	0.000

Panel C: dE/E						
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
$Const$	0.031^{***}	0.018^{***}	0.023^{***}	0.033^{***}	0.038^{***}	0.045^{***}
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Neg_{it}	-0.043^{***}	-0.027^{***}	-0.033^{***}	-0.042^{***}	-0.054^{***}	-0.069^{***}
	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)
$RegFD_{it}$	0.001	0.001	0.003	0.002	0.000	-0.003
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
$RegFD_{it} \times Neg_{it}$	-0.022^{***}	-0.008	-0.013^{**}	-0.020^{***}	-0.035^{***}	-0.028^{***}
	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
$LitRisk_{it}0$	0.008^{***}	0.014^{**}	0.008	-0.003	0.010^{*}	0.006
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$LitRisk_{it} \times Neg_{it}$	-0.026^{***}	-0.031^{***}	-0.039^{***}	-0.013	-0.015	-0.023^{**}
	(0.004)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
$InfoAsymm$	-0.004^{**}	-0.010^{**}	-0.006	-0.012^{***}	-0.001	0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$InfoAsymm \times Neg_{it}$	-0.013^{***}	-0.007	-0.004	-0.012^{*}	-0.012^{*}	-0.022^{***}
	(0.003)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
$FinDistress$	-0.001	-0.007	-0.013	0.001	-0.001	0.007
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$FinDistress \times Neg_{it}$	0.002	0.020^{*}	0.019	-0.021	-0.004	0.000
	(0.006)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)
N	98669	19358	20988	20745	20908	16670
adj. R^2	0.021	0.010	0.013	0.020	0.030	0.045
F-test:						
$\|Const\| = \|Neg\|$	0.000	0.009	0.009	0.019	0.000	0.000

Standard errors in parentheses

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

Table 4.4: *Asymmetric stock price reaction to good vs. bad earnings news*

This table reports the coefficient, t-statistic, the number of observations used, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of either difference of opinion or ambiguity:

$R_{it} = \alpha_0 + \beta_0 Neg_{it} + \delta_1 sue_{it} + \delta_2 sue_{it} * Neg_{it} + \epsilon_{it}$,

where R_{it} is the quarterly excess return over Fama and French (1993) market, size, book-to-market factors and Carhart (2001) momentum factor for firm i in quarter t. Neg is a categorical variable that equals one for negative earnings surprises, and zero otherwise. *A1/D5* refers to the lowest level of ambiguity yet the highest level of difference of opinion, and so forth. dE/P, dE/B, and dE/E are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), or earnings (E) for firm i at time t. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' forecasts are from IBES. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. Standard errors are given in parentheses. The standard errors are corrected for both heteroscedasticity and autocorrelation (Newey and West, 1987). I present the F-tests of whether twice the estimated intercept coefficient is equal in magnitude to coefficient for the dummy variable Neg. The sample period is from Q4/1983 to Q4/2013.

			Panel A: dE/P			
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
Const	0.029***	0.018***	0.019***	0.029***	0.031***	0.048***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neg_{it}	−0.057***	−0.039***	−0.038***	−0.053***	−0.063***	−0.095***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
sue_{it}	0.097***	0.062	0.097**	0.063	0.186***	0.041
	(0.021)	(0.045)	(0.044)	(0.041)	(0.045)	(0.053)
$sue_{it} \times Neg_{it}$	0.642***	0.384***	0.369***	0.476***	0.596***	0.884***
	(0.037)	(0.087)	(0.093)	(0.083)	(0.078)	(0.079)
N	227612	45609	45427	45533	45527	45516
adj. R^2	0.032	0.014	0.014	0.024	0.041	0.071
F-test:						
$2 * \lvert Const \rvert = \lvert Neg \rvert$	0.217	0.096	0.951	0.098	0.849	0.546
			Panel B: dE/B			
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
Const	0.031***	0.020***	0.021***	0.032***	0.036***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neg_{it}	−0.058***	−0.040***	−0.037***	−0.055***	−0.070***	−0.090***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
sue_{it}	−0.020**	−0.043**	0.002	−0.075***	−0.010	0.009
	(0.010)	(0.022)	(0.019)	(0.020)	(0.020)	(0.025)
$sue_{it} \times Neg_{it}$	0.321***	0.199***	0.213***	0.278***	0.276***	0.492***
	(0.017)	(0.036)	(0.038)	(0.038)	(0.036)	(0.041)
N	227438	45507	45449	45523	45485	45474
adj. R^2	0.032	0.013	0.015	0.023	0.037	0.078
F-test:						
$2 * \lvert Const \rvert = \lvert Neg \rvert$	0.000	0.871	0.090	0.001	0.422	0.003
			Panel C: dE/E			
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
Const	0.026***	0.017***	0.019***	0.025***	0.029***	0.042***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Neg_{it}	−0.054***	−0.037***	−0.038***	−0.051***	−0.064***	−0.086***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
sue_{it}	0.372***	0.154**	0.158**	0.369***	0.458***	0.620***
	(0.037)	(0.071)	(0.079)	(0.075)	(0.079)	(0.105)
$sue_{it} \times Neg_{it}$	0.698***	0.624***	0.618***	0.399***	0.498***	0.760***
	(0.057)	(0.125)	(0.141)	(0.127)	(0.118)	(0.133)
N	226774	45479	45225	45371	45348	45351
adj. R^2	0.033	0.014	0.015	0.025	0.038	0.072
F-test:						
$2 * \lvert Const \rvert = \lvert Neg \rvert$	0.334	0.147	0.781	0.875	0.044	0.578

Standard errors in parentheses

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

Table 4.5: *Cross-sectional variations in market reactions to earnings news after controlling for both news leakage and informational content of news per se*

This table reports the coefficient, t-statistic, the number of observations used, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of either difference of opinion or ambiguity:

$R_{it} = \alpha + \beta_0 Neg_{it} + \delta_1 sue_{it} + \delta_2 sue_{it} * Neg_{it} + \beta_1 RegFD_{it} + \beta_2 RegFD_{it} * Neg_{it} + \beta_3 LitRisk_{it} + \beta_4 LitRisk_{it} * Neg_{it} + \beta_5 InfoAsymm_{it} + \beta_6 InfoAsymm_{it} * Neg_{it} + \beta_7 FinDistress_{it} + \beta_7 FinDistress_{it} * Neg_{it} + \epsilon_{it}$,

where R_{it} is the quarterly excess return over Fama and French (1993) market, size, book-to-market factors and Carhart (2001) momentum factor for firm i in quarter t. *A1/D5* refers to the lowest level of ambiguity yet the highest level of difference of opinion, and so forth. Neg_{it} is a categorical variable that equals one for Negative earnings surprises, and zero otherwise. sue_{it} are the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), or earnings (E) for firm i at time t. $RegFD_{it}$ is a dummy variable equal to one if the announcement occurs before the passage of Regulation FD in October 2000, and zero otherwise. $LitRisk_{it}$ is a dummy variable that equals one if the firm has less than median litigation risk calculated using Rogers and Stocken (2005) predictive regression, and zero otherwise. $InfoAsymm_{it}$ is a dummy variable that equals one if the firm is above the median value of a single information asymmetry factor, and zero otherwise. The information asymmetry factor is derived from a factor analysis based on the information asymmetry proxies: market-to-book ratio, stock volatility, high-tech firms, financial leverage, and regulatory status. $FinDistress_{it}$ is a dummy variable that equals one if the firm's Z-score (Zmijewski, 1984) financial distress rank is in the top decile of all firms in a given year, and zero otherwise. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' forecasts are from IBES. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. The sample period is from Q4/1983 to Q4/2013. Standard errors are given in parentheses. The standard errors are corrected for both heteroscedasticity and autocorrelation (Newey and West, 1987). I present the F-tests of whether the estimated intercept coefficient is equal in magnitude to coefficient for the dummy variable Neg_{it}. The sample period is from Q4/1983 to Q4/2013.

Panel A: dE/P						
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
Const	0.029***	0.017***	0.021***	0.033***	0.034***	0.044***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Neg_{it}	−0.030***	−0.019***	−0.026***	−0.034***	−0.034***	−0.050***
	(0.002)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)
sue_{it}	0.108***	0.076	0.135**	0.040	0.243***	0.007
	(0.028)	(0.064)	(0.065)	(0.057)	(0.058)	(0.071)
$sue_{it} \times Neg_{it}$	0.491***	0.380***	0.155	0.363***	0.558***	0.816***
	(0.053)	(0.130)	(0.124)	(0.111)	(0.108)	(0.120)
$RegFD_{it}$	0.001	0.002	0.003	0.001	0.001	−0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
$RegFD_{it} \times Neg_{it}$	−0.025***	−0.011*	−0.015**	−0.021***	−0.038***	−0.031***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
$LitRisk_{it}$	0.007***	0.013**	0.007	−0.003	0.008	0.010
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$LitRisk_{it} \times Neg_{it}$	−0.021***	−0.028***	−0.036***	−0.010	−0.008	−0.019*
	(0.004)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
$InfoAsymm$	−0.005***	−0.010**	−0.006*	−0.012***	−0.002	0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$InfoAsymm \times Neg_{it}$	−0.012***	−0.007	−0.003	−0.012*	−0.011*	−0.020***
	(0.003)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
$FinDistress$	0.001	−0.005	−0.010	0.001	0.001	0.010
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$FinDistress \times Neg_{it}$	−0.007	0.015	0.013	−0.024*	−0.017	−0.016
	(0.006)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)
N	99084	19404	21097	20855	21001	16727
adj. R^2	0.028	0.013	0.014	0.023	0.042	0.058
F-test:						
$\|Const\| = \|Neg\|$	0.299	0.175	0.406	0.642	0.359	0.203

Table 4.5 continued.

Panel B: dE/B						
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
Const	0.030***	0.018***	0.022***	0.034***	0.037***	0.044***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Neg_{it}	−0.032***	−0.023***	−0.025***	−0.032***	−0.040***	−0.051***
	(0.002)	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)
sue_{it}	−0.009	−0.012	0.015	−0.073***	0.008	0.003
	(0.011)	(0.028)	(0.022)	(0.023)	(0.022)	(0.032)
$sue_{it} \times Neg_{it}$	0.199***	0.093**	0.104**	0.224***	0.217***	0.323***
	(0.021)	(0.047)	(0.042)	(0.045)	(0.044)	(0.057)
$RegFD_{it}$	0.001	0.001	0.003	0.001	0.002	−0.002
	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
$RegFD_{it} \times Neg_{it}$	−0.024***	−0.009	−0.013**	−0.021***	−0.040***	−0.029***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
$LitRisk_{it}$	0.008***	0.013**	0.006	−0.003	0.011*	0.010
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$LitRisk_{it} \times Neg_{it}$	−0.025***	−0.029***	−0.032***	−0.012	−0.016*	−0.027***
	(0.004)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
$InfoAsymm$	−0.003	−0.009**	−0.004	−0.007*	−0.001	0.002
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$InfoAsymm \times Neg_{it}$	−0.015***	−0.008	−0.007	−0.020***	−0.011*	−0.019**
	(0.003)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
$FinDistress$	0.001	−0.007	−0.010	0.001	0.001	0.011
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$FinDistress \times Neg_{it}$	−0.006	0.018	0.012	−0.023*	−0.015	−0.014
	(0.006)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)
N	98976	19360	21103	20853	20995	16665
adj. R^2	0.025	0.010	0.013	0.022	0.035	0.058
F-test:						
$\|Const\| = \|Neg\|$	0.814	0.115	0.816	0.476	0.739	0.441

Panel C: dE/E						
	All	*A1/D5*	*A2/D4*	*A3/D3*	*A4/D2*	*A5/D1*
_cons	0.028***	0.017***	0.023***	0.031***	0.033***	0.042***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Neg_{it}	−0.032***	−0.020***	−0.027***	−0.034***	−0.041***	−0.051***
	(0.002)	(0.005)	(0.004)	(0.005)	(0.004)	(0.007)
sue_{it}	0.210***	0.084	−0.004	0.179*	0.418***	0.227
	(0.048)	(0.101)	(0.092)	(0.101)	(0.101)	(0.150)
$sue_{it} \times Neg_{it}$	0.533***	0.527***	0.562***	0.387**	0.310**	0.753***
	(0.075)	(0.164)	(0.180)	(0.167)	(0.149)	(0.190)
$RegFD_{it}$	0.001	0.001	0.003	0.002	0.000	−0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
$RegFD_{it} \times Neg_{it}$	−0.023***	−0.009	−0.014**	−0.021***	−0.034***	−0.030***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
$LitRisk_{it}$	0.007***	0.014**	0.008	−0.003	0.009	0.006
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$LitRisk_{it} \times Neg_{it}$	−0.022***	−0.029***	−0.038***	−0.011	−0.011	−0.017*
	(0.004)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
$InfoAsymm$	−0.004**	−0.010**	−0.006	−0.012***	−0.002	0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$InfoAsymm \times Neg_{it}$	−0.011***	−0.006	−0.002	−0.011	−0.009	−0.017**
	(0.003)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
$FinDistress$	−0.002	−0.007	−0.013	0.000	−0.002	0.006
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$FinDistress \times Neg_{it}$	−0.003	0.018	0.017	−0.024*	−0.009	−0.010
	(0.006)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)
N	98669	19358	20988	20745	20908	16670
adj. R^2	0.025	0.010	0.013	0.022	0.035	0.058
F-test:						
$\|Const\| = \|Neg\|$	0.087	0.350	0.152	0.875	0.059	0.286

Standard errors in parentheses

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

Table 4.6: *Reaction of quarterly returns to earnings surprises under ambiguity and difference of opinion*

This table reports the coefficient, t-statistic, the number of observations used, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of either difference of opinion or ambiguity:

$$R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j A_{it}^j + \beta_0 sue_{it} + \sum_{j=2}^{5} \beta_j sue_{it} A_{it}^j + \lambda lsize_{it} + \epsilon_{it},$$

where sue_{it} is the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), or earnings (E) for firm i at time t. R_{it} is the return for firm i in quarter t. A is calculated as ρ measuring ambiguity. A_5 is the quintile with highest ambiguity and so forth. The first quintile is embedded in the no-dummy variable. $lsize_{it}$ is the natural log of beginning-of-period market capitalization for firm i in quarter t. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' forecasts are from IBES. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. The sample period is from Q4/1983 to Q4/2013. Standard errors are given in parentheses. The standard errors are corrected for both heteroscedasticity and autocorrelation (Newey and West, 1987). The sample period is from Q4/1983 to Q4/2013.

	dE/P		dE/B		dE/E	
Const	0.002**	0.005	0.002***	0.007**	0.003***	0.013***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
A_{it}^2		0.002		0.001		0.002
		(0.002)		(0.002)		(0.002)
A_{it}^3		0.003		0.003		0.004
		(0.002)		(0.002)		(0.002)
A_{it}^4		−0.009***		−0.009***		−0.006***
		(0.002)		(0.002)		(0.002)
A_{it}^5		0.009***		0.007***		0.011***
		(0.002)		(0.002)		(0.002)
sue_{it}	0.711***	0.467***	0.268***	0.160***	1.391***	0.973***
	(0.020)	(0.043)	(0.009)	(0.019)	(0.033)	(0.074)
$sue_{it} \times A_{it}^2$		0.016		0.026		−0.061
		(0.062)		(0.027)		(0.106)
$sue_{it} \times A_{it}^3$		0.105*		0.022		0.230**
		(0.060)		(0.027)		(0.104)
$sue_{it} \times A_{it}^4$		0.377***		0.141***		0.573***
		(0.059)		(0.026)		(0.100)
$sue_{it} \times A_{it}^5$		0.531***		0.288***		0.921***
		(0.062)		(0.029)		(0.101)
$lsize_{it}$	−0.059*	−0.056	−0.085**	−0.083**	−0.181***	−0.171***
	(0.034)	(0.034)	(0.034)	(0.035)	(0.034)	(0.035)
N	227095	227095	226922	226922	226260	226260
adj. R^2	0.016	0.018	0.013	0.016	0.021	0.023

Standard errors in parentheses

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

Table 4.7: *Differential reactions of quarterly returns to positive and negative earnings surprises under ambiguity and difference of opinion*

This table reports the coefficient, t-statistic, the number of observations used, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of either difference of opinion or ambiguity:

$$R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j D_{it}^j (A_{it}^j) + \beta_0 sue_{it} + \sum_{j=2}^{5} \beta_j sue_{it} D_{it}^j (A_{it}^j) + \lambda lsize_{it} + \epsilon_{it},$$

where sue_{it} is the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), or earnings (E) for firm i at time t. R_{it} is the return for firm i in quarter t. $lsize_{it}$ is the natural log of beginning-of-period market capitalization for firm i in quarter t. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' forecasts are from IBES. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. The sample period is from Q4/1983 to Q4/2013. Standard errors are given in parentheses. The standard errors are corrected for both heteroscedasticity and autocorrelation (Newey and West, 1987). The sample period is from Q4/1983 to Q4/2013.

	dE/P		dE/B		dE/E	
	Positive	*Negative*	*Positive*	*Negative*	*Positive*	*Negative*
Const	0.072^{***}	-0.052^{***}	0.079^{***}	-0.059^{***}	0.071^{***}	-0.055^{***}
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
sue_{it}	0.126^{***}	0.814^{***}	-0.021^{**}	0.340^{***}	0.412^{***}	1.189^{***}
	(0.023)	(0.037)	(0.011)	(0.017)	(0.041)	(0.052)
lsize	-0.588^{***}	0.364^{***}	-0.655^{***}	0.486^{***}	-0.603^{***}	0.414^{***}
	(0.039)	(0.065)	(0.039)	(0.064)	(0.040)	(0.064)
N	137549	89546	136233	90689	137157	89103
adj. R^2	0.001	0.014	0.000	0.016	0.001	0.016

Standard errors in parentheses

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

Table 4.8: *Differential reactions of quarterly returns to positive and negative earnings surprises under ambiguity and difference of opinion*

This table reports the coefficient, t-statistic, the number of observations used, and adjusted R^2 of contemporaneous relations between quarterly returns and earnings surprises, and with the interaction of either difference of opinion or ambiguity:

$R_{it} = \alpha_0 + \sum_{j=2}^{5} \alpha_j A_{it}^j + \beta_0 sue_{it} + \sum_{j=2}^{5} \beta_j sue_{it} A_{it}^j + \lambda lsize_{it} + \epsilon_{it},$

where sue_{it} is the seasonally differenced earnings (dE) scaled by beginning-of-period market price (P), book equity (B), or earnings (E) for firm i at time t. R_{it} is the return for firm i in quarter t. A is calculated as ρ measuring ambiguity. A_5 is the quintile with highest ambiguity and so forth. The first quintile is embedded in the no-dummy variable. $lsize_{it}$ is the natural log of beginning-of-period market capitalization for firm i in quarter t. Earnings are before extraordinary items. Earnings, book equity, share price, and shares outstanding data are from Compustat. experts' forecasts are from IBES. Firms are subject to the following screening criteria: 1) data are available for earnings, price, common shares outstanding, book equity this quarter and fthe quarters prior; 2) dates are aligned with calendar quarters; 3) price is larger than \$1; 4) not in the top and bottom 0.5 percentile of firms ranked by dE/P, dE/B, or dE/E for each case; 5) there are at least two experts' forecasts for EPS. The sample period is from Q4/1983 to Q4/2013. Standard errors are given in parentheses. The standard errors are corrected for both heteroscedasticity and autocorrelation (Newey and West, 1987). The sample period is from Q4/1983 to Q4/2013.

	dE/P		dE/B		dE/E	
	Positive	*Negative*	*Positive*	*Negative*	*Positive*	*Negative*
Const	0.056***	−0.035***	0.063***	−0.035***	0.056***	−0.031***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
A_{it}^2	0.000	0.002	−0.000	0.003	0.002	−0.000
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
A_{it}^3	0.012***	−0.004	0.013***	−0.006*	0.010***	−0.006*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
A_{it}^4	0.016***	−0.011***	0.018***	−0.014***	0.013***	−0.014***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
A_{it}^5	0.029***	−0.032***	0.028***	−0.024***	0.024***	−0.028***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)
sue_{it}	0.087	0.513***	−0.053*	0.317***	0.295***	1.202***
	(0.067)	(0.098)	(0.031)	(0.043)	(0.105)	(0.157)
$sue_{it} \times A_{it}^2$	0.162*	0.111	0.081*	0.070	0.033	−0.154
	(0.095)	(0.146)	(0.043)	(0.061)	(0.158)	(0.215)
$sue_{it} \times A_{it}^3$	0.059	0.129	−0.025	0.024	0.186	0.073
	(0.089)	(0.140)	(0.042)	(0.060)	(0.145)	(0.220)
$sue_{it} \times A_{it}^4$	0.193**	0.498***	0.075*	0.168***	0.613***	0.349*
	(0.094)	(0.133)	(0.043)	(0.060)	(0.149)	(0.208)
$sue_{it} \times A_{it}^5$	0.066	0.625***	0.080	0.420***	0.637***	0.829***
	(0.100)	(0.125)	(0.050)	(0.057)	(0.172)	(0.202)
lsize	−0.536***	0.247***	−0.604***	0.332***	−0.543***	0.252***
	(0.038)	(0.060)	(0.038)	(0.059)	(0.039)	(0.060)
N	137549	89546	136233	90689	137157	89103
adj. R^2	0.005	0.017	0.005	0.020	0.006	0.018

Standard errors in parentheses

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

Table 4.9: *Calibration of the model parameters*

This table reports the calibrated values for model parameters. For computing σ_m^2, I firstly take the cross-sectional average for earnings and then calculate the variance of of the time series for EP, EB, and EE, respectively. For computing σ_c^2, I firstly divide data into quintiles in terms of uncertainty (V) and then calculate the variance of the pooled data for each earnings surprise measure for each quintile. Subtraction of σ_m^2 from the calculated variances gives σ_c^2 for each quintile. The "aggregate" σ_c^2 is computed in the same way without splitting the data into quintiles. For computing σ_u^2, I put σ_c^2 and σ_m^2 back to beta equation under no uncertainty with beta equal to 0.7.

	EP(%%)	EB(%%)	EE
σ_m^2	0.122	0.177	0.022
σ_c^2	3.059	17.92	3.125
$\sigma^2(1)_c$	1.119	11.47	1.531
$\sigma^2(2)_c$	1.736	13.21	2.104
$\sigma^2(3)_c$	2.502	16.21	2.684
$\sigma^2(4)_c$	3.459	19.06	3.749
$\sigma^2(5)_c$	5.785	23.64	5.289

Chapter 5

Concluding Remarks

Financial information can be broadly categorized into tangible and intangible information. In this paper, tangible information refers to information related to firms' fundamental accounting-performance, for instance quarterly corporate earnings news. Intangible information refers to information that can not be measured to current accounting system, for example employee satisfaction. Market reacts to tangible information more efficiently, while it often fails to incorporate value-relevant intangible news. This thesis sets out to firstly examine the efficiency of market reactions to intangible news and secondly investigate how characteristics of investors' decision making process affect market reactions to tangible news.

Chapter 2 studies how the relationship between employee satisfaction and stock returns depends critically on the level of a country's labor market flexibility. The alphas documented by Edmans (2011, 2012) for the U.S. are not anomalous in a global context, in terms of economic significance, and do extend to several other countries. However, they do not automatically generalize to every country - being listed as a Best Company to Work For is associated with superior returns only in countries with high labor market flexibility. These results are consistent with the idea that the recruitment, retention, and motivational benefits of employee satisfaction are most valuable in countries in which firms face fewer constraints on hiring and firing. These benefits are lower in countries with inflexible labor markets, leading to a downward shift in the marginal benefit of expenditure on employee welfare. Moreover, in such countries, regulations already provide a floor for worker welfare, leading to a movement down the marginal benefit curve. Both forces reduce the marginal benefit of investing in worker satisfaction, and thus being listed as a Best Company may reflect an agency problem.

The results emphasize the importance of the institutional context for both managers and investors. Edmans (2011, 2012) uses long-run stock returns as the dependent variable to mitigate concerns about reverse causality from firm performance to employee satisfaction - any publicly-available performance measure should be incorporated into the stock price at the start of the return compounding window. However, these papers do not make strong claims about causality, as it may be that a third, unobservable variable (e.g. management quality) drives both employee satisfaction and stock returns. Even if their results are interpreted as causal, it is not the case that managers can hope to increase stock returns by investing in employee satisfaction, as a positive link only exists in countries with high labor market flexibility. Turning to investors, a strategy of investing in firms with high employee satisfaction will only generate superior returns in countries with high labor market flexibility. Given that the vast majority of empirical asset pricing studies that uncover alpha are based on U.S. data, the results emphasize caution in applying these strategies overseas. This caution is especially warranted for strategies that are likely to be dependent on the institutional or cultural environment, such as socially responsible investing strategies. Just as the value of employee satisfaction depends on the flexibility of labor markets and existing regulations on worker welfare, the value of other SRI screens such as gender diversity, animal rights, environmental protection, and operating in an ethical industry also likely depend on the context.

In the third chapter, we investigate how ambiguity affects return-earnings relation on both firm- and aggregate-level. Literature shows that positive firm-level earnings news is informative about a firm's future cash flows, thereby increases its contemporaneous stock price. However, this positive return-earnings relation does not translate into aggregate level. In fact, a negative contemporaneous relationship between market returns and aggregate earnings surprises has been documented in recent literature (see for instance, Kothari, Lewellen, and Warner (2006) and Sadka and Sadka (2009)). The puzzling finding could be explained by either the diversification of firm-specific earnings surprises or the high predictability of aggregate earnings. To shed some lights on the puzzle, we interact two levels of ambiguity with the return-earnings relation on both firm- and aggregate-level. Firm-level ambiguity distorts diversification effect while macroeconomic ambiguity affects the predictability. We provide a model explaining the phenomenon and empirical evidence supporting the hypothesis.

Our results show that individual response coefficient increases with firm-level ambiguity. Firm-level ambiguity increases the aggregate earnings response coefficient. Moreover, this increase is more pronounced when the degree of market-level ambiguity is high. High degree of market-level ambiguity leads to an increase in the earnings response coefficient of high-ambiguity stocks and to a decrease in the earnings response coefficient of the low-ambiguity stocks. Intuitively, when the firm-level ambiguity is high, the response to negative news is particularly amplified due to investor's aversion to ambiguity. This leads to an overall larger reaction to earnings news. Market-wide ambiguity amplifies the negative contribution of the discount rate news. Hence, for earnings response coefficient with low firm-level ambiguity, we observe that high macroeconomic ambiguity decrease the coefficients, and vice versa for coefficient with high firm-level ambiguity. We conclude that the negative aggregate relation comes from the diversification effect as well as an amplifying effect of macroeconomic ambiguity on discount rate news and market-wide cash flow news.

Chapter 4 examines the market asymmetric reaction to good versus bad news and investigates the roles of ambiguity and difference of opinion on the stylized fact. The average negative return generated by bad news is larger in magnitude than the average positive return generated by good news. The asymmetric reaction could be due to either larger amount of negative news on the market or stronger reaction to bad news per se. This chapter shows that it is the latter that causes the differential average return between good and bad news. Literature offers two perspectives for this asymmetric reaction. Firstly, Epstein and Schneider (2008) show in their model that Knightian uncertainty or ambiguity can lead to stronger reaction to bad news versus good news. Kelsey, Kozhan, and Pang (2011) show that this asymmetric reaction to bad versus good news causes asymmetric profitability of momentum strategy. Secondly, recent studies in decision theory raise the question that difference of opinion among experts could contribute to the decision maker's asymmetric assessment of the good versus bad news. Cres, Gilboa, and Vieille (2011), for instance, develop an axiomatized framework of incorporate ambiguity and difference of opinion altogether in the decision maker's assessment of signals. Based on those two strands of literature, this chapter sets out to empirically test and model the effects of both ambiguity and difference of opinion on firm-level return-earnings relation.

The results are striking. I show empirically that both ambiguity and difference of opinion are related to the differential reactions to bad versus good news and their combining effects generate a "yes" tick shape of differential earnings response coefficients in quintile portfolios. To verify the finding, I build a model to capture the return-earnings relation with one decision maker, multiple experts, and multiple firms. Due to lack of information, the ambiguity-averse experts and decision maker lack confidence on the distribution of firms' signals and hence assign a variance internal for the distributions of the signals. In the presence of private information, the gravity center of experts' set of priors differs, resulting in differential assessments of the signals even if the level of ambiguity is the same. Experts's preference exhibit ambiguity aversion and are described by the maxmin expected utility model proposed by Gilboa and Schmeidler (1989). The decision maker exhibits aversion to expert uncertainty and her preferences follow the "maxminmin" expected utility model axiomatized by Cres, Gilboa, and Vieille (2011). Monte Carlo simulation of the model shows that ambiguity and difference of opinion have contrasted effects on investors' reactions on earnings surprises measured by earnings response coefficient. Ambiguity increases the ERC for negative news. Difference of opinion, however, has a muted effect. For positive news, both decrease the response coefficients. By combining ambiguity with difference of opinion, the model generates a "yes" tick shape of differential reactions to negative versus positive news that matches the empirical finding.

The results support our hypothesis that both ambiguity and difference of opinion contribute to the asymmetric market reaction to bad versus good news. The implication for investors is clear. When designing trading strategies based on news, it is important to consider the quality of information environment and the extent of private information on the market. Since ambiguity and difference of opinion generates asymmetric reactions to news, it is interesting to explore for future research that whether both could contribute to other asymmetric phenomena found on the financial markets.

To end, I suggest several areas for future research. The second chapter studies the relation between employee satisfaction and stock returns across the world. It will be interesting to see whether the link exists between asset returns and other aspects of CSR - employee welfare, gender diversity, animal rights, environmental protection, and whether the firm is in a "sin" industry (such as tobacco, alcohol, and gambling). If there are links, whether the heterogeneity of these links across countries is likely to depend on the institutional context, such as regulations and cultural norms. The third chapter assumes high predictability of future expected returns and a negative correlation between earnings surprises and future expected returns. Empirical evidence on these points is weak due to the difficulty of finding appropriate discount rate proxies and lack of consistent methodologies to test them. It will be a good contribution to provide further robust evidence to support this assumption. In addition, the results of chapter three preclude the explanation based on high predictability of aggregate earnings changes. In particular, the study assumes high level macroeconomic ambiguity reduces the predictability of aggregate earnings changes. Although this is intuitive, the rigour of this subject requires a thorough investigation in this matter.

Appendix A

Proof of Conditional Expectations under Ambiguity

A.1 Case of no uncertainty

In order to establish benchmark, I start by considering the case with no ambiguity in information and signals and no difference of opinion among experts. Since all experts and the decision maker have exactly the same opinion regarding the signals, I remove the layer of experts without loss of generality. Hence, $c_{it} \sim N(0, \sigma_{ci}^2)$ for any i and t, $m_t \sim N(0, \sigma_m^2)$, $\eta_t \sim N(0, \sigma_\eta^2)$ and $u_{it} \sim N(0, \sigma_u^2)$.

Denote in matrix form,

$$Z = \begin{pmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{nt} \end{pmatrix}, \ X = \begin{pmatrix} s_{1t} \\ s_{2t} \\ \vdots \\ s_{nt} \end{pmatrix}$$

where $Z \sim N(0, \sum_Z)$, $X \sim N(0, \sum_X)$, $\sum_{ZX} = Cov(Z, X)$, and $\sum_{dX} = Cov(d, X)$.

I am only interested in computing the responses of individual firms' returns to earnings announcements. Given the set of signals s_{it}, the decision maker's expectations about the realization of variables e_{it} and d_t are:

$$E(Z|X) = \Sigma_{ZX}\Sigma_X^{-1}X$$

$$E(d|X) = \Sigma_{dX}\Sigma_X^{-1}X$$

where

$$\begin{aligned}
\Sigma_X &= \begin{pmatrix} \sigma_{c1}^2+\sigma_m^2+\sigma_u^2 & \sigma_m^2 & \dots & \sigma_m^2 \\ \sigma_m^2 & \sigma_{c2}^2+\sigma_m^2+\sigma_u^2 & \dots & \sigma_m^2 \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_m^2 & \sigma_m^2 & \dots & \sigma_{cn}^2+\sigma_m^2+\sigma_u^2 \end{pmatrix} \\
\Sigma_{ZX} &= \begin{pmatrix} \sigma_{c1}^2+\sigma_m^2 & \sigma_m^2 & \dots & \sigma_m^2 \\ \sigma_m^2 & \sigma_{c2}^2+\sigma_m^2 & \dots & \sigma_m^2 \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_m^2 & \sigma_m^2 & \dots & \sigma_{cn}^2+\sigma_m^2 \end{pmatrix} \\
\Sigma_{dX} &= \sigma_m^2 \begin{pmatrix} 1 & 1 & \dots & 1 \end{pmatrix}
\end{aligned}$$

Under no uncertainty, $\sigma_{c1}^2 = \sigma_{c2}^2 = \ldots = \sigma_{cn}^2 =: \sigma_c^2$. As a result,

$$\begin{aligned}
\Sigma_{ZX}\Sigma_X^{-1} &= \begin{pmatrix} \frac{\sigma_c^2+\Delta}{\sigma_c^2+\sigma_u^2} & \frac{\Delta}{\sigma_c^2+\sigma_u^2} & \cdots & \frac{\Delta}{\sigma_c^2+\sigma_u^2} \\ \frac{\Delta}{\sigma_c^2+\sigma_u^2} & \frac{\sigma_c^2+\Delta}{\sigma_c^2+\sigma_u^2} & \cdots & \frac{\Delta}{\sigma_c^2+\sigma_u^2} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\Delta}{\sigma_c^2+\sigma_u^2} & \frac{\Delta}{\sigma_c^2+\sigma_u^2} & \cdots & \frac{\sigma_c^2+\Delta}{\sigma_c^2+\sigma_u^2} \end{pmatrix} \quad \text{where } \Delta = \frac{\sigma_m^2\sigma_u^2}{\sigma_c^2+n\sigma_m^2+\sigma_u^2} \\
\Sigma_{dX}\Sigma_X^{-1} &= \frac{\sigma_m^2}{\sigma_c^2+n\sigma_m^2+\sigma_u^2} \begin{pmatrix} 1 & 1 & \dots & 1 \end{pmatrix}
\end{aligned}$$

Specifically,

$$\begin{aligned}
E_{t-1}[e_{it}|\mathbf{s}] &= \sum_{j=1}^{n} \gamma_i^j s_{jt} \\
E_{t-1}[d_t|\mathbf{s}] &= \delta \bar{s}_t,
\end{aligned}$$

where

$$\begin{aligned}
\gamma_i^j &= \frac{\Delta}{\sigma_c^2+\sigma_u^2} \quad \text{for } i \neq j \\
\gamma_i^i &= \frac{\sigma_c^2+\Delta}{\sigma_c^2+\sigma_u^2}, \\
\delta &= \frac{n\sigma_m^2}{\sigma_c^2+n\sigma_m^2+\sigma_u^2}.
\end{aligned}$$

Hence, the announcement surprises ε_{it} and ω_t are

$$\varepsilon_{it} = e_{it} - E_{t-1}[e_{it}|\mathbf{s}] = e_{it} - \sum_{j=1}^{n} \gamma_i^j s_{jt},$$
$$\omega_t = d_t - E_{t-1}[d_t|\mathbf{s}] = d_t - \delta \bar{s}_t.$$

A.2 Case of ambiguous information

Let us consider now an extension of the model where the experts and decision maker face ambiguity regarding the variance of firm-specific and market-wide cash flow components. The ambiguity of the firm specific component is purely idiosyncratic. I will call it firm-specific ambiguity hereafter. The ambiguity about the market represents the overall ambiguity about the market as whole. I will call it market-wide ambiguity. I consider both level of ambiguity altogether as a whole.

I model both types of ambiguity using the multiple prior model of Gilboa and Schmeidler (1989). More specifically, the experts and decision maker do not observe the variances of c_{it} and m_t and know only their interval ranges: $\sigma_{ci}^2 \in [\underline{\sigma}_c^2, \overline{\sigma}_c^2]$ and $\sigma_m^2 \in [\underline{\sigma}_m^2, \overline{\sigma}_m^2]$. Similar approach has been adopted by Epstein and Schneider (2008) and Kelsey, Kozhan, and Pang (2011). In this case, there is no difference of opinion. Hence the variance ranges will be the same for experts and the decision maker. without loss of generality, the layer of experts in the modeling setup is omitted in this subsection.

Under ambiguity only, $\sigma_{c1}^2 \neq \sigma_{c2}^2 \neq \ldots \neq \sigma_{cn}^2$. As a result,

$$
\begin{aligned}
\Sigma_{ZX}\Sigma_X^{-1} &= \frac{1}{\Gamma}\begin{pmatrix}
\frac{[\Gamma(\sigma_{c1}^2+\sigma_u^2)-\sigma_m^2](\sigma_{c1}^2+\sigma_m^2)}{(\sigma_{c1}^2+\sigma_u^2)^2} - \cdots - \frac{\sigma_m^2\sigma_m^2}{(\sigma_{c1}^2+\sigma_u^2)(\sigma_{cn}^2+\sigma_u^2)} & \cdots & \frac{[\Gamma(\sigma_{cn}^2+\sigma_u^2)-\sigma_m^2]\sigma_m^2}{(\sigma_{cn}^2+\sigma_u^2)^2} - \cdots - \frac{(\sigma_{c1}^2+\sigma_m^2)\sigma_m^2}{(\sigma_{c1}^2+\sigma_u^2)(\sigma_{cn}^2+\sigma_u^2)} \\
\vdots & \vdots & \vdots \\
\frac{[\Gamma(\sigma_{c1}^2+\sigma_u^2)-\sigma_m^2]\sigma_m^2}{(\sigma_{c1}^2+\sigma_u^2)^2} - \cdots - \frac{(\sigma_{cn}^2+\sigma_m^2)\sigma_m^2}{(\sigma_{c1}^2+\sigma_u^2)(\sigma_{cn}^2+\sigma_u^2)} & \cdots & \frac{[\Gamma(\sigma_{cn}^2+\sigma_u^2)-\sigma_m^2](\sigma_{cn}^2+\sigma_m^2)}{(\sigma_{cn}^2+\sigma_u^2)^2} - \cdots - \frac{\sigma_m^2\sigma_m^2}{(\sigma_{c1}^2+\sigma_u^2)(\sigma_{cn}^2+\sigma_u^2)}
\end{pmatrix} \\
\Sigma_{dX}\Sigma_X^{-1} &= \frac{\sigma_m^2}{\Gamma}\begin{pmatrix}
\frac{\Gamma}{\sigma_{c1}^2+\sigma_u^2} - \sum_{k=1}^n \frac{\sigma_m^2}{(\sigma_{c1}^2+\sigma_u^2)(\sigma_{ck}^2+\sigma_u^2)} & \cdots & \frac{\Gamma}{\sigma_{cn}^2+\sigma_u^2} - \sum_{k=1}^n \frac{\sigma_m^2}{(\sigma_{cn}^2+\sigma_u^2)(\sigma_{ck}^2+\sigma_u^2)}
\end{pmatrix} \quad \text{where } \Gamma = 1 + \sum_{i=1}^n \frac{\sigma_m^2}{\sigma_{ci}^2+\sigma_u^2}
\end{aligned}
$$

Specifically,

$$
\begin{aligned}
E_{t-1}[e_{it}|\mathbf{s}] &= \sum_{j=1}^{n} \gamma_i^j s_{jt} \\
E_{t-1}[d_t|\mathbf{s}] &= \sum_{i=1}^{n} \delta_i s_{it},
\end{aligned}
$$

where

$$
\begin{aligned}
\gamma_i^i &= \frac{1}{\Gamma}[\frac{[\Gamma(\sigma_{ci}^2+\sigma_u^2)-\sigma_m^2](\sigma_{ci}^2+\sigma_m^2)}{(\sigma_{ci}^2+\sigma_u^2)^2} - \sum_{k=1,k\neq i}^{n} \frac{\sigma_m^2\sigma_m^2}{(\sigma_{ck}^2+\sigma_u^2)(\sigma_{ci}^2+\sigma_u^2)}] \qquad \text{for } i=j \\
\gamma_i^j &= \frac{1}{\Gamma}[\frac{[\Gamma(\sigma_{cj}^2+\sigma_u^2)-\sigma_m^2]\sigma_m^2}{(\sigma_{cj}^2+\sigma_u^2)^2} - \frac{(\sigma_{ci}^2+\sigma_m^2)\sigma_m^2}{(\sigma_{ci}^2+\sigma_u^2)(\sigma_{cj}^2+\sigma_u^2)} - \sum_{k=1,k\neq i,j}^{n} \frac{\sigma_m^2\sigma_m^2}{(\sigma_{ck}^2+\sigma_u^2)(\sigma_{cj}^2+\sigma_u^2)}] \qquad \text{for } i\neq j, \\
\delta_i &= \frac{\sigma_m^2}{\Gamma}[\frac{\Gamma}{\sigma_{ci}^2+\sigma_u^2} - \sum_{k=1}^{n} \frac{\sigma_m^2}{(\sigma_{ck}^2+\sigma_u^2)(\sigma_{ci}^2+\sigma_u^2)}].
\end{aligned}
$$

Hence, the announcement surprises ε_{it} and ω_t are

$$
\varepsilon_{it} = e_{it} - E_{t-1}[e_{it}|\mathbf{s}] = e_{it} - \sum_{j=1}^{n} \gamma_i^j s_{jt},
$$

$$
\omega_t = d_t - E_{t-1}[d_t|\mathbf{s}] = d_t - \sum_{i=1}^{n} \delta_i s_{it}.
$$

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