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Information Frictions and Stock Returns

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Abstract: The purpose of this paper is to assess the impact of ambiguity on financial analyst forecast incentives and the associated abnormal stock returns. I present a model incorporating ambiguity aversion into a two-period Lucas tree model. The resulting model confirms the role of ambiguity in the determination of asset returns. In particular, the model with ambiguity aversion generates a lower price and a higher required rate of returns compared to the classical model without ambiguity concern. I construct a measure of ambiguity and provide empirical evidence showing that the incentive of analysts to misrepresent information is a function of ambiguity. Analysts are more likely to bias their forecasts when it is more difficult for investors to detect their misrepresentation. Under ambiguity, analysts' optimistic forecasts for good/bad news tend to deteriorate. Moreover, stock returns are positively related with ambiguity. Under ambiguity neither good nor bad news is credible. Investors systematically underreact to good news forecast and overreact to bad news forecast when ambiguity exists.

Keywords: information friction; utility maximization; forecast efficiency

1. Introduction

The literature on financial analyst forecast defines "forecast inefficiency" as forecasts that fail to accurately incorporate new information on a timely basis. If markets treat analysts' forecasts as both rational and statistically optimal, then inefficient forecasts could have important implications for price efficiency in securities markets.

Some researchers attributed the inefficiencies and/or bias to analysts' ability to incorporate new information into their earnings forecasts to a cognitive processing bias, whereby analysts fail to adequately incorporate negative feedback signals (Francis et al. 1997). Empirical studies have also suggested that certain motivational and financial incentives inherent in brokerage firms can lead to optimistic estimates of earnings (Schipper 1991; Francis et al. 1997; McNichols 1989; Dechow et al. 1995; Hayn 1995; Hutton et al. 2003). Some suggest that analysts underreact to information, some conclude that analysts overreact to information and others found that analysts underreact to negative forecast errors, and overreact to positive forecast errors. (e.g., Abarbanell and Bernard 1992; Teoh and Wong 1997). Such systematic under- or overreaction may be perceived as inconsistent with rational forecasts and efficient markets; understanding such biases is important to get a complete picture of analyst behavior and stock market imperfection.

Most of the above studies are based on managerial forecast and not on analyst forecasts. Compared to managerial forecasts, sell-side analysts are pressured to issue more optimistic forecasts/recommendations for several reasons. First, sell-side analysts are not paid directly by investors. Their compensations are based on the profits they help generate for the brokerage firms that employ them. Their compensations are completely unrelated to their stock picking or their earnings estimates. The real money, their bonus, is determined by how much trading they bring in for the sales force and, more importantly, how much business they generate for the firm's investment bankers.

Therefore, their incentives are not always consistent with telling the truth. Second, a positive outlook increases the chances of more funds being financed from investment banks for analysts' employers. Third, being optimistic has historically helped analysts obtain inside information from the firms they cover.

All these pressures induce an optimistic bias to analysts' views while the magnitude of the bias is held in check by reputational concerns (Hutton 2004). Analysts care about their reputation to the extent that it can be deployed to generate trades and attract investment-banking business. Therefore, analysts are constrained from adding an arbitrarily high optimistic bias to their private estimates because systematic optimistic bias is costly. It increases litigation risks and is harmful for analysts' reputations and credibility (Stocken 2000; Williams 1996). Stockholder lawsuits based on earnings disclosures are typically brought under SEC Rule 10b-5, which makes it unlawful for any person "to make any untrue statement of a material fact or to omit to state a material fact necessary in order to make the statement made, in light of the circumstances under which they were made, not misleading." Though analysts have incentives to bias their earnings forecasts, concerned with the cost of biasing, they are constrained because investors can use the subsequent earnings report to assess whether they have misrepresented their information.[1] If the market detects misrepresentation, then analysts' reputations might be damaged and they might suffer legal censure.

However, the threat of litigation is less likely when it is difficult to deter optimistic forecast. Without incentive concerns, an analyst should predict earnings more accurately when there are few ambiguity concerns because investors can better assess the credibility of a forecast.[2] In contrast, when a firm's earnings vary drastically as its circumstances change, it is more difficult for an analyst to accurately forecast earnings and, therefore, more difficult for investors to evaluate the truthfulness of analysts' forecasts. The motivational incentives faced by analysts may exacerbate risky choice behavior during forecast revision, thereby magnifying overestimates of earnings.

One of the fundamental problems of financial analyst forecasts is the analysis of decisions under ambiguity, where the probabilities of potential outcomes are neither specified in advance nor readily assessed on the basis of the available evidence. Ellsberg (1961) demonstrated that the distinction between risk and ambiguity is behaviorally meaningful. Roughly speaking, risk refers to the situation where there is a probability measure to guide choice while ambiguity refers to the situation where the decision makers are uncertain about this probability measure due to informational constraints. One feature of ambiguity is that it responds more directly to possibilities than to probabilities. Ambiguity affects investors' decision choice through ambiguity aversion, which is an anticipatory emotion experienced by investors prior to the resolution of uncertainty. It is related to the negative feeling of living with uncertainty. In contrast, risk aversion is a static concept pertaining to the curvature of the utility function within a period. Ellsberg (1961) argued that people's willingness to act in the presence of uncertainty depends not only on the perceived probability of the event in question, but also on its ambiguity. Because decision makers usually do not know the precise probabilities of potential outcomes when decisions were made, an individual under ambiguity may appear more risk averse.

Theoretical as well as empirical research for ambiguity in the financial market is important because the unique feature of ambiguity can mitigate or exacerbate market inefficiency and biases. However, incredible little research has been done so far to assess the role of ambiguity in financial analyst forecast incentive and the abnormal stock returns associated with it. This study sets up a direct test of financial analyst forecast behavior and stock market reactions under ambiguity. In order to gain an insight of the implications of ambiguity on decision choice, I developed a model incorporating ambiguity aversion into a two-period Lucas tree model. The resulting model shows that the impacts of

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[1] Lev and Penman (1990) argue that analyst forecasts are credible because investors can ex post verify a manager's forecast by comparing it with the audited earnings report.

[2] In an experimental study, Hirst et al. (1999) find that management forecast specificity and prior forecast accuracy affect the confidence of investors' judgment about a firm's earnings.

ambiguity on asset pricing are significant. In particular, the model with ambiguity aversion generates a lower price and a higher required rate of returns compared to the classical model without ambiguity concern. It implies that investors under ambiguity appear more risk averse. It confirms the fact that by ignoring ambiguity, conventional measures of risk aversion underestimate the effect of uncertainty on asset prices. This result can be used to explain why investors appear to overreact/underreact to small probability events. The associated return premium also helps to explain risk-free rate puzzle and equity premium puzzle.

In order to provide empirical evidence of the role of ambiguity, I construct a measure of ambiguity that reflects difficulties in detecting analysts' misrepresentation. Then I examine how the "ambiguity" influences analysts' incentives to offer misleading forecasts and how investors respond to analysts' forecasts made under "ambiguity."

The primary finding is that the incentives of analysts to misrepresent their information vary with the market's ability to detect their misrepresentation. Specifically, I find that analysts' incentive to misrepresent their information is a function of ambiguity that market participants experienced in detecting analyst misrepresentation. Analysts are more likely to bias their forecasts when it is more difficult for investors to detect their misrepresentation. Under ambiguity, analysts' optimistic forecasts for good/bad news tend to deteriorate. These results provide evidence showing that financial analysts forecast errors are to be underestimated when ignoring ambiguity.

Moreover, stock returns are positively related with ambiguity. It implies that investors are compensated for the ambiguity they bear, which confirms the role of ambiguity in the determination of asset returns. Furthermore, empirical results show that under ambiguity neither good nor bad news is credible. Investors systematically underreact to good news forecasts and overreact to bad news forecasts when ambiguity exists.

The paper is organized as follows: I describe the model with ambiguity aversion in Section 2, Hypothesis development is in Section 3, data are reported in Section 4, methodology and empirical analysis are described in Section 5, and Section 6 concludes the paper.

2. Model

In order to gain insight into the implications of ambiguity on the decision choice, I present a simple model by introducing ambiguity aversion into a utility maximization model. Ambiguity aversion is a subjective emotion experienced by individuals reflecting market ambiguity. Although market ambiguity is objective by nature, it affects investors' portfolio choice and stock price through ambiguity aversion. Consider a two-period Lucas tree model of consumption and saving (Stokey and Lucas 1989), where a representative agent is born with an endowment of a consumption good equal to ω_1. The agent is also endowed with n (where $n \in N$) productive assets (normalized to unity), which yield S_n units of the consumption good in period 2. A competitive equilibrium market will decide a price to support the asset allocation, where first-period consumption is equal to the endowment, $c_1 = w_1$; second-period consumption is equal to the random output of the assets $C_2 = \sum s_n$.

Let θ denote the vector of portfolio shares held by the agent, where θ_n is the share holding of asset n. We assume $\phi(\bullet)$ is a differentiable function that measures the investor's anticipation of ambiguity associated with the holdings on risky assets. A representative agent chooses the level of first period consumption and the asset portfolio to maximize the expected utility function,

$$\max \mu_1(c_1, \phi(\theta)) + \beta E[\mu_2(c_2)]$$

subject to the budget constraint,

$$c_1 + \sum_n s_n \theta_n = \omega_1 + \sum_n p_n$$

where $\mu_1(\cdot)$ and $\mu_2(\cdot)$ are utility function, p_n is the price of asset n. The first-order condition for asset n is

$$\frac{\partial \mu_1}{\partial c_1} p_n = \frac{\partial \mu_1}{\partial \phi} \frac{d\phi}{d\theta_n} + \beta E(s_n) \frac{\partial \mu_2}{\partial c_2}$$

rearranging the above equation, we can pin down the price of the asset:

$$p_n = \frac{\left(\frac{\partial}{\partial \phi}\right)\mu_1(w_1, \phi(\theta))\left(\frac{\partial}{\partial \theta_n}\right)\phi(\theta) + \beta E(s_n)\left(\frac{\partial}{\partial c_2}\right)\mu_2(\Sigma_n s_n)}{\left(\frac{\partial}{\partial c_1}\right)\mu_1(w_1, \phi(\theta))}$$

Since $\frac{\partial \mu_1}{\phi} \frac{\partial \mu_1}{\partial \phi}$ is negative, it is immediate that ambiguity generates a lower price and a higher required rate of return. If investors react not only to risk but ambiguity, then asset prices will tend to overreact/underreact to small probability events. For example, a government's announcement of increased oil demand will attract investors' attention on the possibility of an increase in oil price. This will make investors' investment choice more sensitive to the likelihood of an oil price change.

As ambiguity aversion is an anticipatory emotion experienced by investors, it is likely to differ from investor to investor. Nevertheless, it is reasonable to assume that ambiguity is decreasing in the mean of future consumption and increasing in the riskiness of future consumption. Suppose that ambiguity is linear in the mean and variance of second period consumption,

$$(\theta) = -\alpha E\ (c_2) + \beta\ var(c_2)$$

where α and β are positive parameters. Since $c_2 = \Sigma\ s_n \theta_n$, it follows that

$$\frac{d\phi(\theta)}{d\theta_n} = -\alpha E(s_n) + 2\beta cov(c_2, s_n)$$

This equation indicates the effects on ambiguity for a unit increase in asset holding. This equation helps explain both the risk-free rate puzzle and the equity premium puzzle. For a riskless asset, in which s_n is constant,

$$\frac{d\phi}{d\theta_n} = -\alpha s_n < 0.$$

It follows that the price of the riskless asset, $\beta E(s_n)\left(\dfrac{\frac{\partial \mu_2}{\partial c_2}}{\frac{\partial \mu_1}{\partial c_1}}\right)$, is higher than the price which would take in the standard model. In this view, the agent is purchasing "peace of mind" along with the asset, and this justifies the low risk-free rate.

Since stocks are risky, their purchase will tend to increase both the mean and the variance of second-period consumption. The sign of $\frac{d\phi}{d\theta_n}$ will depend on how these two effects balance out. If β is sufficiently large relative to α, the effect through the variance will dominate, and $\frac{d\phi}{d\theta_n}$ will be positive. In this case, ambiguity will reduce the price of stocks and increase their return relative to the standard model. Here, stock ownership entails psychic costs. The agent has to live with the ambiguity that accompanies the holding of a risky portfolio.

Safe assets, by providing secure returns, may reduce ambiguity even before final consumption takes place. They, therefore, provide an extra benefit in addition to the smoothing of final consumption across states, serving to reduce the risk-free rate. Stocks and other risky assets, however, by increasing the variance of the portfolio, increase ambiguity in the period before final consumption takes place. Hence, owning stocks involves an extra cost in addition to increasing the variance of final consumption, which increases their required return. Therefore, ambiguity complements risk aversion in our discussion of the risk-free rate puzzle and the equity premium puzzle.

3. Hypothesis Development

Ambiguity occurs in the situations where available information is scanty or obviously unreliable or highly conflicting; or where expressed expectations of different individuals differ widely. For example, when financial environment is ambiguous and earnings are difficult to predict, analysts are expected to disagree about the forthcoming earnings. I use the standard deviation of analyst forecasts, denoted as STD_AF, to measure the lack of analyst consensus. Therefore, STD_AF is positively associated with ambiguity. Moreover, it is more difficult to forecast a firm's earnings when its "true" earnings are more volatile, which are measured as the standard deviation of daily stock returns, denoted as STD_RET. To examine the effect of ambiguity, I construct a measure of forecasting ambiguity as a function of previous period analyst's consensus forecasting and the standard deviation of daily stock returns 120 days prior to the forecast date. To be classified as having a forecasting ambiguity, the following conditions must hold:

$$STD\_AF_{t-1} > STD\_AF_{t-2} \text{ and,} STD\_RET_{-120,-1} > STD\_RET_{-240,-121}$$

With this measure of forecasting ambiguity, I separate analysts' forecasts with ambiguity from those without ambiguity. I then test whether forecast ambiguity affects the magnitude of accuracy of current period forecast, and the effect of the ambiguity on the post-forecast drift in returns. Therefore, four hypotheses of this study are:

Hypothesis 1. *Analysts' incentive to misrepresent their information is a function of the ambiguity that market participants experienced in detecting analyst misrepresentation. Analysts are more likely to make biased forecasts when it is more difficult for investors to detect their misrepresentation.*

Hypothesis 2. *Under ambiguity, analysts' optimistic forecasts for good/bad news tend to deteriorate.*

Hypothesis 3. *Stock returns are expected to be positively related to ambiguity. In other words, investors require a higher rate of return to compensate the ambiguity they are bearing.*

Hypothesis 4. *Stock-returns responses to analysts' forecasts are consistent with the predictable bias in the forecasts. Thus under ambiguity, stock returns will overreact to bad news forecast and underreact to good news forecast.*

4. Data

Stock return data are drawn from the Center for Research in Securities Prices (CRSP) combined file, which includes NYSE, AMEX, and Nasdaq stocks. Financial analysts' earnings estimates are obtained from the Institutional Brokers Estimate System (IBES). Firms' characteristic variables, such as size, market to book ratio, accruals, and special items are taken from Compustat.

The sample for the study consists of the time period from 1996 to 2006[3]. As legal environment affects analysts' forecasting behavior, I therefore restrict the sample after the enactment of the PSLR act on 22 December 1995[4]. Since I use short-window stock returns reactions to assess investors' response to analysts' earnings forecasts, I delete 2231 observations with more than one forecasts made on the same day. I delete these observations because I cannot separately identify investor reactions to each forecast, and it ensures that the sample observations are independent. Deleting forecasts made within a three-day window reduces the likelihood that other earnings news explains the observed stock

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[3] I used a ten-year span of data to achieve data generality. Though IBES data after 2006 is not available, this sample data period is sufficient and long enough to provide proof evidence of generality for all model results proposed in this study.

[4] The PSLR act, which shelters analysts from litigation arising from unattained forward-looking statements, lowered the expected litigation costs associated with unattained forecasts (Johnson et al. 2001).

returns reactions. I delete observations with missing stock returns, analyst estimates or actual earnings, and missing data on control variables.

I then merge the IBES dataset with stock return data from CRSP and firm characteristics from Compustat. Stocks with share prices lower than five dollars are omitted in order to ensure that the results are not driven by small, illiquid stocks or by bid-ask bounce (Jegadeesh and Titman 1993). I delete observations with insufficient (less than 5 years continuous operations) to estimate earnings persistence. I delete the firms that have less than four individual analysts (Elliot et al. 1995). Finally, all variables that are in the upper 99% and lower 1% are identified as outliers and are eliminated (Ali et al. 1992; Frankel and Lee 1996). I am left with a sample of 35,280 forecasts made by 2586 firms.

Financial analyst forecast error is defined as the difference between analyst forecast and actual earnings scaled by stock prices, which is calculated as follows:

$$FE_t = \frac{F_t^{t-1} - E_t}{P_1}$$

where FE_t denotes the forecast error at year t, E_t is actual earnings for year t, F_t^{t-1} is the earning forecast of year t made at year $t-1$, and P_t is the stock price at the time t. Assuming day 0 is the announcement date, three-day accumulative abnormal returns centered on the announcement date are calculated as follows:

$$CAR_1 = \sum_{t=-1}^{1} (r_{it} - r_{mt})$$

where r_{it} is the return for firm i on time t, r_{mt} is the return on the CRSP Value-Weighted Market Index on time t. Table 1 reports the year-by-year distribution of analyst forecast errors and accumulative stock returns. Untabulated results using raw returns are similar with the market-adjusted returns.

Consistent with previous research, mean forecast errors are significantly positive in all years represented and median forecast errors are significantly positive in all but three years (2000, 2003, and 2005). This implies that financial analysts' forecasts are optimistic on average. The accumulative stock returns have the highest mean and standard deviation in year 1999 and the lowest mean value in 2001. The magnitudes of the forecast errors and stock returns do not consistently move either up or down. This sample meets all data requirements for analysis.

Skinner (1994) provided evidence showing that bad news forecasts were generally considered more believable than good news forecasts. For example, the unconditional stock returns response to bad news forecast was greater than the response to good news forecasts. To assess whether earnings forecasts reveal good or bad news, I consider the forecast EPS and previous period actual EPS. If the forecast EPS is greater than previous period actual EPS, I classify the forecast as conveying good news, where $ESP_{forecast}^t - ESP_{actual}^{t-1} > 0$; otherwise, the forecast conveys bad news.

Table 2 presents summary statistics of financial analysts' forecasts, stock returns, and various firm characteristics. Panel A of Table 2 reports the forecast news, market responses to these forecasts, as well as the forecast errors. The mean forecast errors are positive for both good news and bad news. The median forecast errors are positive for good news and slightly negative for bad news. The mean and median accumulative stock returns are positive for good news and negative for bad news. According to the *t*-test, the mean and median values of forecast errors and CARs are significantly different between good news and bad news.

Panel B of Table 2 partitions the full sample by ambiguity. This panel has three noteworthy features: first, although mean forecast errors are positive for both good and bad news, the magnitudes are larger for the forecasts with ambiguity. For example, for bad news, the mean forecast error is 0.003 without ambiguity, while it is 0.008 with ambiguity. Similarly, for good news, the mean forecast error is 0.005 with no ambiguity, while it is 0.021 with ambiguity. It implies that the analysts tend to make more biased optimistic forecasts under ambiguity.

Table 1. Year-by-year distribution of analyst forecast errors and accumulative stock returns.

	Panel A: Year-by-year Distribution of Analysts' Forecast Error			
Year	**Number of Observations**	**Mean Forecast Error**	**Median Forecast Error**	**Standard Deviations**
1996	3652	0.0051	0.0009	4.358
1997	4531	0.0025	0.0016	3.642
1998	3766	0.0035	0.0007	2.339
1999	5004	0.0049	0.0010	4.569
2000	4812	0.0027	−0.003	3.831
2001	5393	0.0042	0.0006	3.142
2002	6243	0.0020	0.0000	5.911
2003	6807	0.0028	−0.004	1.806
2004	6453	0.0012	0.0040	3.219
2005	5978	0.0024	−0.006	4.094
2006	6254	0.0021	0.0000	2.201
	Panel B: Year-by-year Distribution of CARs			
Year	**Number of Observations**	**Mean Returns**	**Median Returns**	**Standard Deviations**
1996	1039	0.0683	0.0766	3.7928
1997	1252	0.0642	0.0789	3.8639
1998	1331	0.0535	0.0611	4.1267
1999	1467	0.0829	0.0862	5.7886
2000	1458	0.0658	0.0701	5.4512
2001	1529	0.0301	0.0329	3.0829
2002	1446	0.0346	0.0311	3.5761
2003	1538	0.0532	0.0532	3.2336
2004	1551	0.0636	0.0582	2.7912
2005	1543	0.0642	0.0579	2.6458
2006	1522	0.0656	0.0686	2.5701

Panel A is the year-by-year distribution of analyst forecast errors, which is defined as the difference between analyst forecast and actual earnings scaled by stock prices. Panel B reports stock returns, CARs, which is defined as three-day accumulative returns centered on the announcement date.

Table 2. Summary statistics of accumulative stock returns and various firm characteristics.

	Panel A: Forecast Error and Market Returns Associated with Good or Bad News				
		Analysts Forecast Error		**Market Returns CARs**	
	N	**Mean Forecast Error**	**Median Forecast Error**	**Mean Returns**	**Median Returns**
Bad News	10,304	0.0059	−0.001	−0.0341	−0.0175
Good News	26,901	0.0068	0.003	0.0247	0.0210
t-test differences between Good and		2.89 **	6.51 **	3.51 **	5.28 **
Bad News Forecast		0.081	<0.001	0.002	0.000
	Panel B: Sample Partition by Forecast AmbiguityCARS				
		Forecast Error		**Market Returns CARs**	
	N	**Mean Forecast Error**	**Median Forecast Error**	**Mean Returns**	**Median Returns**
Bad News					
No Ambiguity	6022	0.003	0.000	−0.026	−0.019
Ambiguity	4282	0.008	0.003	−0.057	−0.028
t-test diff. between		3.59 **	2.68 **	3.16 **	2.49 *
ambiguity/no ambiguity		0.002	0.001	0.017	0.009
Good News					
No ambiguity	14,800	0.005	0.001	0.0361	0.25
Ambiguity	12,101	0.021	0.005	0.0125	0.08
t-test diff. between		2.61 **	3.29 **	2.87 **	3.49 **
ambiguity/no ambiguity		<0.001	0.005	0.018	0.051

Panel A reports the forecast news, the market responses to these forecast news and the forecast errors. The mean forecast errors are positive for both good news and bad news. The median forecast errors are positive for good news and slightly negative for bad news. Panel B of Table 2 partitions the full sample by ambiguity. According to the *t*-test, forecast errors and stock returns are significantly different between the forecasts with ambiguity and those with no ambiguity. This panel has three noteworthy features: first, though mean forecast errors are positive for both good and bad news, the magnitudes are larger for the forecasts with ambiguity. Second, the mean and median stock-return reactions to good news are much lower for the forecasts with ambiguity than that with no ambiguity. Third, the mean and median stock returns decrease in bad news forecast is deteriorated in the case of ambiguity compared to the forecasts with no ambiguity. *, ** significant at 5% and 1% levels, respectively, using a two-tailed test.

Second, the mean and median stock-return reactions to good news are much lower for the forecasts with ambiguity than those with no ambiguity. It implies that investors are less responsive to good news forecast under ambiguity. Third, the mean and median stock returns decrease in bad news forecasts is deteriorated in the case of ambiguity compared to the case with no ambiguity. This suggests that investors overreact to bad news forecast under ambiguity. According to the *t*-test, forecast errors and stock returns are significantly different between the forecasts with ambiguity and those with no ambiguity.

5. Empirical Analysis

In this section, I examine the four hypotheses developed in Section 3. First, I test the relation between forecast ambiguity and forecast errors, and then, I examine the association between predicted ambiguity and stock-return responses (Hypotheses 1 and 2).

To examine the effect of ambiguity on forecast errors, I estimate the following pooled cross-sectional regression model:

$$FE = \alpha_0 + \alpha_1 Ambiguity + \alpha_2 Good \times News + \alpha_3 Bad \times News + \alpha_4 Ambiguity \times Good \\ \times News + \alpha_5 Ambiguity \times Bad \times News + ControlVariables + \varepsilon. \tag{1}$$

The model's variables are defined and discussed below:

Forecast Error (FE): FE is defined as the difference between analysts' forecast and actual earnings scaled by stock prices. It is calculated as $FE_t = \frac{F_t^{t-1} - E_t}{P_t}$, where FE_t denotes the forecast error at year t, E_t is actual earnings for year t, F_t^{t-1} is the earning forecast of year t made at year $t - 1$, and P_t is the stock price at the time t.

News: is the forecast earnings per share (EPS) minus the previous period actual EPS.

Good: is an indicator variable. Good equals to one if the forecast EPS is greater than previous period actual EPS, where $ESP_{forecast}^t - ESP_{actual}^{t-1} > 0$; and zero otherwise.

Bad: is an indicator variable. Bad equals to one if the forecast EPS is less than the previous period actual EPS, where $ESP_{forecast}^t - ESP_{actual}^{t-1} > 0$; and zero otherwise.

Ambiguity: is an indicator variable. To be classified as having forecasting ambiguity, two conditions: $STD\_AF_{t-1} > STD\_AF_{t-2}$ and, $STD\_RET_{-120,-1} > STD\_RET_{-240,-121}$ must hold. The variable, ambiguity, is assigned a value of one if above conditions hold, and zero otherwise.

Control variables: several variables identified in previous studies as affecting forecasting behavior are introduced as control for cross-sectional differences. These variables include forecast horizon, growth opportunities, accruals, predicted losses, the effects of Reg FD, Size, and special items. First, forecast horizon is introduced because several studies find forecast errors decline as forecasts are issued closer to the fiscal year-end (Johnson et al. 2001). The closer to the end of the fiscal year the forecast is made, the more information the analyst would be able to use in generating the forecast. Hence, forecasts that are made closer to the end of the fiscal year are likely to have higher accuracy. Horizon equals the number of calendar days between the forecast release date and the firm's fiscal year-end. Second, previous studies find forecast behavior is associated with firm size (Baginski et al. 1993; Bamber and Cheon 1995). The natural log of the firm's market capitalization one day prior to the forecast, denoted size, is used to proxy for firm size. Third, Bamber and Cheon (1995) document that growth opportunities affect a firm's forecasting behavior. I use a firm's market value to book value of equity ratio, M/B, as a measure of a firm's growth opportunities. M/B is calculated as the ratio of the firm's market capitalization one day prior to the forecast divided by the previous year's book value of equity. Fourth, earnings management can affect forecast errors because managers can manipulate reported earnings (McNichols 1989; Dechow et al. 1995). Kasznik (1999) finds evidence consistent with managers issuing earnings forecast and then manipulating earnings to fall in line with the forecast. Therefore, the firm's ability to manipulate earnings as reflected by its discretionary accruals is included

as a control. Moreover, I include predicted losses (Hayn 1995), the effects of Reg FD (Heflin et al. 2003), and special items (Bernanke et al. 1988) as control variables.

To conduct a robustness check, I include fixed effects to capture industry variation. I also include a year effect to capture time variation and possible structure change within the sample period. I defined firms within the same industry as the firms reported on Compustat sharing the same SIC code. These robustness checks allow us to evaluate model fitness and out of sample performance. The empirical results are, not reported to save space, consistent with empirical results reported in Tables 3 and 4. It provides strong evidence that the empirical results can be generalized for out of sample time period.

Table 3. The effect of ambiguity on analyst forecast performance.

FE =	α_0+	$\alpha_1 Amb+$	$\alpha_2 GNews+$	$\alpha_3 BNews+$	$\alpha_4 Amb + GNews$	$\alpha_5 Amb + BNews$	$Controls+\epsilon$
Estimate	−0.08	0.023	1.813	1.250	4.668	3.526	
t-statistic	9.21	2.95 **	2.96 **	3.09 **	3.20 **	4.90 **	
F Value of Model = 35.02			R^2 = 36.48%			Adj. R^2 = 32.56%	
Control Variables:		Predicted Sign		Coefficient		t-statistic	
Horizon		+		0.091		3.29 **	
M/B		-		−0.225		1.98 *	
Size		+		0.788		3.27 **	
Accruals		+		0.645		3.49 **	
Reg FD		-		−0.024		0.72	
Predicted Loss		+		0.035		3.39 **	
Special Items		+		0.633		3.52 **	

Table 4. The effect of ambiguity on stock returns.

$CAR_{0,+1} = \alpha_0+$	$\alpha_1 Amb$	$\alpha_2 GNews+$	$\alpha_3 BNews+$	$\alpha_4 Amb + GNews$	$\alpha_5 Amb + Bnews$	$Controls+\epsilon$
Estimate 0.006	1.847	1.025	−1.625	0.431	−2.849	
t-statistic 2.38	4.82 **	3.22 **	3.01 **	2.98 **	3.51 **	
F Value of Model = 31.25		R^2 = 36.52%			Adj. R^2 = 34.08%	
Control Variables:	Predicted Sign		Coefficient		t-statistic	
Horizon	-		−0.056		2.85 **	
M/B	+		0.128		3.17 **	
Size	-		−0.214		1.98 *	
Accruals	+		1.015		3.41 **	
Reg FD	+		0.012		1.14	
Predicted Loss	-		−0.093		4.28 **	
Special Items	-		−2.755		4.52 **	

The pooled cross-section regression examines stock market response to ambiguity. The results of the regression indicate that the overall model is significant with an adjusted R-square of 0.3408. *t*-tests on the independent variables and the interaction term indicate that the coefficients are highly significant, supporting rejection of the null hypothesis of no effect. *, ** significant at 5% and 1% levels, respectively, using a two-tailed test. Untabulated results including fixed effect for industry and years are robust.

In Equation (1), α_1 measures the impact of the ambiguity on forecast errors. α_4 measures the impact of the ambiguity on the responses of forecast errors to good news. α_5 measures the impact of the ambiguity on the responses of forecast errors to bad news. The primary interests are in these three coefficients because they indicate how ambiguity affects financial analyst forecast behavior.

I predict that coefficients on *Ambiguity × Good × News* and *Ambiguity × Bad × News* are positive; that is, $\alpha_4 > 0$ and $\alpha_5 > 0$. That means analysts are more likely to bias their forecasts when it is more difficult for investors to detect their misrepresentation. In contrast, if financial analysts do not consider

the forecast environment when making forecasts or if ambiguity has no effect on analyst forecasts, the coefficients of α_4 and α_5 will be zero.

The pooled cross-section regression examines effects of ambiguity on forecast performance. The results of the regression indicate that the overall model is highly significant with an adjusted R-square of 0.3256. *t*-tests on the independent variables and the interaction term indicate that the coefficients are highly significant, supporting rejection of the null hypothesis of no effect. *, ** significant at 5% and 1% levels, respectively, using a two-tailed test. Untabulated results including fixed effect for industry and years are robust. Table 3 reports the regression results. It indicates that the overall model is highly significant with an adjusted R-square of 0.3256. *t*-tests on the independent variables and the interaction term indicate that the coefficients are highly significant, supporting rejection of the null hypothesis of no effect.

The coefficients for good news and bad news are both positive. This result is consistent with Daniel et al. (1998) and Abarbanell and Bernard (1992), which indicate that financial analysts are optimistic in general. The coefficient on ambiguity is positive. This implies that forecast errors are positively related to ambiguity. Systematically, financial analysts thus tend to make more optimistic (biased) forecasts when ambiguity exists, which support hypothesis one. The coefficients of α_4 are positive and significant. Moreover, the magnitude of α_4 is larger than that of α_2. It implies that for good news, analysts tend to make more optimistic forecasts with ambiguity than without ambiguity. Similarly, the coefficient of α_5 is positive and significantly larger than the coefficient of α_3. This suggests that under ambiguity, analysts tend to make more biased forecasts for bad news than the forecast without ambiguity. This finding supports hypothesis two. Overall, the magnitude of the bias significantly increases when ambiguity is accounted. When ambiguity appears, financial analysts tend to make more biased forecasts than in the situation when ambiguity does not exists. These results provide evidence showing that financial analysts forecast errors are to be underestimated when ignoring ambiguity.

For the control variables, horizon, size, accruals, predicted loss, and special items are significant at 1%; M/B is significant at 5%. All significant coefficients have the expected sign. In particular, horizon, size, accruals, predicted loss, and special items are positively related with analysts' forecast error while M/B and forecast error are negatively associated. Moreover, empirical results show that Reg. FD does not have significant impact on analyst forecast errors.

To investigate the stock-return responses to ambiguity, I test Hypotheses 3 and 4.

The following cross-sectional regression model is used:

$$CAR_{0,+1} = \alpha_0 + \alpha_1 Ambiguity + \alpha_2 Good \times News + \alpha_3 Bad \times News + \alpha_4 Ambiguity \times Good \times News + \alpha_5 Ambiguity \times Bad \times News + ControlVariables + \varepsilon.$$

The model's variables are defined as follows:

Event Returns: the market response to earnings forecast, denoted CARs, is the three-day accumulative abnormal returns centered on the announcement date. $CAR_i = \sum_{t=-1}^{1}(r_{it} - r_{mt})$ Where r_{it} is the return for firm i on day t, r_{mt} is the return on the CRSP Value-Weighted Market Index on day t.

Several control variables identified in previous studies are introduced to control for cross-sectional differences in response coefficients. In particular, I control for forecast horizon (Johnson et al. 2001), growth opportunities (Bamber and Cheon 1995), predicted losses (Hayn 1995), the effects of Reg FD (Heflin et al. 2003), Size (Baginski et al. 1993; Bamber and Cheon 1995), accruals (McNichols 1989; Dechow et al. 1995; Kasznik 1999) and special items (Bradshaw et al. 2003). Lastly, I include industry and year dummies to control fixed effects.

Based on Hypothesis 3, I predict that the coefficient of α_1 is positive and significant. According to Hypothesis 4, I predict that the coefficient on *Ambiguity × Good × News* is positive and the coefficient on *Ambiguity × Bad × News* is negative; that is, $\alpha_4 > 0$ and $\alpha_5 < 0$. In contrast, if the market does not consider ambiguity when responding to forecast news or if ambiguity has no effect on stock returns, then the coefficients of α_4 and α_5 will be zero.

Table 4 presents the regression results which indicate that the overall model is significant with an adjusted R-square of 0.3408. *t*-tests on the independent variables and the interaction term indicate that the coefficients are highly significant, supporting rejection of the null hypothesis of no effect.

As expected, the coefficient on ambiguity, on average, is positive and significant. It provides empirical evidence showing that investors are compensated for the ambiguity they bear. This finding confirms the role of ambiguity in determination of asset returns.

Consistent with prior studies (i.e., Ajinkya and Gift 1984; Waymire 1984), stock returns are positively associated with good news and negatively associated with bad news, that is, the coefficient of α_2 is positive and significant; the coefficient of α_3 is negative and significant. Moreover, the coefficient of α_4 is positive and significant while the magnitude is less than that of α_2. It means that the increase of stock returns to good news forecast is smaller in the situation of ambiguity. In other words, stock returns underreact to good news forecast under ambiguity. On the other hand, the magnitude of α_5 is larger than that of α_3. It shows that the decrease of stock return in response to bad news forecast is deteriorated under ambiguity. This finding suggests that stock returns overreact to bad news forecast under ambiguity. It implies that investors can identify analysts' incentive to make more biased forecasts under a situation of ambiguity. As a consequence, investors underreact to good news forecast and overreact to bad news forecast when ambiguity exists.

For the control variables, horizon, M/B, accruals, predicted loss and special items are significant at 1%; size is significant at 5%, which indicates predicting power. However, RegFD is insignificant from zero. All significant coefficients have the expected sign. In particular, horizon, size, predicted loss and special items are negatively related with stock returns; while M/B and accruals are positively related with stock returns.

6. Discussions and Conclusions

The purpose of this paper is to investigate financial analyst forecast behavior and market reactions under ambiguity. I develop a model incorporating ambiguity aversion into a two-period Lucas tree model. The resulting model shows that the impacts of ambiguity on asset pricing are significant. In particular, the model with ambiguity aversion generates lower prices and higher required rates of return compared to the classical model without ambiguity concern. It confirms the fact that by ignoring ambiguity, conventional measures of risk aversion underestimate the effect of uncertainty on asset prices. This result can be used to explain why investors appear to overreact/underreact to small probability events.

In order to provide empirical evidence of the role of ambiguity, I construct a measure of ambiguity that reflects difficulties in detecting analysts' misrepresentation. Then I examine how the "ambiguity" influences analysts' incentives to offer misleading forecasts and how investors respond to analysts' forecasts made under "ambiguity".

The primary finding is that the incentives of analysts to misrepresent their information vary with the market's ability to detect their misrepresentation. Specifically, I find that analysts' incentive to misrepresent their information is a function of ambiguity that market participants experienced in detecting analyst misrepresentation. Analysts are more likely to bias their forecasts when it is more difficult for investors to detect their misrepresentation.

Moreover, the empirical results show that stock returns are positively related to ambiguity. This confirms the theory finding that ambiguity is associated with higher rate of returns. Moreover, under ambiguity, stock returns overreact to bad news forecasts and underreact to good news forecasts. It confirms the role of ambiguity aversion in the determination of asset returns. Investors can predict and filter out some of the bias in analysts' forecasts according to the market environment. The empirical results show that under ambiguity neither good nor bad news is credible.

Previous research documented that good news is less credible than bad news. Williams (1996) uses an empirical measure of prior forecast usefulness to capture the "believability" of forecasts. She argued that bad news is more credible than good news. She finds analysts consider prior forecast usefulness

when responding to good but not bad news forecasts. Hutton et al. (2003) also argue bad news forecasts are inherently more believable than good news forecasts. This study provides evidence showing that under ambiguous situations neither good nor bad news forecast is credible. When ambiguity occurs, investors can predict some of the bias in analysts' forecasts according to market environment, and they systematically underreact to good news forecast and overreact to bad news forecast.

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